The Contribution of Foreign Migration to Local Labor Market Adjustment

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Abstract

The US suffers from large regional disparities in employment rates which have persisted for many decades. It has been argued that foreign migration offers a remedy: it "greases the wheels" of the labor market by accelerating the adjustment of local population. Remarkably, I find that new migrants account for 30 to 60 percent of the average population response to local demand shocks since 1960. However, population is not significantly more responsive in locations better supplied by new migrants: the larger foreign contribution is almost entirely offset by a reduced contribution from internal mobility. This is fundamentally a story of "crowding out": I estimate that new foreign migrants to a commuting zone crowd out existing US residents one-for-one. The magnitude of this effect is puzzling, and it may be somewhat overstated by undercoverage of migrants in the census. Nevertheless, it appears to conflict with much of the existing literature, and I attempt to explain why. Methodologically, I offer tools to identify the local impact of immigration in the context of local dynamics.

1 Introduction

The US suffers from large regional disparities in employment-population ratios (from here on, "employment rates") which have persisted for many decades (Kline and Moretti, 2013; Amior and Manning, 2018). Concern has grown about these inequities in light of the Great Recession and a secular decline in manufacturing employment (Kroft and Pope, 2014; Acemoglu et al., 2016), whose impact has been heavily concentrated geographically (Moretti, 2012; Autor, Dorn and Hanson, 2013). In principle, these disparities should

be eliminated by regional mobility, but this has itself been in secular decline in recent decades (Molloy, Smith and Wozniak, 2011; Dao, Furceri and Loungani, 2017; Kaplan and Schulhofer-Wohl, 2017).

In the face of these challenges, it has famously been argued that foreign migration offers a remedy. Borjas (2001) claims that new immigrants "grease the wheels" of the labor market: given they have already incurred the fixed cost of moving, they are very responsive to regional differences in economic opportunity - and therefore accelerate local population adjustment.[1] And in groundbreaking work on the Great Recession period, Cadena and Kovak (2016) argue further that foreign-born workers (or at least low skilled Mexicans) continue to "grease the wheels" even some years after arrival. In terms of policy, if migrants are indeed regionally flexible, forcibly dispersing them within receiving countries may actually hurt natives as well as the migrants themselves.[2] Basso, Peri and Rahman (2017) have extended the hypothesis beyond geography: they find that immigration attenuates the impact of technical change on local skill differentials.

I revisit the original question of geographical adjustment using decadal US data spanning 722 commuting zones (CZs) and 50 years - and using an empirical model which explicitly accounts for dynamic adjustment. Remarkably, I find that foreign migrants (and specifically new arrivals) account for around half of the average population response to local demand shocks. But in areas better supplied by new migrants, population growth is not significantly larger nor more responsive to these shocks. I claim that foreign migration crowds out the contribution from internal mobility that would have materialized in the counterfactual. This is not to say that natives gain little from the contribution of foreign migration. As I argue below, undercoverage of unauthorized migrants in the census may overstate the crowding out effect - and understate the foreign contribution to adjustment. And in any case, conditional on the overall level of immigration, a regionally flexible migrant workforce may save natives from incurring potentially steep moving costs themselves. As Molloy, Smith and Wozniak (2017) suggest, this may in principle shed a more positive light on the decline in regional mobility since the 1980s.

I underpin these results with a dynamic model of local labor market adjustment which builds on Amior and Manning (2018). I define local equilibrium for a given population using a competitive Rosen-Roback framework (Rosen, 1979; Roback, 1982). 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. To the extent that foreign

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[1]Borjas (1999), Card and Lewis (2007), Jaeger (2007), Kerr (2010), Cadena (2013, 2014), Basso, Peri and Rahman (2017), Beerli, Indergand and Kunz (2017) and Albert and Monras (2018) offer additional evidence that new migrants' location decisions respond strongly to local economic conditions. The idea of "greasing the wheels" is not 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]Fasani, Frattini and Minale (2018) find adverse effects of such dispersal policies on the wages of asylum seekers in Europe.

inflows are responsive to local conditions, local utility differentials will be narrower at any point in time. But this will discourage existing residents from themselves relocating over the path of adjustment. Crucially, as internal population flows become more sensitive, their contribution to local adjustment will be increasingly (and in the limit, fully) "crowded out". In other words, foreign migration will only "grease the wheels" (i.e. accelerate local population adjustment) if the wheels are not already greased.

The model yields an "error correction" specification, where decadal changes in log population depend on contemporaneous changes in log employment and the lagged log employment rate (the initial deviation from steady-state). Amior and Manning show 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). This approach already has precedent in the migration literature: Pischke and Velling (1997) control for lagged unemployment when estimating local labor market effects. 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. And new to this paper, I adjust local employment rates for demographic composition: this is to account for heterogeneous preferences for leisure, not least between natives and foreign-born individuals (see Borjas, 2016).

The model fits the data well. On average, population responds to the current employment change and lagged employment rate with elasticities of 0.75 and 0.55 respectively: i.e. large but incomplete adjustment over one decade. Remarkably, new foreign migrants (arriving within the decadal interval) account for over 30 per cent of the former effect and close to 60 per cent of the latter - despite accounting for just 4 percent of the population. Interestingly, this is partly explained by the well-documented preference of new migrants to settle in large co-patriot communities. Conveniently, these communities are disproportionately located in high-employment areas: itself a consequence of persistent local demand shocks. Nevertheless, existing US residents also make a substantial contribution to adjustment, and this is almost entirely due to natives. The latter result appears to be at odds with Cadena and Kovak (2016): at least among the low educated, they find that the local native population is inelastic. In Appendix H, I attempt to reconcile our results: once I account for local dynamics, I do identify a large native response even in their data.

To study the implications of foreign migration for overall population adjustment, I exploit variation across space and time in the supply of new migrants - building on the methodology of Cadena and Kovak (2016) and also Basso, Peri and Rahman (2017). I identify the local supply using the migrant shift-share popularized by Altonji and Card (1991) and Card (2001). This predicts the local foreign inflow by allocating new arrivals from each origin country to CZs according to the initial spatial distribution of co-patriot communities. Surprisingly, I cannot reject the hypothesis that population growth is no

larger - and responds to shocks no faster - in CZs better supplied by new migrants. The larger foreign contribution to adjustment in these areas is almost entirely offset by a reduced contribution from internal mobility - and specifically from natives. Thus, unlike Cadena and Kovak (2016), I do not find that foreign migrants smooth local employment rates: neither those of natives, nor those of the migrants themselves.

This analysis of the impact of the migrant shift-share can be seen as "reduced form": it makes no claims on the underlying mechanisms. My "structural" interpretation is that *realized* foreign inflows are crowding out internal reallocation. In the second part of the paper, I impose this interpretation more explicitly, identifying the impact of realized foreign inflows themselves - and now using the migrant shift-share as an instrument. I estimate that each new foreign arrival to a CZ crowds out one existing US resident (or more precisely, 1.1), with a standard error of just 0.13. Appendix E.4 shows the effect is entirely driven by a reduction in internal inflows rather than larger outflows, consistent with Dustmann, Schoenberg and Stuhler (2017) - and hence my preference for the "crowding out" terminology over (the more typical) "displacement". This analysis is based on CZs; but in Appendix E.5, I cannot reject one-for-one crowd-out across US states either. As Borjas, Freeman and Katz (1997) note, this result has broader methodological implications: local estimates of the impact of immigration may then understate any aggregate-level effect.

Of course, there are important threats to identifications. I do find substantial crowding out effects in each individual decade, though they disappear in some cases when I remove right hand side controls (both demand proxies and local climate). The importance of these controls is to be expected, given the limitations of the migrant shift-share instrument. In a world with persistent shocks or sluggish adjustment, it may be positively correlated with local utility (Pischke and Velling, 1997; Borjas, 1999); and to the extent that these effects are unobserved, this may bias the crowding out estimate towards zero. A related concern, raised by Jaeger, Ruist and Stuhler (2018), is strong local persistence in the instrument itself - which makes it difficult to disentangle the impact of current and historical foreign inflows. But in principle, the lagged employment rate control should account for the entire history of shocks (including past foreign inflows), and further exploration of the dynamics suggests it is performing its function well. These concerns may alternatively be addressed by exploiting well-defined natural experiments, but such experiments typically restrict analysis to specific historical episodes. In contrast, my approach allows me to study a more general setting, covering 50 years of US experience.

The magnitude of the crowding out effect is certainly puzzling. First, it is surprising that population should adjust fully to labor supply shocks within one decade, given the response to demand shocks is somewhat sluggish. And second, I find small but significant effects of foreign inflows on local employment rates[3]: despite one-for-one crowding out,

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[3]See also Smith (2012), Edo and Rapoport (2017) and Gould (forthcoming).

the evidence does not point to full adjustment. How can this be interpreted? An "excess" internal response to foreign inflows may be driven by natives' distaste for migrant enclaves, but this should put upward pressure on local employment rates - and I find the opposite. Alternatively, it may be that migrants are more productive than natives (in the sense of doing the same work for less), so local adjustment may be incomplete even under one-for-one crowd-out. And finally, the crowding effect may be overstated due to undercoverage of unauthorized migrants in the census.

Other studies have also identified substantial geographical crowd-out (e.g. Filer, 1992; Frey, 1995; 1996; Borjas, Freeman and Katz, 1997; Hatton and Tani, 2005; Borjas, 2006), though Peri and Sparber (2011) and Card and Peri (2016) have disputed Borjas' (2006) methodology. Monras (2015b) identifies a one-for-one effect following the short run surge of Mexican migrants during the Peso crisis of 1995, but he finds much less crowding out over longer horizons. In complementary work, Burstein et al. (2018) show that migrants crowd out natives from employment in migrant-intensive non-tradable jobs, but this is specifically a within-CZ effect. Dustmann, Schoenberg and Stuhler (2017) find that Czech workers who were permitted to commute across the German border in the early 1990s crowded out German residents one-for-one in local employment. The bulk of the effect (about two thirds) materializes in local non-employment rather than population, though this decomposition only relates to a three year horizon.

Still, the US literature has more typically gravitated to small negative or even positive effects on native population. See, for example, Butcher and Card (1991), Wright, Ellis and Reibel (1997), Card and DiNardo (2000), Card (2001, 2005, 2009a), Card and Lewis (2007), Cortes (2008), Boustan, Fishback and Kantor (2010), Wozniak and Murray (2012), Hong and McLaren (2015), Edo and Rapoport (2017) and Piyapromdee (2017); see Pischke and Velling (1997) for similar results for Germany, and Sanchis-Guarner (2014) for Spain; and see Peri and Sparber (2011) and Lewis and Peri (2014) for recent surveys. There are various possible theoretical explanations. One is that native-born workers are relatively immobile geographically (Cadena and Kovak, 2016). Alternatively, labor demand may adjust endogenously to foreign migration, whether through production technology or migrants' consumption: see Lewis (2011), Dustmann and Glitz (2015) and Hong and McLaren (2015). And third, migrants and natives may be imperfect substitutes in production: see Card (2009b); Manacorda, Manning and Wadsworth (2012); Ottaviano and Peri (2012). For example, Peri and Sparber (2009), D'Amuri and Peri (2014) and Foged and Peri (2016) argue that natives have a comparative advantage in communication-intensive tasks.

In the final part of the paper, I attempt to reconcile my crowding out results with the existing literature. The seminal work has typically addressed the challenge of omitted local effects by exploiting variation across skill groups *within* geographical areas (e.g. Card and DiNardo, 2000; Card, 2001, 2005; Borjas, 2006; Cortes, 2008; Monras, 2015b).

That is, they study the effect of skill-specific foreign inflows on local skill composition. But small composition effects are not necessarily inconsistent with large geographical crowd-out - for two reasons. First, these effects reflect not only differential internal mobility, but also changes in the characteristics of local birth cohorts. Indeed, I find that cohort effects have historically offset the impact of geographical crowd-out. And second, as Card (2001) and Dustmann, Schoenberg and Stuhler (2016) point out, within-area estimates do not account for the impact that new migrants exert *outside* their own skill group - the importance of which depends on elasticities of substitution. This can be seen in the sensitivity of my within-area estimates to the delineation of skill groups.

I set out my model in the following section, and Section 3 describes the data. I present estimates of the population response to local employment shocks in Section 4, but I find little evidence of local heterogeneity along the support of the migrant shift-share. This is suggestive of crowding out effects, and I test for these more explicitly in Section 5 - exploiting the shift-share as an instrument. Finally, Section 6 offers estimates which exploit variation within areas, based on a modified version of the model.

2 Model of local population adjustment

2.1 Local equilibrium conditional on population

I base my model on Amior and Manning (2018), but now distinguish between the contributions of foreign and internal migration to population adjustment. The model has two components: first, a characterization of local equilibrium conditional on population (based on the classic Rosen-Roback framework); and second, dynamic equations describing how population flows to higher-utility areas. Once I have set out the model, I derive the effect of a larger foreign supply of migrants on population adjustment. And I also show how the question can be explicitly reformulated in terms of crowding out.

To ease the exposition, I make no distinction between the labor supplied by natives and migrants in production. Of course, to the extent that they are imperfect substitutes, the model will then overstate any impact of foreign migration on native outcomes. But in line with the methodology of Beaudry, Green and Sand (2012), I do not impose any such theoretical restrictions in the empirical estimation. Instead, I use various instruments to identify the relationships described in the model, and I test the validity of the assumptions ex post. As it happens, in the data, both foreign inflows and employment shocks have remarkably similar effects on the (composition-adjusted) employment rates of natives and migrants. Together with the large crowding out effects, this suggests there may be no great loss from these assumptions in practice. In a similar spirit, I do not account for skill distinctions here, but see Appendix A.6 for an exposition which does.

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:

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

Let N_r and L_r be employment and population respectively in area r, and suppose all employed individuals earn a wage W_r. The standard Rosen-Roback model assumes labor supply is fixed, so there is no meaningful difference between employment and population. But I allow labor supply to be 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 variables denote logs, 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 (see e.g. Appendix A.4) is then sufficient to solve for all the endogenous variables in terms of population l_r alone.

I write indirect utility in area r as a function of the real consumption wage $w_r - p_r$ and local amenities a_r:

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

Crucially, the real wage can be replaced using the labor supply curve (2). And the employment rate can then serve as a sufficient statistic for local labor market conditions:

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

This result is fundamental to the analysis which follows. In practice, this interpretation of the local employment rate may be compromised by heterogeneous preferences for leisure. But as I argue in Section 3.2, this may be addressed by adjusting local employment rates for demographic composition. Another possible concern is heterogeneity in the price index: in particular, Albert and Monras (2018) argue that migrants place less weight on local (and more weight on foreign) prices. But this should not affect the validity of the sufficient statistic result.[4] Beyond this, Amior and Manning (2018) show the result is robust to numerous possible extensions: multiple traded and non-traded sectors[5], agglomeration effects, endogenous amenities and frictional labor markets.

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[4]Suppose natives and migrants face different price indices in a given area r. The labor supply functions of natives and migrants will then depend on their respective indices. And so, the real consumption wage in both natives' and migrants' indirect utility can still be replaced by the employment rate, at least after adjusting it for demographic composition.

[5]Hong and McLaren (2015) emphasize that migrants support local labor demand through consumption. Within my framework, such effects are observationally equivalent to a flatter labor demand curve.

2.2 Local dynamics

In the long run, the model is closed with a spatial arbitrage condition which imposes that v_r is invariant geographically. This determines the steady-state population l_r in each area. But I allow for dynamic adjustment to this steady-state, with population responding sluggishly to local utility differentials. And I distinguish between the contributions of internal and foreign migration to these population changes:

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

where λ_r^I is the instantaneous rate of net internal inflows (i.e. from within the US) to area r, and λ_r^F is the rate of foreign inflows, relative to local population. I do not account for emigration here, but I return to this point when discussing the data.

I assume λ_r^I and λ_r^F are increasing linearly in local utility v_r. The former is given by:

$$\lambda_r^I = \gamma^I \left(n_r - l_r - z_r^s + a_r \right) \tag{7}$$

where $\gamma^I \geq 0$ represents the speed of adjustment. I have abstracted from a national-level intercept in this expression, but one might redefine the amenity effect a_r 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 local shocks. In such an environment, it is not possible to ascribe a structural interpretation to γ^I, but this is not my intent. Turning now to foreign inflows:

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

where μ_r is the local "migrant intensity", the foreign inflow rate in the absence of local utility differentials.[6] Importantly, I permit μ_r to vary across areas r: intuitively, absorption into the US may entail fixed costs (due to job market access, language or culture), and these entry costs may be lower in some areas than others. Once migrants have entered the US (and paid any fixed costs), I assume they behave identically to natives. In practice, Appendix C shows the newest migrants do make more internal long-distance moves than natives, but the differential is eliminated within five years of entry. One might alternatively account for differential foreign inflows by incorporating migrant-specific amenities (with implications for utility), but this would complicate the exposition without adding significant insight - at least for the questions I am studying.

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[6]Notice that γ^F in (8) is the elasticity of the *flow* from abroad, while γ^I in (7) is the elasticity of the *stock* of existing local residents. But as I show in Appendix A.1, γ^I can also be expressed in terms of the elasticities of internal inflows and outflows.

Summing (7) and (8), aggregate population growth can then be written as:

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

where

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

is the (heterogeneous) aggregate population elasticity in area r.

2.3 Discrete-time specification

To estimate the population response in (9), I need a discrete-time expression. Assuming the supply effect z_r^s, amenity effect a_r and employment n_r change at a constant rate within each discrete interval, and assuming also that local migrant intensity μ_r is constant within intervals, I show in Appendix A.2 that (9) can be written as:

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

where $z_{rt}^{sa} \equiv z_{rt}^s - a_{rt}$ represents the combined supply and amenity effects at time t, μ_{rt} denotes the migrant intensity between $t-1$ and t, and γ_{rt} is the aggregate population elasticity in the same interval.

Equation (11) is an error correction model in population and employment: the change in local population Δl_{rt} depends on the change in employment Δn_{rt} and the lagged employment rate $(n_{rt-1} - l_{rt-1})$, which accounts for the initial conditions. The coefficients on both these terms are monotonically increasing in γ_{rt}, and are bounded by 0 below (as $\gamma_{rt} \to 0$) and 1 above (as $\gamma_{rt} \to \infty$). A coefficient of 1 on Δn_{rt} would indicate that population adjusts fully to contemporaneous employment shocks, and a coefficient of 1 on $(n_{rt-1} - l_{rt-1})$ that any initial steady-state deviation is fully eliminated in the subsequent period by population adjustment. Conversely, coefficients closer to zero would be indicative of sluggish adjustment.

Using (7) and (8), the discrete-time population response can then be disaggregated into foreign and internal contributions:

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

and

$$\lambda_{rt}^I = \frac{\gamma^I}{\gamma_{rt}} \left[\left(1 - \frac{1 - e^{-\gamma_{rt}}}{\gamma_{rt}} \right) \left(\Delta n_{rt} - \Delta z_{rt}^{sa} - \mu_{rt} \right) + \left(1 - e^{-\gamma_{rt}} \right) \left(n_{rt-1} - l_{rt-1} - z_{rt-1}^{sa} \right) \right] \tag{13}$$

where $\lambda_{rt}^F \equiv \int_{t-1}^t \lambda_r^F (\tau) \, d\tau$ and $\lambda_{rt}^I \equiv \int_{t-1}^t \lambda_r^I (\tau) \, d\tau$. See Appendix A.2 for derivations.

2.4 Response to migrant intensity, μ_{rt}

The supply of foreign migrants, μ_{rt}, exerts two distinct effects on local population. First, a direct effect: μ_{rt} enters the foreign inflow one-for-one in (12), though there is a compensating reduction of population growth equal to $\left(1 - \frac{1-e^{-\gamma_{rt}}}{\gamma_{rt}}\right)\mu_{rt} < \mu_{rt}$. This comes through partial crowd-out of both the foreign and internal contributions, as the larger supply of migrants puts downward pressure on the local employment rate.

But there is also an indirect effect: through changes in the aggregate population elasticity, γ_{rt}. This modifies the response of λ_{rt}^F and λ_{rt}^I to local employment shocks, and it is this mechanism which motivates the paper. To see it more clearly, it is useful to take a linear approximation around $\mu_{rt} = 0$. As I show in Appendix A.3, this yields:

$$\lambda_{rt}^F \approx \mu_{rt} + \frac{\gamma^F \mu_{rt}}{\gamma^I}\left[\left(1 - \frac{1-e^{-\gamma^I}}{\gamma^I}\right)(\Delta n_{rt} - \Delta z_{rt}^{sa}) + \left(1 - e^{-\gamma^I}\right)(n_{rt-1} - l_{rt-1} - z_{rt-1}^{sa})\right] \quad (14)$$

and

$$\begin{aligned}
\lambda_{rt}^I &\approx \left(1 - \frac{1-e^{-\gamma^I}}{\gamma^I}\right)(\Delta n_{rt} - \Delta z_{rt}^{sa} - \mu_{rt}) + \left(1 - e^{-\gamma^I}\right)(n_{t-1} - l_{t-1} - z_{rt-1}^{sa}) \\
&\quad - \frac{\gamma^F \mu_{rt}}{\gamma^I}\left(1 - 2\frac{1-e^{-\gamma^I}}{\gamma^I} + e^{-\gamma^I}\right)(\Delta n_{rt} - \Delta z_{rt}^{sa}) \\
&\quad - \frac{\gamma^F \mu_{rt}}{\gamma^I}\left(1 - e^{-\gamma^I} - \gamma^I e^{-\gamma^I}\right)(n_{rt-1} - l_{rt-1} - z_{rt-1}^{sa})
\end{aligned} \quad (15)$$

As the bracketed term of (14) shows, a larger supply of foreign migrants μ_{rt} makes foreign inflows λ_{rt}^F more responsive to local employment shocks. However, (15) shows that a larger μ_{rt} also moderates the internal response: both $\left(1 - 2\frac{1-e^{-\gamma^I}}{\gamma^I} + e^{-\gamma^I}\right)$ and $\left(1 - e^{-\gamma^I} - \gamma^I e^{-\gamma^I}\right)$ exceed zero for $\gamma^I > 0$. Intuitively, the larger foreign contribution makes the local employment rate (and therefore utility) less sensitive to employment shocks; and narrower utility differentials discourage workers from moving internally, along the path of adjustment.[7]

Summing (14) and (15) gives the (approximate) aggregate population response:

$$\begin{aligned}
\Delta l_{rt} &\approx \frac{1-e^{-\gamma^I}}{\gamma^I}\mu_{rt} + \left(1 - \frac{1-e^{-\gamma^I}}{\gamma^I}\right)(\Delta n_{rt} - \Delta z_{rt}^{sa}) + \left(1 - e^{-\gamma^I}\right)(n_{rt-1} - l_{rt-1} - z_{rt-1}^{sa}) \\
&\quad + \gamma^F \mu_{rt}\left[\frac{1}{\gamma^I}\left(\frac{1-e^{-\gamma^I}}{\gamma^I} - e^{-\gamma^I}\right)(\Delta n_{rt} - \Delta z_{rt}^{sa}) + e^{-\gamma^I}(n_{rt-1} - l_{rt-1} - z_{rt-1}^{sa})\right]
\end{aligned} \quad (16)$$

All the coefficients on the μ_{rt} terms in this equation exceed zero. In words, as migrant intensity μ_{rt} expands, population grows more (i.e. the direct effect) and becomes more responsive to local employment shocks (the indirect effect). However, crucially, the coefficients on the

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[7]There is no crowding out of the foreign response in equation (14), but this is an artificial consequence of linearizing around $\mu_{rt} = 0$.

μ_{rt} terms are also monotonically decreasing in the elasticity of the (offsetting) internal response, γ^I; and they all go to zero as $\gamma^I \to \infty$. Intuitively, foreign migration does not "grease the wheels" if the wheels are already greased.

2.5 "Semi-structural" specification for crowding out

The "direct" and "indirect" effects of μ_{rt} are both manifestations of geographical crowd-out. But this can be addressed more explicitly by asking: what is the effect of *realized* foreign inflows λ_{rt}^F on net internal inflows λ_{rt}^I? This question identifies the same crowding out effect because of the exclusion restriction embedded in (7) and (8): i.e. that μ_{rt} enters the system exclusively through λ_{rt}^F. In exploiting this restriction, this approach may be interpreted as "semi-structural"; while conversely, (14)-(16) are "reduced form" in that they collapse the impact of foreign inflows to the original μ_{rt} shock. To derive a semi-structural specification, I first write a new expression for the instantaneous change in log population (in place of (9)), but this time taking the foreign contribution λ_r^F as given:

$$dl_r = \lambda_r^F + \gamma^I \left(n_r - l_r - z_r^{sa} \right) \tag{17}$$

This defines the evolution of the local employment rate. And given this, as I show in Appendix A.5, I can derive the discrete-time internal contribution λ_{rt}^I:

$$\lambda_{rt}^I = \left(1 - \frac{1 - e^{-\gamma^I}}{\gamma^I} \right) \left(\Delta n_{rt} - \lambda_{rt}^F - \Delta z_{rt}^{sa} \right) + \left(1 - e^{-\gamma^I} \right) \left(n_{rt-1} - l_{rt-1} - z_{rt-1}^{sa} \right) \tag{18}$$

In contrast to (15), migrant intensity μ_{rt} does not appear: its effect is fully summarized by λ_{rt}^F. Given the initial conditions (encapsulated by the lagged employment rate and z_{rt-1}^{sa}), the effect of λ_{rt}^F expands monotonically from 0 to -1, as the internal response becomes perfectly 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 the pure mobility response to an equal change in local utility, as summarized by the local employment rate.

However, the coefficient on λ_{rt}^F in (18) is not a "true" crowding out effect: it conditions on employment growth Δn_{rt}, which may itself be an important margin of adjustment. To derive an "unconditional" effect, it is necessary to reduce Δn_{rt} to its exogenous components. This requires a specification of the housing market, as local prices shift labor supply (2) but not demand (3). Assuming individuals spend a fixed share of their income on housing (i.e. Cobb-Douglas utility) and abstracting from non-labor income, Appendix A.4 shows that changes in local prices p_r can be specified as:

$$\Delta \left(p_{rt} - p_t \right) = \frac{1}{\kappa} \left[\frac{1}{\epsilon^s} \left(\Delta n_{rt} - \Delta l_{rt} - \Delta z_{rt}^s \right) + \Delta n_{rt} \right] \tag{19}$$

where $\kappa > 0$ and goes to infinity with the elasticity of housing supply.[8] In Appendix A.5, I then show that eliminating Δn_{rt} from (18) and replacing z_r^{sa} with $z_r^s - a_r$ (the individual labor supply and amenity effects) yields:

$$\lambda_{rt}^I = \frac{\left(\frac{\gamma^I}{1-e^{-\gamma^I}} - 1\right)\eta}{1 + \left(\frac{\gamma^I}{1-e^{-\gamma^I}} - 1\right)\eta} \left(\frac{\kappa}{\kappa + \epsilon^d}\Delta z_{rt}^d - \lambda_{rt}^F - \Delta z_{rt}^s + \frac{1}{\eta}\Delta a_{rt}\right) \tag{20}$$
$$+ \frac{\gamma^I}{1 + \left(\frac{\gamma^I}{1-e^{-\gamma^I}} - 1\right)\eta} \left(n_{rt-1} - l_{rt-1} - z_{rt-1}^s + a_{rt-1}\right)$$

where

$$\eta \equiv \left(1 + \frac{\kappa+1}{\kappa + \epsilon^d} \cdot \frac{\epsilon^d}{\epsilon^s}\right)^{-1} < 1 \tag{21}$$

As before, the crowding out effect of λ_{rt}^F goes to -1 as internal flows become perfectly elastic ($\gamma^I \to \infty$). But given I am no longer conditioning on current employment, the impact of λ_{rt}^F is now moderated by an expansion of local labor demand - and potentially also of housing supply. To see this, notice the effect of λ_{rt}^F in (20) is identical to (18) for $\eta = 1$, and it becomes smaller as η declines. Looking at (21), as the elasticity of labor demand ϵ^d grows relative to the supply elasticity ϵ^s, η converges to zero: in the limit, adjustment is fully manifested in changes in local employment rather than population (i.e. no crowding out). The effect of the housing supply elasticity (represented by κ), though, is theoretically ambiguous.[9]

To the extent that crowding out is incomplete (i.e. less than one-for-one), the model predicts that foreign inflows should reduce the local employment rate. This offers another overidentifying restriction which I test below. As I show in Appendix A.5:

$$\Delta\left(n_{rt} - l_{rt} - z_{rt}^s\right) = \frac{\eta}{1 + \left(\frac{\gamma^I}{1-e^{-\gamma^I}} - 1\right)\eta} \left[\frac{\kappa}{\kappa + \epsilon^d}\Delta z_{rt}^d - \lambda_{rt}^F - \Delta z_{rt}^s - \left(\frac{\gamma^I}{1-e^{-\gamma^I}} - 1\right)\Delta a_{rt}\right]$$
$$- \frac{\gamma^I\eta}{1 + \left(\frac{\gamma^I}{1-e^{-\gamma^I}} - 1\right)\eta} \left(n_{rt-1} - l_{rt-1} - z_{rt-1}^s + a_{rt-1}\right) \tag{22}$$

Notice the impact of foreign inflows λ_{rt}^F goes to zero as γ^I increases.

Finally, crowding out in the model is driven entirely by the labor market impact of immigration. 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 rather than the labor market. Having said that, this should not necessarily trigger sorting across CZs:

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[8]Specifically, $\kappa \equiv \frac{1-\nu+\epsilon_r^{hs}}{\nu}$, where ν is the (fixed) share of income spent on housing, and ϵ_r^{hs} is the housing supply elasticity.

[9]η (and therefore the crowding out effect) are decreasing in κ (and hence in the elasticity of housing supply) if and only if $\varepsilon^d > 1$. This condition ensures that the local wage bill (and therefore housing demand) expands in the face of foreign inflows.

natives can also escape migrant communities by switching neighborhoods within CZs (see e.g. Saiz and Wachter, 2011, on neighborhood segregation). In the context of the crowding out equations (18) and (20), a disamenity effect is observationally equivalent to a negative correlation between the foreign inflow λ_{rt}^F and the amenity change Δa_{rt}. Interestingly, given the negative coefficient on Δa_{rt} in (22), this would imply a less negative (or even positive) effect of foreign inflows on the local employment rate - as native flight would tighten the labor market. I exploit this prediction below.

3 Data

3.1 Population

I use decadal census data on individuals aged 16-64 across 722 Commuting Zones (CZs) in the Continental US over 1960-2010.[10] The model disaggregates the change in log local population Δl_{rt} into contributions from foreign and internal migration, i.e. λ_{rt}^F and λ_{rt}^I. However, since I only observe population at discrete intervals, I cannot precisely identify λ_{rt}^F and λ_{rt}^I in the data - though I can offer an approximation. Let L_{rt}^F be the foreign-born population in area r and time t who arrived in the US in the previous ten years (i.e. since $t-1$). The total population change ΔL_{rt} may then be disaggregated into L_{rt}^F and a residual, $\Delta L_{rt} - L_{rt}^F$. And the log change can be written as:

$$\Delta l_{rt} \equiv \log\left(\frac{L_{rt}}{L_{rt-1}}\right) \equiv \log\left(\frac{L_{rt-1} + L_{rt}^F}{L_{rt-1}}\right) + \log\left(\frac{L_{rt} - L_{rt}^F}{L_{rt-1}}\right) - \log\left(1 + \frac{L_{rt}^F}{L_{rt}} \cdot \frac{\Delta L_{rt} - L_{rt}^F}{L_{rt-1}}\right) \tag{23}$$

Given this, I approximate λ_{rt}^F and λ_{rt}^I with $\hat{\lambda}_{rt}^F$ and $\hat{\lambda}_{rt}^I$ respectively, where:

$$\hat{\lambda}_{rt}^F \equiv \log\left(\frac{L_{rt-1} + L_{rt}^F}{L_{rt-1}}\right) \tag{24}$$

$$\hat{\lambda}_{rt}^I \equiv \log\left(\frac{L_{rt} - L_{rt}^F}{L_{rt-1}}\right) \tag{25}$$

which leaves the final term of (23) 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 (24)

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[10]CZs were originally developed as an approximation to local labor markets by Tolbert and Sizer (1996), based on county groups, and recently popularized by Autor and Dorn (2013) and Autor, Dorn and Hanson (2013). Where possible, I base my data on published county-level aggregates from the US census, extracted from the National Historical Geographic Information System (Manson et al., 2017). Where necessary, I supplement this with information from microdata census extracts and (for the 2010 cross-section) American Community Survey samples of 2009-11, taken from the Integrated Public Use Microdata Series (Ruggles et al., 2017). This follows the approach of Amior and Manning (2018); see Appendix B.1 for further details on data construction. I begin the analysis in 1960 because of data limitations: I do not observe migrants' year of arrival in 1960, so I cannot identify the contribution of new foreign migrants to local population in the 1950s.

and (25) 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 covers 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 presumably more relevant for the foreign-born (consider e.g. return migration), so it is useful to additionally study the component of $\hat{\lambda}_{rt}^I$ which is driven by natives alone:

$$\hat{\lambda}_{rt}^{I,N} \equiv \log \left(\frac{L_{rt-1} + \Delta L_{rt}^N}{L_{rt-1}} \right) \tag{26}$$

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

An important concern in constructing $\hat{\lambda}_{rt}^F$ is undercoverage of unauthorized migrants in the data. Surprisingly perhaps, many unauthorized migrants do respond to the census (Warren and Passel, 1987), but a significant fraction do not. The US Department of Homeland Security (2003) estimates that almost half the migrants who entered the US in the 1990s did not have legal status, and that the census understated the total 1990s foreign inflow by about 7 percent. The undercount was more severe in earlier years: see Card and Lewis (2007). For example, Marcelli and Ong (2002) find that 10-15 percent of unauthorized Mexicans were missed by the 2000 census; Van Hook and Bean (1998) estimate that 30 percent were missed in 1990; and Borjas, Freeman and Lang (1991) estimate an undercount of 40 percent in 1980. Any such undercoverage will cause me to underestimate the true foreign contribution to local labor market adjustment, and also to overstate the extent of geographical crowd-out.

3.2 Employment

One contribution of this paper beyond Amior and Manning (2018) is to adjust the employment variables for local demographics. I have shown above how the employment rate can serve as a sufficient statistic for local economic opportunity. But if different worker types have different propensities to work (for given labor prices), the employment rate will be conflated with variation in local demographic composition. Though the model does not explicitly account for such heterogeneity, these compositional effects may be represented by variation in the local supply shifter z_r^s. This variation is not a problem if the instruments (Bartik shift-shares) can exclude it. But the exclusion restriction will be violated if demographic groups with higher employment rates (such as the high educated or foreign-born men[11]) also differ systematically in geographical mobility.

My strategy is to construct an employment rate variable, denoted $\tilde{ER}_{rt}$, which adjusts for local demographic composition. To this end, I run probit regressions of employment

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[11]See Borjas (2016) on the latter.

on a detailed range of individual characteristics[12] and a set of location fixed effects, separately for each census cross-section. I then compute $\tilde{ER}_{rt}$ by taking the mean predicted employment rate in each area r for a distribution of local demographic characteristics identical to the full national sample:

$$\tilde{ER}_{rt} = \int_i \Omega \left(X_{it}\hat{\theta}_t + \hat{\theta}_{rt} \right) g\left(X_{it} \right) di \tag{27}$$

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} at time t.

What are the implications for the estimating equation? Notice the log of the composition-adjusted rate (at some unspecified time) can be written as:

$$\log \tilde{ER}_r \equiv n_r - l_r - \tilde{z}_r^s \tag{28}$$

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

$$\tilde{n}_r \equiv n_r - \tilde{z}_r^s \equiv \log \tilde{ER}_r + l_r \tag{29}$$

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

$$dl_r = \mu_r + \gamma_r \left[\tilde{n}_r - l_r - (z_r^s - \tilde{z}_r^s) + a_r \right] \tag{30}$$

where $(z_r^s - \tilde{z}_r^s)$ is the residual component of the local supply shifter (which cannot be attributed to local composition). In discrete time, by symmetry with (11), local population changes Δl_{rt} will then depend on (i) the current change in the composition-adjusted employment level, $\Delta \tilde{n}_{rt} \equiv \Delta \log \tilde{ER}_{rt} + \Delta l_{rt}$, and (ii) the lagged log composition-adjusted rate $(\tilde{n}_{rt-1} - l_{rt-1}) \equiv \log \tilde{ER}_{rt-1}$. The identifying conditions are now weaker: conditional on the right hand side controls, the Bartik instruments need only exclude the *residual* supply effect $(z_r^s - \tilde{z}_r^s)$ and any unobserved amenities in a_r.

3.3 Shift-share instruments

I identify changes in local demand using the pervasive Bartik (1991) industry shift-share, which I denote b_{rt}. The intention is to exclude unobserved supply and amenity effects in z_r^s and a_r. The Bartik predicts local employment growth, conditional on initial industrial composition, by assuming employment in each industry i grows at the average rate

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[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 migrants, together with a rich set of interactions. See Appendix B.2.

elsewhere in the country:

$$b_{rt} = \sum_i \phi^i_{rt-1} \Delta n_{i(-r)t} \tag{31}$$

where ϕ^i_{rt-1} is the share of workers in area r at time $t-1$ employed in a 2-digit industry i; and $\Delta n_{i(-r)t}$ is the change in log employment nationally in industry i, excluding area r.[13] I instrument the current employment growth $\Delta \tilde{n}_{rt}$ and the lagged employment rate $(\tilde{n}_{rt-1} - l_{rt-1})$ using the current and lagged Bartiks (b_{rt} and b_{rt-1}) respectively. In principle, the lagged employment rate will depend on a distributed lag of historical shocks, but I find the first lag alone has sufficient power for the first stage.

Similarly, I proxy local migrant intensity μ_{rt} with a migrant shift-share, popularized by Altonji and Card (1991) and Card (2001). New migrants are known to cluster around established co-patriot communities, whether because of family ties, job networks (Munshi, 2003) or cultural amenities (Gonzalez, 1998). The shift-share predicts the supply of new migrants to each area r by allocating new arrivals proportionately to the size of these communities. To express this predicted supply (which I denote $\hat{\mu}_{rt}$) in terms of its contribution to the *log* population change Δl_{rt}, I use an identical functional form to (24):

$$\hat{\mu}_{rt} = \log\left(\frac{L_{t-1} + \sum_o \phi^o_{rt-1} L^F_{o(-r)t}}{L_{rt-1}}\right) \tag{32}$$

where $\sum_o \phi^o_{rt-1} L^F_{o(-r)t}$ is the predicted number of new arrivals: ϕ^o_{rt-1} is the share of origin country o migrants who live 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. This is expressed relative to the initial aggregate local population, L_{rt-1}. In the "semi-structural" specification (20), $\hat{\mu}_{rt}$ serves as an instrument for foreign inflows $\hat{\lambda}^F_{rt}$: it should in principle exclude unobserved components of z^s_r, a_r and also demand shocks z^d_r.

I construct both the Bartik and migrant shift-shares using census and American Community Survey (ACS) microdata: see Appendix B.3 for further details.

3.4 Amenity controls

I control for a range of observable amenity effects in my empirical specifications, identical to those in Amior and Manning (2018). These consist of (i) a binary indicator for the presence of coastline[14] (ocean or Great Lakes); (ii) climate indicators, specifically maximum January temperature, maximum July temperature and mean July relative humidity (Rappaport, 2007, shows that Americans have been moving to places with more pleasant weather); (iii) log population density in 1900; and (iv) an index of CZ isolation, specifically the log distance to the closest CZ, where distance is measured between

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[13]This exclusion, recommended by Goldsmith-Pinkham, Sorkin and Swift (2018), was proposed by Autor and Duggan (2003) to address concerns about endogeneity to local supply shocks.

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

population-weighted centroids in 1990. Because the impact of some of these might vary over time (see Rappaport and Sachs, 2003; Rappaport, 2007), I interact each of them with a full set of year effects in the regressions below.

I do not control for time-varying amenities which may be endogenous to labor market conditions, such as crime and local restaurants, since these present challenges for identification. This means the estimated coefficients on the employment shocks should be interpreted as "reduced form" effects, accounting for both their direct (labor market) effect on population and any indirect effects driven by changes in local amenity values (see Diamond, 2016).

4 Population response to local employment shocks

4.1 Average contribution of foreign migration

I begin by studying the average contribution of foreign migration to local population adjustment, initially abstracting away from heterogeneity in the local migrant intensity μ_{rt}. In line with equation (11), I implement the following error correction model:

$$\Delta l_{rt} = \beta_0 + \beta_1 \Delta \tilde{n}_{rt} + \beta_2 \left(\tilde{n}_{rt-1} - l_{rt-1} \right) + A_{rt} \beta_A + \varepsilon_{rt} \tag{33}$$

where t denotes time periods at decadal intervals, and Δ is a decadal change. I regress the change in log population Δl_{rt} on the the change in log (composition-adjusted) employment $\Delta \tilde{n}_{rt}$ and the lagged (composition-adjusted) employment rate $(\tilde{n}_{rt-1} - l_{rt-1})$, i.e. the initial deviation from steady-state. The vector A_{rt} contains observable components (amenity effects) from the Δz_{rt}^{sa} and z_{rt-1}^{sa} terms in (11), as well as a full set of time effects. The error ε_{rt} includes any unobserved supply or amenity effects. All observations are weighted by the lagged local population share, and standard errors are clustered by state.[15] It should be emphasized that (33) is misspecified, in the sense that it neglects the dependence of the β parameters on local migrant intensity.

[Tables 1 and 2 here]

I set out estimates of β_1 and β_2 in Panel A of Table 1. The OLS responses of the aggregate population Δl_{rt} are 0.86 and 0.25 respectively (column 1). These cannot be interpreted causally: unobserved supply shocks will bias OLS estimates of β_1 upwards; and β_2 estimates may be biased downwards if these shocks are persistent. For example, a positive supply shock should raise local population growth but reduce the employment

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[15]In line with Autor, Dorn and Hanson (2013), CZs which straddle state lines are allocated to the state which accounts for the largest population share. This leaves me with 48 states: Alaska and Hawaii are excluded from the sample, and the Washington CZ is allocated to Maryland.

rate. To address these concerns, I instrument the two endogenous variables with the current and lagged Bartiks. I set out the first stage estimates in columns 1-2 of Table 2. I have marked in bold where one should theoretically expect positive effects. As one might hope, the current Bartik accounts for the entire effect on $\Delta \tilde{n}_{rt}$, and the lagged Bartik for the effect on $(\tilde{n}_{rt-1} - l_{rt-1})$, with large associated Sanderson-Windmeijer (2016) F-statistics (which account for multiple endogenous variables). The IV estimates of β_1 and β_2 in column 5 are 0.75 and 0.55 respectively (and the associated standard errors are small), so the OLS bias is in the expected direction. These numbers indicate large but incomplete population adjustment over one decade to contemporaneous employment shocks and initial conditions. Interestingly, they are somewhat larger than estimates based on raw (i.e. non-adjusted) employment variables: see Appendix D.1.[16]

Columns 2 and 6 replace the dependent variable with the approximate foreign contribution $\hat{\lambda}_{rt}^F$ (as defined in Section 3.1), and columns 3 and 7 with the residual contribution $\hat{\lambda}_{rt}^I$. The approximation appears reasonable: for IV, the β_1 estimates in columns 6 and 7 sum to 0.76, and the β_2 estimates to 0.58 - very close to the column 5 estimates. Again looking at IV, new migrants account for 32 percent of the overall population response to contemporaneous shocks (β_1), and remarkably, 57 percent of the response to the lagged employment rate (β_2) - despite accounting for just 4 percent of the population on average.[17] To the extent that new migrants are under-reported in the census, the true contribution may be even larger. The numbers are much smaller for OLS however: 6 and 36 percent respectively. I also report the contribution of natives alone, i.e. $\hat{\lambda}_{rt}^{I,N}$ from (26). The IV estimates are very similar to column 7, which suggests old migrants (i.e. those already living in the US in $t-1$) contribute little to the response to employment shocks: it appears emigration does not play an important role.

In Panel B, I control additionally for the local migrant shift-share $\hat{\mu}_{rt}$ (which proxies for migrant intensity), as defined in (32). There are two key messages here. First, the inclusion of $\hat{\mu}_{rt}$ wipes away about half the foreign response to local employment shocks (column 6). Thus, the large contribution of new migrants to local adjustment is partly explained by their preference to settle in co-patriot communities - which happen to be disproportionately located in high-employment areas. This should come as no surprise: the coincidence of migrant enclaves with high employment is a natural consequence of the persistence of local demand shocks.

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[16]Appendix D.1 places these at 0.63 and 0.39 for β_1 and β_2 respectively. The difference is intuitive. For example, the college educated population is known to respond more strongly (see e.g. Amior and Manning, 2018), but these individuals also have higher employment rates. As a result, the raw change in total employment (the right hand side variable) should exceed the change for individuals of fixed characteristics - so estimates based on raw employment should understate the population response.

[17]As one might expect, the average foreign contribution is smaller once I omit population weights (see Appendix D.3): this is because new migrants typically cluster in larger CZs. This speaks to the misspecification of (33): it does not account for local heterogeneity. In Appendix D.4, I break down the foreign contribution by country or region of origin, but the response is not dominated by particular origins.

On the other hand, the overall population response is unaffected (column 5): holding $\hat{\mu}_{rt}$ fixed, the now smaller foreign contribution to adjustment is offset by a larger residual contribution (column 7). This speaks to the "indirect" effect of migrant intensity μ_{rt} (on the response to local shocks) discussed above, and I address this more explicitly in what follows. Notice also that $\hat{\mu}_{rt}$ elicits a clear "direct" effect: a one-for-one increase in the foreign contribution (column 6), offset by a similar decline in the residual (column 7).

4.2   Local heterogeneity

Exploiting variation in the migrant shift-share $\hat{\mu}_{rt}$ across space and time, I now study heterogeneity in the local population response. In line with (16), I estimate:

$$
\begin{aligned}
\Delta l_{rt} &= \beta_0^c + \beta_1^c \Delta \tilde{n}_{rt} + \beta_2^c \left(\tilde{n}_{rt-1} - l_{rt-1} \right) + A_{rt} \beta_A^c \\
&\quad + \left[\beta_{0\mu}^c + \beta_{1\mu}^c \Delta \tilde{n}_{rt} + \beta_{2\mu}^c \left(\tilde{n}_{rt-1} - l_{rt-1} \right) + A_{rt} \beta_{A\mu}^c \right] \hat{\mu}_{rt} + \varepsilon_{rt}
\end{aligned}
\tag{34}
$$

where $\hat{\mu}_{rt}$ is now interacted with the change in log employment $\Delta \tilde{n}_{rt}$, the lagged employment rate $(\tilde{n}_{rt-1} - l_{rt-1})$ and the amenity effects in A_{rt}. I have introduced two new endogenous variables, so I need two additional instruments: I use interactions between migrant intensity $\hat{\mu}_{rt}$ and the current and lagged Bartiks. The first stage estimates are reported in columns 5-8 of Table 2. Each instrument has a strong positive effect (with a small standard error) on its corresponding endogenous variable - as marked in bold.

[Table 3 here]

Table 3 reports OLS and IV estimates of (34). It is useful to begin with columns 2 and 6, where I replace the dependent variable with the foreign contribution $\hat{\lambda}_{rt}^F$. Consistent with (14) in the model, the interactions pick up the entire effect of employment shocks: i.e. employment growth attracts no foreign inflows in CZs with $\hat{\mu}_{rt} = 0$. In OLS, the responses to both $\Delta \tilde{n}_{rt}$ and $(\tilde{n}_{rt-1} - l_{rt-1})$ increase to about 0.2 at $\hat{\mu}_{rt} = 0.1$, which is the 98th percentile of $\hat{\mu}_{rt}$ (the maximum value is 0.29: the distribution is heavily skewed). And in IV, they increase to a remarkable 0.49 and 0.74 respectively at $\hat{\mu}_{rt} = 0.1$.

As the model predicts, these larger foreign contributions are offset by reduced residual contributions. The story is mixed in OLS, but the patterns are much starker for IV: in areas better supplied by new migrants, aggregate population growth is not significantly larger nor more responsive to employment shocks (column 5). This entails a substantial reduction in the residual contribution (column 7): moving from $\hat{\mu}_{rt} = 0$ to $\hat{\mu}_{rt} = 0.1$, it declines from 0.81 to 0.28 for the $\Delta \tilde{n}_{rt}$ response, and from 0.60 to -0.06 for $(\tilde{n}_{rt-1} - l_{rt-1})$. And at least for IV, the residual contribution also fully offsets the "direct" effect of $\hat{\mu}_{rt}$ (i.e. independent of the employment shocks) on local population. Having said that, it is worth stressing that the estimates do also admit the possibility of incomplete crowding

out: the standard errors on the offsetting residual response (column 7) are close to half the magnitude of the $\beta_{0\mu}^c$ and $\beta_{2\mu}^c$ coefficients (though it is smaller for $\beta_{1\mu}^c$).

Columns 4 and 8 report the contribution of natives alone. The interaction effects in all specifications exceed those in columns 3 and 7, implying that old migrants amplify the contribution of new migrants to adjustment - while natives account for the entire crowding out effect. The impact of old migrants is intuitive: they disproportionately reside in areas with large migrant shift-shares $\hat{\mu}_{rt}$, so they should mechanically contribute more to population adjustment in these places.

Appendix D subjects the IV estimates in Tables 1 and 3 to a range of robustness tests. First, in an effort to account for unobserved time-invariant amenity or supply effects, I control for CZ fixed effects (which pick up local population trends). This is a demanding test in such a short panel, but the crowding out patterns are unaffected. They are also robust to dropping the dynamic term (the lagged employment rate) and using raw (instead of composition-adjusted) employment variables. This latter result should be reassuring: since adjusting local employment for observable characteristics makes little difference to the results, one may be less concerned about the influence of unobservables. Omitting the amenity-$\hat{\mu}_{rt}$ interacted controls makes little difference to the coefficients, but the standard errors do become much larger. One may be concerned that the crowding out effects are driven by outliers with very large $\hat{\mu}_{rt}$ (given the skew in this variable), but dropping observations with $\hat{\mu}_{rt} > 0.1$ makes little difference. And finally, for CZs whose population exceeded 50,000 in 1960, the crowding out result is also robust to removing the population weights.

4.3 Evolution of local employment rates

Importantly, the model treats natives and migrants as perfect substitutes. The large crowding out effects indicated by Table 3 suggest there may be no great loss from this assumption - at least at the aggregate level. Nevertheless, one may be concerned that the local demand shocks (and the population responses to these shocks) affect natives and migrants differently. As it happens though, I find no significant difference in the effect on their respective employment rates.

[Table 4 here]

In Table 4, I re-estimate (33) and (34) using the same instruments as before, but replacing the dependent variable with changes in log (composition-adjusted) employment rates: 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 3.2, but

with the sample restricted to natives or migrants.[18] Notice the column 1 estimates are merely transformations of those in column 5 of Table 1: the coefficient on the employment change is equal to $1 - \beta_1$ in (33), while the coefficient on the lagged employment rate is simply $-\beta_2$. In words, a larger population response to an employment shock implies a smaller employment rate effect. But importantly, the responses of the native and migrant employment rates in columns 2 and 3 are similar in magnitude.

Columns 4-6 account additionally for local heterogeneity, in line with (34). This specification is comparable to Cadena and Kovak's (2016) tests for the "employment smoothing" effects of Mexican enclaves. Again, the coefficients in column 4 are merely transformations of those in column 5 of Table 3. The insignificant effects of the interactions suggest that foreign migration does not smooth local fluctuations in employment rates. And the same applies to the native and migrant employment rates individually.

5 "Semi-structural" estimates of crowding out

5.1 Estimates of crowding out

The analysis above offers a "reduced form" perspective on the impact of local migrant intensity μ_{rt}. The results suggest it has no significant effect on the evolution of local population or employment rates. The natural interpretation is that new migrants crowd out the contribution of internal mobility to local population growth - both directly and in the response to local employment shocks. But this crowding out effect can be tested more explicitly using a "semi-structural" specification, imposing that the entire effect of $\hat{\mu}_{rt}$ in Table 3 comes through *realized* foreign inflows. The question then becomes: for a given foreign inflow, what is the net outflow? A key advantage of this approach is a much less demanding empirical specification than (34) (with its four endogenous variables), and this should allow for greater precision in the estimates. In line with equation (20) in the model, I estimate the following specification:

$$\hat{\lambda}_{rt}^I = \delta_0 + \delta_1 \hat{\lambda}_{rt}^F + \delta_2 \left(\tilde{n}_{rt-1} - l_{rt-1} \right) + \delta_3 b_{rt} + A_{rt} \delta_A + \varepsilon_{rt} \tag{35}$$

where $\hat{\lambda}_{rt}^I$ and $\hat{\lambda}_{rt}^F$ are the approximate residual and foreign contributions, and the crowding out effect is given by δ_1. The lagged employment rate is in principle a sufficient statistic for all historical labor demand and supply shocks, including past foreign inflows. I instrument the current foreign inflow $\hat{\lambda}_{rt}^F$ with the migrant shift-share $\hat{\mu}_{rt}$, and the lagged employment rate with the lagged Bartik b_{rt-1}. I include the current Bartik b_{rt} as a control to proxy for contemporaneous demand shocks, Δz_r^d. Any unobserved components of

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[18]11 small CZs in the 1960s are omitted from the migrant employment rate regressions. These CZs do not offer a sufficient migrant sample in the microdata to deliver fixed effect estimates in the probit regression, preventing me from computing composition-adjusted employment rates.

supply or demand shocks are contained in the residual ε_{rt}. Since I am not conditioning on the contemporaneous change in employment, δ_1 will depend not only on the speed of internal population adjustment but also on the elasticities of labor demand, labor supply and housing supply: see equation (20).

I present estimates of (35) and various deviations in columns 1-6 of Table 5 (I return to columns 7-8 in Section 5.2). The broad message is a substantial crowding out effect, consistent with the results in the previous section. Column 1 offers OLS estimates, with δ_1 taking a value of -0.76. That is, a foreign inflow which contributes 1 log point to local population is associated with a net outflow (of natives or earlier migrants) which removes 0.76 points. However, omitted local shocks (which influence foreign inflows) make it difficult to interpret the OLS estimates.

[Tables 5 and 6 here]

Column 2 reports IV estimates of (35), using the migrant shift-share $\hat{\mu}_{rt}$ and lagged Bartik b_{rt-1} as instruments. The associated first stage regressions have substantial power (see columns 1 and 4 of Table 6), with the right instruments explaining the right endogenous variables (as marked in bold). The IV estimate is larger than OLS, with δ_1 reaching -1.1: i.e. exceeding (though insignificantly different from) one-for-one crowd-out. This effect is precisely estimated, with a standard error of 0.13. The fact that IV exceeds OLS is consistent with the traditional concern of unobserved demand shocks (e.g. Altonji and Card, 1991).

One important concern is that $\hat{\lambda}_{rt}^F$ may be picking up the response to both current and historical foreign inflows (in a world with sluggish adjustment), given the tight local persistence in these inflows and in the migrant shift-share instrument $\hat{\mu}_{rt}$ (Jaeger, Ruist and Stuhler, 2018). For example, the correlation between the time-demeaned $\hat{\mu}_{rt}$ and its lag is 81 percent.[19] In principle, the lagged employment rate should summarize the impact of all historical shocks (including foreign inflows), and $\hat{\lambda}_{rt}^I$ does respond strongly to this variable. To test whether this "sufficient statistic" is performing its function effectively, I now control for the lagged migrant shift-share $\hat{\mu}_{rt-1}$ (following Jaeger, Ruist and Stuhler). As column 5 of Table 6 shows, $\hat{\mu}_{rt-1}$ does adversely affect the lagged employment rate in the first stage. But reassuringly, it has no effect conditional on the lagged employment rate in the *second* stage (column 3 of Table 5). In contrast, when I drop the lagged employment rate in column 4 (and replace it with its lagged Bartik instrument), $\hat{\mu}_{rt-1}$ picks up much of the negative effect. Notice also that the crowding out effect in column 4 is somewhat dented: δ_1 falls from -1.1 to -0.79. One intuition is the following: the lagged employment rate in column 3 accounts additionally for the impact of unobserved *demand* shocks, which are positively correlated with the supply of new migrants.

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[19]This reflects a combination of stickiness in local migrant settlement patterns and national-level persistence of foreign inflows by country of origin.

In recent work, Peri (2016) has emphasized the importance of checking for pre-trends when identifying the local impact of immigration. The simplest approach is to replace the dependent variable (the residual contribution, $\hat{\lambda}^I_{rt}$) with its lag. I necessarily lose one decade of data (the 1960s), but this does not seem to matter: compare columns 4 and 5. In column 6, the lagged $\hat{\lambda}^I_{rt-1}$ is fully explained by the *lagged* migrant shift-share $\hat{\mu}_{rt-1}$ 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 am able to empirically disentangle current from historical shocks in this data.

But serial correlation in the enclave instrument $\hat{\mu}_{rt}$ is by no means the only concern. In a world with persistent shocks or sluggish adjustment, any omitted variation which raises local utility (whether supply or demand-driven) is liable to correlate positively with $\hat{\mu}_{rt}$ (Pischke and Velling, 1997; Borjas, 1999). This is a natural consequence of the large foreign contribution to local adjustment (documented in Table 1), which over time expands migrant population shares in high-utility areas. As Goldsmith-Pinkham, Sorkin and Swift (2018) emphasize, it is endogeneity of these shares which threatens the validity of shift-share instruments. To the extent this variation is unobserved, this may bias the δ_1 estimate towards zero - if it simultaneously attracts inflows of new migrants and existing US residents.

In this environment, right-hand side controls take on a crucial role. In Table 7, I study the sensitivity of my basic IV estimate of δ_1 (in column 2 in Table 5) to the choice of controls and also decadal sample. Without any controls, the estimates vary substantially over time: there is little crowd-out before 1990, but much more thereafter. Card (2009a) finds something similar, and see also Borjas, Freeman and Katz (1997) on the instability of spatial correlations: this 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 current Bartik and lagged employment rate (column 6). And once I include the various amenity effects (and climate in particular), I cannot statistically reject a δ_1 of at least -1 in any decade. Interestingly, after including all the controls, δ_1 is now much larger in the 1960s and 1970s than later decades - which may reflect more severe undercoverage of unauthorized migrants in those years. I return to this question below.

[Table 7 here]

The final column of Table 7 shows about two thirds of the δ_1 effect is driven by natives rather than old migrants. But this result overlooks some important heterogeneity: exceptionally, in the 2000s, old migrants account for the entire crowding out effect (see Appendix E.3). This is despite my finding of a strong native population response to demand shocks in the same decade (Appendix H). The discrepancy may be driven by substantial return migration of Mexicans in the 2000s: see Hanson, Liu and McIntosh (2017).

Appendix E shows the crowding out effect is robust to dropping population weights and various other specification changes. My specification of the foreign and residual contributions is almost identical to that of Card and DiNardo (2000) and Card (2001), as recommended by Peri and Sparber (2011) and Card and Peri (2016). While they regress $\frac{\Delta L_{rt} - L_{rt}^F}{L_{rt-1}}$ on $\frac{L_{rt}^F}{L_{rt-1}}$, I am regressing $\log\left(\frac{L_{rt} - L_{rt}^F}{L_{rt-1}}\right)$ on $\log\left(\frac{L_{rt-1} + L_{rt}^F}{L_{rt-1}}\right)$, following the guidance of my model.[20] The appendix shows this change has a negligible effect on the δ_1 estimate. I also offer estimates based on an alternative approach recommended by Wozniak and Murray (2012), which specifies the key variables in levels, i.e. regressing $\left(\Delta L_{rt} - L_{rt}^F\right)$ on L_{rt}^F, without normalizing by initial population. Additionally, I cannot reject one-for-one crowding out when I control for CZ fixed effects[21] (intended to pick up time-invariant local supply or demand effects), though the estimates become less stable. The effect is robust to basing the migrant shift-share instrument in (32) on 1960 origin shares (rather than lagged-once shares) in all decades. Also, graphical plots of the δ_1 estimates show they are not driven by outliers. Borjas (2006) finds less crowding out across states than metropolitan areas, but I cannot reject a δ_1 of -1 using state-level data. I also show the effect is entirely driven by reductions of migratory inflows to the affected CZs, rather than increase in outflows. This is consistent with evidence from Coen-Pirani (2010), Monras (2015a), Dustmann, Schoenberg and Stuhler (2017) and Amior and Manning (2018), who document a disproportionate role for inflows in driving local population adjustment.

5.2 Why is the crowding out effect so large?

The size of the crowding out effect is certainly surprising, given the population response to demand-driven changes in employment is somewhat sluggish (see Table 1). These results are even harder to reconcile in the context of elastic labor demand or imperfect substitutability between natives and migrants: both should moderate any effect of foreign inflows on existing residents. On the other hand, as I show below, the one-for-one crowding out does not appear to bring about full adjustment. These contradictions become more conspicuous once I control for current employment growth $\Delta\tilde{n}_{rt}$ in the crowding out equation (35). This yields a specification which reflects (18) in the model:

$$\hat{\lambda}_{rt}^I = \delta_0^c + \delta_1^c \hat{\lambda}_{rt}^F + \delta_2^c \Delta\tilde{n}_{rt} + \delta_3^c \left(\tilde{n}_{rt-1} - l_{rt-1}\right) + A_{rt}\delta_A^c + \varepsilon_{rt} \tag{36}$$

The current Bartik b_{rt} is now excluded from the right hand side and serves instead as an instrument for $\Delta\tilde{n}_{rt}$. δ_1^c is a "conditional" crowding out effect: employment may be an important margin of adjustment to foreign inflows, but its contribution is now

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[20]My $\hat{\lambda}_{rt}^F$ specification in (24) shares with Peri and Sparber (2011) and Card and Peri (2016) the advantage of depending only on new foreign inflows - and not on changes in the population of longer term US residents (which might otherwise introduce a spurious correlation with $\hat{\lambda}_{rt}^I$)

[21]This approach is similar in spirit to the double differencing methodology of Borjas, Freeman and Katz (1997) and is recommended by Hong and McLaren (2015).

partialled out. Equation (18) predicts the residual contribution $\hat{\lambda}^I_{rt}$ responds equally to foreign inflows and employment shocks: i.e. $\delta^c_1 = -\delta^c_2$. As I explain in Section 2.5, these elasticities represent (in principle) pure mobility responses to changes in local welfare.

I report IV estimates of (36) in column 7 of Table 5 above. δ^c_1 exceeds δ^c_2 by 0.17 in magnitude. This differential (the "excess response" to foreign inflows) is statistically significant: the p-value on a test for equality is 0.013. Notice also the coefficient on $\hat{\lambda}^F_{rt}$ is actually smaller in column 7 (when I control for current employment) than column 2 (when I do not). Thus, any changes in local employment appear to *amplify* (rather than moderate) the impact of foreign inflows. I show this more explicitly in column 8: somewhat perversely, total employment *contracts* in response to foreign inflows.

[Table 8 here]

Indeed, despite one-for-one crowding out, I identify small adverse effects of foreign inflows on local employment rates - consistent with Smith (2012), Edo and Rapoport (2017) and Gould (forthcoming). In Table 8, I re-estimate (35) using the same instruments as before, but replacing the dependent with changes in the (composition-adjusted) employment rates of natives or migrants. In my preferred specification (column 1), the elasticity of the native employment rate to foreign inflows is -0.21. The coefficient of -0.4 on the lagged employment rate suggests the effect is largely dissipated within two decades. As in Table 5, the lagged migrant shift-share control $\hat{\mu}_{rt-1}$ in column 2 makes little difference, which suggests the lagged employment rate is successfully accounting for the initial conditions. Once I drop the lagged employment rate in column 3, I identify a larger initial impact of foreign inflows (-0.35) - though the rate of adjustment implied by $\hat{\mu}_{rt-1}$ (which now takes a positive offsetting effect) is similar to before. Columns 4 and 5 (which exclude the 1960s) show what happens when I replace the dependent with its lag. Reassuringly, as in Table 5, $\hat{\mu}_{rt-1}$ picks up the entire (negative) effect on the lagged dependent, and the current inflow $\hat{\lambda}^F_{rt}$ becomes insignificant. The final column re-estimates my preferred IV specification (column 1) for the migrant employment rate: the effect is remarkably similar to natives, consistent with the evidence in Table 4 above. Appendix F.2 shows that using raw (instead of composition-adjusted) employment rates makes little difference to the results: given that observable characteristics do not matter, one may be less concerned about the influence of unobservables.

To summarize, the residual population does appear to respond "excessively" to foreign inflows. But it also seems that one-for-one crowding out is insufficient for full adjustment. How can these results be interpreted? One explanation is that the migrant shift-share instrument $\hat{\mu}_{rt}$ is *negatively* correlated with unobserved demand shocks. But this hypothesis conflicts with the evidence in Table 1 (on the effect of the $\hat{\mu}_{rt}$ control): there is good reason to believe migrant enclaves are disproportionately located in high-demand areas.

An interesting variant of this hypothesis is an agglomeration effect (triggered by foreign inflows) which favors migrants at the expense of natives. But an agglomeration story does not sit comfortably with the apparent contraction of the local employment stock.

Alternatively, the excess response may be driven by natives' distaste for migrant enclaves. As I note in the discussion following equation (22), this has testable implications: to the extent that natives leave (on net) for non-labor market reasons, this should put upward pressure on local employment rates - or at least those of natives. But Table 8 shows the opposite effect.

A third possibility is that migrants are more productive than natives, in the sense of doing the same work for less pay (see e.g. Nanos and Schluter, 2014; Albert, 2017; Amior, 2017b). This story is consistent with evidence of migrants downgrading in occupation (Dustmann, Schoenberg and Stuhler, 2016). If migrants offer more "efficiency units" than natives, crowd-out in excess of one-for-one may be required for complete local adjustment.

And finally, the census data may be overstating the "true" crowding out effect because of undercoverage of unauthorized migrants. For example, suppose the "true" δ_1^c in (36) is equal to $-\delta_2^c$, and any estimated difference is due to mismeasurement. Looking at column 7 of Table 5, this would imply the foreign inflow is understated in the census by $\frac{0.913-0.743}{0.913} = 19$ per cent. This number seems reasonable in light of the evidence on undercoverage in Section 3.1.

5.3 Education-specific effects

In Appendix F (and Table A9), I study heterogeneity in the impact of foreign inflows across education groups. My strategy is to replace the dependent variable of (35) with various education-specific outcomes: population, employment rates, wages and housing expenses. Interestingly, the results show that the foreign inflow elicited by the migrant shift-share $\hat{\mu}_{rt}$ resembles the existing local population in terms of college graduate share - though high school dropouts are disproportionately represented among the new arrivals. Still, such statistics may understate the labor market pressure on low educated natives - to the extent that new migrants downgrade in occupation, and that undercoverage is more severe among low educated migrants.

Indeed, the adverse effect of foreign inflows on native employment rates falls entirely on those without college degrees. One might then expect these individuals to account for the bulk of the net internal outflow. But the local attrition of natives and earlier migrants is surprisingly balanced in terms of education. This may be explained by educational differentials in geographical mobility[22], though it is worth emphasizing (as I do below)

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[22]See e.g. Bound and Holzer (2000); Wozniak (2010); Notowidigdo (2011); Amior (2017a). In particular, using the same data as this paper, Amior and Manning (2018) show the college graduate population adjusts fully to local employment shocks within one decade; and any sluggishness in local adjustment is due to non-graduates.

that changes in local education stocks may also reflect changes in the characteristics of local birth cohorts.

In principle, lower employment rates should be reflected in lower real consumption wages. While I find no impact on natives' average residualized nominal wages[23], housing costs do respond positively (see also Saiz, 2007) - though the effect is statistically insignificant. However, this masks some interesting heterogeneity: there is a small positive effect on the wages of graduate natives, but they also experience larger increases in housing expenditures (purged of local housing characteristics). Whether this reflects changes in unobserved housing consumption or prices is open to interpretation, as I discuss in the appendix. Certainly, an analysis of the impact on real consumption wages is challenging - and not least because it is difficult to construct credible local wage deflators. This underscores the potential advantages of studying welfare effects using local employment rates, relying on the sufficient statistic result of Amior and Manning (2018).

6 Within-area estimates

6.1 Empirical specification

In contrast to my approach above, the seminal work in the literature has typically exploited variation in migration shocks *within* geographical areas. In principle, this should help address the challenge of omitted local effects highlighted by Table 7. Peri and Sparber (2011) recommend the following estimating equation:

$$\hat{\lambda}^I_{srt} = \delta^w_0 + \delta^w_1 \hat{\lambda}^F_{srt} + d_{rt} + d_{st} + \varepsilon_{srt} \tag{37}$$

where $\hat{\lambda}^F_{srt}$ and $\hat{\lambda}^I_{srt}$ are the foreign and residual contributions to population in skill group s in area r. I specify these analogously to (24) and (25):

$$\hat{\lambda}^F_{srt} \equiv \log\left(\frac{L_{srt-1} + L^F_{srt}}{L_{srt-1}}\right) \tag{38}$$

$$\hat{\lambda}^I_{srt} \equiv \log\left(\frac{L_{srt} - L^F_{srt}}{L_{srt-1}}\right) \tag{39}$$

where L^F_{srt} is the stock of new migrants (arriving in the US since $t-1$) of skill s in area r. d_{rt} are area-time interacted fixed effects, which absorb local shocks common to all skill groups; and d_{st} are skill-time interacted effects, which account for national-level trends across skill groups. Note this approach differs from the analysis in Section 5.3, which studies education-specific responses to *aggregate*-level CZ shocks.

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[23]Wage effects may be difficult to interpret in the context of declining employment rates, if it is the lowest paid natives who are leaving employment: see Card (2001) and Bratsberg and Raaum (2012).

The coefficient of interest, δ_1^w, identifies the impact of skill-specific foreign inflows on local skill composition - or more precisely, on the contribution of existing US residents to local skill composition. Comparable estimates of δ_1^w in the literature are typically small and sometimes positive (Card and DiNardo, 2000; Card, 2001, 2005; Cortes, 2008), though Borjas (2006) and Monras (2015b) offer alternative views.[24] Either way, a small δ_1^w is not necessarily inconsistent with large geographical crowd-out. This is for two reasons. First, changes in local skill composition reflect not only differential internal mobility, but also changes in the characteristics of local birth cohorts. And second, as Card (2001) and Dustmann, Schoenberg and Stuhler (2016) point out, δ_1^w does not account for the labor market impact that new migrant arrivals exert outside their own skill group s.

Regarding the latter point, it is useful to consider a simple example. Suppose production technology in area r, for the tradable good priced at P, is a CES function (see e.g. Card, 2001) over skill-defined local labor inputs: $Y_{rt} = \psi_{rt} \left(\sum_s \alpha_{srt} N_{srt}^\sigma \right)^{\frac{\rho}{\sigma}}$, where ψ_{rt} is an aggregate productivity shifter, $\frac{1}{1-\sigma}$ is the elasticity of substitution between labor inputs, and the exponent $\rho \leq 1$ allows for diminishing local returns. Assuming competitive labor markets, local wage growth for skill type s can then be expressed as:

$$\Delta \left(w_{srt} - p_t \right) = \Delta \log \alpha_{srt} - (1 - \sigma) \Delta n_{srt} + \frac{\sigma}{\rho} \Delta \log \psi_{rt} + \frac{\rho - \sigma}{\rho} \Delta y_{rt} \qquad (40)$$

Consider a skill-specific expansion of local employment Δn_{srt}, driven by foreign migration. The area-time fixed effects d_{rt} in (37) will absorb the local wage effect which is common to all skill groups, as encapsulated by Δy_{rt} in (40). Conditional on the d_{rt}, the wage response is then the inverse of the elasticity of substitution, i.e. $1 - \sigma$. Intuitively, for larger σ, the impact on wages is more diffused across the various skill groups - and the same will be true of any mobility response. So even in the absence of cohort effects, δ_1^w will not in general identify an aggregate-level crowding-out effect akin to δ_1 in (35). The single exception is the case of an additively separable production function (i.e. $\sigma = \rho$), which ensures no diffusion of wage effects. In Appendix A.6, I offer a more formal mapping of this multi-skill model onto the empirical specification (37), accounting for skill-specific population dynamics.

6.2 Estimates of δ_1^w

In practice, we do not know the "true" skill delineation: this is ultimately a decision for the researcher. But in light of the discussion above, empirical estimates of δ_1^w are likely to be sensitive to this decision, as different skill delineations will artificially engender

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[24]Borjas' (2006) estimates imply that each new migrant crowds out 0.61 natives (within skill groups) across metropolitan areas, though his methodology is disputed by Peri and Sparber (2011) and Card and Peri (2016). Monras (2015b) identifies a substantial negative δ_1^w (insignificantly different from one-for-one) using annual variation - in the year following the Mexican Peso crisis of 1995. But he estimates a small effect for a longer decadal interval.

different elasticities of substitution. In Table 9, I present estimates of δ_1^w in (37) for four different education-based[25] "skill" delineations: (i) college graduates / non-graduates; (ii) at least one year of college / no college (see Monras, 2015b); (iii) high school dropouts / all others (Card, 2005; Cortes, 2008); (iv) four groups: dropouts, high school graduates, some college and college graduates (e.g. Borjas, 2006).

[Table 9 here]

To explore the role of cohort effects, I also present estimates using both pooled census cross-sections and (to isolate an impact on internal mobility) a longitudinal dimension of the census: respondents were asked where they lived five years previously. This question, previously exploited by Card (2001) and Borjas (2006), is available in the 1980, 1990 and 2000 census extracts, yielding information on migratory flows over 1975-1980, 1985-1990 and 1995-2000.[26] To preserve comparability, I restrict the pooled cross-section sample to the same three decades: the 1970s, 1980s and 1990s.

For the purposes of the longitudinal estimates, I continue to define $\hat{\lambda}_{srt}^I$ and $\hat{\lambda}_{srt}^F$ according to (38) and (39), but time intervals are now five years: so L_{srt}^F is the stock of migrants who arrived in the US within the previous five years; and the initial population L_{srt-1} is constructed using information on where current census respondents lived five years previously. As a result, the residual contribution $\hat{\lambda}_{srt}^I$ will not account for emigration from the US. But to the extent that emigration is a response to an individual's local economic environment, my estimate should then understate any crowding out effect.

In an effort to exclude skill-specific local demand shocks (α_{srt} in the model), I instrument the foreign inflow $\hat{\lambda}_{srt}^F$ in (37) using a skill-specific migrant shift-share - following the methodology of Card (2001). Building on equation (32) above:

$$\hat{\mu}_{srt} = \log \left(\frac{L_{srt-1} + \sum_o \phi_{rt-1}^o L_{os(-r)t}^F}{L_{srt-1}} \right) \qquad (41)$$

where new migrants of origin o and skill s are allocated proportionately according to the initial co-patriot geographical distribution. Again, for the longitudinal specification, the pre-period relates to five years previously, and $\hat{\mu}_{srt}$ is constructed to predict the contribution of new migrants to the CZ-skill cell over five years (rather than a decade). As is clear from columns 1 and 4, $\hat{\mu}_{srt}$ is a strong instrument in all specifications.

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[25] A key drawback of the education classifications is occupational downgrading of migrants. Card (2001) addresses this concern by probabilistically assigning individuals to broad occupation groups (conditional on education and demographic characteristics), separately for natives and migrants. I offer estimates using these imputed occupation groups in Appendix I.

[26] Previous residence is only classified by state in the 1970 census microdata, and the ACS (after 2000) only reports place of residence 12 months previously. See Appendix B.4 for further data details. I exploit this same census question to disaggregate the contributions of inflows and outflows to the aggregate-level crowding out effect in Appendix E.4.

The pooled cross-section estimates of δ_1^w are remarkably large, ranging from 1 to 1.5 for the full residual contribution in column 2 (accounting for both natives and old migrants). That is, each new foreign migrant in a given CZ-skill cell *attracts* an additional 1-1.5 workers to the same cell (relative to other cells). A comparison with column 3 reveals that these positive effects are (more than) entirely driven by natives.

In contrast, the longitudinal estimates of δ_1^w in column 5 are universally negative. They also vary considerably in magnitude, ranging from -3.6 for the college graduate/non-graduate delineation to just -0.19 for the four-group delineation. In most cases, natives contribute substantially to these effects (column 6). The model offers a rationale for this variation: finer delineations (such as the four-group) should engender greater substitutability in production (i.e. larger σ) and consequently lower estimates of δ_1^w. Also, if high school dropouts are close substitutes with other non-college workers (see e.g. Card, 2009a), the relatively low δ_1^w in the third row (-0.43) is perhaps understandable. Using identical longitudinal data (from the 1990 census), Card (2001) estimates a δ_1^w which is somewhat positive. In Appendix I, I find the divergence of our estimates is mostly explained by the choice of right hand side controls and geographical sample.[27]

6.3 Cohort effects

The difference between the pooled cross-section and longitudinal estimates is suggestive of large cohort effects. In Appendix G, I offer more direct evidence for cohort effects by exploiting census information on individuals' state of birth. Specifically, using the same estimating equation (37), I show that foreign inflows to a given state exert a larger impact on the education composition of natives born in that state than on those residing in it.

As an example, consider a CZ which receives an inflow of low educated immigrants. Despite large geographical crowd-out of low educated natives, the native college share will typically contract relative to elsewhere. This is because the crowding out effect is more than offset by a decline in the education levels of local birth cohorts.

At first sight, these cohort effects may appear counterintuitive. Low-skilled immigration should raise the return to education and stimulate greater investment (see Hunt, 2017). But the effect could in principle go the other way: Llull (2017) argues a fall in wages may discourage labor market attachment and the accumulation of human capital.

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[27]Card controls for a range of demographic means at time $t-5$ within the skill-area cells (age, education, migrants' years in US), and he restricts his sample to the top 175 MSAs. Of course, the controls may be picking up important skill-specific shocks which I have neglected; and similarly, there may be good reasons to prefer his MSA restriction. The purpose of Appendix I is merely to show how our results can be reconciled.

7   Conclusion

The US suffers from large and persistent regional disparities in employment rates. It is often claimed that foreign migration offers a remedy: given that new migrants are more mobile geographically, they "grease the wheels" of the labor market and accelerate local adjustment (Borjas, 2001). In terms of policy, if migrants are indeed regionally flexible, forcibly dispersing them within receiving countries may actually hurt natives as well as the migrants themselves.

Building on important work by Cadena and Kovak (2016), I find that new foreign migrants account for 30 to 60 percent of the local population response to Bartik-identified employment shocks. However, I find that population growth is not significantly larger in areas better supplied by new migrants, nor more responsive to these shocks. This is fundamentally a story of "crowding out": I estimate that new foreign migrants to commuting zones crowd out existing US residents one-for-one. This effect is entirely driven by a reduction in migratory inflows, rather than larger outflows. The crowding out result does conflict with some of the existing literature, but I attempt to show how these estimates can be reconciled. The magnitude of the effect is certainly puzzling, given sluggishness in the migratory response to demand shocks, as well as the adverse effect of foreign inflows on local employment rates. However, undercoverage of unauthorized migrants in the census may be overstating the crowding out effect - and understating the foreign contribution to local adjustment.

Methodologically, I offer tools to identify the local impact of migration shocks in the context of local dynamics. Building on Pischke and Velling (1997) and Amior and Manning (2018), I account for an area's initial conditions using the lagged employment rate, which (new to this paper) I adjust for local demographic composition. And I present empirical evidence that this sufficient statistic approach can help address some of the principal threats to identification discussed in the migration literature.

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Appendix contents

A   Theoretical extensions and derivations

A.1   Expressing γ^I in terms of flow elasticities

The parameter γ^I in (7) is the elasticity of the *stock* of existing local residents, while γ^F in (8) is the elasticity of the *flow* from abroad. Here, I offer a brief sketch of how γ^I can itself be expressed in terms of flow elasticities. Suppose there are individuals moving both to and from area r even in the absence of local utility differentials, due perhaps to idiosyncratic amenity or job shocks. Let λ_r^{Ii} and λ_r^{Io} denote the contributions to local population growth from internal inflows and outflows respectively, where the net inflow λ_r^I is equal to $\lambda_r^{Ii} - \lambda_r^{Io}$. In steady-state, i.e. in the absence of local utility differentials, suppose these are both equal to μ_r^I. And suppose also that the response of these inflows and outflows takes the same form as (8), so:

$$\frac{\lambda_r^{Ii} - \mu_r^I}{\mu_r^I} = \gamma^{Ii}\left(n_r - l_r - z_r^{sa}\right) \tag{A1}$$

and

$$\frac{\lambda_r^{Io} - \mu_r^I}{\mu_r^I} = -\gamma^{Io}\left(n_r - l_r - z_r^{sa}\right) \tag{A2}$$

It then follows that:

$$\lambda_r^I = \mu_r^I\left(\gamma^{Ii} + \gamma^{Io}\right)\left(n_r - l_r - z_r^{sa}\right) \tag{A3}$$

And thus, γ^I in (7) can be expressed as $\mu_r^I\left(\gamma^{Ii} + \gamma^{Io}\right)$, where γ^{Ii} and γ^{Io} are the elasticities of the internal *flows* (both in and out), and μ_r^I is the steady-state rate of internal in- (and out-) migration. The empirical evidence suggests the internal population response to local differentials is largely driven by γ^{Ii} rather than γ^{Io}: see Appendix E.4.

A.2   Moving to discrete time: Derivations of (11), (12) and (13)

I first show how equation (9) can be discretized to yield (11), following similar steps to Amior and Manning (2018). I assume local migrant intensity μ_r is constant within discrete time intervals, and I denote μ_{rt} as the migrant intensity in the interval $(t-1, t]$. Similarly, γ_{rt} is the aggregate elasticity in area r in the interval $(t-1, t]$, where:

$$\gamma_{rt} = \gamma^I + \gamma^F \mu_{rt} \tag{A4}$$

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:

$$\frac{\partial e^{\gamma_{rt}t} l_r(\tau)}{\partial \tau}\Big|_{\tau=t} = e^{\gamma_{rt}t}\mu_{rt} + \gamma_{rt}e^{\gamma_{rt}t}\left[n_r(t) - z_r^{sa}(t)\right] \tag{A5}$$

This has as a solution:

$$e^{\gamma_{rt}t}l_r(t) = l_r(t-1) + \int_{t-1}^{t} e^{\gamma_{rt}\tau} \left[\mu_{rt} + \gamma_{rt}n_r(\tau) - \gamma_{rt}z_r^{\tau a}(\tau)\right] d\tau \tag{A6}$$

Rearranging:

$$
\begin{aligned}
l_r(t) - l_r(t-1) &= \int_{t-1}^{t} e^{-\gamma_{rt}(t-\tau)} \left[\mu_{rt} + \gamma_{rt}n_r(\tau) - \gamma_{rt}n_r(t-1) - \gamma_{rt}z_r^{\tau a}(\tau)\right] d\tau \\
&\quad + \left(1 - e^{-\gamma_{rt}t}\right)\left[n_r(t-1) - l_r(t-1)\right]
\end{aligned} \tag{A7}
$$

and again:

$$
\begin{aligned}
l_r(t) - l_r(t-1) &= \int_{t-1}^{t} e^{-\gamma_{rt}(t-\tau)} d\tau \cdot \mu_{rt} + \left[n_r(t) - n_r(t-1)\right] \\
&\quad - \left[z_r^{sa}(t) - z_r^{sa}(t-1)\right] - \int_{t-1}^{t} e^{\gamma_{rt}(\tau-t)} \left[\dot{n}_r(\tau) - \dot{z}_r^{sa}(\tau)\right] d\tau \\
&\quad + \left(1 - e^{-\gamma_{rt}t}\right)\left[n_r(t-1) - l_r(t-1) - z_r^{sa}(t-1)\right]
\end{aligned} \tag{A8}
$$

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

$$
\begin{aligned}
l_r(t) - l_r(t-1) &= \left(\frac{1 - e^{-\gamma_{rt}}}{\gamma_{rt}}\right)\mu_{rt} \\
&\quad + \left(1 - \frac{1 - e^{-\gamma_{rt}}}{\gamma_{rt}}\right)\left[n_r(t) - n_r(t-1) - z_r^{sa}(t) + z_r^{sa}(t-1)\right] \\
&\quad + \left(1 - e^{-\gamma_{rt}t}\right)\left[n_r(t-1) - l_r(t-1) - z_r^{sa}(t-1)\right]
\end{aligned} \tag{A9}
$$

which is (11).

I now derive discrete-time formulations of the foreign and internal contributions to local population change, i.e. λ_{rt}^F and λ_{rt}^I respectively. I begin by substituting (9) for $(n_r - l_r - z_r^{sa})$ in (8). This yields:

$$\lambda_r^F(\tau) = \mu_{rt} + \frac{\gamma^F \mu_{rt}}{\gamma} \left[dl_r(\tau) - \mu_{rt}\right] \tag{A10}$$

for $\tau \in (t-1, t]$. Integrating this expression between $t-1$ and t then gives:

$$\lambda_{rt}^F = \mu_{rt} + \frac{\gamma^F \mu_{rt}}{\gamma} \left(\Delta l_{rt} - \mu_{rt}\right) \tag{A11}$$

where $\lambda_{rt}^F \equiv \int_{t-1}^{t} \lambda_{rt}^F(\tau) d\tau$ is the foreign contribution over the interval. Equation (12) can then be derived by substituting (11) for the aggregate population change Δl_{rt}.

One can follow an identical procedure for the internal contribution. Substituting (9) for $(n_r - l_r - z_r^{sa})$ in (7):

$$\lambda_r^I(\tau) = \frac{\gamma^I}{\gamma} \left[dl_r(\tau) - \mu_{rt} \right] \tag{A12}$$

for $\tau \in (t-1, t]$. Then, integrating between $t-1$ and t:

$$\lambda_{rt}^I = \frac{\gamma^I}{\gamma} \left(\Delta l_{rt} - \mu_{rt} \right) \tag{A13}$$

and equation (13) follows after substituting (11) for Δl_{rt}.

A.3 Population responses to μ_{rt}: Derivations of (14) and (15)

It is useful to begin by characterizing (12) and (13) as functions of μ_{rt}. Replacing the aggregate elasticity γ_{rt} with $\gamma^I + \gamma^F \mu_{rt}$:

$$
\begin{aligned}
f_F(\mu_{rt}) &= \mu_{rt} + \frac{\gamma^F \mu_{rt}}{\gamma^I + \gamma^F \mu_{rt}} \left(1 - \frac{1 - e^{-\gamma^I - \gamma^F \mu_{rt}}}{\gamma^I + \gamma^F \mu_{rt}} \right) \left(\Delta n_{rt} - \Delta z_{rt}^s - \mu_{rt} \right) \\
&\quad + \frac{\gamma^F \mu_{rt}}{\gamma^I + \gamma^F \mu_{rt}} \left(1 - e^{-\gamma^I - \gamma^F \mu_{rt}} \right) \left(n_{t-1} - l_{t-1} - z_{rt-1}^s \right)
\end{aligned} \tag{A14}
$$

and

$$
\begin{aligned}
f_I(\mu_{rt}) &= \frac{\gamma^I}{\gamma^I + \gamma^F \mu_{rt}} \left(1 - \frac{1 - e^{-\gamma^I - \gamma^F \mu_{rt}}}{\gamma^I + \gamma^F \mu_{rt}} \right) \left(\Delta n_{rt} - \Delta z_{rt}^s - \mu_{rt} \right) \\
&\quad + \frac{\gamma^I}{\gamma^I + \gamma^F \mu_{rt}} \left(1 - e^{-\gamma^I - \gamma^F \mu_{rt}} \right) \left(n_{t-1} - l_{t-1} - z_{rt-1}^s \right)
\end{aligned} \tag{A15}
$$

which summarize the foreign and internal contributions to local population growth respectively. Taking first order approximations of these functions around $\mu_{rt} = 0$:

$$f_F(\mu_{rt}) \approx f_F(0) + \mu_{rt} f_F'(0) \tag{A16}$$

and

$$f_I(\mu_{rt}) \approx f_I(0) + \mu_{rt} f_I'(0) \tag{A17}$$

which yield equations (14) and (15) in the main text.

A.4 Housing market specification: Derivation of (19)

Given the sufficient statistic result (which allows me to focus exclusively on stocks rather than prices), a formal specification of the housing market is not required to derive most of the population adjustment equations in Section 2. However, such a specification is necessary to derive the "unconditional" crowding out equation (20), and I offer a tractable version here.

Suppose workers have Cobb-Douglas preferences over the traded good and housing, so they spend a fixed fraction ν of their income on housing. See Davis and Ortalo-Magne (2011) for empirical evidence in support of this assumption. This implies a simple linear expression for the local price index:

$$p_{rt} = \nu p_{rt}^h + (1 - \nu) p_t \tag{A18}$$

For simplicity, I assume non-employed individuals receive no income. Housing demand in area r can then be written as:

$$H_{rt}^d = \nu \frac{W_{rt} N_{rt}}{P_{rt}^h} \tag{A19}$$

and in logarithms:

$$h_{rt}^d = \log \nu + w_{rt} + n_{rt} - p_{rt}^h \tag{A20}$$

I now turn to housing supply. Again for simplicity, I assume housing production does not depend on local labor, but see the Online Appendices of Amior and Manning (2018) for such an extension. Suppose housing supply can be written as:

$$h_{rt}^s = \epsilon^{hs} \left(p_{rt}^h - p_t \right) \tag{A21}$$

Equating supply and demand, and substituting (A18) for p_{rt}^h:

$$p_{rt} - p_t = \frac{\nu}{1 - \nu + \epsilon^{hs}} \left[\log \nu + \frac{1}{\epsilon^s} \left(n_{rt} - l_{rt} - z_{rt}^s \right) + n_{rt} \right] \tag{A22}$$

Taking first differences then yields equation (19) in the main text:

$$\Delta \left(p_{rt} - p_t \right) = \frac{1}{\kappa} \left[\frac{1}{\epsilon^s} \left(\Delta n_{rt} - \Delta l_{rt} - \Delta z_{rt}^s \right) + \Delta n_{rt} \right] \tag{A23}$$

where

$$\kappa \equiv \frac{1 - \nu + \epsilon_r^{hs}}{\nu} \tag{A24}$$

is increasing in the elasticity of housing supply.

A.5 Semi-structural equations: Derivations of (18), (20) and (22)

Following the procedure outlined in Appendix A.2, (17) can be discretized to yield:

$$\Delta l_{rt} = \lambda_{rt}^F + \left(1 - \frac{1 - e^{-\gamma^I}}{\gamma^I} \right) \left(\Delta n_{rt} - \lambda_{rt}^F - \Delta z_{rt}^{sa} \right) + \left(1 - e^{-\gamma^I} \right) \left(n_{rt-1} - l_{rt-1} - z_{rt-1}^{sa} \right) \tag{A25}$$

Equation (18) then follows after subtracting the foreign contribution λ_{rt}^F on both sides:

$$\lambda_{rt}^I = \left(1 - \frac{1 - e^{-\gamma^I}}{\gamma^I}\right)\left(\Delta n_{rt} - \lambda_{rt}^F - \Delta z_{rt}^{sa}\right) + \left(1 - e^{-\gamma^I}\right)\left(n_{rt-1} - l_{rt-1} - z_{rt-1}^{sa}\right) \quad \text{(A26)}$$

I now turn to the "unconditional" crowding out specification, (20). This requires a solution for local employment. Using the labor supply and demand curves, (2) and (3), changes in local employment can be expressed as:

$$\Delta n_{rt} = \frac{\epsilon^s}{\epsilon^s + \epsilon^d}\Delta z_{rt}^d + \frac{\epsilon^d}{\epsilon^s + \epsilon^d}\left(\Delta l_{rt} + \Delta z_{rt}^s\right) - \frac{\epsilon^s \epsilon^d}{\epsilon^s + \epsilon^d}\Delta\left(p_{rt} - p_t\right) \quad \text{(A27)}$$

Replacing the local price deviation $\Delta\left(p_{rt} - p_t\right)$ with (A23):

$$\Delta n_{rt} = \eta\frac{\kappa}{\kappa + \epsilon^d}\Delta z_{rt}^d + (1 - \eta)\left(\Delta l_{rt} + \Delta z_{rt}^s\right) \quad \text{(A28)}$$

and disaggregating local population growth Δl_{rt} into foreign and internal contributions:

$$\Delta n_{rt} = \eta\frac{\kappa}{\kappa + \epsilon^d}\Delta z_{rt}^d + (1 - \eta)\left(\lambda_{rt}^F + \lambda_{rt}^I + \Delta z_{rt}^s\right) \quad \text{(A29)}$$

where

$$\eta \equiv \left(1 + \frac{\kappa + 1}{\kappa + \epsilon^d}\cdot\frac{\epsilon^d}{\epsilon^s}\right)^{-1} \quad \text{(A30)}$$

Equation (20) can then be derived by substituting (A29) for Δn_{rt} in (A26).

To derive the response of the local employment rate $\Delta\left(n_{rt} - l_{rt}\right)$, I first subtract Δl_{rt} from (A29):

$$\Delta\left(n_{rt} - l_{rt}\right) = \eta\frac{\kappa}{\kappa + \epsilon^d}\Delta z_{rt}^d + (1 - \eta)\Delta z_{rt}^s - \eta\left(\lambda_{rt}^F + \lambda_{rt}^I\right) \quad \text{(A31)}$$

where I have again disaggregated Δl_{rt} into λ_{rt}^I and λ_{rt}^F. Equation (22) then follows after substituting (20) for λ_{rt}^I.

A.6   Derivation of within-area empirical specification

In this appendix, I show how the multi-skill model described in Section 6.1 can be mapped onto the empirical specification (37), accounting for skill-specific population dynamics.

In line with (2) in Section 2, I first write a skill-specific equation for labor supply:

$$n_{sr} = l_{sr} + \epsilon^s\left(w_{sr} - p_r\right) + z_{sr}^s \quad \text{(A32)}$$

Similarly, I rewrite indirect utility (4) for skill group s. This depends on the skill-specific amenity value and real consumption wage, which itself can be replaced with the employ-

ment rate using (A32)

$$v_{sr} = w_{sr} - p_r + a_{sr} \tag{A33}$$

$$= \frac{1}{\epsilon^s}\left(n_{sr} - l_{sr} - z_{sr}^s\right) + a_{sr}$$

Notice that local labor market conditions for skill group s can be fully summarized by the skill-specific employment rate $(n_{sr} - l_{sr})$: this is a skill-specific version of the sufficient statistic result in Section 2. Skill s subscripts can also be applied to the dynamic population responses, equations (7) and (8). That is, skill population adjusts (sluggishly) with elasticities γ^I and γ^F to skill-specific differentials in local utility v_{sr}. For simplicity, I assume here that the elasticities γ^I and γ^F are common to all skill groups, but I permit skill heterogeneity in the migrant intensity μ_{sr}:

$$\lambda_{sr}^I = \gamma^I\left(n_{sr} - l_{sr} - z_{sr}^s + a_{sr}\right) \tag{A34}$$

$$\frac{\lambda_{sr}^F - \mu_{sr}}{\mu_{sr}} = \gamma^F\left(n_{sr} - l_{sr} - z_{sr}^s + a_{sr}\right) \tag{A35}$$

By symmetry with the model in Section 2, these equations can be discretized to yield a skill-specific version of (18):

$$
\begin{aligned}
\lambda_{srt}^I = {} & \left(1 - \frac{1 - e^{-\gamma^I}}{\gamma^I}\right)\left(\Delta n_{srt} - \lambda_{srt}^F - \Delta z_{srt}^s + \Delta a_{srt}\right) \\
& + \left(1 - e^{-\gamma^I}\right)\left(n_{srt-1} - l_{srt-1} - z_{srt-1}^s + a_{srt-1}\right)
\end{aligned}
\tag{A36}
$$

To derive the unconditional crowding out effect, I require a solution for local skill-specific employment Δn_{srt}. Given (A32) and the skill demand relationship in (40), this can be characterized as:

$$
\begin{aligned}
\Delta n_{srt} = {} & \frac{\epsilon^s}{1 + \epsilon^s\left(1 - \sigma\right)}\left(\Delta \log \alpha_{srt} + \frac{\sigma}{\rho}\Delta \log \psi_{rt} + \frac{\rho - \sigma}{\rho}\Delta y_{rt} - \Delta p_{rt} + \Delta p_t\right) \\
& + \frac{1}{1 + \epsilon^s\left(1 - \sigma\right)}\left(\Delta l_{srt} + \Delta z_{srt}^s\right)
\end{aligned}
\tag{A37}
$$

Substituting this for Δn_{srt} in (A36), this yields:

$$
\begin{aligned}
\lambda_{srt}^I = {} & \frac{\left(\frac{\gamma^I}{1 - e^{-\gamma^I}} - 1\right)\zeta}{1 + \left(\frac{\gamma^I}{1 - e^{-\gamma^I}} - 1\right)\zeta}\left(\frac{1}{1 - \sigma}\Delta \log \alpha_{srt} - \lambda_{srt}^F - \Delta z_{srt}^s + \frac{1}{\zeta}\Delta a_{srt}\right) \\
& + \frac{\left(\frac{\gamma^I}{1 - e^{-\gamma^I}} - 1\right)\zeta}{1 + \left(\frac{\gamma^I}{1 - e^{-\gamma^I}} - 1\right)\zeta}\cdot\frac{1}{1 - \sigma}\left(\frac{\sigma}{\rho}\Delta \log \psi_{rt} + \frac{\rho - \sigma}{\rho}\Delta y_{rt} - \Delta p_{rt} + \Delta p_t\right) \\
& + \frac{\gamma^I}{1 + \left(\frac{\gamma^I}{1 - e^{-\gamma^I}} - 1\right)\zeta}\left(n_{srt-1} - l_{srt-1} - z_{srt-1}^s + a_{srt-1}\right)
\end{aligned}
\tag{A38}
$$

where

$$\zeta \equiv \frac{\epsilon^s (1 - \sigma)}{1 + \epsilon^s (1 - \sigma)} \tag{A39}$$

Now consider how this maps onto the within-area empirical specification (37). The area-time fixed effects d_{rt} will absorb the contents of the second line of (A38). The skill-time fixed effects d_{st} will absorb any skill-time varying components of the skill-specific demand shock $\Delta \log \alpha_{srt}$, skill-specific supply shock Δz^s_{srt}, skill-specific amenity shock Δa_{srt} and the initial conditions on the final line of (37). All remaining variation will fall into the error term ε_{srt}, so the IV exclusion restriction requires that it is uncorrelated with the skill-specific migrant shift-share $\hat{\mu}_{srt}$. Under these conditions (and the model's various assumptions), the coefficient of interest δ^w_1 will identify the coefficient on λ^F_{srt} in (A38):

$$\delta^w_1 = \frac{\left(\frac{\gamma^I}{1 - e^{-\gamma^I}} - 1 \right) \zeta}{1 + \left(\frac{\gamma^I}{1 - e^{-\gamma^I}} - 1 \right) \zeta} \tag{A40}$$

As I state in Section 6.1, δ^w_1 is increasing in the internal mobility response γ^I, but decreasing in the elasticity of substitution σ between skill types in production.

B Data manipulation

B.1 Population

I take local population counts of individuals aged 16-64 from published county-level census statistics (based on 100 percent 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). Like Amior and Manning (2018), 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.

Following Amior and Manning (2018), 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) microdata 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.[28] Similarly to Autor and

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[28]The 1940 and 1950 census extracts divide the continental US into 467 State Economic Areas, the

Dorn (2013) and Autor, Dorn and Hanson (2013), I estimate population counts at the intersection of the available geographical identifiers and CZs[29], 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.

B.2   Employment

Section 3.2 describes how I construct composition-adjusted local employment rates. Here, I offer further detail on the specifics. I begin by running probit regressions of a binary employment indicator on a detailed set of individual characteristics and a full set of location fixed effects, separately for each census cross-section (1960, 1970, 1980, 1990 and 2000) and the pooled ACS cross-sections of 2009-11. The individual controls consist of: age and age squared; four education indicators[30], 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.

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.

[29]To this end, 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 1940 and 1950; 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 have relied 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 have generated population counts using the MABLE/Geocorr applications at the Missouri Census Data Center: *http://mcdc.missouri.edu/websas/geocorr_index.shtml*.

[30]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.

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

Regarding the location fixed effects, I include indicators for the local geographies available in each census year (see Section B.1) in the probit regressions. Using the probit output, I then predict the average employment rate in each local area - for a distribution of local demographic characteristics identical to the full national sample. 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 B.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.

B.3 Shift-share instruments

I construct the Bartik industry shift-shares in identical fashion to Amior and Manning (2018). The sample 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[31], aggregated to the 2-digit level[32] (yielding 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 migrant shift-share $\hat{\mu}_{rt}$, I impute CZ-level migrant population counts (across 77 origin countries) by weighting across these same identifiers. A key input to $\hat{\mu}_{rt}$ 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. $L^F_{o(-r)t}$ in equation (32) in Section 3.3. This information is available in all census years from 1970 inclusive, thus covering foreign inflows from the 1960s onwards. However, in some empirical specifications, I require values of $\hat{\mu}_{rt}$ 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

---

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

[32]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.

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).

B.4 Longitudinal information on place of residence

In Section 6.2, I exploit longitudinal residential information in the 1980, 1990 and 2000 IPUMS census microdata to estimate δ_1^w in equation (37). These census years include data on respondents' place of residence five years previously, using various sub-state geographical identifiers.[33] I compute population (both current and 5-year historical) in the various cells of interest (native, foreign-born, recent foreign arrival, by education category) at the level of the available geographical identifiers. And I impute CZ-level data by taking weighted averages of these, using the population weights described in footnote 29.

C Effect of years in US on long-distance 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 2016. 2.8 percent 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 percent of the foreign born.[34] 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 control for these, I estimate complementary log-log models for the annual incidence of cross-state migration (see e.g. Amior, 2017a). Let $MigRate(X_i)$ 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 probability:

$$\Pr(Mig_i^\tau = 1) = 1 - \exp(-MigRate(X_i)\tau) \tag{A41}$$

[33]See also footnote 28. The 1980 census extract identifies both current and historical residence in the continental US using the same 1,148 county groups. The 1990 extract identifies current residence using 1,713 Public Use Microdata Areas (PUMAs) and historical residence using 1,139 areas (PUMAs or PUMA combinations). In 2000, current residence is classified by 2,057 PUMAs and historical residence by 1,017 PUMAs or PUMA combinations. For 1990 and 2000, I conduct my analysis at the higher level of aggregation.

[34]As an aside, a larger share of foreign-born individuals (2.9 percent) report living abroad one year ago.

This gives rise to a complementary log-log model:

$$\Pr\left(Mig_i^{\tau} = 1\right) = 1 - \exp\left(-\exp\left(\pi'X_i\right)\tau\right) \qquad (A42)$$

where the π parameters (to be estimated) are the 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 implicitly normalize τ to one year. The X_i vector includes the following variables:

$$\pi'X_i = \sum_{k=1}^{20} \pi_k^{YRS} YrsUS_k + \sum_{k=1981}^{2015} \pi_k^{YRI} YrImmig_k + \sum_{k=2001}^{2016} \pi_k^{YRI} YrObs_k \qquad (A43)$$

The sample for this exercise consists of (1) natives aged 16-64 living in the US one year previously (22.6m observations) and (2) foreign-born individuals aged 16-64 with between 1 and 20 years in the US (2.2m). Thus, there are 21 demographic groups: natives, migrants with 1 years in US, migrants with 2 years, ..., migrants with 20 years. I include in the X_i vector binary indicators for the final 20 groups, i.e. $YrsUS_k$ for k between 1 and 20, so natives are the omitted category. I also control for a full set of entry cohort effects, $YrImmig_k$ (ranging from 1981 to 2015 in my sample, with natives again the omitted category), and a full set of observation year effects, $YrObs_k$. I assume here that the observation year effects are common to natives and migrants.

Panel A of Figure A1 reports the basic coefficient estimates on the years in US dummies, together with the 95 percent 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 93 log points. But this falls to zero by year 6 and becomes negative thereafter, dropping to -49 log points by year 20.

[Figure A1 here]

In Panel B, I estimate the same empirical model, but this time controlling for a full set of single-year age effects. Age effects are important here because individuals with fewer years in the US will typically be younger, and the young are known to be more mobile for other reasons (see e.g. Kennan and Walker, 2011). Thus, without age controls, I am likely to overestimate mobility of new immigrants relative to natives. And indeed, this is what the results suggest: the deviation at year 1 is now somewhat lower, at 68 log points. The gradient in Panel B is still negative, but shallower than Panel A: the coefficient touches zero at year 5 and reaches -31 log points by year 20.

D Supplementary estimates of contributions to local adjustment

D.1 Robustness to specification

In Tables A1, A2 and A3, I study the robustness of my IV estimates of the foreign contribution to local adjustment - both the average contributions (in columns 1-4 of each table) and heterogeneity in these contributions along the support of the migrant shift-share (columns 5-8), together with the associated internal population responses.

[Table A1 here]

Table A1 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 5-8 of Table 1 (without the migrant shift-share control, $\hat{\mu}_{rt}$) and the heterogeneous contributions in columns 5-8 of Table 3. 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 migrant shift-share $\hat{\mu}_{rt}$ (which is locally very persistent); and Table 1 in the main text shows that controlling for $\hat{\mu}_{rt}$ 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 contribution in high-$\hat{\mu}_{rt}$ areas (though the response to contemporaneous employment shocks is smaller), and this foreign contribution is fully crowded out by the residual contribution. 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 A1, I omit the lagged employment rate and its associated (lagged Bartik) instrument - together with their interactions with the migrant intensity 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 similar in proportionate terms. 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. Despite this, the foreign contribution in column 2 is similar in proportionate terms; and columns 5-8 show a similar crowding out effect. This result should be reassuring: since adjusting local employment for observable characteristics makes little difference to the results, one may be less concerned about the influence of unobservables.

D.2 Robustness to amenity controls

In Table A2, 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 complete crowding out, though the standard errors are now very large: the interactions effects are statistically insignificant.

[Table A2 here]

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 local migrant intensity, $\hat{\mu}_{rt}$. 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 percent level. However, on the basis of the model in the main text, it is should be emphasized that the omission of the amenity-$\hat{\mu}_{rt}$ controls is a misspecification: see equations (14), (15) and (16).

Panel C controls additionally for the amenity-$\hat{\mu}_{rt}$ interactions. Columns 5-8 are now identical to columns 5-8 of Table 3 in the main text. The foreign contribution to the average response in column 2 is smaller than before. This reflects what happens in Table 1 in the main text when I control for migrant intensity $\hat{\mu}_{rt}$.

D.3 Robustness to sample and weights

In Table A3, I vary the sample and weighting. Until now, I have studied local heterogeneity along a linear migrant intensity $\hat{\mu}_{rt}$ effect: this follows the first order approximation imposed in equation (14) in the model. But as I note in the main text, the $\hat{\mu}_{rt}$ distribution is very skewed: the 98th percentile is 0.1, and the maximum is 0.29. In Panel A, I consider the implications of omitting observations with $\hat{\mu}_{rt}$ 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 complete crowding out. This suggests the results are not driven by a small number of outlying observations of $\hat{\mu}_{rt}$, and the linear approximation may not be so unreasonable.

[Table A3 here]

All the estimates in the main text are weighted by lagged population share. In Panel B of Table A3, I study unweighted estimates. This places more emphasis on smaller CZs which typically admit fewer foreign migrants. Unsurprisingly, the average foreign contribution is now substantially lower. Column 6 shows the foreign contribution is increasing with $\hat{\mu}_{rt}$, but the effect is smaller than before. However, there is now no crowding out effect in column 7. It turns out this result is driven by some small towns close to the Mexican border with unusually large migrant intensity (which contribute little to the weighted estimates). Once I exclude CZs with 1960 population (of 16-64s) below 25,000 (which account for 2 percent of the national population), column 7 now shows evidence of crowding out. And the crowding out effect becomes effectively one-for-one 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 percent of the national population.

D.4 Average contributions by country/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 A4. Column 1 reports the average foreign contribution (among all origins groups) - which is identical to column 2 of Table 1 in the main text, based on the empirical specification (33). 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. Looking at the IV estimates, all the origin groups contribute significantly to the

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overall foreign response. And none particularly stand out, given the associated standard errors and the shares of foreign migration reported in the penultimate row.

[Table A4 here]

E   Supplementary estimates of crowding out

E.1   Graphical illustration of crowding out estimates

I now consider the robustness of my "semi-structural" crowding out estimates in Section 5. One concern is that my estimates of the coefficient of interest, δ_1, in equation (35) 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 5.

[Figure A2 here]

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 lagged employment rate, the current Bartik shift-share, 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 two endogenous variables (the contribution of new migrants, $\hat{\lambda}_{rt}^F$, and the lagged employment rate, $\tilde{n}_{rt-1} - l_{rt-1}$), based on the first stage regressions (using the migrant shift-share $\hat{\mu}_{rt}$ and lagged Bartik b_{rt-1} instruments). 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* lagged employment rate, the current Bartik shift-share, 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 5. 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.

E.2   Alternative IV strategies

The migrant shift-share instrument has faced a number of criticisms in the literature. First, it may not successfully exclude shocks to local labor demand, especially if these shocks are persistent. And second, if the migration shocks themselves are persistent, estimated effects may be conflated with dynamic adjustment (see Jaeger, Ruist and Stuhler, 2018). Addressing these challenges has been a major focus of this paper. But there are other possible concerns, and I attempt to address some of these in Table A5.

[Table A5 here]

Panel A offers estimates weighted by lagged population share, in line with the main text. Column 1 reproduces the basic IV crowding out estimate in column 2 of Table 5, based on equation (35). I instrument the foreign inflow $\hat{\lambda}_{rt}^F$ using the migrant shift-share $\hat{\mu}_{rt}$ and the lagged employment rate using a lagged Bartik. Panel B offers unweighted estimates of δ_1: the coefficient is not much different (-0.94 rather than -1.1), though the standard error is somewhat larger. This suggests the effects are not merely driven by large CZs, consistent with the patterns in Figure A2.

Recall the migrant shift-share instrument $\hat{\mu}_{rt}$ is given by $\log\left(\frac{L_{rt-1}+\Lambda_{rt-1}^F}{L_{rt-1}}\right)$, where $\Lambda_{rt-1}^F \equiv \sum_o \phi_{rt-1}^o L_{o(-r)t}^F$ is a shorthand for the predicted number of incoming migrants between $t-1$ and t: see equation (32). Notice I am using the $t-1$ migrant settlement patterns (in ϕ_{rt-1}^o) to predict foreign inflows in each subsequent decade. But other studies have taken a different approach: for example, Hunt (2017) predicts inflows in all decades from 1940 to 2010 using the 1940 settlement patterns. In column 2, I replace my instrument with $\log\left(\frac{L_{rt-1}+\Lambda_{rt-1}^{F60}}{L_{rt-1}}\right)$, where $\Lambda_{rt-1}^{F60} \equiv \sum_o \phi_{r60}^o L_{o(-r)t}^F$ predicts the migrant inflow based on 1960 settlement patterns, ϕ_{r60}^o, for every decade. The weighted and unweighted estimates are now somewhat larger (-1.4 and -1.5 respectively), though they are not significantly different from -1.

In my basic crowding out specification (35), I approximate the foreign and residual contributions (to the change in log population) as $\log\left(\frac{L_{rt-1}+L_{rt}^F}{L_{rt-1}}\right)$ and $\log\left(\frac{L_{rt}-L_{rt}^F}{L_{rt-1}}\right)$ respectively. But much of the literature has taken a first order approximation, defining them as $\frac{L_{rt}^F}{L_{rt-1}}$ and $\frac{\Delta L_{rt}-L_{rt}^F}{L_{rt-1}}$: see e.g. Card (2001), Peri and Sparber (2011) and Card and Peri (2016). Column 3 re-estimates (35) using these definitions; and to maintain symmetry, I replace the instrument with $\frac{\Lambda_{rt}^F}{L_{rt-1}}$. But this makes little difference to the estimate.

Another possible concern is the predictive power of the instrument. Suppose the predicted number of incoming migrants, Λ_{rt}^F, is largely noise. Then variation in L_{rt-1} may generate artificial positive correlation between the endogenous variable and the instrument. This problem becomes worse if the L_{rt}^F component of the endogenous variable, $\frac{L_{rt}^F}{L_{rt-1}}$, is itself also noisy. Indeed, Aydemir and Borjas (2011) argue that measurement error in the local migrant share can result in substantial attenuation bias, especially in

the presence of fixed effects (which may absorb much of the meaningful variation). To address this concern, in column 4, I replace the instrument (which is expressed *relative* to the initial population) with the predicted inflow of new migrants in *levels*, Λ_{rt}^F. But again, this has little effect on the crowding out estimate or even its standard error.

An important reference in this context is Wozniak and Murray (2012), who estimate geographical crowd-out using a specification entirely expressed in levels. Building on equation (35), a specification in levels would be:

$$\Delta L_{rt} - L_{rt}^F = \delta_0 + \delta_1^L L_{rt}^F + \delta_2^L b_{rt} + \delta_3^L \left(\tilde{n}_{rt-1} - l_{rt-1}\right) + A_{rt}\delta_A^L + \varepsilon_{rt} \qquad \text{(A44)}$$

where the dependent variable is the change in local population, less the stock of new foreign migrants; and the key regressor L_{rt}^F is simply the number of new foreign migrants. I estimate δ_1^L in column 5, yielding a coefficient on just -0.23 in Panel A. However, local population is an important omitted variable in this specification (Wright, Ellis and Reibel, 1997; Peri and Sparber, 2011; Wozniak and Murray, 2012): local population may be correlated with both the inflow of new migrants and subsequent population change. To address this concern, Wozniak and Murray recommend controlling for local fixed effects. Once I include CZ fixed effects (column 6), my estimate of δ_1^L is again remarkably close to -1 irrespective of weighting.

In column 7, I apply CZ fixed effects directly to the basic specification in column 1. These effectively partial out CZ-specific linear trends in population. This approach is similar in spirit to the double differencing methodology (comparing changes before and after 1970) of Borjas, Freeman and Katz (1997) and is recommended by Hong and McLaren (2015). In terms of theory, the purpose of the fixed effects is to account for time-invariant unobserved components of the amenity, supply or demand effects in equation (20). But as I emphasize in Section (D.1), their inclusion in empirically demanding in such a short panel, especially given the strong persistence in the migrant shift-share instrument $\hat{\mu}_{rt}$. And as Aydemir and Borjas (2011) argue, measurement error may be more of a problem here. With population weights, I estimate a δ_1 of -0.63 with a very large standard error (0.61). In column 8, to ease the demands of the specification, I replace the lagged employment rate (i.e. the initial conditions) with historical shocks: a lagged Bartik b_{rt-1} (originally used as an instrument) and a lagged migrant shift-share $\hat{\mu}_{rt-1}$. I now estimate a much larger δ_1: -1.35, with a standard error of just 0.26. Without population weights, I attain perversely large estimates of δ_1 (in excess of -2) in both columns 7 and 8, though the standard errors are also large. However, the first stage F-statistics for the foreign inflow $\hat{\lambda}_{rt}^F$ are small in the unweighted specifications: about 6 in each case. I do not report fixed effect estimates using the 1960-based migrant shift-share: this instrument has no power under fixed effects.

E.3 Robustness of native contribution

The final column of Table 7 studies the robustness of the native contribution to the crowding out effect, assessing the importance of various right hand side controls. But the estimates in this column mask some important heterogeneity across decades. To address this point, Table A6 reproduces the first six columns of Table 7, but replacing the dependent variable $\hat{\lambda}_{rt}^{I}$ with the native-only contribution $\hat{\lambda}_{rt}^{I,N}$.

[Table A6 here]

The general patterns are very similar to Table 7. Without any right hand side controls, the crowding out effects vary substantially over time; but as the controls (both demand and amenity effects) are progressively added, the crowding out estimates become more substantial (close to or exceeding one-for-one) in almost every decade. There is one important exception: the 2000s. Even with the full set of right hand side controls, the response of the native contribution is effectively zero. This is despite the large crowding out effect for the full residual contribution (i.e. natives and old migrants combined) in the same decade in Table 7. In other words, previous migrants account for the entire δ_1 effect in that decade. A natural explanation is large return migration of Mexicans in the 2000s (see e.g. Hanson, Liu and McIntosh, 2017), driven in part by the construction bust and the Great Recession.

E.4 Contributions of inflows and outflows to crowding out

It turns out that the geographical crowd-out is entirely driven by a reduction in migratory inflows to the affected CZ - rather than an increase in migratory outflows. And I present the evidence in this appendix. Similarly to Section 6, I exploit the longitudinal dimension of the census: respondents were asked where they were living five years previously. The census publishes statistics on gross migratory flows between all county pairs. In line with analysis in the Online Appendix of Amior and Manning (2018), I use data for the periods 1965-70, 1975-80, 1985-90 and 1995-2000, and I aggregate all flows to CZ level.[35] The flow data is available for individuals aged 15-64, rather than my usual 16-64 sample. One might also use the microdata (as I do in Section 6.2), but the published statistics are based on larger samples and require no geographical imputation.

My strategy is to re-estimate the crowding out equation (35), but replacing the foreign and residual contributions to decadal population growth with 5-year flows. In particular,

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[35]I thank Jack DeWaard for sharing the 1965-70 and 1975-80 flow data. I take the 1985-90 flow data from the Socioeconomic Data and Application Center at Columbia University: see the P1 STP-28 tables at *http://sedac.ciesin.columbia.edu/data/set/acrp_enhance-migration-1990*. I construct the 1995-2000 flows using 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*. Comparable data is not available for 2005-2010.

my specification is:

$$\hat{\lambda}_{rt}^{I5} = \delta_0 + \delta_1 \hat{\lambda}_{rt}^{F5} + \delta_2 b_{rt} + \delta_3 \left(\tilde{n}_{rt-10} - l_{rt-10} \right) + A_{rt}\delta_A + \varepsilon_{rt} \qquad (A45)$$

where the t subscript now designates years, rather than decades (as in the main text), and $\hat{\lambda}_{rt}^{F5}$ and $\hat{\lambda}_{rt}^{I5}$ are respectively the 5-year foreign and internal contributions to the change in log population. These are constructed in line with equations (24) and (25). Specifically, $\hat{\lambda}_{rt}^{F5} \equiv \log \left(\frac{L_{rt-5} + L_{rt}^{F5}}{L_{rt-5}} \right)$, where L_{rt}^{F5} is the 5-year flow into area r from abroad, and L_{rt-5} is the local population at time $t-5$ (based on census respondents' reported place of residence five years previously). And in turn, $\hat{\lambda}_{rt}^{I} \equiv \log \left(\frac{L_{rt-5} + L_{rt}^{Ii5} - L_{rt}^{Io5}}{L_{rt-5}} \right)$, where L_{rt}^{Ii5} and L_{rt}^{Io5} are respectively the 5-year inflows and outflows to/from others parts of the US. Notice that, by construction, $L_{rt} \equiv L_{rt-5} + L_{rt}^{F5} + L_{rt}^{Ii5} - L_{rt}^{Io5}$. Given that the flows are based on the reports of time t residents, individuals who emigrated from the US between $t-5$ and t are excluded from this data.

I do not observe employment outcomes between census years (i.e. at 5 year intervals), so I choose to use the same right hand side variables as in equation (35): the decadal Bartik shift-share b_{rt} (which predicts employment growth between $t-10$ and t), the employment rate lagged ten years, and the amenity controls. The mismatch in time periods is not ideal, and one should keep this in mind when interpreting the estimates.

I report OLS and IV estimates in Table A7. I instrument $\hat{\lambda}_{rt}^{F5}$ using a five-year migrant shift-share, constructed to predict the 5-year flow and based on migrant settlement patterns in $t-5$. I construct these settlement patterns using migrants' reported historical residence in the census microdata of year t (i.e. following a similar procedure to the longitudinal estimates of Section 6.2). I instrument the lagged employment rate using the lagged decadal Bartik shift-share.

[Table A7 here]

The standard errors on the OLS estimates are too large to make definitive statements. But the IV estimates tell a much clearer story. Column 4 reports the basic δ_1 estimate, based on equation (A45). This points to a large crowding out effect (-1.6), somewhat in excess of one-for-one. In the next two columns, I disaggregate the effect into (approximate) contributions from internal inflows and outflows: column 5 replaces the dependent variable with $\hat{\lambda}_{rt}^{Ii5} \equiv \log \left(\frac{L_{rt-5} + L_{rt}^{Ii5}}{L_{rt-5}} \right)$; and column 6 replaces it with $\hat{\lambda}_{rt}^{Io5} \equiv \log \left(\frac{L_{rt-5} + L_{rt}^{Io5}}{L_{rt-5}} \right)$. The crowding out effect is entirely driven by variation in inflows rather than outflows. The effect on outflows is statistically insignificant.

E.5   State-level estimates of crowding out

In Section 5 of the main text, I have estimated the extent of geographical crowd-out across specifically CZs. Interestingly, Borjas (2006) finds that the extent of crowd-out

is smaller at higher-level geographical units, based on comparisons of estimates across census divisions, states and metropolitan areas. The idea is intuitive: US residents are less mobile across longer distances. In this appendix, I estimate crowding out effects across states - but I still cannot reject one-for-one crowding out. However, given the loss of variation in moving to state-level, the coefficients are less precisely estimated.

As before, I base my estimates on equation (35) in the main text, though I replace the lagged employment rate control $(n_{rt-1} - l_{rt-1})$ with a lagged Bartik shift-share b_{rt-1} control. This is because I cannot successfully identify the lagged employment rate using the lagged Bartik as an instrument in the state-level data. In line with my CZ estimates (see Section 3.4), I control for state-level amenity effects: a binary indicator for a coastal state (ocean or Great Lakes), maximum January temperature, maximum July temperature, mean July relative humidity, and log state-level population density in 1900. I also control for year effects and a full set of interactions between the amenity variables and year effects. My sample consists of five decadal observations of 49 geographical units: the 48 states of the continental US plus the District of Columbia.

[Table A8 here]

I present my results in Table A8. Using OLS, I estimate a δ_1 of -0.67 (column 1). The IV estimate in column 2 is -1.3, a little larger than the CZ-based estimate in Table 5 - though the standard error is also larger. In column 3, I control additionally for the lagged migrant shift-share $\hat{\mu}_{rt-1}$. This picks up part of the negative impact of $\hat{\lambda}_{rt}^F$, though the coefficient on $\hat{\lambda}_{rt}^F$ remains close to -1. Columns 4-5 assess the effect of replacing the dependent variable with its lag (as a test for pre-trends), based on the restricted 1970-2010 sample. As one would expect, the coefficient on $\hat{\mu}_{rt-1}$ in column 5 now becomes much larger (and more negative), though there is also a large *positive* effect of $\hat{\lambda}_{rt}^F$. The latter point suggests some difficulty in disentangling the effects of the current and lagged migrant shift-shares in the state-level data, though any bias arising from pre-trends appears to go against my crowding out hypothesis.

The associated first stage estimates are presented in columns 6-8: the current migrant shift-share $\hat{\mu}_{rt}$ is a strong instrument for $\hat{\lambda}_{rt}^F$ in every specification.

F Impact of foreign inflows on other CZ outcomes

F.1 Education composition

In Section 5, I estimate the impact of foreign inflows (elicited by the migrant shift-share instrument) on two aggregate CZ-level outcomes: population and employment rates. The purpose of this appendix is to explore heterogeneity across demographic groups (specifically education) and also to assess additional outcomes (wages and housing costs).

I begin by studying the impact of foreign inflows on local education composition. To this end, I replace the dependent variable of (35) with education group s population changes (I use s for "skill", for consistency with the notation in Section 6), but keeping the right hand side identical:

$$\Delta l_{srt} = \delta_{0s} + \delta_{1s}\hat{\lambda}_{rt}^F + \delta_{2s}b_{rt} + \delta_{3s}\left(\tilde{n}_{rt-1} - l_{rt-1}\right) + A_{rt}\delta_{As} + \varepsilon_{srt} \qquad (A46)$$

Note that this specification estimates the education-specific outcomes of *aggregate*-level shocks (the "pure spatial" approach in Dustmann, Schoenberg and Stuhler, 2016), in contrast to equation (37) in Section 6 which exploits variation in shocks *within* CZs (the "mixture approach"). There are two endogenous variables (the foreign inflows and lagged employment rate), and I instrument these with the migrant shift-share and lagged Bartik - as in Section 5.

The top row of Table A9 reports IV estimates of δ_{1s} in (A46), estimated for all individuals (aged 16-64) and separately for different education groups. And in the next two rows, I disaggregate the change in education-specific population into its foreign and residual contributions: that is, I re-estimate δ_{1s} after replacing Δl_{srt} in (A46) with $\hat{\lambda}_{srt}^F$ and $\hat{\lambda}_{srt}^I$ respectively, as defined by equations (38) and (39) in the main text.

[Table A9 here]

It is useful to begin with the second row. The coefficient in the first column is 1 by construction: the left hand and right hand side variables are identical. But the coefficients are also close to 1 in the next two columns: 0.82 for college graduates and 1.03 for non-graduates. Thus, the migrant shift-share instrument $\hat{\mu}_{rt}$ attracts an educationally balanced group of new foreign migrants (in terms of the graduate share), relative to the existing local population. The third row shows the residual contribution's response is negative and a little larger in each case. As a result, the response of local graduate and non-graduate populations are both small and slightly negative (-0.26 and -0.15), so the graduate share is little affected. Having said that, to the extent that new migrants downgrade in occupation and that undercoverage is disproportionate among low educated migrants, this may understate the labor market pressure on low educated natives.

The remaining columns study finer education groups. Among the non-graduate stock, inflows bring an expansion of the local share of high school dropouts. The importance of this for local outcomes will depend on the substitutability between high school dropouts and graduates in production.[36] It is also worth emphasizing (as I do in Section 6) that education-specific residual contributions may reflect changes in the characteristics of local birth cohorts and not just geographical mobility.

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[36]See the debate between e.g. Ottaviano and Peri (2012) and Borjas, Grogger and Hanson (2012).

F.2 Raw employment rates

In Panel B of Table A9, I replace the dependent variable of (A46) with the change in *raw* native and migrant employment rates, i.e. without adjusting for demographic composition.[37] Again, the first column presents estimates for the full sample of individuals (not disaggregated by education): -0.22 and -0.20 for natives and migrants respectively. These are very similar to the effects on the composition-adjusted rates (-0.21 and -0.24): see columns 1 and 6 of Table 8. This should be reassuring: given that adjusting local employment rates for observable characteristics makes little difference, one may be less concerned about the influence of unobservables.

The impact largely falls on lower educated individuals: for natives in particular, there is no effect on those with college degrees. This suggests the minimal effect of foreign inflows on the college graduate share (see first row of Table A9) may indeed understate the labor market pressure on the low educated. Given this, it is perhaps surprising that the residual response $\hat{\lambda}^I_{srt}$ is similarly large across all education groups (third row). One explanation is demographic disparities in the speed of local population adjustments: see e.g. Bound and Holzer (2000); Wozniak (2010); Notowidigdo (2011). In particular, using the same data as this paper, Amior and Manning (2018) show that the college graduate population adjusts fully to local employment shocks within one decade; and any sluggishness in the population response is due to lower educated individuals.

F.3 Wages and housing costs

The remaining rows of Table A9 explore the impact of foreign inflows on local wages and housing costs. Given the (moderate) adverse effect on local employment rates, one would expect a small negative effect on real consumption wages - based on the labor supply relationship in equation (2). Unfortunately, local wage deflators are notoriously difficult to construct (and typically rely on strong theoretical assumptions), especially for the detailed geographies and long time series in my data: see e.g. Koo, Phillips and Sigalla (2000), Albouy (2008) and Phillips and Daly (2010). Nevertheless, one can at least study the effects on nominal wages and housing costs separately.

In line with Amior and Manning (2018), I use residualized indices of wages, housing rents and housing prices. I compute hourly wages as the ratio of annual labor earnings to the product of weeks worked and usual hours per week in the census and ACS microdata. I restrict my wage sample to employees aged 16-64, excluding those in group quarters; and I also exclude wage observations below the 1st and above the 99th percentiles within each geographical unit in the microdata.[38] For each census cross-section, I then regress

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[37]In notation, I estimate the impact on $\Delta (n_{rt} - l_{rt})$ rather than $\Delta (\tilde{n}_{rt} - l_{rt})$.

[38]See footnote 28 above.

log hourly wages on a rich set of demographic controls[39], and I compute the mean residual within each geographical unit (for the nativity/education group of interest). I then impute CZ-level wages by taking weighted averages across these units, using the population weights described in Section B.1.

My housing sample consists of houses and apartments; I exclude farms, units with over 10 acres of land, and units with commercial use. To construct the rental index, I regress the monthly rents of privately rented units on a rich set of housing characteristics[40] (restricting attention to prices between the 1st and 99th percentiles, within each geographical unit, from the sample), separately for each census cross-section. And I compute the local mean of the residuals within each geographical unit. I residualize local housing prices in the same way, though the sample is now restricted to owner-occupied units. As with wages, I impute CZ-level housing cost measures by taking weighted averages across the geographical units available in each microdata sample, again applying the population weights from Section B.1.

In Panel C, I replace the dependent variable of (A46) with changes in the log residualized wage. Looking at the first column (covering the full sample), the impact on native and migrant wages is close to zero and statistically insignificant. However, this masks some heterogeneity: there is a small positive response for college graduates (an elasticities of 0.17 for natives) and a smaller negative (but insignificant) effect among the low educated. It is also worth noting that Card (2009b) and Gould (forthcoming) identify positive effects of foreign inflows on local within-group wage inequality. On the other hand, given the adverse effect on local employment rates, the wage effects among non-graduates are perhaps difficult to interpret. It may be that the lowest paid workers are selecting out of employment: see e.g. Card (2001) and Bratsberg and Raaum (2012).

Turning to housing costs, there is a positive but statistically insignificant effect on both rents and prices (Panels D and E) for the full sample (column 1), with elasticities of 0.11 and 0.32 respectively. See also Saiz (2007), who finds positive effects of immigration on local housing costs in the US. But to the extent that housing units are not perfect substitutes within CZs (e.g. due to particular characteristics or neighborhoods), this may mask part of the story. For example, Albouy and Zabek (2016) have recently documented growing inequality in housing prices within cities, driven mostly by changes in the relative value of locations. This also relates to the "superstar city" story of Gyourko, Mayer and Sinai (2013). To study this further, I compute the mean of local housing cost residuals within native/migrant and education groups. Specifically, I define a household's

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[39]These are the same controls I use for adjusting local employment rates: age, age squared, five education indicators, black/Asian/Hispanic indicators, gender, foreign-born status, and where available, years in US and its square for migrants, together with a rich set of interactions. See Appendix B.2.

[40]Specifically, number of rooms (9 indicators) and bedrooms (6 indicators); an interaction between number of rooms and bedrooms; building age (up to 9 indicators, depending on cross-section), presence of kitchen, complete plumbing and condominium status; I also control for a house/apartment dummy, together with interactions between this and all previously-mentioned variables.

education as that of its most educated member; and I define a household as a "migrant household" if at least one of its members was born abroad. It turns out that the positive response of local housing costs is mostly driven by better educated households: the elasticities of rents and prices for college graduate households (column 2) are 0.26 and 0.63 respectively (and both are statistically significant). Of course, this may simply reflect an improvement in these households' housing characteristics (on unobservable dimensions), but it may also reflect increasing prices of housing characteristics disproportionately consumed by these households. To the extent the latter interpretation is true, one may not be able to conclude that real consumption wages have grown for this group[41] - despite the improvement in nominal wages. And this would be consistent with the negligible effect on college graduate employment rates. As an aside, the question here is somewhat analogous to that posed by Moretti (2013) regarding variation across MSAs. He finds that college graduates are increasingly concentrating in more costly cities, but the welfare implications depend on whether they are doing so because of labor demand shocks or preferences for unobserved local amenities.

Certainly, an analysis of the impact on real consumption wages is challenging - and not least because it is difficult to construct credible local wage deflators. This underscores the potential advantages of relying on changes in local employment rates, based on the sufficient statistic result of Amior and Manning (2018).

G   Cohort effects in within-area estimates

The difference between the pooled cross-section and longitudinal estimates in Section 6.2 is suggestive of large cohort effects, though perhaps not conclusively so. For example, it could be that the disparity is driven by events in the initial five years of each decade (excluded from the longitudinal sample).

In Table A10, I test for cohort effects more explicitly by exploiting information in the census on natives' state of birth. As a reference, the first three columns present again the CZ-level pooled cross-section estimates of δ_1^w in equation (37), identical to Table 9 in the main text. Columns 4-6 then offer state-level estimates of δ_1^w, again using pooled cross-sections. My sample consists of 49 geographical units (the 48 states of the continental US plus the District of Columbia) and three decadal observations (over 1970-2000, for comparability with the estimates in Table 9). As with the CZ estimates, the first stage (using the education-specific migrant shift-share instrument $\hat{\mu}_{srt}$) has substantial power for all education delineations. And the IV estimates of the native-only response (column 5) look very similar to the comparable estimates for CZs (column 3).

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[41]This depends of course on the importance of housing rents and prices in local wage deflators: see e.g. Albouy (2008) and Davis and Ortalo-Magne (2011).

[Table A10 here]

Recall the dependent variable in column 5, $\hat{\lambda}_{srt}^{I,N}$, is the contribution of natives to "skill" (in practice, education) s population growth among state r residents. In column 6, I now replace this with $\hat{\lambda}_{BPsrt}^{I,N}$: the contribution of natives to skill s population growth among those *born* (rather than residing) in state r. The column 6 estimate should now proxy for the contribution of cohort effects to education composition in state r - though given that one third of individuals live outside their state of birth, it should understate any such effects. Remarkably, the effects are all larger than the state of residence estimate in column 5 - and for the first two delineations, substantially so. In other words, foreign inflows to a given state exert a larger impact on the education composition of natives born in that state than on those residing in it. This suggests any contribution of internal mobility to the δ_1^w estimate in column 5 is more than fully offset by cohort effects.

H   Reconciliation with Cadena and Kovak (2016)

H.1   Summary

In important work, Cadena and Kovak (2016) study the contribution of (specifically Mexican) migrants to local labor market adjustment, exploiting variation in historical settlement patterns. My paper builds on their contribution and implements a similar identification strategy. But their results appear to diverge from mine in three ways. First, Cadena and Kovak find that low educated natives contribute negligibly to local adjustment - in contrast to Mexican-born workers. Second, they find that Mexicans respond heavily even after arriving in the US - while in my paper, the migrant response is entirely driven by new arrivals. And third, they find that Mexicans do not "crowd out" the native population response, but rather, smooth local fluctuations in employment rates. Based on the intuition from my model, notice that the final claim follows theoretically from the first: migrants "grease the wheels" because the wheels are not already greased.

There are some important differences in empirical setting. Cadena and Kovak focus on the contribution of specifically Mexican-born migrants between 2006 and 2010 (during the Great Recession) across 94 Metropolitan Statistical Areas (MSAs).[42] And they find that Mexicans accelerate local adjustment specifically in the low skilled market (less than college): college-educated natives do respond strongly to local demand. In contrast, my focus is the overall contribution of all migrants to the aggregate labor market over a broader period: 1960-2010.

Nevertheless, I show here that there are also differences in empirical specification between our papers which can help bridge the gap. In what follows, I focus specifically

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[42]Attention is restricted to MSAs with adult population exceeding 100,000, Mexican-born sample exceeding 60, and non-zero samples for all other studied demographic groups.

on the elasticities of the native and migrant populations. Once I account for dynamics, I find that the native population does respond strongly to local shocks.

H.2 Empirical model

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

$$\Delta l_{gr} = \omega_{0g} + \omega_{1g} IndShock_{gr} + X_r \omega_{Xg} + \varepsilon_{gr} \tag{A47}$$

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:

$$IndShock_{gr} \equiv \sum_i \phi_{gr}^i \Delta n_{ir} \tag{A48}$$

where the weights ϕ_{gr}^i 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 (31) 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 employment legislation. Like Cadena and Kovak, I weight all estimates using inverse sample variances.

Notice the conceptual framework here is somewhat different to mine. My approach 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 (A47) 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 skilled population will respond more strongly to a given employment shock in cities with larger initial Mexican enclaves; and therefore, these cities will suffer weaker fluctuations in local employment rates.

Beyond this broad conceptual point, there are also some differences in the empirical details. First, (A47) studies the response to a within-industry employment shock $IndShock_{gr}$, rather than a change in overall employment Δn_{gr} which accounts addi-

tionally for between-industry shifts. Second, (A47) does not account for dynamics: in particular, it does not control for the lagged employment rate. In principle, these dynamics may be more consequential for the short 2006-2010 interval than the decadal intervals in my own analysis. And third, Cadena and Kovak do not control for local amenity effects such as climate.

H.3 Estimates

I explore the implications of these three specification features in Table A11, relying on data and programs published alongside Cadena and Kovak's article. I restrict attention to low skilled workers (and specifically men) - who account for Cadena and Kovak's headline results. Columns 1-4 of Panel A of Table A11 replicate Panel A of Table 4 in their paper. The response of low skilled natives to local demand shocks 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.

[Table A11 here]

In Panel B, I replace the within-industry employment shock $IndShock_{gr}$ with a simple change in (group-specific) log employment Δn_{gr}. 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 lagged group-specific employment rate (i.e. in 2006), which I instrument using a Bartik industry shift-share for 2000-6.[43] The specification now has the form of an error correction model, regressing the change in (group-specific) log population on the change in (group-specific) log employment and the lagged (group-specific) log employment rate. The responses from the overall population (column 1) and natives (column 2) are now substantially larger - and it is not possible to statistically reject complete adjustment (i.e. coefficients of 1) over the period. Interestingly, the native response now exceeds the overall population response - though the difference is not statistically significant. The impact of controlling for dynamics is intuitive. As Cadena and Kovak note, MSAs experiencing larger upturns before 2006 experienced larger downturns thereafter. Thus, 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

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

lagged 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 specifications.

In columns 5-8, I repeat the same regressions but controlling for the local amenity effects described in Section 3 in the main text (using population allocations to map CZ data to MSAs): climate, coastline, historical population and isolation. In Panel A (without the dynamics), there is now a small positive response from natives. And as before, the native response becomes larger once I control for dynamics, though the standard errors are also much larger (and the first stage F-statistics much smaller).

I Reconciliation with Card (2001)

The seminal reference in the geographical crowding out literature is Card (2001). He offers within-area estimates of crowding out, i.e. δ_1^w in (37), but exploiting longitudinal residential information in the US census (respondents were asked where they lived five years previously: see Section 6.2). This approach should address possible concerns about cohort effects, but he still estimates a positive value for δ_1^w - with each new foreign migrant to an area-skill cell attracting (on net) 0.25 additional residents. This appears to conflict with my own longitudinal estimates in column 5 of Table 9 in the main text. In this appendix, I attempt to reconcile my results with his. It appears the divergence of our estimates is mostly explained by the choice of right hand side controls and the sample of geographical areas.

I begin my attempting to replicate Card's results. In line with his paper, I study variation across the 175 largest MSAs in the 5 percent census extract of 1990.[44] The sample is restricted to individuals aged 16 to 68 with more than one year of potential experience. In constructing his sample, Card uses all foreign-born individuals in the census extract and a 25 percent random sample of the native-born. I instead use the full sample of natives, and this may (at least partly) account for some small discrepancies between his estimates and my replication. Card delineates six skill groups by probabilistically assigning individuals into broad occupation categories (laborers and low skilled services; operative and craft; clerical; sales; managers; professional and technical), conditional

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[44]The 1990 census microdata includes sub-state geographical identifiers known as Public Use Microdata Areas (PUMAs), and a concordance between PUMAs and MSAs can be found at: *https://usa.ipums.org/usa/volii/puma.shtml*. A number of PUMAs straddle MSA boundaries; and following Card, I allocate the population of a given PUMA to an MSA if at least half that PUMA's population resides in the MSA.

on their education and demographic characteristics. This assignment is based on predictions from a multinomial logit model, estimated separately for native men, native women, migrant men and migrant women; and I follow the procedure set out in his appendix. This approach offers the advantage of accounting for any occupational downgrading of migrants (see e.g. Dustmann, Schoenberg and Stuhler, 2016).

Card estimates a specification very similar to (37), except he uses first order approximations of $\hat{\lambda}_{srt}^I$ and $\hat{\lambda}_{srt}^F$. Specifically:

$$\frac{\left(L_{sr,1990} - L_{sr,1990}^F\right) - L_{sr,1985}}{L_{sr,1985}} = \delta_0^w + \delta_1^w \frac{L_{sr,1990}^F}{L_{sr,1985}} + X_{sr}\delta_X^w + d_s + d_r + \varepsilon_{sr} \qquad \text{(A49)}$$

where $L_{sr,1990}$ is the population of skill group s in area r in the census year (1990); $L_{sr,1985}$ is the local population five years previously, based on responses to the 1990 census; and $L_{sr,1990}^F$ is the number of foreign migrants in the skill-area cell in 1990 who were living abroad in 1985. Thus, the dependent variable is the contribution of natives and earlier (pre-1985) migrants to population growth (net of emigrants from the US, who do not appear in the sample), and the regressor $\frac{L_{sr,1990}^F}{L_{sr,1985}}$ is the contribution of foreign migration to that growth. To be more precise, Card actually uses the total (within-cell) population growth $\frac{L_{sr,1990} - L_{sr,1985}}{L_{sr,1985}}$ as the dependent variable, but this is a cosmetic difference: it simply adds a value of 1 to the δ_1^w coefficient.[45] X_{sr} is a vector of mean characteristics of individuals in the (s, r) cell: these consist of mean age, mean age squared, mean years of schooling and fraction black, separately for both natives and migrants in the cell, and (for migrants only) mean years in the US. Finally, d_s and d_r are full sets of skill and area fixed effects respectively.

The instrument for $\frac{L_{sr,1990}^F}{L_{sr,1985}}$ is a first order approximation of (41) in the main text, specifically $\frac{\sum_o \phi_{r,1985}^o L_{os,1990}^F}{L_{sr,1985}}$, where $\phi_{r,1985}^o$ is the share of origin o migrants who lived in area r in 1985, and $L_{os,1990}^F$ is the number of new origin o migrants who arrived in the US between 1985 and 1990. I use the 17 origin country groups described by Card.

In his baseline OLS specification (with 175 MSAs and observations weighted by cell population), Card estimates δ_1^w as 0.25, with a standard error of 0.04: i.e. a "negative crowding out" effect.[46] And Card's IV estimate is also 0.25, but with a standard error of 0.05. I record these estimates in column 1 of Table A12.

[Table A12 here]

I attempt to replicate these estimates in column 2 and achieve similar numbers for Card's six-group occupation scheme (bottom row). In the remaining rows, I re-estimate

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[45]See Peri and Sparber (2011) for a discussion of this point.

[46]Using his population growth dependent variable, this comes out as 1.25 - from which I subtract 1. See final column of Table 4 of Card (2001).

the model for the four education delineations from Table 9 in the main text: (i) college graduates / non-graduates; (ii) at least one year of college / no college; (iii) high school dropouts / all others; (iv) four groups: dropouts, high school graduates, some college and college graduates. In the fifth row, I also study a classification with two imputed occupation groups: all those two-digit occupations with less than 40 percent college share in 1990, versus all those with more than 40 percent.[47] I assign individuals probabilistically to these groups using the same multinomial logit procedure (conditioning on the same demographic characteristics) as for Card's six group delineation in the final row. Looking at column 2, it appears that the choice of skill delineation makes no significant difference to the estimates. In column 3, I cluster the errors by state: the standard errors are now larger, but the difference is not dramatic.

Much of the action comes in column 4, when I exclude the mean demographic controls in X_{sr} from the right hand side. All the estimates of δ_1^w are now negative, and they are statistically significant for the college graduate, college and two-group occupation schemes, with IV coefficients of -2.14, -0.45 and -0.47 respectively. Of course, these controls may be picking up important skill-specific shocks which I have neglected: the purpose of this exercise is merely to understand how our results can be reconciled.

Column 5 extends the geographical sample to all identifiable MSAs (raising the total from 175 to 320), and column 6 extends it to cover 49 additional regions consisting of the non-metro areas in each state[48] (so 369 areas in total). The latter modification ensures the area sample is comprehensive of the US, similarly to the CZs I use in the main text. There may be good reason to exclude the smaller CZs; but again, the purpose of this exercise is merely to reconcile our results. These sample extensions make the coefficients larger (more negative) for all skill delineations, and the IV estimates in column 6 are now statistically significant for all but the four-group education delineation.

In the final column, I replace the left and right hand side variables with $\hat{\lambda}_{sr,1990}^I$ and $\hat{\lambda}_{sr,1990}^F$ respectively, as defined by equations (38) and (39): i.e. $\log\left(\frac{L_{sr,1990} - L_{sr,1990}^F}{L_{sr,1985}}\right)$ and $\log\left(\frac{L_{sr,1985} + L_{sr,1990}^F}{L_{sr,1985}}\right)$. This makes a negligible difference to the results. The final column can now be compared to my longitudinal estimates in the main text (column 5 of Table 9): the results look similar. Just as with the education groups, moving to a finer occupation classification (i.e. from the penultimate to the final row) yields a smaller δ_1^w estimate; the discussion in Section 6.2 offers an intuition for this result.

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[47]As it happens, the occupational distribution in college share is strongly bipolar, and 40 percent is the natural dividing line.

[48]Based on the allocation procedure described above, all of New Jersey is already classified as part of an MSA. The "49 additional regions" cover the remaining 49 states.

Tables and figures

Table 1: Average contributions to local population adjustment

	OLS				IV			
	Aggregate response	Foreign contribution	Residual contribution		Aggregate response	Foreign contribution	Residual contribution	
	Δl_{rt}	$\hat{\lambda}_{rt}^F$	All: $\hat{\lambda}_{rt}^I$	Natives: $\hat{\lambda}_{rt}^{I,N}$	Δl_{rt}	$\hat{\lambda}_{rt}^F$	All: $\hat{\lambda}_{rt}^I$	Natives: $\hat{\lambda}_{rt}^{I,N}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: No $\hat{\mu}_{rt}$ control								
Δ log emp	0.857***	0.050***	0.838***	0.781***	0.748***	0.237**	0.527***	0.571***
	(0.013)	(0.017)	(0.024)	(0.019)	(0.043)	(0.093)	(0.090)	(0.054)
Lagged log ER	0.246***	0.089*	0.172***	0.131***	0.551***	0.313***	0.270*	0.258**
	(0.020)	(0.052)	(0.053)	(0.040)	(0.097)	(0.119)	(0.150)	(0.110)
Panel B: Controlling for $\hat{\mu}_{rt}$								
Δ log emp	0.858***	0.056***	0.833***	0.778***	0.735***	0.130***	0.624***	0.629***
	(0.014)	(0.011)	(0.016)	(0.016)	(0.040)	(0.039)	(0.049)	(0.042)
Lagged log ER	0.243***	0.068***	0.191***	0.142***	0.530***	0.126*	0.441***	0.360***
	(0.019)	(0.024)	(0.031)	(0.030)	(0.096)	(0.065)	(0.123)	(0.096)
$\hat{\mu}_{rt}$	0.133***	0.955***	-0.847***	-0.498***	0.110*	0.952***	-0.870***	-0.517***
	(0.040)	(0.085)	(0.099)	(0.065)	(0.060)	(0.085)	(0.108)	(0.082)
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 OLS and IV estimates of β_1 and β_2 in (33), across 722 CZs and five (decadal) time periods, for different dependent variables: first, the aggregate change in log population, and then its (approximate) components. All specifications control for year effects and the amenity variables (interacted with year effects) described in Section 3.4. Panel B controls additionally for the local migrant shift-share, $\hat{\mu}_{rt}$. Errors are clustered by state, and robust standard errors are reported in parentheses. Each observation is weighted by the lagged local population share. *** p<0.01, ** p<0.05, * p<0.1.

Table 2: First stage for estimates of average and heterogeneous contributions

	First stage for Table 1				First stage for Table 3			
	Δ log emp	Lagged log ER	Δ log emp	Lagged log ER	Δ log emp	Δ log emp * $\hat{\lambda}_{rt}^F$	Lagged log ER	Lagged log ER * $\hat{\lambda}_{rt}^F$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Current Bartik	**0.823***	-0.135*	**0.839***	-0.134*	**0.993***	-0.007	-0.175***	0.004
	(0.130)	(0.072)	**(0.124)**	(0.069)	**(0.123)**	(0.006)	(0.065)	(0.003)
Current Bartik * $\hat{\mu}_{rt}$					-4.543	**1.302***	1.440	-0.556***
					(3.110)	**(0.173)**	(1.025)	(0.074)
Lagged Bartik	0.102	**0.369***	0.122*	**0.371***	0.095*	0.012***	**0.337***	-0.004**
	(0.068)	**(0.061)**	(0.068)	**(0.063)**	(0.056)	(0.002)	**(0.061)**	(0.002)
Lagged Bartik * $\hat{\mu}_{rt}$					0.928	-0.245**	-0.434	**0.446***
					(2.038)	(0.106)	(1.416)	**(0.095)**
$\hat{\mu}_{rt}$			-0.233**	-0.022	-2.429	-0.216*	-0.691	-0.900***
			(0.113)	(0.122)	(2.012)	(0.111)	(1.815)	(0.167)
SW F-stat	74.65	55.46	78.91	56.41	111.24	22.84	54.94	15.91
Amenity×yr controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Amenity×$\hat{\mu}_{rt}$ 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 presents first stage estimates corresponding to the IV specifications in Tables 1 and 3. The Sanderson-Windmeijer (2016) F-statistics account for multiple endogenous variables. All specifications control for year effects, the amenity variables described in Section 3.4 and interactions between the two. The first stages for the Table 3 specifications control additionally for interactions between the amenity variables and local migrant intensity. I have marked in **bold** the effect of each instrument on its corresponding endogenous variable, i.e. where one should theoretically expect to see positive effects. Errors are clustered by state, and robust standard errors are reported in parentheses. Each observation is weighted by the lagged local population share. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Heterogeneity in contributions to population adjustment

	OLS				IV			
	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)
Δ log emp	0.852***	0.004	0.859***	0.852***	0.791***	-0.006	0.809***	0.825***
	(0.015)	(0.012)	(0.015)	(0.018)	(0.036)	(0.028)	(0.046)	(0.043)
Δ log emp * $\hat{\mu}_{rt}$	0.169	1.930***	-1.030***	-2.877***	-0.689	4.908***	-5.326***	-8.410***
	(0.247)	(0.376)	(0.379)	(0.515)	(0.804)	(1.180)	(1.127)	(1.325)
Lagged log ER	0.224***	0.021	0.211***	0.211***	0.560***	0.007	0.595***	0.579***
	(0.019)	(0.012)	(0.020)	(0.021)	(0.114)	(0.055)	(0.131)	(0.126)
Lagged log ER * $\hat{\mu}_{rt}$	1.842***	1.757***	0.501	-2.384***	1.693	7.407***	-6.551***	-11.857***
	(0.653)	(0.647)	(0.535)	(0.377)	(1.938)	(2.203)	(2.482)	(3.542)
$\hat{\mu}_{rt}$	1.491	1.441	-0.029	-0.428	1.536	6.062*	-5.681**	-8.042**
	(1.118)	(1.289)	(0.838)	(0.708)	(2.449)	(3.220)	(2.594)	(3.805)
Amenity×yr controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Amenity×$\hat{\mu}_{rt}$ controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,610	3,610	3,610	3,610	3,610	3,610	3,610	3,610

This table reports OLS and IV estimates of equation (34), across 722 CZs and five (decadal) time periods. As in Table 1, 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 3.4, interactions between the amenity variables and year effects, and (unlike Table 1) interactions between the amenity variables and local migrant intensity. Errors are clustered by state, and robust standard errors are reported in parentheses. Each observation is weighted by the lagged local population share. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Evolution of local employment rates (IV estimates)

	All	Natives	Migrants	All	Natives	Migrants
	(1)	(2)	(3)	(4)	(5)	(6)
Δ log emp	0.252***	0.251***	0.167*	0.209***	0.200***	0.193**
	(0.043)	(0.045)	(0.098)	(0.036)	(0.038)	(0.089)
Δ log emp * $\hat{\mu}_{rt}$				0.689	1.159	-1.551
				(0.804)	(0.773)	(1.502)
Lagged log ER	-0.551***	-0.560***	-0.609***	-0.560***	-0.577***	-0.577**
	(0.097)	(0.099)	(0.216)	(0.114)	(0.119)	(0.253)
Lagged log ER * $\hat{\mu}_{rt}$				-1.693	-1.168	-2.405
				(1.938)	(1.772)	(4.192)
$\hat{\mu}_{rt}$				-1.536	-1.472	-0.952
				(2.449)	(2.208)	(4.371)
Amenity×yr controls	Yes	Yes	Yes	Yes	Yes	Yes
Amenity×$\hat{\mu}_{rt}$ controls	No	No	No	Yes	Yes	Yes
Observations	3,610	3,610	3,599	3,610	3,610	3,599

Columns 1-3 replicate the IV estimate of column 5 of Table 1 (Panel A), but replacing the dependent variable with changes in log (composition-adjusted) employment rates: separately for all individuals, natives and migrants. Columns 4-6 do the same for the IV estimate of column 5 of Table 3. The observation count is a little smaller in columns 3 and 6: I am unable to compute composition-adjusted migrant employment rates for 11 small CZs in the 1960s (see footnote 18). Errors are clustered by state, and robust standard errors are reported in parentheses. Each observation is weighted by the lagged local population share. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Estimates of crowding out across CZs

	Basic crowding out estimates						Cond. on emp	Emp response
	$\hat{\lambda}^I_{rt}$	$\hat{\lambda}^I_{rt}$	$\hat{\lambda}^I_{rt}$	$\hat{\lambda}^I_{rt}$	$\hat{\lambda}^I_{rt}$	$\hat{\lambda}^I_{rt-1}$	$\hat{\lambda}^I_{rt}$	$\Delta\tilde{n}_{rt}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Foreign contrib: $\hat{\lambda}^F_{rt}$	-0.761***	-1.096***	-1.109***	-0.787***	-0.786***	-0.235	-0.913***	-0.245**
	(0.200)	(0.130)	(0.153)	(0.167)	(0.184)	(0.228)	(0.065)	(0.102)
Δ log emp							0.743***	
							(0.043)	
Lagged log ER	0.520***	0.831***	0.833***				0.556***	0.370*
	(0.072)	(0.207)	(0.221)				(0.105)	(0.191)
Current Bartik	0.646***	0.677***	0.679***	0.524***	0.421***	-0.071		0.911***
	(0.109)	(0.099)	(0.096)	(0.119)	(0.161)	(0.168)		(0.103)
Lagged Bartik				0.290***	0.287***	0.907***		
				(0.060)	(0.085)	(0.103)		
$\hat{\mu}_{rt-1}$			0.016	-0.388***	-0.340***	-0.984***		
			(0.161)	(0.124)	(0.116)	(0.167)		
Specification	OLS	IV	IV	IV	IV	IV	IV	IV
Instruments	-	$\hat{\mu}_{rt}, b_{rt-1}$	$\hat{\mu}_{rt}, b_{rt-1}$	$\hat{\mu}_{rt}$	$\hat{\mu}_{rt}$	$\hat{\mu}_{rt}$	$\hat{\mu}_{rt}, b_{rt-1}$	$\hat{\mu}_{rt}, b_{rt-1}$
Amenity×yr controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year sample	60-10	60-10	60-10	60-10	70-10	70-10	60-10	60-10
Observations	3,610	3,610	3,610	3,610	2,888	2,888	3,610	3,610

Columns 1-6 report variants of the crowding out equation (35). There are (up to) two endogenous variables: the contribution of new migrants to local population growth, $\hat{\lambda}^F_{rt}$, and the lagged log employment rate. The corresponding instruments are the migrant shift-share $\hat{\mu}_{rt}$ and the lagged Bartik b_{rt-1}. Columns 5-6 exclude observations from the 1960s, and column 6 replaces the dependent variable with its lag. Column 7 reports estimates of equation (36), which replaces the current Bartik control with the current change in log employment (with the current Bartik b_{rt} deployed instead as a third instrument). Column 8 re-estimates column 2, but replacing the dependent variable with the change in the log employment stock. All specifications control for year effects and the amenity variables (interacted with year effects) described in Section 3.4. Errors are clustered by state, and robust standard errors are reported in parentheses. Each observation is weighted by the lagged local population share. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: First stage for crowding out estimates

	Foreign contribution: $\hat{\lambda}^F_{rt}$			Lagged log ER		Δ log emp
	(1)	(2)	(3)	(4)	(5)	(6)
Current Bartik	0.092***	0.078***	0.121***	-0.134*	-0.156**	**0.839*** **
	(0.025)	(0.026)	(0.034)	(0.069)	(0.067)	**(0.124)**
Lagged Bartik	0.063***	0.064***	0.160***	**0.371*** **	**0.373*** **	0.122*
	(0.019)	(0.019)	(0.028)	**(0.063)**	**(0.062)**	(0.068)
$\hat{\mu}_{rt}$	**0.919*** **	**1.229*** **	**1.173*** **	-0.022	0.475***	-0.233**
	(0.084)	**(0.119)**	**(0.105)**	(0.122)	(0.175)	(0.113)
$\hat{\mu}_{rt-1}$		-0.399***	-0.377***		-0.640***	
		(0.056)	(0.053)		(0.139)	
SW F-test: 2 endog vars	126.47	54.88	-	34.70	31.00	-
SW F-test: 3 endog vars	93.68	-	-	56.93	-	84.09
Amenity×yr controls	Yes	Yes	Yes	Yes	Yes	Yes
Year sample	60-10	60-10	70-10	60-10	60-10	60-10
Observations	3,610	3,610	2,888	3,610	3,610	3,610

This table reports first stage estimates corresponding to the crowding out specifications in Table 5. I report Sanderson-Windmeijer F-statistics which account for multiple endogenous variables, both for those Table 5 specifications with two endogenous variables (i.e. $\hat{\lambda}^F_{rt}$ and the lagged employment rate) and those with three (as before, plus the current change in log employment). All specifications control for year effects and the amenity variables (interacted with year effects) described in Section 3.4. I have marked in **bold** the effect of each instrument on its corresponding endogenous variable, i.e. where one should theoretically expect to see positive effects. Errors are clustered by state, and robust standard errors are reported in parentheses. Each observation is weighted by the lagged local population share. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Robustness of IV crowding out effects to controls and decadal sample

	Natives and old migrants: $\hat{\lambda}_{rt}^I$						Natives only: $\hat{\lambda}_{rt}^{I,N}$
	1960s	1970s	1980s	1990s	2000s	All years	All years
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Year effects	0.273	-0.726	-0.041	-0.943***	-0.538**	-0.526**	-0.224
	(0.944)	(0.635)	(0.250)	(0.225)	(0.252)	(0.246)	(0.172)
+ Current Bartik	-0.745	-0.268	-0.455	-0.921***	-0.572**	-0.689***	-0.396**
	(1.134)	(0.466)	(0.350)	(0.260)	(0.251)	(0.217)	(0.158)
+ Lagged log ER (instrumented)	-0.709	-0.238	-0.744*	-0.327	-0.564**	-0.753***	-0.448**
	(1.139)	(0.318)	(0.441)	(0.421)	(0.246)	(0.239)	(0.176)
+ Climate controls	-1.967**	-2.088***	-0.973***	-1.343***	-0.845***	-1.396***	-0.973***
	(0.908)	(0.467)	(0.302)	(0.256)	(0.180)	(0.192)	(0.146)
+ Coastline dummy	-2.032**	-2.087***	-0.865**	-1.119***	-0.637***	-1.263***	-0.846***
	(0.947)	(0.473)	(0.350)	(0.251)	(0.189)	(0.228)	(0.172)
+ Log pop density 1900	-1.657***	-1.797***	-0.726***	-1.100***	-0.558***	-1.107***	-0.721***
	(0.610)	(0.220)	(0.201)	(0.276)	(0.215)	(0.256)	(0.218)
+ Log distance to closest CZ	-1.626**	-1.917***	-0.877***	-1.203***	-0.638***	-1.137***	-0.751***
	(0.634)	(0.197)	(0.188)	(0.298)	(0.236)	(0.251)	(0.215)
+ Amenity×yr effects	-1.626**	-1.917***	-0.877***	-1.203***	-0.638***	-1.096***	-0.715***
	(0.634)	(0.197)	(0.188)	(0.298)	(0.236)	(0.130)	(0.127)
Observations	722	722	722	722	722	3,610	3,610

This table tests the robustness of my IV crowding out estimate δ_1 (in column 2 of Table 5) to the choice of controls and decadal sample. 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 migrant shift-share, $\hat{\mu}_{rt}$) and year effects. The second row controls additionally for a current Bartik, b_{rt}; the third row includes the (endogenous) lagged employment rate (together 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 5. The first six columns report estimates of δ_1, separately for each decade and for all decades together; and the final column replaces the dependent variable with the contribution of natives alone, $\hat{\lambda}_{rt}^{I,N}$. Errors are clustered by state, and robust standard errors are reported in parentheses. Each observation is weighted by the lagged local population share. *** p<0.01, ** p<0.05, * p<0.1.

Table 8: IV effects of foreign inflows on change in log employment rate

	Native					Migrant
	Current	Current	Current	Current	Lagged	Current
	(1)	(2)	(3)	(4)	(5)	(6)
Foreign contrib: $\hat{\lambda}_{rt}^F$	-0.210***	-0.190**	-0.350***	-0.399***	-0.022	-0.236***
	(0.057)	(0.092)	(0.075)	(0.072)	(0.061)	(0.055)
Lagged log ER	-0.411***	-0.414***				-0.469**
	(0.087)	(0.091)				(0.204)
Current Bartik	0.259***	0.255***	0.333***	0.483***	0.024	0.192**
	(0.036)	(0.034)	(0.038)	(0.051)	(0.058)	(0.081)
Lagged Bartik			-0.144***	-0.098***	0.069*	
			(0.024)	(0.034)	(0.036)	
$\hat{\mu}_{rt-1}$		-0.024	0.177**	0.201***	-0.216***	
		(0.079)	(0.076)	(0.073)	(0.063)	
Instruments	$\hat{\mu}_{rt}, b_{rt-1}$	$\hat{\mu}_{rt}, b_{rt-1}$	$\hat{\mu}_{rt}$	$\hat{\mu}_{rt}$	$\hat{\mu}_{rt}$	$\hat{\mu}_{rt}, b_{rt-1}$
Amenity×yr controls	Yes	Yes	Yes	Yes	Yes	Yes
Year sample	60-10	60-10	60-10	70-10	70-10	60-10
Observations	3,610	3,610	3,610	2,888	2,888	3,599

This table reports estimates of the crowding out equation (35), with the dependent variable replaced with the change in the log (composition-adjusted) employment rate - either of natives or migrants. See the notes under Table 5 for further details about the empirical specification, and see Table 6 for the first stage estimates. All specifications control for year effects and the amenity variables (interacted with year effects) described in Section 3.4. The observation count is a little smaller in column 6: I am unable to compute composition-adjusted migrant employment rates for 11 small CZs in the 1960s (see footnote 18). Errors are clustered by state, and robust standard errors are reported in parentheses. Each observation is weighted by the lagged local population share. *** p<0.01, ** p<0.05, * p<0.1.

Table 9: Within-area IV estimates of δ_1^w

	Pooled cross-sections			Longitudinal			Observations
	First stage coefficient	Full residual contrib: $\hat{\lambda}_{srt}^I$	Natives only: $\hat{\lambda}_{srt}^{I,N}$	First stage coefficient	Full residual contrib: $\hat{\lambda}_{srt}^I$	Natives only: $\hat{\lambda}_{srt}^{I,N}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
CG / < CG	0.539***	1.502***	1.638***	0.475***	-3.587**	-2.798**	4,332
	(0.067)	(0.295)	(0.369)	(0.074)	(1.518)	(1.244)	
Coll / < Coll	0.662***	1.040***	1.046***	0.778***	-1.129***	-0.794***	4,332
	(0.044)	(0.132)	(0.162)	(0.056)	(0.094)	(0.140)	
HSD / > HSD	0.785***	0.980***	1.410***	0.841***	-0.425***	-0.252***	4,332
	(0.031)	(0.088)	(0.261)	(0.039)	(0.090)	(0.067)	
4 edu groups	0.744***	1.330***	1.521***	0.817***	-0.194*	-0.041	8,664
	(0.035)	(0.095)	(0.209)	(0.038)	(0.117)	(0.085)	

This table reports within-area estimates of δ_1^w based on equation (37). The first three columns are based on pooled decadal cross-sections between 1970 and 2000, and columns 4-6 exploit longitudinal information on changes in residence over 1975-1980, 1985-1990 and 1995-2000. Columns 1 and 4 report the first stage coefficients on the skill-specific migrant shift-share, $\hat{\mu}_{srt}$. And the remaining columns report IV estimates of δ_1^w, both for the full residual contribution (natives and old migrants) and for natives only. The four rows offer estimates for different education-based skill delineations: (i) college graduates / non-graduates, (ii) at least one year of college / no college, (iii) high school dropouts / all others, and (iv) four groups: high school dropouts, high school graduates, some college and college graduates. All specifications control for both CZ-year and skill-year interacted fixed effects. Errors are clustered by state, and robust standard errors are reported in parentheses. Each observation is weighted by the lagged cell-specific population share. *** p<0.01, ** p<0.05, * p<0.1.

	Aggregate response Δl_{rt} (1)	Foreign contribution $\hat{\lambda}^F_{rt}$ (2)	Residual contribution All: $\hat{\lambda}^I_{rt}$ (3)	Natives: $\hat{\lambda}^{I,N}_{rt}$ (4)	Aggregate response Δl_{rt} (5)	Foreign contribution $\hat{\lambda}^F_{rt}$ (6)	Residual contribution All: $\hat{\lambda}^I_{rt}$ (7)	Natives: $\hat{\lambda}^{I,N}_{rt}$ (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 * $\hat{\mu}_{rt}$					-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 * $\hat{\mu}_{rt}$					1.693	7.407***	-6.551***	-11.857***
					(1.938)	(2.203)	(2.482)	(3.542)
$\hat{\mu}_{rt}$					1.536	6.062*	-5.681**	-8.042**
					(2.449)	(3.220)	(2.594)	(3.805)
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 * $\hat{\mu}_{rt}$					-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 * $\hat{\mu}_{rt}$					-1.039	7.299***	-9.201***	-15.586***
					(2.092)	(2.133)	(1.920)	(2.849)
$\hat{\mu}_{rt}$					3.731	5.729**	-3.035	-6.198*
					(2.484)	(2.546)	(2.174)	(3.535)
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 * $\hat{\mu}_{rt}$					-0.468	3.175***	-3.127***	-4.982***
					(0.396)	(0.787)	(0.643)	(0.672)
$\hat{\mu}_{rt}$					-0.148	-0.603	0.042	2.459***
					(0.708)	(0.541)	(0.910)	(0.680)
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 * $\hat{\mu}_{rt}$					-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 * $\hat{\mu}_{rt}$					2.328	6.291***	-4.309***	-8.509***
					(2.012)	(1.718)	(1.526)	(1.827)
$\hat{\mu}_{rt}$					2.489	5.403	-3.701*	-5.378*
					(3.449)	(3.777)	(2.134)	(3.048)
Amenity×yr controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Amenity×$\hat{\mu}_{rt}$ 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 5-8 (Panel A) of Table 1 and columns 5-8 of Table 3, subject to various changes of specification. Employment variables are composition-adjusted in all specifications except in Panel D. Errors are clustered by state, and robust standard errors are reported in parentheses. Each observation is weighted by the lagged local population share. *** p<0.01, ** p<0.05, * p<0.1.

Table A2: Robustness of IV contributions to local adjustment: Amenity controls

	Aggregate response Δl_{rt} (1)	Foreign contribution $\hat{\lambda}^F_{rt}$ (2)	Residual contribution All: $\hat{\lambda}^I_{rt}$ (3)	Residual contribution Natives: $\hat{\lambda}^{I,N}_{rt}$ (4)	Aggregate response Δl_{rt} (5)	Foreign contribution $\hat{\lambda}^F_{rt}$ (6)	Residual contribution All: $\hat{\lambda}^I_{rt}$ (7)	Residual contribution Natives: $\hat{\lambda}^{I,N}_{rt}$ (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 * $\hat{\mu}_{rt}$					-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 * $\hat{\mu}_{rt}$					-0.027	11.284	-13.054	-16.914
					(1.237)	(13.308)	(15.582)	(15.559)
$\hat{\mu}_{rt}$					0.306	4.477	-4.822	-5.700
					(0.430)	(4.388)	(5.098)	(5.111)
*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 * $\hat{\mu}_{rt}$					-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 * $\hat{\mu}_{rt}$					2.174	16.061	-15.370*	-19.784**
					(4.261)	(10.327)	(8.908)	(10.076)
$\hat{\mu}_{rt}$					0.989	6.239*	-5.845*	-6.888**
					(1.478)	(3.534)	(3.034)	(3.460)
*Panel C: ... + amenity * $\hat{\mu}_{rt}$ interactions*								
Δ log emp	0.753***	0.093***	0.686***	0.658***	0.791***	-0.006	0.809***	0.825***
	(0.041)	(0.032)	(0.051)	(0.050)	(0.036)	(0.028)	(0.046)	(0.043)
Δ log emp * $\hat{\mu}_{rt}$					-0.689	4.908***	-5.326***	-8.410***
					(0.804)	(1.180)	(1.127)	(1.325)
Lagged log ER	0.571***	0.101**	0.509***	0.416***	0.560***	0.007	0.595***	0.579***
	(0.112)	(0.049)	(0.125)	(0.113)	(0.114)	(0.055)	(0.131)	(0.126)
Lagged log ER * $\hat{\mu}_{rt}$					1.693	7.407***	-6.551***	-11.857***
					(1.938)	(2.203)	(2.482)	(3.542)
$\hat{\mu}_{rt}$					1.536	6.062*	-5.681**	-8.042**
					(2.449)	(3.220)	(2.594)	(3.805)
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 5-8 (Panel A) of Table 1 and columns 5-8 of Table 3, subject to various combinations of right hand side controls. Errors are clustered by state, and robust standard errors are reported in parentheses. Each observation is weighted by the lagged local population share. *** p<0.01, ** p<0.05, * p<0.1.

Table A3: Robustness of IV contributions to local adjustment: 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 $\hat{\mu}_{rt} > 0.1$ (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 * $\hat{\mu}_{rt}$					-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 * $\hat{\mu}_{rt}$					-0.230	6.510*	-7.763	-11.487
					(3.367)	(3.712)	(7.486)	(7.667)
$\hat{\mu}_{rt}$					-1.157	6.894**	-9.904	-10.971
					(3.601)	(2.921)	(6.332)	(6.795)

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 * $\hat{\mu}_{rt}$					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 * $\hat{\mu}_{rt}$					4.565***	3.592***	1.091	-7.071***
					(1.708)	(0.783)	(2.057)	(1.908)
$\hat{\mu}_{rt}$					-0.157	2.628***	-2.720	-4.598***
					(1.682)	(0.631)	(1.742)	(1.415)

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 * $\hat{\mu}_{rt}$					-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 * $\hat{\mu}_{rt}$					1.699	4.171***	-2.456	-8.771***
					(1.496)	(0.618)	(1.616)	(1.478)
$\hat{\mu}_{rt}$					0.949	3.688***	-2.927	-4.789**
					(1.944)	(0.849)	(1.906)	(1.994)

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 * $\hat{\mu}_{rt}$					-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 * $\hat{\mu}_{rt}$					0.875	5.051***	-4.108**	-10.391***
					(1.999)	(0.866)	(1.796)	(1.791)
$\hat{\mu}_{rt}$					1.089	4.616***	-3.684***	-6.749***
					(1.919)	(1.463)	(1.304)	(1.404)
Amenity×yr controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Amenity×$\hat{\mu}_{rt}$ controls	No	No	No	No	Yes	Yes	Yes	Yes

This table replicates the IV estimates from columns 5-8 (Panel A) of Table 1 and columns 5-8 of Table 3, subject to various weighting choices (i.e. with or without lagged local population share weights) and sample choices. Errors are clustered by state, and robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A4: Average foreign contributions by country/region of origin

	Total foreign contribution	Mexico	Other Latin America	Europe and former USSR	Asia	Other
	(1)	(2)	(3)	(4)	(5)	(6)
OLS						
Δ log emp	0.050***	0.020**	0.006	0.008***	0.012*	0.007***
	(0.017)	(0.009)	(0.010)	(0.002)	(0.007)	(0.002)
Lagged log ER	0.089*	0.012	0.033	0.015**	0.020*	0.011*
	(0.052)	(0.013)	(0.037)	(0.006)	(0.011)	(0.006)
IV						
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 migration	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 contributions in columns 2 and 6 (Panel A) of Table 1 into approximate contributions from origin country groups. For each origin group o, I replace the dependent variable of equation (33) 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 those in Table 1. Errors are clustered by state, and robust standard errors are reported in parentheses. Each observation is weighted by the lagged local population share. *** p<0.01, ** p<0.05, * p<0.1.

Table A5: Estimates of crowding out across CZs: Alternative IV strategies

	$\hat{\lambda}^I_{rt}$ (1)	$\hat{\lambda}^I_{rt}$ (2)	$\frac{\Delta L_{rt}-L^F_{rt}}{L_{rt-1}}$ (3)	$\frac{\Delta L_{rt}-L^F_{rt}}{L_{rt-1}}$ (4)	$\Delta L_{rt}-L^F_{rt}$ (5)	$\Delta L_{rt}-L^F_{rt}$ (6)	$\hat{\lambda}^I_{rt}$ (7)	$\hat{\lambda}^I_{rt}$ (8)
Panel A: Weighted estimates								
$\hat{\lambda}^F_{rt}$	-1.096***	-1.393***					-0.631	-1.351***
	(0.130)	(0.262)					(0.611)	(0.262)
$\frac{L^F_{rt}}{L_{rt-1}}$			-1.090***	-1.077***				
			(0.143)	(0.163)				
L^F_{rt}					-0.228***	-0.971***		
					(0.085)	(0.273)		
Lagged log ER	0.831***	0.943***	0.893***	0.888***	2×10⁶***	4×10⁶**	1.269**	
	(0.207)	(0.172)	(0.227)	(0.203)	(7×10⁵)	(2×10⁶)	(0.496)	
Current Bartik	0.677***	0.737***	0.791***	0.788***	2×10⁵	-2×10⁵	0.615***	0.580***
	(0.099)	(0.106)	(0.116)	(0.124)	(3×10⁵)	(2×10⁵)	(0.086)	(0.080)
Lagged Bartik								0.162***
								(0.063)
$\hat{\mu}_{rt-1}$								0.078
								(0.119)
SW F-stat for foreign contrib	126.47	40.26	116.05	91.63	262.07	92.07	58.33	40.30
SW F-stat for lagged ER	34.70	45.18	34.99	40.63	39.10	49.08	45.51	-
Panel B: Unweighted estimates								
$\hat{\lambda}^F_{rt}$	-0.940***	-1.538***					-2.288***	-2.400***
	(0.266)	(0.458)					(0.448)	(0.589)
$\frac{L^F_{rt}}{L_{rt-1}}$			-1.005***	-1.210***				
			(0.285)	(0.293)				
L^F_{rt}					-0.147	-1.186***		
					(0.151)	(0.273)		
Lagged log ER	0.578***	0.664***	0.667***	0.697***	6×10⁵***	3×10⁵***	0.654***	
	(0.183)	(0.188)	(0.218)	(0.227)	(2×10⁵)	(1×10⁵)	(0.247)	
Current Bartik	0.604***	0.650***	0.679***	0.696***	2×10⁵***	-9×10³	0.442***	0.410***
	(0.106)	(0.115)	(0.127)	(0.130)	(6×10⁴)	(3×10⁴)	(0.074)	(0.070)
Lagged Bartik								0.117***
								(0.042)
$\hat{\mu}_{rt-1}$								0.210
								(0.166)
SW F-stat for foreign contrib	51.13	50.09	42.80	14.59	121.72	42.95	6.27	5.61
SW F-stat for lagged ER	25.77	32.27	26.03	25.61	30.32	52.55	53.13	-
Instruments	$\hat{\mu}_{rt}, b_{rt-1}$	$\hat{\mu}^{60}_{rt}, b_{rt-1}$	$\frac{\Lambda^F_{rt}}{L_{rt-1}}, b_{rt-1}$	Λ^F_{rt}, b_{rt-1}	Λ^F_{rt}, b_{rt-1}	Λ^F_{rt}, b_{rt-1}	$\hat{\mu}_{rt}, b_{rt-1}$	$\hat{\mu}_{rt}, b_{rt-1}$
Amenity×yr controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CZ fixed effects	No	No	No	No	No	Yes	Yes	Yes
Observations	3,610	3,610	3,610	3,610	3,610	3,610	3,610	3,610

This table offers alternative estimates of δ_1 in equation (35), implementing different IV strategies and variable specifications. Panel A reports estimates weighted by the lagged population share, and Panel B reports unweighted estimates. Columns 1-5 in each panel do not control for CZ fixed effects, while columns 6-8 do. The dependent variable in each specification is reported in the field above the column number. The instruments I use in each specification are reported at the bottom of the table. The Sanderson-Windmeijer (2016) F- statistics account for multiple endogenous variables. All specifications control for the lagged employment rate (always instrumented with the lagged Bartik b_{rt-1}), the current Bartik b_{rt}, year effects and the amenity variables (interacted with year effects) described in Section 3.4. Errors are clustered by state, and robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A6: Robustness of IV crowding out effects: Native response

	Basic specification					
	1960s	1970s	1980s	1990s	2000s	All years
	(1)	(2)	(3)	(4)	(5)	(6)
Year effects	0.922	-0.695	0.033	-0.678***	0.159	-0.224
	(0.728)	(0.520)	(0.165)	(0.174)	(0.153)	(0.172)
+ Current Bartik	-0.139	-0.362	-0.405	-0.661***	0.144	-0.396**
	(0.891)	(0.409)	(0.261)	(0.208)	(0.155)	(0.158)
+ Lagged log ER (instrumented)	-0.116	-0.336	-0.636*	-0.148	0.139	-0.448**
	(0.896)	(0.291)	(0.355)	(0.366)	(0.151)	(0.176)
+ Climate controls	-1.193*	-1.976***	-0.825***	-0.981***	-0.057	-0.973***
	(0.716)	(0.403)	(0.224)	(0.257)	(0.141)	(0.146)
+ Coastline dummy	-1.250*	-2.000***	-0.725***	-0.776***	0.112	-0.846***
	(0.736)	(0.403)	(0.273)	(0.256)	(0.163)	(0.172)
+ Log pop density 1900	-0.942**	-1.747***	-0.628***	-0.759***	0.182	-0.721***
	(0.454)	(0.189)	(0.183)	(0.280)	(0.186)	(0.218)
+ Log distance to closest CZ	-0.926*	-1.873***	-0.751***	-0.870***	0.101	-0.751***
	(0.476)	(0.190)	(0.176)	(0.302)	(0.194)	(0.215)
+ Amenities x year effects	-0.926*	-1.873***	-0.751***	-0.870***	0.101	-0.715***
	(0.476)	(0.190)	(0.176)	(0.302)	(0.194)	(0.127)
Observations	722	722	722	722	722	3,610

This table replicates the specifications from Table 7 in the main text, except replacing the dependent variable (the full residual contribution, $\hat{\lambda}_{rt}^{I}$) with the contribution of natives alone, $\hat{\lambda}_{rt}^{I,N}$. Note that column 6 in this table is identical to column 7 of Table 7. Errors are clustered by state, and robust standard errors are reported in parentheses. Each observation is weighted by the lagged local population share. *** p<0.01, ** p<0.05, * p<0.1.

Table A7: Contribution of inflows and outflows to crowding out across CZs

	OLS			IV		
	Net flow $\hat{\lambda}_{rt}^{I5}$ (1)	Inflow $\hat{\lambda}_{rt}^{Ii5}$ (2)	Outflow $\hat{\lambda}_{rt}^{Io5}$ (3)	Net flows $\hat{\lambda}_{rt}^{I5}$ (4)	Inflow $\hat{\lambda}_{rt}^{Ii5}$ (5)	Outflow $\hat{\lambda}_{rt}^{Io5}$ (6)
Foreign contrib: $\hat{\lambda}_{rt}^{F5}$	-0.500	-0.296	0.147	-1.555***	-1.661***	-0.320
	(0.319)	(0.385)	(0.152)	(0.269)	(0.388)	(0.222)
Log ER lagged 10 yrs	0.199***	0.162***	-0.016	0.556***	0.758***	0.285**
	(0.047)	(0.051)	(0.033)	(0.191)	(0.179)	(0.118)
Current decadal Bartik	0.286**	0.400***	0.161***	0.442***	0.566***	0.190***
	(0.126)	(0.115)	(0.047)	(0.115)	(0.120)	(0.067)
SW F-stat for foreign contrib	-	-	-	88.92	88.92	88.92
SW F-stat for lagged ER	-	-	-	26.37	26.37	26.37
Observations	2,166	2,166	2,166	2,166	2,166	2,166

This table offers OLS and IV estimates of the 5-year net crowding out effect, based on equation (A45), and disaggregates these into the (approximate) contributions from internal inflows and outflows. Variable definitions and data sources are given in Section E.4. The flow data covers the intervals 1965-70, 1975-80, 1985-90 and 1995-2000. The 5-year foreign contribution is instrumented with a 5-year migrant shift-share in the IV specification, based on settlement patterns five years previously. The log employment rate, lagged ten years (e.g. measured at 1960 for the 1965-70 flow interval), is instrumented using a lagged decadal Bartik. I also control for a current decadal Bartik, year effects and the amenity variables (interacted with year effects) described in Section 3.4. Errors are clustered by state, and robust standard errors are reported in parentheses. Each observation is weighted by the 5-year lagged local population share. *** p<0.01, ** p<0.05, * p<0.1.

Table A8: State-level estimates of crowding out

	OLS and IV					First stage for foreign contrib		
	$\hat{\lambda}_{rt}^{I}$ (1)	$\hat{\lambda}_{rt}^{I}$ (2)	$\hat{\lambda}_{rt}^{I}$ (3)	$\hat{\lambda}_{rt}^{I}$ (4)	$\hat{\lambda}_{rt-1}^{I}$ (5)	$\hat{\lambda}_{rt}^{F}$ (6)	$\hat{\lambda}_{rt}^{F}$ (7)	$\hat{\lambda}_{rt}^{F}$ (8)
Foreign contrib: $\hat{\lambda}_{rt}^{F}$	-0.672**	-1.294***	-0.949**	-1.027**	0.804**			
	(0.251)	(0.345)	(0.379)	(0.440)	(0.324)			
Current Bartik	-0.024	0.204	0.136	0.090	-0.576*	0.097**	0.066	0.172**
	(0.236)	(0.236)	(0.239)	(0.359)	(0.300)	(0.037)	(0.043)	(0.069)
Lagged Bartik	0.185**	0.307***	0.300***	0.156	0.384**	0.063	0.076	0.165**
	(0.088)	(0.107)	(0.105)	(0.178)	(0.152)	(0.040)	(0.051)	(0.066)
$\hat{\mu}_{rt}$						1.069***	1.403***	1.287***
						(0.068)	(0.082)	(0.091)
$\hat{\mu}_{rt-1}$			-0.469**	-0.198	-2.246***		-0.424***	-0.424***
			(0.223)	(0.199)	(0.320)		(0.095)	(0.081)
Specification	OLS	IV	IV	IV	IV	-	-	-
Corresponding IV spec	-	-	-	-	-	Col 2	Col 3	Cols 4-5
Amenity×yr controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year sample	60-10	60-10	60-10	70-10	70-10	60-10	60-10	70-10
Observations	245	245	245	196	196	245	245	196

Columns 1-5 report state-level OLS and IV estimates of equation (35), though replacing the lagged employment rate with the lagged Bartik on the right hand side. In the IV specifications, the foreign contribution $\hat{\lambda}_{rt}^{F}$ is instrumented with a migrant shift-share $\hat{\mu}_{rt}$. Columns 6-8 report the first stage estimates. In addition to the variables reported in the tables, all specifications control for year effects and all the amenity variables (interacted with year effects) described in Section E.5. The full sample consists of five decadal observations of 49 geographical units (the 48 states of the continental US plus the District of Columbia) over five decadal periods. Columns 4-5 (and the corresponding first stage in column 8) omit the 1960-70 period. Errors are clustered by state, and robust standard errors are reported in parentheses. Each observation is weighted by the lagged state population share. *** p<0.01, ** p<0.05, * p<0.1.

Table A9: IV effects of foreign inflows by education

	All individuals (1)	College graduates (2)	Non-graduates (3)	Postgrad degree (4)	Undergrad degree (5)	Some college (6)	High-school graduates (7)	High-school dropouts (8)
Panel A: Population								
Δ log pop	-0.061	-0.261*	-0.145	-0.338	-0.146	-0.805***	-0.368*	0.968***
	(0.122)	(0.159)	(0.135)	(0.240)	(0.142)	(0.270)	(0.223)	(0.158)
Foreign contrib	1	0.816***	1.033***	0.721***	0.896***	0.673***	0.930***	1.446***
		(0.041)	(0.011)	(0.059)	(0.049)	(0.035)	(0.027)	(0.063)
Residual contrib	-1.096***	-0.977***	-1.274***	-1.022***	-0.877***	-1.444***	-1.334***	-0.924***
	(0.130)	(0.184)	(0.136)	(0.272)	(0.147)	(0.257)	(0.235)	(0.154)
Panel B: Employment rates (raw)								
Δ log native ER	-0.222***	-0.023	-0.357***	0.019	-0.033	-0.248***	-0.213***	-1.006***
	(0.058)	(0.020)	(0.070)	(0.015)	(0.034)	(0.059)	(0.057)	(0.122)
Δ log migrant ER	-0.202***	-0.110**	-0.255***	-0.085	-0.096	-0.339***	-0.293**	-0.322***
	(0.065)	(0.047)	(0.076)	(0.063)	(0.097)	(0.106)	(0.120)	(0.122)
Panel C: Wages (residualized)								
Δ log native wages	0.019	0.167**	-0.040	0.195***	0.162*	-0.073	-0.034	-0.138
	(0.124)	(0.077)	(0.130)	(0.064)	(0.091)	(0.093)	(0.116)	(0.139)
Δ log migrant wages	-0.032	0.185	-0.112	0.030	0.348	0.005	-0.103*	-0.247*
	(0.086)	(0.183)	(0.100)	(0.197)	(0.221)	(0.189)	(0.060)	(0.130)
Panel D: Housing rents (residualized)								
Δ log rents	0.105	0.259**	0.020	0.288**	0.242**	0.103	0.089	-0.050
	(0.114)	(0.109)	(0.109)	(0.113)	(0.112)	(0.113)	(0.110)	(0.209)
Δ log rents: natives	0.145	0.318***	0.041	0.322***	0.315***	0.132	0.064	-0.503**
	(0.114)	(0.109)	(0.109)	(0.111)	(0.118)	(0.115)	(0.090)	(0.243)
Δ log rents: migrants	0.288***	0.292***	0.217**	0.356***	0.194*	0.203*	0.258**	0.208
	(0.102)	(0.105)	(0.107)	(0.136)	(0.106)	(0.107)	(0.111)	(0.241)
Panel E: Housing prices (residualized)								
Δ log prices	0.319	0.625**	0.321	0.648**	0.603**	0.572**	0.421	0.576*
	(0.284)	(0.278)	(0.291)	(0.283)	(0.279)	(0.288)	(0.287)	(0.299)
Δ log prices: natives	0.373	0.687**	0.350	0.717***	0.652**	0.586**	0.413	0.620
	(0.278)	(0.273)	(0.289)	(0.274)	(0.279)	(0.293)	(0.276)	(0.475)
Δ log prices: migrants	0.428	0.648**	0.423	0.673**	0.575**	0.569**	0.504*	0.574
	(0.289)	(0.269)	(0.298)	(0.264)	(0.265)	(0.281)	(0.292)	(0.405)

This table reports IV estimates of δ_{1s} in (A46), i.e. the coefficient on CZ-level foreign inflows $\hat{\lambda}_{rt}^F$ (instrumented with the migrant shift-share), estimated for a range of outcomes - both for the full sample and separately by education group. See Appendix F for a description of the various outcomes. All specifications include 3,610 observations (722 CZs over five decadal periods) with the exception of some migrant-specific outcomes: in some small CZs, the sample of some census extracts does not include migrants in all education cells. The right hand side of the estimating equation is identical to that of column 2 (Panel A) of Table 5. All specifications control for a second endogenous variable: the lagged log employment rate, instrumented with the lagged Bartik. I also control for the current Bartik, year effects and the amenity variables (interacted with year effects) described in Section 3.4. Errors are clustered by state, and robust standard errors are reported in parentheses. Each observation is weighted by the lagged local population share. *** p<0.01, ** p<0.05, * p<0.1.

Table A10: Within-area IV estimates of δ_1^w: Cohort effects

	CZs: Pooled cross-sections			States: Pooled cross-sections			Observations	
	First stage coefficient	Full residual contrib: $\hat{\lambda}_{srt}^I$	Natives only: $\hat{\lambda}_{srt}^{I,N}$	First stage coefficient	Natives only: $\hat{\lambda}_{srt}^{I,N}$	Natives only: $\hat{\lambda}_{BPsrt}^{I,N}$	CZs	States
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CG / < CG	0.539***	1.502***	1.638***	0.596***	1.618**	2.245***	4,332	294
	(0.067)	(0.295)	(0.369)	(0.102)	(0.663)	(0.423)		
Coll / < Coll	0.662***	1.040***	1.046***	0.820***	1.212***	2.272***	4,332	294
	(0.044)	(0.132)	(0.162)	(0.047)	(0.146)	(0.206)		
HSD / > HSD	0.785***	0.980***	1.410***	0.970***	1.435***	1.620***	4,332	294
	(0.031)	(0.088)	(0.261)	(0.033)	(0.344)	(0.248)		
4 edu groups	0.744***	1.330***	1.521***	0.932***	1.484***	1.768***	8,664	588
	(0.035)	(0.095)	(0.209)	(0.032)	(0.246)	(0.195)		

This table explores the presence of cohort effects in the pooled cross-section IV estimates of δ_1^w in equation (37), using a range of education-based skill delineations. As a reference, the first three columns reproduce the CZ-level pooled cross-section estimates of δ_1^w from Table 9 in the main text, based on the three decadal periods between 1970 and 2000. Columns 4 reproduces the first stage estimates using state-level data (more specifically the 48 states of the continental US plus the District of Columbia). Column 5 estimates the IV effect of skill-specific foreign inflows $\hat{\lambda}_{rt}^F$ on the native contribution to skill s population growth in state r: i.e. the state-level version of column 3. Column 6 replaces the dependent variable with the contribution of natives to skill-specific population growth among those born (rather than residing) in state r. All specifications control for both area-year and skill-year interacted fixed effects. Errors are clustered by state, and robust standard errors are reported in parentheses. Each observation is weighted by the lagged cell-specific population share. *** p<0.01, ** p<0.05, * p<0.1.

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

	All (1)	Natives (2)	Mexican migrants (3)	Other migrants (4)	All (5)	Natives (6)	Mexican migrants (7)	Other migrants (8)
Panel A: Cadena and Kovak's Panel A, Table 4								
W/i-industry shock: group-specific	0.223	0.007	0.992**	-0.675**	0.527***	0.303**	1.103*	-0.602
	(0.166)	(0.090)	(0.468)	(0.278)	(0.168)	(0.126)	(0.590)	(0.496)
Panel B: As above, but replace IndShock$_{ar}$ with Δn_{ar}								
Δ log emp: group-specific	0.301*	0.013	0.771***	1.413***	0.540***	0.366***	0.839***	0.957**
	(0.170)	(0.159)	(0.104)	(0.356)	(0.097)	(0.093)	(0.128)	(0.378)
Panel C: Control for dynamics								
Δ log emp: group-specific	0.654***	0.871**	0.380	1.470***	0.598***	0.698	0.930***	0.798***
	(0.199)	(0.441)	(0.413)	(0.552)	(0.099)	(0.503)	(0.266)	(0.248)
Log ER in 2006: group-specific	0.680**	0.745***	-2.429	-0.519	0.235	0.826	0.623	-0.669
	(0.305)	(0.284)	(2.651)	(2.753)	(0.304)	(0.969)	(2.257)	(1.017)
Panel D: First stage for Δ log emp in Panel C specification								
Bartik 2006-10	2.928***	1.789**	7.805***	-3.342*	2.751***	2.789***	4.799**	-5.963**
	(0.763)	(0.734)	(1.661)	(1.814)	(0.764)	(0.796)	(2.150)	(2.363)
Bartik 2000-06	0.223	0.558	-2.013*	1.387	0.494	0.002	0.270	3.671**
	(0.575)	(0.548)	(1.208)	(1.337)	(0.690)	(0.625)	(1.444)	(1.629)
Panel E: First stage for log ER in 2006 in Panel C specification								
Bartik 2006-10	-2.777***	-3.936***	-1.075**	-0.643	-1.927**	-1.901**	-0.937	-0.322
	(0.625)	(1.352)	(0.501)	(0.812)	(0.753)	(0.940)	(0.703)	(0.812)
Bartik 2000-06	1.402***	1.507***	0.029	0.506	1.060*	0.708	0.246	0.704
	(0.485)	(0.513)	(0.303)	(0.697)	(0.564)	(0.756)	(0.435)	(0.712)
SW F-stats for Panel C								
Δ log emp	5.30	5.54	1.05	0.62	10.48	0.77	0.71	2.72
Log ER in 2006	4.94	5.42	0.97	0.32	3.33	0.66	0.57	1.44
Amenity controls	No	No	No	No	Yes	Yes	Yes	Yes
Observations	94	94	94	94	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 (A47). 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. Columns 1-4 of Panel A reproduce 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. Columns 5-8 control additionally for the local amenity effects described in Section 3.4 in the main text (using population allocations to map CZ data to MSAs): climate, coastline, historical population and isolation. *** p<0.01, ** p<0.05, * p<0.1.

Table A12: Reconciliation with 1985-1990 within-area estimates from Card (2001)

	Card (2001): 175 MSAs, weighted (1)	Replication (2)	... with errors clustered by state (3)	... excluding demog controls (4)	... with remaining MSAs (5)	... with full area sample (6)	... replacing LHS var with $\hat{\lambda}^I_{sr,1990}$, and RHS with $\hat{\lambda}^F_{sr,1990}$ (7)
Panel A: OLS							
CG / < CG	-	-0.153	-0.153	-1.948***	-3.270***	-3.595***	-3.878***
		(0.441)	(0.572)	(0.549)	(1.124)	(1.099)	(1.145)
Coll / < Coll	-	0.212	0.212	-0.346***	-0.393***	-0.642***	-0.725***
		(0.172)	(0.248)	(0.111)	(0.101)	(0.143)	(0.150)
HSD / > HSD	-	0.118	0.118	-0.084	-0.105	-0.259***	-0.291***
		(0.101)	(0.161)	(0.090)	(0.088)	(0.095)	(0.102)
4 edu groups	-	0.162	0.162*	-0.117	-0.191**	-0.349***	-0.409***
		(0.103)	(0.097)	(0.076)	(0.096)	(0.129)	(0.144)
2 occup groups	-	0.106	0.106	-0.486***	-0.801***	-0.942***	-1.036***
		(0.185)	(0.248)	(0.145)	(0.244)	(0.287)	(0.299)
6 occup groups	0.25***	0.214***	0.214**	-0.071	-0.181***	-0.230***	-0.267***
	(0.04)	(0.045)	(0.098)	(0.046)	(0.055)	(0.067)	(0.072)
Panel B: IV							
CG / < CG	-	0.563	0.563	-2.143***	-1.687*	-2.350**	-2.615***
		(1.280)	(2.912)	(0.750)	(0.867)	(0.927)	(0.949)
Coll / < Coll	-	0.389***	0.389	-0.449***	-0.499***	-0.747***	-0.846***
		(0.144)	(0.254)	(0.132)	(0.121)	(0.168)	(0.175)
HSD / > HSD	-	0.297***	0.297**	-0.059	-0.096	-0.262***	-0.295***
		(0.080)	(0.133)	(0.073)	(0.071)	(0.080)	(0.085)
4 edu groups	-	0.484***	0.484***	0.004	0.041	-0.136	-0.162*
		(0.117)	(0.118)	(0.077)	(0.084)	(0.086)	(0.090)
2 occup groups	-	0.244*	0.244	-0.469***	-0.653***	-0.809***	-0.895***
		(0.139)	(0.298)	(0.100)	(0.109)	(0.138)	(0.141)
6 occup groups	0.25***	0.255***	0.255**	-0.054	-0.123***	-0.169***	-0.192***
	(0.05)	(0.045)	(0.115)	(0.043)	(0.044)	(0.051)	(0.053)

This table offers a reconciliation with Card's (2001) within-area estimates of geographical crowd-out, based on equation (A49). Card's OLS and IV estimates of δ^w_1 (for his six-group imputed occupation scheme) are presented in column 1. These are taken from Table 4 of his paper, based on the 175 largest MSAs of the 1990 census extract, with observations weighted by cell populations. (Card reports his estimates as the effect on aggregate population growth within the cell, but I substract one from his numbers for comparability with my specification; see Peri and Sparber, 2011.) I attempt to replicate his results in column 2. In columns 3, I cluster standard errors by state. Column 4 excludes the demographic controls from the regression. Column 5 extends the geographical sample to all identifiable MSAs (raising the total to 320), and column 6 extends it to cover 49 additional regions consisting of the non-metro areas in each state (so 369 areas in total). Finally, column 7 replaces the left hand side variable with $\hat{\lambda}^I_{sr,1990}$ and the right hand side variable with $\hat{\lambda}^F_{sr,1990}$. I present estimates for both Card's six-group occupation scheme and the other skill delineations described in Appendix I. *** p<0.01, ** p<0.05, * p<0.1.
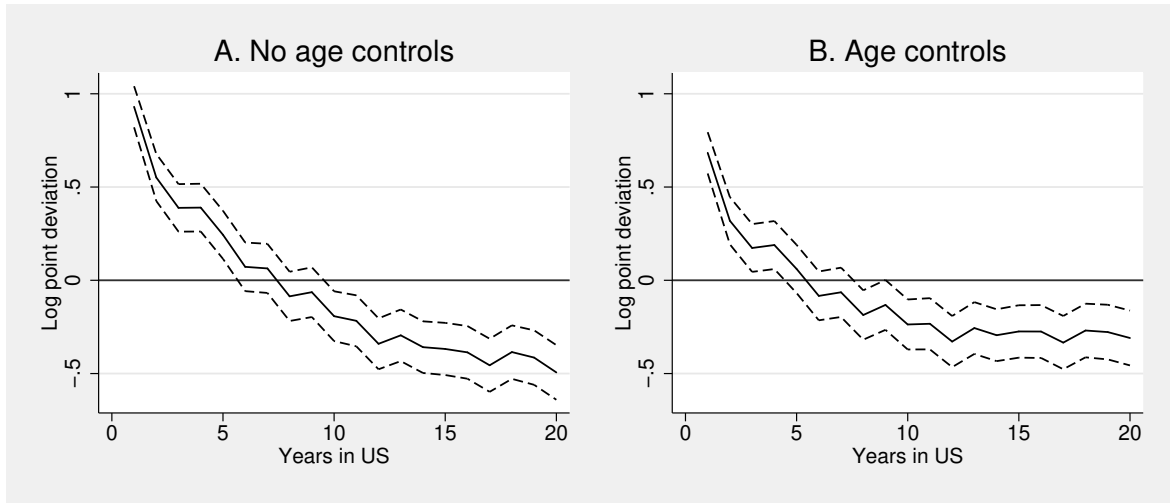
Figure A1: Effect of years in US on cross-state mobility

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. In addition to these, the model in Panel B controls for a full set of age effects. The sample consists of individuals aged 16-64 in ACS waves between 2000 and 2016. See Appendix C for further details.
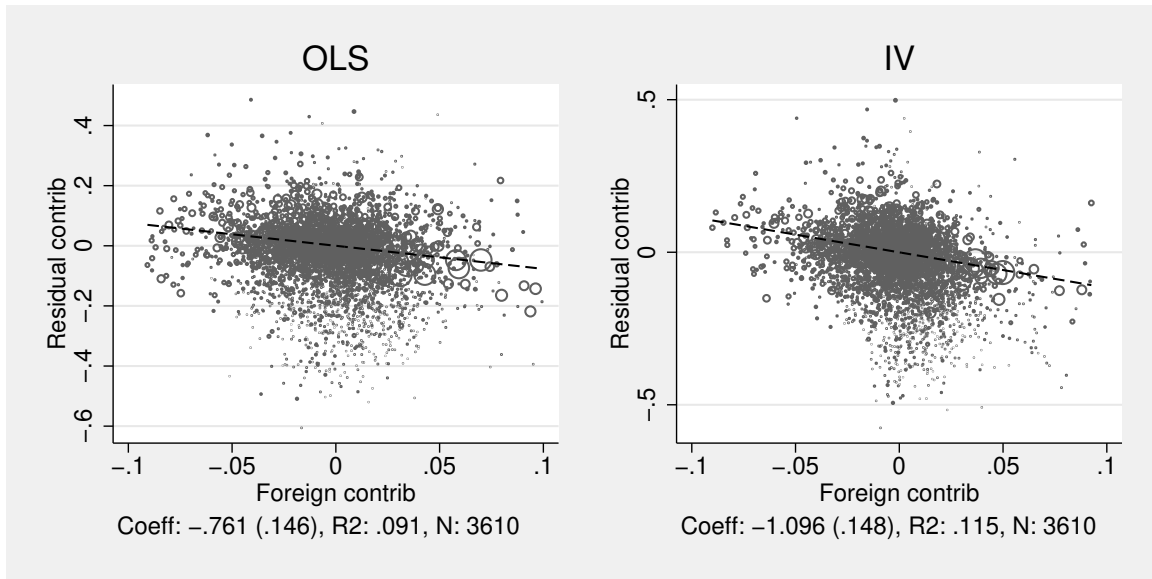

Figure A2: Graphical illustration of crowding out estimates

This figure presents Frisch-Waugh type plots for the δ_1 estimates in columns 1 and 2 of Table 5. See Appendix E.1. To restrict the range of the x-axis, I have excluded a small number of outlying data points: 9 observations in the OLS panel and 15 for IV.