The Contribution of Foreign Migration to Local Labor Market Adjustment

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PRELIMINARY AND INCOMPLETE

Abstract

It is commonly argued that foreign migrants "grease the wheels" of the labor market, in that they accelerate the adjustment of local population following a shock to local demand. Using US evidence, I confirm that migrants do indeed contribute disproportionately to local labor market adjustment. But, I also show that the speed of adjustment is no faster in those markets which are better supplied by migrants. That is, the migrant population response "crowds out" the contribution of natives. This is fundamentally a story of geographical displacement, which can be tested more explicitly: using the census data, I cannot reject the hypothesis that new migrant arrivals displace natives (and earlier migrants) one-for-one from areas with large co-patriot communities. These results differ markedly from much of the existing literature, and I identify three reasons for this: choice of sample and right hand side controls, cohort effects, and the delineation of skill groups.

1 Introduction

Public discourse on immigration has often focused on a perceived threat to natives' jobs. But, a famous hypothesis in the economic literature reverses this logic entirely. Borjas (2001) argues that foreign migrants "grease the wheels" of the labor market, since they are relatively mobile geographically. Intuitively, new arrivals from abroad are a self-selected group who

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have already incurred the fixed cost of moving. Cadena and Kovak (2016) also emphasize the role of stronger labor market attachment and long-distance co-patriot job networks, even some years after arrival in the US. Given their superior mobility, it is claimed that migrants hasten the adjustment of local labor markets in the US to equilibrium. And in this way, they may actually *protect* the jobs of immobile natives in areas suffering declining demand - by reducing the supply of labor.

Exploiting decadal census data since 1950 across commuting zones (CZs), I confirm that migrants do indeed contribute disproportionately to local labor market adjustment, though this is only true of new arrivals. But, I also find that migrants "crowd out" the native contribution to adjustment: so in regions better supplied by new migrants, local population adjustment is no faster. This is not to say that natives gain nothing from the geographical mobility of migrants: in particular, if moving is costly, a mobile migrant workforce can save natives from having to incur these costs themselves. But, the claim that migrants "grease the wheels" is not supported by the evidence.

I underpin these results with a model of local labor market adjustment proposed by Amior and Manning (2015). Local equilibrium is defined in a competitive Rosen-Roback framework (Rosen, 1979; Roback, 1982), which is supplemented with an ad hoc equation for net population flows to areas offering higher utility. If new foreign migrants are indeed relatively mobile, they should - all else equal - bring local labor markets to equilibrium more quickly. But all else is not equal: given that local utility differentials would be narrower at any point in time, natives (and earlier migrants) would be discouraged from relocating over the path of adjustment. Of course, any such "crowding out" effect will only materialize if the existing population is responsive to local differentials in the first place. And indeed, the evidence has pointed to a relatively swift adjustment of local population: see e.g. Blanchard and Katz (1992); Beaudry, Green and Sand (2014*b*); Amior and Manning (2015). This suggests that large "crowding out" effects are theoretically plausible.

Following Amior and Manning (2015), I estimate the overall speed of adjustment using an error correction model (ECM), where changes in log population are regressed on changes in log employment and the lagged log employment rate (the disequilibrium term); and I instrument the right hand side variables using the current and lagged industry shift-shares (following Bartik, 1991). 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 difficult to measure for detailed local geographies). The inclusion of the disequilibrium term (the lagged employment rate) is essential if adjustment is not instantaneous. And indeed, Amior and Manning show these dynamics matter even over the decadal intervals between census years.

I then confirm that new foreign migrants contribute disproportionately to the population response. On average, they account for one fifth of the response to contemporaneous employment changes and, remarkably, over half the response to the lagged employment rate.

However, as I have explained above, this does not necessarily mean that migrants "grease the wheels" - if the contribution of new migrants crowds out that of existing residents. To test for crowding out, I exploit variation across time and space in the supply of new migrants. I identify the local supply of migrants using the shift-share instrument popularized by Altonji and Card (1991) and Card (2001). This predicts the local inflow of new migrants by allocating new arrivals from each origin country to CZs according to the initial spatial distribution of co-patriot communities.[1] I show the speed of adjustment is no faster in those markets which are better supplied by migrants. This is because a stronger migrant response in these areas is counterbalanced by a weaker native response. This result appears to contradict Cadena and Kovak (2016), who find a larger population response to employment shocks in the late 2000s in cities with initially large Mexican population shares. However, Monras (2015*a*) argues that their analysis is compromised by the omission of pre-existing local population trends.

This is fundamentally a story of geographical displacement. The question of displacement is a controversial one in the literature, not only in its own right but also because of its broader methodological implications. A popular strategy to identify the effect of immigration (on a number of dimensions) is to exploit geographical variation, commonly known as the "area approach". But it is well known that the area approach will underestimate the aggregate-level impact of immigration in the presence of geographical displacement (see e.g. Borjas et al., 1997).

In the second part of the paper, I address the question of displacement more directly. In particular, using the census data, I cannot reject the hypothesis that new migrants geographically displace natives and (earlier migrants) one-for-one - again, using the migrant shift-share as an instrument. This result is robust to controlling for CZ fixed effects. Interestingly though, despite this one-for-one estimate, inflows of new migrants exert a significant negative effect on local employment rates (with an elasticity ranging between -0.1 and -0.2, for both natives and migrants) - which is indicative of large but incomplete adjustment of local labor markets. See also Gould (2016), who identifies adverse effects on low skilled

[1] It is well known that migrants tend to cluster in those areas where their communities have historically settled, whether because of job networks (Munshi, 2003) or cultural amenities (Gonzalez, 1998).

employment. This would be consistent with one-for-one displacement if migrants were more productive than natives. Alternatively, the displacement effect may be slightly overestimated due to under-reporting of new (and undocumented) migrants in the census. Still, the true effect is unlikely to be much smaller: the employment rate response suggests a displacement elasticity of -0.8 to -0.9 rather than -1.

Other studies have also identified substantial displacement (e.g. Frey, 1995; 1996, Borjas et al., 1997, and Borjas, 2006), though Peri and Sparber (2011) argue Borjas' empirical specification artificially biases his findings towards displacement. The recent US literature has more typically gravitated to small or zero displacement - or even a positive effect on native population.[2] See, for example, Card and DiNardo (2000), Card (2001, 2005, 2009*a*), Cortes (2008), Wozniak and Murray (2012); and see Peri and Sparber (2011) and Lewis and Peri (2014) for recent surveys. Various theoretical explanations have been offered. One view is that production technology adjusts endogenously to changes in labor supply or the skill mix; and Lewis (2011), for example, provides some evidence for this. But, this contradicts the spirit of Blanchard and Katz (1992) and Amior and Manning (2015), who find that local adjustment comes almost entirely through changes in population rather than labor demand. An alternative hypothesis is that migrants and natives are imperfect substitutes in production: see Card (2009*b*); Manacorda, Manning and Wadsworth (2012); Ottaviano and Peri (2012). For example, Peri and Sparber (2009) argue that natives have a comparative advantage in communication-intensive tasks.

I offer three reasons why my findings on displacement differ so starkly from the literature: (i) the choice of sample and right hand side controls, (ii) cohort effects and (iii) the delineation of skill groups. First, at the aggregate level, important drivers of local population (specifically climate and local demand shocks) are correlated with the migrant shift-share instrument - and in some decades more than others. I show that controlling for these yields a much larger displacement effect; and interestingly, pooling more historical data to increase the sample size has a similar effect.

Many studies in the literature have addressed this problem by exploiting variation across

[2]An interesting exception is Monras (2015*b*), who identifies one-for-one displacement following the short run surge of Mexican migrants during the Peso crisis of 1995 - but he finds little displacement over longer horizons. Moving outside the US, Dustmann, Schoenberg and Stuhler (2015) exploit a policy allowing Czechs to commute across the German border for work: they find a one-for-one displacement effect in employment, with about a third of that effect materializing in net-out migration from the affected border areas. On the other hand, using Spanish data, Sanchis-Guarner (2014) finds that foreign migration leads to net *inflows* of natives.

skill groups *within* geographical areas (see Card and DiNardo, 2000; Card, 2001, 2005; Borjas, 2006; Cortes, 2008; Monras, 2015*b*). These have typically found that skill-specific migrant inflows have large effects on local skill composition (at least over decadal intervals), consistent with little to no displacement. I corroborate these results with my data. But the within-area approach faces its own challenges. In particular, changes in local skill composition are not necessarily indicative of migratory flows - but may merely reflect changes in the characteristics of local cohorts. These cohort effects can be identified by exploiting a longitudinal dimension of the census data[3] (following the example of Card, 2001) and using information on individuals' state of birth.

But there is a further problem with the within-area approach: these estimates do not account for the impact that new migrants exert *outside* their own skill group. The importance of such effects will depend on the elasticity of substitution between skill groups; and indeed, I show that within-area estimates of displacement are very sensitive to the delineation of skill groups. For certain delineations (and using the longitudinal dimension of the census), I cannot reject substantial displacement effects.

In the following section, I set out the basic model of local labor market adjustment. Section 3 describes the data; and Section 4 presents estimates of population adjustment, allowing also for heterogeneous responses by CZ. In Section 5, I estimate displacement effects directly by exploiting the migrant shift-share as an instrument. And in Section 6, I re-estimate the displacement equation exploiting skill group variation within CZs, based on a modified version of the model. I conclude in Section 7.

As an aside, if new foreign migrants do crowd out the native contribution to local adjustment (as I claim), immigration from abroad may help explain part of the decline in cross-state mobility (as documented by e.g. Molloy, Smith and Wozniak, 2011). A back-of-the envelope estimate suggests immigration might explain at most about one third of the decline. I discuss this point briefly in the conclusion.

2 Model of local population adjustment

2.1 Local equilibrium conditional on population

I base my analysis on the model of local population adjustment from Amior and Manning (2015), but here distinguishing between the contributions of internal and foreign migration.

[3] Respondents were asked where they lived five years previously

The model has two components. First, I characterise local equilibrium conditional on local population, based on the classic Rosen-Roback framework (Rosen, 1979; Roback, 1982). And I then combine this with dynamic equations describing how population flows to areas offering higher utility. I set out the essential details here. Those who are interested in a more complete presentation with various extensions (multiple traded and non-traded sectors, agglomeration effects, endogenous amenities, frictional labor markets) can consult the original paper, and I offer a version with heterogeneous skills in Section 6 below.

There are two consumption goods in the economy: (i) a single tradable good, priced at P in all local areas r; and (ii) a non-traded good, housing, whose price P_r^h varies geographically. Assuming preferences are homothetic, a unique price index can be derived in each area r:

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

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 local employment is identical to local population. But, I allow for a labor supply curve which is somewhat elastic to the real consumption wage:

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

where lower case variables denote logs, and z_r^s is an area-specific labor supply shifter.[4] As Amior and Manning (2015) show, after specifying housing supply and demand (and imposing equilibrium in the housing market), p_r^h and therefore p_r can be expressed as a function of local population and employment. A (downward-sloping) labor demand curve is then sufficient to solve for all local endogenous variables as a function of population l_r:

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

where z_r^d is a local demand shifter. I assume local utility depends on the employment rate $n_r - l_r$, the real consumption wage $w_r - p_r$ and local amenities a_r:

$$u_r = \pi \left(n_r - l_r\right) + \left(w_r - p_r\right) + a_r \tag{4}$$

Importantly, the real wage can be substituted using the labor supply curve (2) - so the

[4] As noted by Amior and Manning (2015), (2) can be interpreted as an elastic labor supply curve in a competitive labor market, or as a “wage curve” (Blanchflower and Oswald, 1994) in the presence of frictions.

employment rate can serve as a sufficient statistic for local employment conditions:

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

This result is fundamental to the analysis which follows. In the long run, the model is closed with a spatial arbitrage equation, which requires u_r to be invariant across space in equilibrium. This determines the equilibrium population l_r in each area.

2.2 Internal and foreign migratory responses

Following Amior and Manning (2015), I allow for dynamic adjustment in continuous time to this long run equilibrium, with population responding to the gap between local utility u_r and aggregate utility u. Moving beyond Amior and Manning, I distinguish between the contributions of internal and foreign migration to the population response:

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

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 foreign inflow rate to area r (from abroad), relative to the population in area r. For simplicity, I do not allow for emigration in the model, though I discuss the empirical implications in the sections that follow.

Suppose the net internal inflow rate responds to local utility in the following way:

$$\begin{aligned} \lambda_r^I &= g^I (u_r - u) \\ &= \gamma^I (\tilde{a}_r + n_r - l_r) \end{aligned} \tag{7}$$

where λ_r^I is zero in the absence of local utility differentials. For simplicity, I assume the g function is linear, where $\gamma^I \in (0, \infty)$ denotes the speed of adjustment. The second line substitutes (5) for $u_r(t)$, with $\tilde{a}_r$ denoting a linear combination of the local amenity effect a_r and labor supply shifter z_r^s.

And I assume the foreign inflow rate behaves as follows:

$$\frac{\lambda_r^F - \hat{\lambda}_r^F}{\hat{\lambda}_r^F} = \gamma^F (\tilde{a}_r + n_r - l_r) \tag{8}$$

where $\hat{\lambda}_r^F$ is the local "migrant intensity", the foreign inflow rate in the absence of local utility differentials - which I assume to be positive. Importantly, I permit $\hat{\lambda}_r^F$ to vary across areas r. Intuitively, absorption into the US may entail fixed costs (due to job market access, language or cultural learning), and these entry costs may be lower in some neighborhoods than others. In particular, Munshi (2003) and Gonzalez (1998) emphasize the value of living close to existing co-patriot networks. In this exposition, once migrants have arrived in the country (and paid any fixed costs), I assume they behave identically to natives. The location choices of new migrants might alternatively be modeled using 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.

The γ^I parameter in (7) can be interpreted as the elasticity of the *stock* of existing local residents, while γ^F in (8) is the elasticity of the *flow* from abroad. As an aside, it is worth noting that γ^I can also be expressed in terms of flow elasticities - in a more complete model. In particular, suppose there are individuals moving both to and from area r even in the absence of local utility differentials, driven perhaps by idiosyncratic amenity or job shocks. Let λ_r^{Ii} and λ_r^{Io} denote the internal inflows and outflows respectively, where the net inflow λ_r^I is equal to $\lambda_r^{Ii} - \lambda_r^{Io}$. In spatial equilibrium, i.e. in the absence of local utility differentials, suppose these are equal to $\hat{\lambda}_r^{Ii}$ and $\hat{\lambda}_r^{Io}$ respectively, where $\hat{\lambda}_r^{Ii} = \hat{\lambda}_r^{Io}$, such that $\hat{\lambda}_r^I = 0$. Now, suppose the response of these inflows and outflows takes the same form as (8), so $\frac{\lambda_r^{Ii} - \hat{\lambda}_r^{Ii}}{\hat{\lambda}_r^{Ii}} = \gamma^{Ii} \left(\tilde{a}_r + n_r - l_r\right)$ and $\frac{\lambda_r^{Io} - \hat{\lambda}_r^{Io}}{\hat{\lambda}_r^{Io}} = -\gamma^{Io} \left(\tilde{a}_r + n_r - l_r\right)$. It then follows that $\frac{\lambda_r^I}{L_r} = \frac{\hat{\lambda}_r^{Ii}}{L_r} \left(\gamma^{Ii} + \gamma^{Io}\right) \left(\tilde{a}_r + n_r - l_r\right)$. And thus, γ^I in (7) can be expressed as $\frac{\hat{\lambda}_r^{Ii}}{L_r} \left(\gamma^{Ii} + \gamma^{Io}\right)$, where γ^{Ii} and γ^{Io} are the elasticities of the internal *flows* (both in and out), and $\frac{\hat{\lambda}_r^{Ii}}{L_r}$ is the spatial equilibrium rate of internal in-migration (and out-migration).

2.3 Aggregate population adjustment

Based on (6), aggregate population growth can then be expressed as:

$$dl_r = \hat{\lambda}_r^F + \gamma \left(\tilde{a}_r + n_r - l_r\right) \tag{9}$$

where

$$\gamma = \gamma^I + \gamma^F \hat{\lambda}_r^F \tag{10}$$

is the aggregate population elasticity. I show in Appendix A that (9) can be discretized to yield:

$$\Delta l_{rt} = \hat{\lambda}^F_{rt} + \left(1 - \frac{1 - e^{-\gamma}}{\gamma}\right)\left(\Delta n_{rt} + \Delta \tilde{a}_{rt} - \hat{\lambda}^F_{rt}\right) + \left(1 - e^{-\gamma}\right)\left(n_{t-1} - l_{t-1} + \tilde{a}_{rt-1}\right) \quad (11)$$

where I have assumed that employment n_r and the supply shifter $\tilde{a}_r$ change at a constant rate within each discrete time unit (between $t-1$ and t), and local migrant intensity $\hat{\lambda}^F_r$ is constant within each discrete time unit. $\hat{\lambda}^F_{rt}$ is the total migrant intensity integrated between $t-1$ and t.

As Amior and Manning (2015) note, (11) can intuitively be interpreted as an ECM in population and employment: the change in local population Δl_{rt} depends on the change in local employment Δn_{rt} and a disequilibrium term $n_{rt-1} - l_{rt-1}$, which is simply the employment rate. The coefficients on both these terms are bounded by 0 below (for $\gamma = 0$) and 1 above (as $\gamma \to \infty$). A coefficient of 1 on Δn_{rt} would indicate that population fully adjusts to contemporaneous employment shocks, and a coefficient of 1 on $n_{rt-1} - l_{rt-1}$ would imply that any initial disequilibrium is eliminated in the subsequent time interval through population adjustment. And coefficients closer to zero would be indicative of sluggish adjustment. At the same time, the local economy is subject to supply shocks in the form of changes in amenity values $\Delta \tilde{a}_{rt}$ and local migrant intensity $\hat{\lambda}^F_{rt}$.

I now disaggregate the population response into contributions from internal and foreign migration. Let $\lambda^I_{rt} = \int_{t-1}^{t} \lambda^I_r(s)\, ds$ and $\lambda^F_{rt} = \int_{t-1}^{t} \lambda^F_r(s)\, ds$ denote the internal and foreign contributions to the change in overall log population in area r, between $t-1$ and t, where:

$$\lambda^I_{rt} = \frac{\gamma^I}{\gamma}\left[\left(1 - \frac{1 - e^{-\gamma}}{\gamma}\right)\left(\Delta n_{rt} + \Delta \tilde{a}_{rt} - \hat{\lambda}^F_{rt}\right) + \left(1 - e^{-\gamma}\right)\left(n_{t-1} - l_{t-1} + \tilde{a}_{rt-1}\right)\right] \quad (12)$$

and

$$\lambda^F_{rt} = \hat{\lambda}^F_{rt} + \frac{\gamma^F \hat{\lambda}^F_{rt}}{\gamma}\left[\left(1 - \frac{1 - e^{-\gamma}}{\gamma}\right)\left(\Delta n_{rt} + \Delta \tilde{a}_{rt} - \hat{\lambda}^F_{rt}\right) + \left(1 - e^{-\gamma}\right)\left(n_{t-1} - l_{t-1} + \tilde{a}_{rt-1}\right)\right] \quad (13)$$

The migrant intensity $\hat{\lambda}^F_{rt}$ is the key parameter of interest. Notice that $\hat{\lambda}^F_{rt}$ enters (12) and (13) directly and also indirectly through changes in the aggregate population elasticity γ. The direct effect is simple to interpret: $\hat{\lambda}^F_{rt}$ has a 1-for-1 effect on foreign inflows λ^F_{rt} in (13), but there is a compensating reduction of population growth of $\left(1 - \frac{1-e^{-\gamma}}{\gamma}\right) < 1$. This adjustment comes through partial displacement of both (net) internal inflows and foreign inflows, as the larger supply of migrants puts downward pressure on the local employment rate (and utility).

The indirect effect of migrant intensity $\hat{\lambda}^F_{rt}$ through changes in γ is the "crowding out" effect which motivates this paper. To study this effect, it is useful to take a first order approximation around $\hat{\lambda}^F_{rt} = 0$. As I show in Appendix A, this yields:

$$\begin{aligned} \lambda^I_{rt} \approx & \left(1 - \frac{1 - e^{-\gamma^I}}{\gamma^I}\right)\left(\Delta n_{rt} + \Delta\tilde{a}_{rt} - \hat{\lambda}^F_{rt}\right) + \left(1 - e^{-\gamma^I}\right)\left(n_{t-1} - l_{t-1} + \tilde{a}_{rt-1}\right) \\ & - \frac{\gamma^F}{\gamma^I}\left[\left(1 - 2\frac{1 - e^{-\gamma^I}}{\gamma^I} + e^{-\gamma^I}\right)\left(\Delta n_{rt} + \Delta\tilde{a}_{rt}\right) + \left(1 - e^{-\gamma^I} - \gamma^I e^{-\gamma^I}\right)\left(n_{t-1} - l_{t-1} + \tilde{a}_{rt-1}\right)\right]\hat{\lambda}^F_{rt} \end{aligned} \tag{14}$$

and

$$\lambda^F_{rt} \approx \hat{\lambda}^F_{rt} + \frac{\gamma^F}{\gamma^I}\left[\left(1 - \frac{1 - e^{-\gamma^I}}{\gamma^I}\right)\left(\Delta n_{rt} + \Delta\tilde{a}_{rt}\right) + \left(1 - e^{-\gamma^I}\right)\left(n_{t-1} - l_{t-1} + \tilde{a}_{rt-1}\right)\right]\hat{\lambda}^F_{rt} \tag{15}$$

As the second term of (15) shows, a larger supply of foreign migrants (i.e. a larger $\hat{\lambda}^F_{rt}$) makes foreign inflows λ^F_{rt} more responsive to local employment shocks, both contemporaneous (Δn_{rt}) and historical ($n_{t-1} - l_{t-1}$). However, as (14) shows, a larger $\hat{\lambda}^F_{rt}$ also weakens the response of internal inflows to local shocks. Intuitively, in the presence of a larger $\hat{\lambda}^F_{rt}$, the local employment rate (and utility) become less sensitive to employment shocks; and narrower utility differentials discourage workers from moving internally, along the path of adjustment. In this way, foreign inflows crowd out the contribution of internal inflows to local population adjustment that would have materialized in the counterfactual.

Summing (14) and (15) yields an approximation for the overall population response:

$$\begin{aligned} \Delta l_{rt} \approx & \hat{\lambda}^F_{rt} + \left(1 - \frac{1 - e^{-\gamma^I}}{\gamma^I}\right)\left(\Delta n_{rt} + \Delta\tilde{a}_{rt} - \hat{\lambda}^F_{rt}\right) + \left(1 - e^{-\gamma^I}\right)\left(n_{t-1} - l_{t-1} + \tilde{a}_{rt-1}\right) \\ & + \frac{\gamma^F}{\gamma^I}\left[\left(\frac{1 - e^{-\gamma^I}}{\gamma^I} - e^{-\gamma^I}\right)\left(\Delta n_{rt} + \Delta\tilde{a}_{rt}\right) + \gamma^I e^{-\gamma^I}\left(n_{t-1} - l_{t-1} + \tilde{a}_{rt-1}\right)\right]\hat{\lambda}^F_{rt} \end{aligned} \tag{16}$$

Importantly, both the direct and indirect effects of migrant intensity $\hat{\lambda}^F_{rt}$ on population are decreasing in γ^I, the elasticity of internal inflows to local utility. Regarding the direct effect, as $\gamma^I \to \infty$, foreign inflows displace the local population internally 1-for-1, as $\left(1 - \frac{1-e^{-\gamma^I}}{\gamma^I}\right) \to 1$ in (16). And similarly, as $\gamma^I \to \infty$, the contribution of new migrants to population adjustment (to employment shocks) fully crowds out the contribution of internal migration. To see this, notice the term in square brackets in (16) converges to zero.

2.4 Geographical displacement

The effects described above are manifestations of geographical displacement of natives by migrants, a topic which has received much attention in the immigration literature. Until now, I have studied the impact of migrant intensity $\hat{\lambda}^F_{rt}$ on the system. But the extent of displacement can be assessed more explicitly: i.e. what is the effect of *realized* foreign inflows λ^F_{rt} on internal inflows λ^I_{rt}? Given the entire effect of $\hat{\lambda}^F_{rt}$ materializes through λ^F_{rt} , the former can be interpreted as a "reduced form" characterization of the latter. As a first step, I eliminate $\hat{\lambda}^F_{rt}$ in (12) using (13):

$$\begin{aligned} \lambda^I_{rt} &= \frac{\gamma^I\left(\frac{1}{1-e^{-\gamma}}-\frac{1}{\gamma}\right)}{1+\gamma^I\left(\frac{1}{1-e^{-\gamma}}-\frac{1}{\gamma}\right)}\left(\Delta n_{rt}+\Delta\tilde{a}_{rt}-\lambda^F_{rt}\right) \\ &\quad +\frac{\gamma^I}{1+\gamma^I\left(\frac{1}{1-e^{-\gamma}}-\frac{1}{\gamma}\right)}\left(n_{t-1}-l_{t-1}+\tilde{a}_{rt-1}\right) \end{aligned} \tag{17}$$

where migrant intensity $\hat{\lambda}^F_{rt}$ (and its interactions with Δn_{rt}) is omitted and can serve as an instrument for realized foreign inflows, λ^F_{rt}. But the coefficient on λ^F_{rt} is not a true displacement effect because (17) conditions on changes in employment, Δn_{rt}; and employment may be an important margin of adjustment for areas receiving new migrants. As I show in Appendix A, eliminating Δn_{rt} from (17) yields:

$$\begin{aligned} \lambda^I_{rt} &= \frac{(1-\eta)\,\gamma^I\left(\frac{1}{1-e^{-\gamma}}-\frac{1}{\gamma}\right)}{1+(1-\eta)\,\gamma^I\left(\frac{1}{1-e^{-\gamma}}-\frac{1}{\gamma}\right)}\left(\Delta z^d_{rt}-\lambda^F_{rt}+\frac{\Delta\tilde{a}_{rt}+\eta\Delta z^s_{rt}}{1-\eta}\right) \\ &= +\frac{\gamma^I}{1+(1-\eta)\,\gamma^I\left(\frac{1}{1-e^{-\gamma}}-\frac{1}{\gamma}\right)}\left(n_{t-1}-l_{t-1}+\tilde{a}_{rt-1}\right) \end{aligned} \tag{18}$$

where

$$\eta=\frac{-\epsilon^d}{-\epsilon^d+\epsilon^s}$$

is the ratio of the elasticity of labor demand to the sum of the supply and demand elasticities. The displacement effect is the coefficient on λ^F_{rt} in (18): i.e. for each new arrival from abroad, how many workers leave (on net), relative to the initial population? This effect is evaluated conditional on demand and supply shocks, i.e. Δz^d_{rt}, Δz^s_{rt} and $\Delta\tilde{a}_{rt}$, as well as initial utility, as encapsulated by the lagged employment rate and $n_{t-1} - l_{t-1}$ and amenity value $\tilde{a}_{rt-1}$.

Similarly to the crowding out effect described above, the displacement effect depends on the elasticity of internal flows, γ^I. Holding other parameters fixed, the displacement effect converges to -1 as internal population flows become perfectly elastic. But given I am no longer controlling for local employment, the displacement effect also depends on the relative elasticities of labor demand and supply. As the elasticity of labor demand grows (relative to supply), η converges to 1, and displacement converges to zero. Intuitively, in the limit, adjustment is fully manifested in changes in local employment rather than population.

To the extent that displacement is incomplete (i.e. less than 1-for-1), the arrival of new migrants will have a negative effect on the local employment rate. As I show in Appendix A, the change in the employment rate can be summarized as:

$$\begin{aligned}\Delta\left(n_{rt} - l_{rt}\right) \quad = \quad & \frac{1-\eta}{1+(1-\eta)\gamma^I\left(\frac{1}{1-e^{-\gamma}} - \frac{1}{\gamma}\right)}\left(\Delta z_{rt}^d - \lambda_{rt}^F\right) + \frac{\eta}{1+(1-\eta)\gamma^I\left(\frac{1}{1-e^{-\gamma}} - \frac{1}{\gamma}\right)}\Delta z_{rt}^s \\ & - \frac{(1-\eta)\gamma^I\left(\frac{1}{1-e^{-\gamma}} - \frac{1}{\gamma}\right)}{1+(1-\eta)\gamma^I\left(\frac{1}{1-e^{-\gamma}} - \frac{1}{\gamma}\right)}\Delta\tilde{a}_{rt} - \frac{\gamma^I}{1+(1-\eta)\gamma^I\left(\frac{1}{1-e^{-\gamma}} - \frac{1}{\gamma}\right)}\left(n_{t-1} - l_{t-1} + \tilde{a}_{rt-1}\right)\end{aligned} \tag{19}$$

This is a useful expression for evaluating the fit of the model, and I return to it in the empirical analysis below.

3 Data

3.1 Local population and employment

I use decadal census data[5] on local population and employment across 722 Commuting Zone (CZ) in the Continental US since 1960.[6] CZs were originally developed as an approximation to local labor markets by Tolbert and Sizer (1996), based on county groups, and recently

[5]Where possible, I based the data on published county-level aggregates from the US census, extracted from the National Historical Geographic Information System (Minnesota Population Center, 2011). Not all demographic cells of interest are covered by these published results, so we supplement this with information from the microdata census extracts and American Community Survey of 2009-11, taken from the Integrated Public Use Microdata Series (Ruggles et al., 2010).

[6]I begin the analysis in 1960 because migrants' year of arrival cannot be identified before the 1970 census microdata. This means that, for changes over the 1950s, I cannot distinguish between new migrants from abroad and earlier ones (who arrived before 1950).

popularized by Autor and Dorn (2013) and Autor, Dorn and Hanson (2013).[7] Unless otherwise specified, the sample includes all individuals aged 16-64. See the appendices of Amior and Manning (2015) for further details on the construction of the dataset.

An important concern is under-coverage of undocumented migrants in the census - and undocumented Mexicans in particular. Card and Lewis (2007) summarize some of the evidence, noting that the problem had eased considerably by the 2000 census. In particular, about 40 percent of undocumented Mexicans were overlooked in the 1980 census (Borjas, Freeman and Lang, 1991) and 30 percent in the 1990 census (Van Hook and Bean, 1998), but just 10 percent in 2000 (US Department of Homeland Security, 2003). Equivalently, 25 percent of all Mexican migrants were missed in 1980, 20 percent in 1990, and 6-8 percent in 2000.

3.2 Disaggregating local population growth

In the model, I have disaggregated the change in log local population into contributions from internal and foreign migration, i.e. λ_{rt}^{I} and λ_{rt}^{F} in equations (14) and (15) respectively. However, since I only observe local population at discrete intervals, I cannot precisely identify λ_{rt}^{I} and λ_{rt}^{F} in the data. A natural approach is to approximate these with their contributions to decadal population growth. This is of course a first order approximation, which is more precise for small population changes. 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 $t-1$). Then, local population growth can be disaggregated in the following way:

$$\frac{\Delta L_{rt}}{L_{rt-1}} = \frac{L_{rt}^{F}}{L_{rt-1}} + \frac{L_{rt} - L_{rt}^{F}}{L_{rt-1}} \tag{20}$$

where $\frac{L_{rt}-L_{rt}^{F}}{L_{rt-1}}$ is the residual, i.e. the component of local population growth which is not explained by new foreign arrivals. This will of course account for internal migration, but it is of course conflated with other factors, specifically "natural" population growth and emigration to outside the US.

This specification focusing on contributions to overall population growth follows the

[7] Amior and Manning (2015) make just one modification to the Tolbert-Sizer CZ scheme to enable us to allow construction of consistent geographies over time. Specifically, La Paz County (AZ) is incorporated into the same CZ as Yuma County (AZ). Tolbert and Sizer allocated La Paz and Yuma to different CZs, but the two counties only separated in 1983. CZs have two advantages over Metropolitan Statistical Areas (MSAs). First, MSAs cover only a limited proportion of the US landmass (unlike CZs whose coverage is universal). And second, there have been changes in MSA definitions over time: this would be particularly problematic for the very long run analysis of this study.

approach of Card and DiNardo (2000) and Card (2001), as recommended by Peri and Sparber (2011). There is much disagreement in the literature regarding the extent of geographical displacement, and Peri and Sparber argue that some of the discrepancies may be explained by empirical specification. In particular, they suggest that Borjas' (2006) finding of large displacement may have been the product of an artificial bias introduced by his choice of functional form. They show instead that Card and DiNardo's specification is immune to these concerns.

3.3 Instruments

I identify changes in local demand using industry shift-shares (following Bartik, 1991), which should theoretically exclude supply-side effects. And, I identify the local migrant intensity $\hat{\lambda}_{rt}^{F}$ in the model above using migrant shift-shares (following Altonji and Card, 1991, and Card, 2001), to exclude local demand shocks. These shift-share variables are pervasive in the urban and migration literatures (see e.g. Blanchard and Katz, 1992; Bound and Holzer, 2000; Saiz, 2007; Cortes, 2008; Notowidigdo, 2011; Peri and Sparber, 2011; Beaudry et al., 2012, 2014*a*, 2014*b*). I use them as either instruments or controls at various points in the analysis.

The Bartik shift-share b_{rt} predicts the growth of local labor demand (over one decade), assuming the stock of employment in each industry i grows at the average rate elsewhere in the country:

$$b_{rt} = \sum_{i} \phi_{rt-1}^{i} \left[n_{i(-r)t} - n_{i(-r)t-1} \right] \tag{21}$$

where ϕ_{rt-1}^{i} is the share of workers in area r at time $t-1$ employed in industry i. The term $\left[n_{i(-r)t} - n_{i(-r)t-1} \right]$, expressed in logs, is the growth of employment nationally in industry i, excluding area r. This exclusion was proposed by Autor and Duggan (2003) to address concerns about endogeneity to local employment counts.

Following Amior and Manning (2015), I use the contemporaneous Bartik shift-share b_{rt}^{N} as an instrument for current employment growth Δn_{rt}, and I use the lagged shift-share b_{rt-1} to instrument for the lagged employment rate $(n_{rt-1} - l_{rt-1})$. The intuition for the lagged instrument is that the employment rate, at any point in time, can be written as a distributed lag of past labor demand shocks. In practice, it is sufficient to instrument using the first lag alone. I construct these instruments using 2-digit industry data from the IPUMS micro-data: see Amior and Manning (2015) for further details.

I predict the local migrant intensity $\hat{\lambda}^F_{rt}$ using a migrant shift-share, based on the initial geographical distribution of migrants. As is well known, migrants are often guided in their location choice by the presence of established co-patriot communities, whether because of job networks (Munshi, 2003) or cultural amenities (Gonzalez, 1998). In the empirical migration literature, there has been a long tradition of proxying these preferences with historical local settlement patterns. An early example is Altonji and Card (1991), and Card (2001) extends it by exploiting varying settlement patterns by origin country. Ruist, Stuhler and Jaeger (2017) offer a useful survey of the empirical literature. I construct the shift-share m_{rt} as follows:

$$m_{rt} = \frac{\sum_o \phi^o_{rt-1} L^F_{ot}}{L_{rt-1}} \tag{22}$$

where ϕ^o_{rt-1} is the share of population in area r at time $t-1$ which is native to origin o. L^F_{ot} is the stock of new migrants at time t, native to origin o, who arrived in the US in the previous ten years (i.e. between $t-1$ and t).[8] The numerator of equation (22) then gives the predicted inflow of all migrants over those ten years to area r. This is scaled by L_{rt-1}, the initial population of area r. I construct this migrant shift-share variable using census and ACS micro-data from IPUMS, based on 79 origin countries: see Amior and Manning for further details.

For the purposes of the empirical analysis which follows, I construct the migrant intensity $\hat{\lambda}^F_{rt}$ using a linear projection of $\frac{L^F_{rt}}{L_{rt-1}}$ (the contribution of new migrants to population growth) on m_{rt}, based on the following OLS regression:

$$\frac{L^F_{rt}}{L_{rt-1}} = \alpha_0 + \alpha_1 m_{rt} + \varepsilon_{rt} \tag{23}$$

where observations are weighted by the lagged local population share. The coefficient α_0 is estimated as 0.01, α_1 is 0.84, and the R squared is 81 percent.

3.4 Amenity controls

Aside from the Card shift-share, we control for a range of observable supply effects or amenities in our empirical specifications. The set of controls is identical to those in Amior and

[8] One might also choose to exclude migrants to area r in constructing L^F_{ot}, in the same way as I do for the Bartik shift-shares: see Amior and Manning (2015). However, to preserve consistency with the rest of the migration literature, I choose not to do so here. As it happens, the effect of this exclusion on the results is negligible.

Manning (2015), and further details on their construction can be found there. To summarize, these include: (i) a binary indicator for the presence of coastline (ocean or Great Lakes); (ii) climate indicators (specifically maximum January temperature, maximum July temperature and mean July relative humidity); (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 population-weighted centroids in 1990. Because the impact of some of these might vary over time, I interact each of them with a full set of year effects in the regressions below.

We do not control for amenities which are likely to be endogenous to current labor market conditions, such as crime and local restaurants, since these present challenges for identification. As Amior and Manning (2015) point out, this means the estimated coefficients on employment shocks must be interpreted as reduced form effects. That is, these coefficients will account for *all* effects of employment on utility (and local population growth), both the direct labor market effects (discussed in Section 2 above) and the indirect effects due to changes in local amenities such as crime (see Diamond, 2016).

4 Estimates of population response to employment shocks

4.1 Average contribution of foreign migrants

In this section, I study the average contribution of foreign migrants to local population adjustment across CZs, abstracting away from heterogeneity in the local migrant intensity, $\hat{\lambda}^F_{rt}$. I return to this heterogeneity below. I begin by estimating the overall population response to local employment shocks. In line with equation (11) and Amior and Manning (2015), I use the following error correction model:

$$\Delta l_{rt} = \beta_0 + \beta_1 \Delta n_{rt} + \beta_2 \left(n_{rt-1} - l_{rt-1}\right) + \tilde{A}_{rt}\beta_A + \varepsilon_{rt} \tag{24}$$

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 employment, Δn_{rt}, and the disequilibrium term, the lagged employment rate $(n_{rt-1} - l_{rt-1})$. I control for a vector of supply effects $\tilde{A}_{rt}$, driven by amenities or the labor supply shifter. Note $\tilde{A}_{rt}$ contains a full set of time effects reflecting changes in the aggregate level of utility in (7). The error term ε_{rt} includes any supply effects which are unobserved. All observations are weighted by the lagged local population share, and standard errors are clustered by CZ.

[Table 1 here]

I set out estimates of (24) in column 1 of Table 1. For completeness, I present OLS estimates in column 1 at the top of Panel A. I report only the coefficients of interest, β_1 and β_2, the elasticities of local population to contemporaneous employment shocks and the lagged employment rate. These are estimated as 0.80 and 0.18 respectively. As discussed by Amior and Manning (2015), these cannot be interpreted causally. In particular, unobserved supply-side shocks will bias OLS estimates of β_1 upwards. And, β_2 estimates may be biased downwards if these shocks are persistent. For example, an improvement in local amenities should affect local population growth positively and the employment rate negatively. Following Amior and Manning, I offer IV estimates where I instrument the log employment change with the current Bartik shock and the lagged employment rate with the lagged Bartik. The first stage results (Panel B) strongly support the identification strategy: both instruments have power, but remarkably only for the endogenous variables they are intended to explain. The IV estimates of β_1 and β_2 are 0.63 and 0.40 respectively[9] (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 employment conditions.

I next study the average contribution of foreign migrants to these population responses. For the reasons discussed in Section 3, I approximate the change in log population Δl_{rt} with local population growth $\frac{\Delta L_{rt}}{L_{rt-1}}$, which I disaggregate using the scheme in equation (20). In column 2, I re-estimate (11) but replacing the dependent variable with local population growth $\frac{\Delta L_{rt}}{L_{rt-1}}$. The IV estimates are similar to column 1, with β_1 and β_2 taking 0.76 and 0.44 respectively. Column 3 estimates the contribution of new migrants to local population growth, replacing the dependent variable with $\frac{L^F_{rt}}{L_{rt-1}}$, where L^F_{rt} is defined as the local stock of foreign-born migrants at time t who arrived in the US in the previous ten years (i.e. since $t-1$). Looking at the IV specification, new migrants account for one fifth of the overall population response to contemporaneous shocks (β_1), and remarkably, over half the overall response to the lagged employment rate (β_2). Column 4 reports the residual component of population growth, $\frac{\Delta L_{rt}-L^F_{rt}}{L_{rt-1}}$, due to natives and "old" migrants (i.e. those who arrived over ten years previously, before $t-1$). This is driven to some extent by internal migration, though the estimates are conflated with emigration and "natural" population growth. In column 5, I report the contribution of natives only, i.e. $\frac{\Delta L^N_{rt}}{L_{rt-1}}$, where L^N_{rt} is the local stock of natives. The IV estimates are very similar to column 4, which suggests old migrants

[9]These numbers are similar but not identical to the basic estimates of Amior and Manning (2015). This is because I have omitted one decade of data in this study, as the 1960 census does not report migrants' year of arrival. See Section 3 above.

contribute little to the response to employment shocks.

In the final four columns, I replicate columns 2-5, but now conditioning on local migrant intensity $\hat{\lambda}_{rt}^{F}$, which I predict using the migrant shift share (22) as described in Section 3 above. There are two key messages here. First, my estimate of $\hat{\lambda}_{rt}^{F}$ explains away a large portion of new migrants' disproportionate contribution to local adjustment. While the overall population response is unaffected (column 6), the relative contribution of new migrants (column 7) is now markedly lower: conditional on the shift share, new migrants now account for 10 and 22 percent of the β_1 and β_2 response respectively (down from 53 and 21 percent) in the IV specification. This is indicative of a tight correlation between the migrant shift share and the Bartik instruments. This is a natural consequence of the large decadal persistence in local demand shocks described by Amior and Manning (2015). Intuitively, new foreign arrivals are attracted to areas with strong demand conditions (or in the language of Bartik instruments, areas specialized in high-growth industries), resulting in large migrant enclaves in these areas. This attracts even more migrants in the future, which aids population adjustment - given these areas continue to experience positive demand shocks. However, the fact that the overall population response in column 6 is unaffected hints at foreign migrants crowding out the internal response to employment shocks - and I explore this in the following section.

But columns 7-9 also point to a more direct displacement effect: a one point increase in the shift share raises the contribution of new migrants by 0.96 (column 7), but reduces the contribution of natives and old migrants by 0.89 (column 8). The effect on overall population growth is statistically insignificant (column 7). Thus, I cannot reject the hypothesis that a local migrant inflow (driven by historical migrant settlement) displaces other workers geographically 1-for-1. A large displacement effect should not be surprising, given the substantial population response of natives and old migrants to employment shocks; though a 1-for-1 effect is larger than might be expected: equation (14) above predicts a displacement effect equal to β_1, which takes a value of 0.68 for natives and old migrants (column 8). In any case, the claim of large displacement is controversial in the literature, and I offer a more rigorous analysis in Section 5 below.

4.2 Testing for "crowding out"

The results above suggest that new foreign arrivals do contribute disproportionately to local adjustment, and this is entirely due to new arrivals. This is broadly consistent with the existing literature (though Cadena and Kovak, 2016, find that old migrants are also relatively mobile). But, I argue it does not necessarily follow that migrants "grease the wheels" as Borjas (2001) has claimed - if the the response of migrants crowds out the response of other workers, along the path of adjustment.

A natural approach to test for crowding out is to exploit geographical (and temporal) variation in local migrant intensity $\hat{\lambda}_{rt}^F$ - as predicted by the migrant shift share (22). In Table 2, based on (14) and (15), I present estimates of the following equation:

$$\begin{aligned} \frac{X_{rt}}{L_{rt-1}} &= \beta_0 + \beta_1 \Delta n_{rt} + \beta_2 \left(n_{rt-1} - l_{rt-1} \right) + \tilde{A}_{rt} \beta_A \\ &\quad + \left[\beta_{0\lambda} + \beta_{1\lambda} \Delta n_{rt} + \beta_{2\lambda} \left(n_{rt-1} - l_{rt-1} \right) + \tilde{A}_{rt} \beta_{A\lambda} \right] \hat{\lambda}_{rt}^F + \varepsilon_{rt} \end{aligned} \tag{25}$$

where $\frac{X_{rt}}{L_{rt-1}}$ is the contribution of new migrants ($X_{rt} = L_{rt}^F$) or other workers ($X_{rt} = \Delta L_{rt} - L_{rt}^F$) to local population growth, and where the change in log employment $(n_{rt-1} - l_{rt-1})$ and the lagged employment rate $(n_{rt-1} - l_{rt-1})$ are now interacted with migrant intensity $\hat{\lambda}_{rt}^F$. Notice the model also suggests migrant intensity should be interacted with the vector of amenity controls $\tilde{A}_{rt}$ (including year effects). The first four columns of Panel A of Table 2 do not control for these $\hat{\lambda}_{rt}^F$-amenity interactions, and the latter four do.

[Table 2 here]

I report OLS estimates of (25) in the top half of Panel A. Column 1 shows the overall population response to employment shocks does not vary with migrant intensity $\hat{\lambda}_{rt}^F$. That is, population adjustment is no faster in those areas which are better supplied by new foreign arrivals. But this masks some important effects. As equation 15 predicts, column 2 shows the contribution of new migrants to the population response is increasing in $\hat{\lambda}_{rt}^F$. The contributions of new migrants to the Δn_{rt} and $(n_{rt-1} - l_{rt-1})$ responses are statistically insignificant at $\hat{\lambda}_{rt}^F = 0$ (as the model predicts); and for example, they increase to 0.17 and 0.26 respectively at $\hat{\lambda}_{rt}^F = 0.1$, which is the 98th percentile of $\hat{\lambda}_{rt}^F$ (the maximum value is 0.31: the distribution is heavily skewed). But this larger contribution from new migrants for larger is entirely offset by a smaller contribution from other workers (column 3), such that the evolution of local population is no different in areas with a large or small supply of new migrants (column 1). The crowding out effect is somewhat smaller for Δn_{rt} when I control for the $\hat{\lambda}_{rt}^F$-amenity interactions in columns 5-8, but I still cannot reject the hypothesis that new foreign arrivals add nothing to the overall population response (column 5).

The bottom half of Table 2 presents the IV estimates. I have introduced two new endogenous variables, so I need two further instruments to identify the model: I use interactions between migrant intensity $\hat{\lambda}_{rt}^{F}$ and the current and lagged Bartik shocks. The first stage estimates are reported in columns 1-4 of Panel B of Table 2. I have marked in bold where one should theoretically expect to see positive significant effects. These predictions are confirmed in each case and with small standard errors.

Just as with the OLS estimates, I cannot reject the claim that new migrants fully crowd out the population response of other workers to employment shocks. Again, both columns 1 and 5 (without and including amenity interactions, respectively) shows the population response does not vary significantly with migrant intensity $\hat{\lambda}_{rt}^{F}$. The response of new migrants, however, is steeply increasing in $\hat{\lambda}_{rt}^{F}$ (columns 2 and 6) from a base of zero, and this is fully offset by the response of other workers (columns 3 and 7). The interactions effects are larger than in OLS. Controlling for amenity interactions for example, the contributions of new migrants to the Δn_{rt} and $(n_{rt-1} - l_{rt-1})$ responses reach 0.32 and 0.46 respectively at $\hat{\lambda}_{rt}^{F} = 1$ (column 6), while the contributions of other workers decline to 0.37 and -0.06 (column 7).

Columns 4 and 8 report the contribution of natives alone. The interaction effects in all specifications exceed those in columns 3 and 7, implying natives account for the entire crowding out effect. This is intuitive: those areas with larger migrant intensity will have larger stocks of old migrants, so old migrants should mechanically contribute more to population adjustment.

5 Geographical displacement: aggregate-level estimates

5.1 Empirical specification

The analysis above suggests that a larger supply of new migrants is offset by a weaker contribution of other workers to population adjustment. This is fundamentally a story of geographical displacement, though in the context of local demand fluctuations. But geographical displacement can be tested more explicitly: i.e. for each new arrival from abroad, how many other workers leave (on net)? This is what I turn to next.

In line with (18) in Section 2 above, I estimate the magnitude of displacement using the following specification:

$$\frac{\Delta L_{rt} - L^F_{rt}}{L_{rt-1}} = \delta_0 + \delta_1 \frac{L^F_{rt}}{L_{rt-1}} + \delta_2 b_{rt} + \delta_3 \left(n_{rt-1} - l_{rt-1}\right) + \tilde{A}_{rt}\delta_A + \varepsilon_{rt} \tag{26}$$

where $\frac{L^F_{rt}}{L_{rt-1}}$ is the contribution of new migrants to local population growth, and $\frac{\Delta L_{rt} - L^F_{rt}}{L_{rt-1}}$ is the contribution of other workers (i.e. natives and old migrants), and the displacement effect is given by δ_1. The Bartik shift-share b_{rt} and the amenity vector $\tilde{A}_{rt}$ account for observed components of demand and supply shocks respectively, and the unobserved components are contained in the residual ε_{rt}.

There are two endogenous variables: $\frac{L^F_{rt}}{L_{rt-1}}$ and $(n_{rt-1} - l_{rt-1})$, so two instruments are required. The simplest approach is to use the local migrant intensity $\hat{\lambda}^F_{rt}$, as predicted by the migrant shift share, together with the lagged Bartik shock b_{rt-1}. I also offer IV estimates which exploit two further instruments: interactions between $\hat{\lambda}^F_{rt}$ and both the current and lagged Bartik shocks, b_{rt} and b_{rt-1}. This is motivated by (15), which predicts the effect of local demand on the realized contribution of new migrants $\frac{L^F_{rt}}{L_{rt-1}}$ is increasing in the local migrant intensity $\hat{\lambda}^F_{rt}$.

There is already a broad empirical literature which estimates geographical displacement due to foreign migration. My specification of the population variables in terms of *contributions* to overall population growth is consistent with the approach of Card and DiNardo (2000) and Card (2001), as recommended by Peri and Sparber (2011). There is much disagreement in the literature regarding the magnitude of displacement, and Peri and Sparber argue that some of the discrepancies may be explained by empirical specification. In particular, they suggest that Borjas' (2006) finding of large displacement may have been the product of an artificial bias introduced by his choice of functional form. They show instead that Card and DiNardo's specification is immune to these concerns. My specification deviates from the existing literature however in controlling for initial conditions, as represented by the lagged employment rate $(n_{rt-1} - l_{rt-1})$. I therefore also consider an alternative specification which replaces $(n_{rt-1} - l_{rt-1})$ with the lagged Bartik shift-share in (26), which can control (to some extent) for historical demand shocks:

$$\frac{\Delta L_{rt} - L^F_{rt}}{L_{rt-1}} = \delta_0 + \delta_1 \frac{L^F_{rt}}{L_{rt-1}} + \delta_2 b_{rt} + \delta_3 b_{rt-1} + \tilde{A}_{rt}\delta_A + \varepsilon_{rt} \tag{27}$$

I instrument $\frac{L^F_{rt}}{L_{rt-1}}$ using the migrant intensity $\hat{\lambda}^F_{rt}$; and as before, I also report estimates including the $\hat{\lambda}^F_{rt}$-Bartik interactions as further instruments.

Moving beyond the existing literature, I also estimate regressions including CZ fixed effects. These will absorb the time-invariant components of unobserved labor supply shocks

Δz^s_{rt} and amenity effects, and in the case of the unconditional displacement specification (26), unobserved labor demand shocks Δz^d_{rt}. Identification in this demanding specification relies on the fact that migrant inflows to different areas have grown at different speeds. This identification is similar in spirit to the double differencing methodology (comparing changes before and after 1970[10]) of Borjas et al. (1997). Such an approach may be particularly valuable in the case of specification (27): since the initial conditions $(n_{rt-1} - l_{rt-1})$ are omitted, historical shocks (including historical migrant inflows) will fall into the residual term ε_{rt}, and large serial correlation in these inflows (see Ruist, Stuhler and Jaeger, 2017) may then pose challenges to identification in cross-sectional specifications. On the other hand, this large serial correlation also makes this an empirically demanding specification.

[Table 3 here]

There are several US studies in the literature which specify the key variables in the same way as (27), as recommended by Peri and Sparber (2011). I set out results from a range of these studies in Table 3. I restrict attention to IV estimates, which in all cases use a variant of the migrant enclave instrument. The displacement effects, equivalent to my δ_1 coefficient, are reported in the final column. The empirical methods do vary. While Card (2009*a*) offers estimates based on aggregate CZ-level variation (as in (27)), other studies have exploited variation across skill groups *within* geographical areas: I consider this empirical set-up in Section 6.3 below. Also, Card (2001) exploits a longitudinal dimension of the census (respondents reported where they lived five years previously), while the other studies pool census cross-sections to generate variation. In any case, most of these studies suggest displacement effects are small or even *negative* (with natives moving on net to areas experiencing larger migrant inflows). An interesting exception is Monras (2015*b*), who estimates substantial displacement in the year following the Mexican Peso crisis of 1995 (which was associated with a sudden increase in migration from Mexico), but finds small displacement effects over a longer decadal interval.

5.2 Estimates of displacement

In contrast to the existing literature, almost all specifications in Panel A of Table 4 point to a substantial displacement effect. Column 1 offers OLS estimates of equation (26), with

[10] Ruist, Stuhler and Jaeger (2017) emphasize that the Immigration and Nationality Act of 1965, which facilitated much larger inflows of non-European migrants, was an important structural break.

δ_1 taking a value of -0.76. That is, for each new migrant entering a given CZ, 0.76 natives or earlier migrants leave on net (relative to the initial population). The effect is similar when I control for CZ fixed effects at the bottom of the table. In column 2, I replace the lagged employment rate with the lagged Bartik shift-share (i.e. (27)), and the δ_1 estimate changes little. One concern is that the displacement effect may be artificially driven by return migration: i.e. migrants moving to some CZ in the US, and returning back to their country of origin shortly afterwards. However, column 3 shows that natives account for three quarters of the displacement effect in the basic specification and for the entire effect when I control for fixed effects.[11]

[Table 4 here]

Columns 4-6 of Panel A report IV estimates of (26) and (27), using the migrant shift-share $\hat{\lambda}_{rt}^F$ as an instrument for the new migrant contribution and the lagged Bartik shift share b_{t-1} as an instrument for the lagged employment rate (in column 5). The first stage estimates have substantial power in both the basic and fixed effect specifications (column 1 and 3 in Panel B). In the basic specification, the IV estimate of displacement is somewhat larger than OLS, with δ_1 reaching -1.1, i.e. exceeding (though insignificantly different from) 1-for-1 displacement. These effects are estimated reasonably precisely, with standard errors of approximately 0.13. The IV estimates are expected to be larger than OLS if we believe variation in the contribution of new migrants $\frac{L_{rt}^F}{L_{rt-1}}$ is conflated with unobserved local demand shocks. Similar to OLS, column 6 suggests that natives account for the bulk of the displacement effect.

When I control for fixed effects in column 4 however, the displacement effect becomes insignificantly different from 0, though the standard errors are very large. However, when I replace the lagged employment rate with its lagged Bartik instrument in column 5, δ_1 is again estimated as -1..

To address this apparent lack of power in the fixed effects specification, I include interactions between migrant intensity $\hat{\lambda}_{rt}^F$ and the current and lagged Bartik shift-shares as further instruments - as suggested by equation (15) in the model. The first stage estimates are reported in columns 2 and 4 of Panel B: the interaction effects are positive and statistically significant. The second stage estimates are presented in columns 7-9 of Panel A. The results looks very similar to the basic IV estimates (without the interacted instruments) in columns

[11] In column 3, I replace the dependent variable in column 2 with the contribution of natives alone: that is, the ratio of the decadal change in the native population to the initial total population.

4-6. However, the standard errors on the fixed effects estimates of δ_1 are now much smaller (around 0.2), and the coefficients are now very close to -1.

[Table 5 here]

How can these results be reconciled with earlier estimates? In particular, using aggregate-level variation across metropolitan areas, Card (2009*a*) finds no conclusive evidence of displacement (see Table 3). It seems this can be explained by choices of controls and sample years. In Table 5 in the Appendix, I study the robustness of my IV estimates in column 5 of Table 4 to these considerations. When I include no regression controls, the displacement estimates vary greatly across decades. In particular, these results suggest little displacement before 1990 and significant displacement thereafter; and indeed, Card (2009*a*) finds something similar. But once I include the Bartik shift-share and climate controls (which Card, 2009*a*, does not include), the IV estimates cannot reject displacement of at least one-for-one in any decade. In other words, the migrant shift-share instrument appears to be correlated with important supply and demand-side drivers of population omitted from Card's (2009) specification. The other studies listed in Table 3 exploit variation across skill groups within areas, and I return to this in Section 6 below.

5.3 Impact on local employment rates

In the context of the results presented above, a 1-for-1 displacement effect is somewhat surprising. For example, the population response to employment shocks is estimated as 0.63, significantly below 1 (see the IV estimate in column 4, Panel A, Table 1). And more importantly, 1-for-1 displacement sits uneasily with estimates of the effect on local employment rates. In particular, if there is indeed 1-for-1 displacement, the arrival of new migrants should have no effect on the local employment rate - as equation (19) shows. But in fact, the evidence suggests that local employment rates (among both natives and migrants) fall significantly in response to foreign inflows - though, it should be stressed, the effect is not large. See also Gould (2016), who identifies similar effects. Two possible explanations for this apparent inconsistency are that (i) migrants are more productive than natives (in the sense that they may do the same work for less) or (ii) there is under-reporting of new migrants in the census.

To study this further, I re-estimate (27), but this time replacing the dependent variable with the change in the local log employment rate, $\Delta (n_{rt} - l_{rt})$. I present the results in Table

6. The first three columns report estimates for the basic employment rate, separately for the full sample of 16-64s, natives and migrants. In the final three columns, I repeat this exercise for employment rates adjusted for local demographic composition.[12]

[Table 6 here]

Almost all estimates of δ_1 in Table 6 fall between -0.1 and -0.2, and most of these estimates are strongly significant. It is worth emphasizing that the responses of the native and migrant employment rates are similar, as are the responses of the basic (unconditional) and composition-adjusted employment rates. This suggests my assumption in Section 2 that natives and migrants are perfect substitutes may be a reasonable approximation in this context; and further, I may not lose much by assuming workers are homogeneous (as I do in Section 2).

Now, consider a δ_1 estimate of -0.2, at the upper end of the range. If one is willing to assume that migrants and natives are equally productive (and perfect substitutes), we should then expect a displacement effect of -0.8 - according to the model. This is still a substantial effect of course, and the discrepancy with the estimates in Table 4 might be ascribed to under-reporting of new undocumented arrivals.

6 Geographical displacement: skill variation

6.1 Motivation

In this section, I study estimates of displacement which exploit variation across skill groups *within* geographical areas - a popular approach in the literature. Card (2001) notes that recent migrants are concentrated in different occupations to natives; and consequently, the labor market impact of an additional migrant will vary by skill group within areas. For example, consider the following empirical specification, building on (27):

$$\frac{\Delta L_{srt} - L_{srt}^F}{L_{srt-1}} = \delta_0 + \delta_1 \frac{L_{srt}^F}{L_{srt-1}} + \delta_2 b_{srt} + \delta_3 b_{srt-1} + d_{rt} + d_{st} + \varepsilon_{srt} \tag{28}$$

[12] To do this, I run logit regressions of employment on a detailed range of individual characteristics (age and age squared; four education indicators, each interacted with age and age squared; a gender dummy, interacted with all the earlier-mentioned variables; and black, Hispanic and foreign-born indicators) and a set of location fixed effects, separately for each census cross-section and separately for the full, native and migrant samples. I then predict the average employment rate in each location - assuming the local demographic composition in each location is identical to the national composition.

where $\frac{L^F_{srt}}{L_{srt-1}}$ is the contribution of new migrants to local population growth in skill group s, and $\frac{\Delta L_{srt}-L^F_{srt}}{L_{srt-1}}$ is the contribution of other workers (i.e. natives and old migrants). 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. Finally, one might also include skill-specific Bartik shift shares b_{srt} and b_{srt-1}, constructed using skill-specific employment counts, which can proxy for current and historical skill-specific demand shocks.

The exploitation of variation within areas r can help allay concerns about shocks in the error term ε_{srt} which happen to be correlated with the variable of interest, $\frac{L^F_{srt}}{L_{srt-1}}$. However, this approach faces two important challenges. First, if one uses pooled cross-sectional data, it will not be possible to distinguish between genuine net migratory flows and local changes in skill composition across cohorts. And second, this approach will not account for the impact that new migrant arrivals exert *outside* their own skill group s. As Card (2001) shows, the importance of such effects will depend on the elasticity of substitution between skill groups. Consequently, estimates of δ_1 are very sensitive to the delineation of skill groups.

I begin this analysis by setting out an extension to the model of Section 2 with heterogeneous skills. This helps clarify the importance of substitutability of skill groups in production. I then discuss the choice of skill delineation, and I return to the question of cohort effects when discussing the empirical estimates.

6.2 Model

Suppose production technology in area r, for the tradable good priced at P, is a CES function over skill-defined local labor inputs:

$$Y_r = \theta_r \left(\sum_s \alpha_{sr} N^{\sigma}_{sr} \right)^{\frac{\rho}{\sigma}} \tag{29}$$

where θ_r is an aggregate productivity shifter, and $\frac{1}{1-\sigma}$ is the elasticity of substitution between labor inputs in production, where $\sigma \in [-\infty, 1]$. The term $\left(\sum_s \alpha_{srt} N^{\sigma}_{srt}\right)^{\frac{1}{\sigma}}$ may be interpreted as an aggregate labor component, and the exponent $\rho \leq 1$ allows for diminishing returns to labor. Assuming markets are competitive, the labor demand curve for skill s in area r can be written as:

$$w_{sr} - p = \log \alpha_{sr} + \log \rho + \frac{\sigma}{\rho} \log \theta_r + \frac{\rho - \sigma}{\rho} y_r - (1 - \sigma)\, n_{sr} \tag{30}$$

conditional on local output y_r. And using the same structure as (2) in Section 2 above, I write the skill-specific labor supply as:

$$n_{sr} = l_{sr} + \epsilon^s \left(w_{sr} - p_r \right) + z^s_{sr} \tag{31}$$

In the same way, the utility equation (5) in Section 2 can be rewritten with s subscripts, so utility depends on the skill-specific local employment rate and real consumption wage. And similarly, s subscripts can be applied to equations (7) and (8), so skill-specific population adjusts (sluggishly) with elasticity γ to skill specific differentials in local utility u_{sr}. Following the same procedure outlined in Section 2, after discretizing the model, one can then derive an (almost) identical expression to (18) for the internal contribution λ^I_{srt} to local population growth in skill group s:

$$\begin{aligned}
\lambda^I_{srt} \quad = \quad & \frac{(1-\eta)\,\gamma^I \left(\frac{1}{1-e^{-\gamma}} - \frac{1}{\gamma}\right)}{1 + (1-\eta)\,\gamma^I \left(\frac{1}{1-e^{-\gamma}} - \frac{1}{\gamma}\right)} \cdot \frac{1}{1-\sigma} \left(\Delta \log \alpha_{srt} + \frac{\sigma}{\rho} \Delta \log \theta_{rt} + \frac{\rho - \sigma}{\rho} \Delta y_{rt} \right) \\
& + \frac{(1-\eta)\,\gamma^I \left(\frac{1}{1-e^{-\gamma}} - \frac{1}{\gamma}\right)}{1 + (1-\eta)\,\gamma^I \left(\frac{1}{1-e^{-\gamma}} - \frac{1}{\gamma}\right)} \left(\frac{\Delta \tilde{a}_{rt} + \eta \Delta z^s_{rt}}{1-\eta} - \lambda^F_{srt} \right) \\
& + \frac{\gamma^I}{1 + (1-\eta)\,\gamma^I \left(\frac{1}{1-e^{-\gamma}} - \frac{1}{\gamma}\right)} \left(n_{srt-1} - l_{srt-1} + \tilde{a}_{rt-1} \right)
\end{aligned} \tag{32}$$

where, as before,

$$\eta = \frac{1}{1 + (1-\sigma)\,\epsilon^s}$$

is the ratio of the elasticity of labor demand to the sum of the supply and demand elasticities.

Now, consider again the empirical specification (28) in light of (32). The area fixed effect d_{rt} absorbs variation in local output y_{rt} and the aggregate productivity shock θ_{rt}. The error term ε_{srt} will contain any unobserved components of the skill-specific local productivity shifters α_{srt}, after conditioning on the Bartik shift-shares. Now, suppose the effect of the foreign migrant contribution to population, $\frac{L^F_{srt}}{L_{srt-1}}$ (which proxies for λ^F_{srt}), is consistently identified; that is, conditional on the fixed effects and the Bartik shift-shares, $\frac{L^F_{srt}}{L_{srt-1}}$ is uncorrelated with the error term ε_{srt}. Then, the coefficient of interest δ_1 in (28) will be equal to:

$$\delta_1 = \frac{(1-\sigma)\,\epsilon^s \gamma^I \left(\frac{1}{1-e^{-\gamma}} - \frac{1}{\gamma}\right)}{1 + (1-\sigma)\,\epsilon^s \left[1 + \gamma^I \left(\frac{1}{1-e^{-\gamma}} - \frac{1}{\gamma}\right)\right]} \tag{33}$$

But in general, this is not the same as the "true" displacement effect - which I define as the number of workers who leave (on net) for each new arrival from abroad. Intuitively, this is because the impact of immigration to skill group s is partly diffused across the local economy (i.e. in local output y_{rt}) - to the extent that skill types are substitutable in production. But the empirical specification holds y_{rt} fixed by virtue of the area fixed effects d_{rt}, so any component of the displacement effect weighing equally on all skill groups is necessarily neglected. For example, notice that δ_1 goes to zero as σ converges to 1, i.e. as skill types become perfect substitutes - and the impact of immigration is fully diffused. But of course, perfect substitutability does not preclude the existence of displacement effects.

More specifically, δ_1 will only reveal the true displacement effect if wages in each skill group s depend only on employment in s and not in other skill groups. In that case, skill-specific markets can be treated independently, and shocks are not diffused across the local economy. This requires an additively separable production function - which, by inspection of (30), is only true under the knife-edge condition $\sigma = \rho$. If σ is larger than ρ, the cross-elasticities are negative, and δ_1 will underestimate the true displacement effect. Intuitively, group s will suffer from migratory inflows elsewhere in the local economy, but these cross-group effects are not picked up by the δ_1 coefficient. And conversely, if σ is larger than ρ, the cross-elasticities are positive, so δ_1 will overestimate the true displacement effect.

Of course, the $\sigma = \rho$ condition is only relevant to a CES production function with a single nest. If there is a more complex nesting structure, with the elasticities of substitution varying across hierarchical nests, additive separability can never be satisfied - so δ_1 can never equal the true displacement effect.

In any case, we cannot know the "true" CES production function in practice, so the delineation of skill groups is ultimately a choice made by the researcher. But this choice matters for estimates of δ_1, as δ_1 conflates both the displacement effect and substitutability in production. Different skill delineations will effectively be associated with different levels of σ (i.e. substitutability in production), and as (33) shows, δ_1 is sensitive to σ. Ideally, one may want to choose a skill delineation which yields a σ as close as possible to ρ (if there happens to be a single nest), but these parameters are difficult to identify.

In light of these challenges, the aggregate-level estimates of displacement (in Section 5) may appear more attractive. Even though the underlying assumptions of the aggregate-level model (i.e. homogeneous workers) may be problematic, at least the empirical counterpart is informative: ultimately, it identifies the average net outflow triggered by the arrival of an average foreign migrant. Nonetheless, it is useful to study how estimates of δ_1 vary across different skill delineations, and this is my focus for the remainder of this section.

6.3 Skill delineation

The most natural approach is to define skill by education, which is relatively "exogenous" compared to other skill measures. As Table 7 shows, a similar share of natives and migrants (just under 30 percent) have college degrees, though migrants are much more likely to have less than 12 years of schooling.

[Table 7 here]

Various education classifications have been applied in the displacement literature. Mechanically, finer classifications are likely to entail a higher degree of group substitutability in production (i.e. larger σ) - and consequently a lower estimate of δ_1. Finer classifications will also typically be associated more complex nesting structures, which make it harder to interpret estimates of δ_1. For example, Borjas (2006) estimates displacement effects using a relatively detailed four-group classification: high school dropouts, high school graduates, some college and college graduates. Card (2005) and Cortes (2008) divide the labor market into just two groups: high school dropouts and all others (their motivation is that the largest impact of immigration on the education distribution falls at this margin, as Table 7 illustrates). But, Goldin and Katz (2008), Card (2009*a*) and Ottaviano and Peri (2012) argue that high school dropouts are close substitutes in production with high school graduates.[13] If so, much of the impact of migrant dropouts may be diffused across skill categories and consequently absorbed into the area fixed effects (rather than into the δ_1 estimate). These diffusion effects are likely to be important in this context, given that non-college natives tend to have high school diplomas, whereas non-college migrants usually do not.

As Card (2009*a*) argues, a more natural approach may be to split the sample into college and non-college workers - following the example of the traditional labor literature on skill wage differentials (see e.g. Katz and Murphy, 1992; Card and Lemieux, 2001). But, this simple two-group classification may not do justice in the particular context of immigration: much of the evidence suggests that similarly educated natives and migrants are not perfect

[13] This claim is disputed by Borjas, Grogger and Hanson (2012).

substitutes (see Card, 2009*b*; Manacorda, Manning and Wadsworth, 2012; Ottaviano and Peri, 2012, though Borjas, Grogger and Hanson, 2012, dispute this). Dustmann and Preston (2012) and Dustmann, Frattini and Preston (2012) suggest this imperfect substitutability is a consequence of migrants working in lower skilled occupations than their schooling would otherwise warrant.

Card and DiNardo (2000) and Card (2001) offer a practical method to address this concern. They probabilistically assign individuals into broad occupation groups, conditional on their education and demographic characteristics. This assignment is based on predictions from a multinomial logit model; and crucially, this model is estimated separately for natives and migrants - thus accounting for any downgrading effect. Card and DiNardo (2000) use a classification of three occupation groups (based on average weekly wages in each occupation), and Card (2001) uses six groups (laborers and low skilled services; operative and craft; clerical; sales; managers; professional and technical). However, as I argue above, a classification with more groups will mechanically entail a higher degree of substitutability and a more complex nesting structure. This is illustrated in Table 8, which sets out the education shares in each imputed occupation group. The bottom two groups look very similar in terms of education, as do the middle two and the top two groups.

[Table 8 here]

I propose an alternative classification with just two imputed occupation groups: (i) all those two-digit occupations with less than 50 percent college share in 2010; and (ii) all those with more than 50 percent. As it happens, the occupational distribution in college share is strongly bipolar, as Figure 1 shows, and 50 percent is the natural dividing line. Unsurprisingly, Table 8 shows the education composition of these two groups is very different.

[Figure 1 here]

6.4 Estimates of displacement: decadal cross-sections

I next estimate the empirical specification (28) separately for five skill delineations: (i) college graduates and non-graduates; (ii) high school dropouts and all others; (iii) four education groups: dropouts, high school graduates, some college and college graduates; (iv) six imputed occupation groups, following Card's (2001) scheme; and (v) two imputed occupation groups based on my scheme. For the latter two delineations, I allocate individuals to occupations in each year based on multinomial logit estimates using the 1990 census. For each skill group, the data includes 5 decades of 722 CZ observations - as in the specifications above.

The right-hand side variable, the contribution of new migrants $\frac{L^F_{srt}}{L_{srt-1}}$ to local population in skill cell s, is endogenous to unobserved skill-area specific demand shocks contained in the error term ε_{srt}. I again address this problem using a migrant shift-share instrument. Card (2001) shows this instrument can be applied elegantly to predict the migrant contribution to skill cells within local areas. Specifically, the instrument takes the form:

$$m_{srt} = \frac{\sum_o \phi^o_{rt-1} L^F_{ost}}{L_{rst-1}} \tag{34}$$

where new migrants of origin o and skill s are allocated proportionally according to the initial co-patriot geographical distribution.

[Table 9 here]

In the top half of Table 9, I present IV estimates of the displacement effect δ_1 from equation (28), based on decadal differences in census cross-sections. I include the first stage estimates in column 1: that is, the effect of the skill-specific migrant shift share instrument m_{srt} on the new migrant contribution $\frac{L^F_{srt}}{L_{srt-1}}$. The rows of the table correspond to different skill delineations. Throughout, I control for interacted skill-year fixed effects and interacted CZ-year fixed effects, as well as the current and lagged skill-specific Bartik shocks.

As column 1 shows, the skill-specific migrant shift-share is a strong instrument for all skill delineations, with the coefficient ranging from 0.4 to 0.8. But, controlling for CZ fixed effects, IV estimates of the displacement parameter δ_1 within CZ-year cells (in column 2) are very sensitive to skill delineation. The imputed occupation classifications yield zero population responses among natives and old migrants, whereas the responses are positive and significant (between 0.6 and 1.2) for the education group classifications. Interestingly, comparing columns 2 and 3, the positive effects are (more than) entirely driven by natives: the contribution of old migrants is negative. So, while there is large displacement of natives at the aggregate level (see Table 4), this result is not at all reflected *within* CZ-year cells (across skill groups). How can this apparent discrepancy be understood? The key point is that δ_1 does not merely identify relocation of workers, but also changes in the skill composition of local cohorts.

6.5 Estimates of displacement: longitudinal dimension

Fortunately, it is possible to study the impact on residential decisions directly by exploiting a longitudinal dimension of the census data: between 1970 and 2000, respondents were asked where they lived five years ago. This approach has precedent: Card (2001) uses this data (in the 1990 census extract) to test for displacement. I restrict attention to the period 1980-2000, since previous residence is only classified by state in 1970. Using this data, I construct CZ population counts (for individuals aged 16-64) by current residence in each census extract, together with CZ counts for the same individuals by residence five years earlier. Of course, I do not observe emigrants from the US, but this omission should bias my findings against displacement - if emigration is partly a response to an individual's *local* economic environment (i.e. at the CZ level); and indeed, Cadena and Kovak (2016) present some evidence in favor of this claim for returning Mexicans.

With this in mind, I re-estimate equation (28) using five year differences:

$$\frac{\left(L_{srt} - L^F_{srt}\right) - L_{srt-5}}{L_{srt-5}} = \delta_0 + \delta_1 \frac{L^F_{srt}}{L_{srt-5}} + \delta_2 b_{srt} + \delta_3 b_{srt-10} + d_{rt} + d_{st} + \varepsilon_{srt} \tag{35}$$

where t now denotes years (as opposed to decades), L^F_{srt} is the stock of "new" migrants (who arrived in the US less than five years previously), and $L_{srt} - L^F_{srt}$ is the local stock of workers who were living in the US for more than five years. Thus, the expression $\left(L_{srt} - L^F_{srt}\right) - L_{srt-5}$ identifies the net migratory flow of these longer-term residents between $t-5$ and t. As described above, my data covers three census extracts: 1980, 1990 and 2000. I also reconstruct the skill-specific migrant shift-share instrument m_{srt}, to predict the contribution of new migrants to the local population over five years (rather than a decade). Since the census (in the years under study) does not report industry five years previously, I continue to use the decadal (current and lagged) Bartik shift-shares as controls.

I present the first stage and IV estimates in the bottom half of Table 9. Unsurprisingly, the first stage estimates look similar to those in the decadal data. But this time, estimates of δ_1 are universally negative. The overall response (of both natives and old migrants) is reported in column 2, and these do vary considerably in magnitude by skill delineation. The response for the college grad/non-grad decomposition (first row) is -3, implying an unrealistic three-for-one displacement, though the standard error is very large. The estimate of δ_1 is -0.38 for the high school dropout/non-dropout decomposition and -0.15 for the 4 education group classification, with the latter estimate insignificantly different from zero. However, as I have described above, these education classifications are potentially problematic because of misallocation of migrants to native skill groups, as well as the general concerns about substitutability in production.

The final two rows report results for the imputed occupation classifications. I estimate δ_1 to be -1.23 for the two group decomposition and -0.38 for six groups. The difference in these estimates is statistically significant, and this makes sense in light of the predictions from the model above. A classification with more skill groups admits greater substitutability in production, so a larger amount of the displacement effect is diffused across skill groups - and absorbed by the CZ-year interacted fixed effects. The contribution of natives to these δ_1 estimates is substantial in each.

Using a similar set-up, Card (2001) finds no evidence of geographical displacement: see Table 3. This is largely explained by his use of a six-group occupation delineation, which is presumably subject to larger substitutability in production. However, in the final row of Table 9, I do estimate statistically significant displacement effects even in this six-group set-up (though much smaller than for the two-group delineation). I study this further in Appendix B, where I attempt a replication of Card's (2001) results. The difference can be explained by three additional factors. First, Card's results are based on the 1990 census only; but the results in Table 9 additionally pool data from 1980 and 2000, and the displacement effects are larger in 2000 than in the earlier years. Second, his restriction of the sample to the top 175 MSAs attenuates the effect: this suggests part of the displacement effect is manifested in migration between this set of 175 MSAs and the rest of the country. And third, he controls for a range of demographic means at time $t-5$ within the skill-area cells (age, education, migrants' years in US), and this also appears to attenuate the effect somewhat.

6.6 Estimates of cohort effects

These cohort effects can be observed directly (at least among the native-born) by exploiting data on individuals' state of birth (also reported in the census). I begin by re-estimating equation (28) using state-level data. I report the results in Table 10. The first stage in column 1 shows substantial power, and the range of coefficients (across skill delineations) is similar to the CZ-level estimates in the top half of Table 9. Column 2 offers estimates of δ_1, replicating the second column of Table 9 (top half) for state-level data. Again, the coefficients look very similar to the CZ results.

[Table 10 here]

In column 3, I re-estimate equation (28), but replacing the dependent variable with $\frac{\Delta L_{sbt}}{L_{sbt-1}}$, where L_{sbt-1} is the population aged 16-64 at time $t-1$ with skill s and *born* in state b. And thus, ΔL_{sbt} is the decadal change in the population aged 16-64 of skill s, among those born in state b. This variable is a useful proxy for the contribution of cohort effects to skill composition in state b. The coefficients are remarkably large (close to 1 in several cases) - and mostly larger than the δ_1 estimates by state of residence in column 2 (the one exception is the college graduate specification in row 1, though these coefficients are estimated with substantial error). And it should also be emphasized that the effects in column 3 will likely underestimate the true cohort effects, given that many individuals (approximately one third of the sample) do not live in their state of birth.

To summarize then, the evidence points to substantial geographical displacement even within skill groups - exploiting the longitudinal aspect of the census. But these effects are not manifested in decadal census changes because of substantial cohort effects. For example, California has received a large inflow of low skilled migrants from abroad. On net, there has also been a large outflow of low skilled natives and earlier migrants (relative to high skilled). All else equal, this would have left the local skill composition unchanged overall. But the native Californian population has also downgraded in terms of skills over time - which has undone the contribution of native relocation decisions to local skill composition.

At first sight, these cohort effects may appear strange: low skilled Californians might be expected to respond to low skilled immigration by acquiring *more* education. One explanation is that the composition of cohorts is driven by the children of earlier migrants - but I find that excluding self-identifying Hispanics does not affect the results. Alternatively, the cohort effects may be driven by selection. Suppose that, among the low skilled, the more productive workers responded more heavily through relocating (i.e. moving on net away from California). The families of these more productive workers (whether the movers themselves or their children) are more likely to be on the margin of acquiring college education, particularly in the context of the large roll-out of college education in recent decades. So over time, education levels among native Californians would then have decreased relative to elsewhere. But of course, this kind of reasoning can only be speculative.

7 Conclusion

It is often claimed that migrants "grease the wheels" of the labor market (see Borjas, 2001; Cadena and Kovak, 2016), as they are more mobile geographically. Rather than "taking jobs" from natives, they may actually protect the employment of immobile natives in areas suffering declining demand - by moving elsewhere and reducing the supply of labor.

The evidence in this study confirms that new migrants do indeed contribute disproportionately to the adjustment of local population to demand shocks. However, I also show that the speed of adjustment is no faster in those areas which are better supplied by migrants, as indicated by the migrant shift share instrument. This is because migrants "crowd out" the contribution of natives to local adjustment. Indeed, I present more direct evidence that new migrants have displaced natives (and earlier migrants) one-for-one from areas with large co-patriot communities. This result materializes both at the aggregate CZ level and also in variation across skill groups within CZ-year cells, though only after controlling for cohort effects in the latter case. These findings differ markedly from much of the existing the literature, and I have attempted to explain why.

This is not to say that natives do not benefit from the mobility of new foreign migrants. In particular, if moving is costly, a mobile migrant workforce may save natives from having to incur these costs themselves. But, my evidence casts doubt on the claim that migrants protect native jobs by "greasing the wheels".

On a final note, if new foreign migrants do indeed crowd out the native contribution to local adjustment, substantial immigration from abroad in recent decades may help explain part of the decline in cross-state mobility since 1980 (see e.g. Molloy, Smith and Wozniak, 2011). One back-of-the-envelope approach would be to compare (i) the decline of the annual rate of cross-state migration with (ii) the (net) annual inflow of foreign migrants. For example, based on the CPS, Molloy, Smith and Wozniak (2011) show that annual cross-state mobility has fallen by about 1 percentage point between 1980 and 2010 (from 2.5 to 1.5 percent). This compares with a 0.3 percentage point net annual inflow of migrants.[14] So, the growth of immigration might explain at most about one third of the decline in cross-state mobility. But of course, this is merely speculative; and there are alternative hypotheses. In particular, Kaplan and Schulhofer-Wohl (2012*b*) point to a decline in the geographical specificity of returns to occupations, together with improving communications technology; and Molloy, Smith and Wozniak (2014) emphasize the declining rate of job transitions.

[14]The stock of migrants has grown by about 10 percentage points between 1980 and 2010, or about 0.3 percentage points annually.

Tables and figures

Table 1: Average contributions to local population adjustment

PANEL A: OLS and IV

	Δ log pop	Contributions to local population growth							
		All	New migrants	Natives and old migrants	Natives only	All	New migrants	Natives and old migrants	Natives only
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
OLS									
Δ log emp	0.798***	0.951***	0.040***	0.912***	0.862***	0.952***	0.048***	0.904***	0.857***
	(0.015)	(0.023)	(0.013)	(0.025)	(0.021)	(0.023)	(0.008)	(0.020)	(0.018)
Lagged log ER	0.183***	0.193***	0.096***	0.097***	0.058**	0.192***	0.083***	0.109***	0.066***
	(0.014)	(0.018)	(0.035)	(0.037)	(0.024)	(0.018)	(0.012)	(0.017)	(0.017)
$\hat{\lambda}^F_{rt}$						0.073	0.963***	-0.891***	-0.571***
						(0.047)	(0.043)	(0.063)	(0.066)
IV									
Δ log emp	0.630***	0.758***	0.156**	0.602***	0.606***	0.754***	0.076***	0.678***	0.655***
	(0.036)	(0.049)	(0.076)	(0.086)	(0.062)	(0.048)	(0.024)	(0.052)	(0.049)
Lagged log ER	0.397***	0.443***	0.235***	0.208**	0.196**	0.436***	0.096***	0.339***	0.281***
	(0.055)	(0.065)	(0.062)	(0.095)	(0.082)	(0.065)	(0.028)	(0.072)	(0.067)
$\hat{\lambda}^F_{rt}$						0.050	0.964***	-0.915***	-0.593***
						(0.082)	(0.044)	(0.088)	(0.096)
Observations	3,610	3,610	3,610	3,610	3,610	3,610	3,610	3,610	3,610

PANEL B: First stage

	Δ log emp		Lagged log ER	
	(1)	(2)	(3)	(4)
Current Bartik	0.926***	0.943***	-0.064	-0.058
	(0.114)	(0.106)	(0.076)	(0.069)
Lagged Bartik	0.097	0.120*	0.560***	0.569***
	(0.065)	(0.068)	(0.058)	(0.060)
$\hat{\lambda}^F_{rt}$		-0.254**		-0.097
		(0.100)		(0.172)
Observations	3,610	3,610	3,610	3,610

Panel A reports OLS and IV estimates of β_1 and β_2 in the population response equation (24), across 722 CZs and five (decadal) time periods. The dependent variable in column 1 is the log change in the population of all individuals aged 16-64. In the remaining columns, I replace the dependent variables with components of local population growth. For reasons discussed in Section 3, I approximate the change in log population Δl_{rt} with local population growth $\frac{\Delta L_{rt}}{L_{rt-1}}$ (column 2), which I disaggregate using the scheme in equation (20). Column 3 replaces the dependent variable with the contribution of new migrants (arriving in the previous ten years), $\frac{L^F_{rt}}{L_{rt-1}}$; column 4 with the contribution of other workers, $\frac{\Delta L_{rt}-L^F_{rt}}{L_{rt-1}}$; and column 5 with the contribution of natives alone. Columns 6-9 replicate the previous four columns, but now controlling for local migrant intensity, $\hat{\lambda}^F_{rt}$, as specified in equations (22) and (23). Panel B presents the first stage results associated with the IV estimates. There are two endogenous variables (the change in log employment and the lagged log employment rate) and two corresponding instruments (the current and lagged Bartik shift shares). I report the first stage estimates for each endogenous variable, both with and without the migrant intensity control (which appears in the IV specifications in columns 6-9). Beyond local migrant intensity, all specifications control for a full set of time effects, three climate variables (the maximum January and July termperatures, and mean July relative humidity), a dummy for the presence of coastline, the log population density in 1900, the log distance to the closest CZ centroid; and these controls are also interacted with the time effects. Errors are clustered by CZ, 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: Heterogeneity in contributions to population adjustment

PANEL A: OLS and IV

	All	New migrants	Natives and old migrants	Natives only	All	New migrants	Natives and old migrants	Natives only
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OLS								
Δ log emp	0.968***	0.001	0.967***	0.965***	0.946***	-0.008	0.953***	0.947***
	(0.022)	(0.013)	(0.025)	(0.023)	(0.020)	(0.006)	(0.019)	(0.019)
Δ log emp * $\hat{\lambda}^F_{rt}$	-0.399	1.754***	-2.153***	-3.658***	0.889	2.124***	-1.234***	-2.817***
	(0.382)	(0.393)	(0.418)	(0.410)	(0.577)	(0.237)	(0.427)	(0.352)
Lagged log ER	0.171***	-0.012	0.183***	0.170***	0.177***	-0.007	0.184***	0.173***
	(0.024)	(0.008)	(0.024)	(0.020)	(0.023)	(0.010)	(0.022)	(0.019)
Lagged log ER * $\hat{\lambda}^F_{rt}$	0.526	2.688***	-2.162***	-3.102***	0.459	1.850***	-1.390***	-2.299***
	(0.646)	(0.512)	(0.698)	(0.469)	(0.730)	(0.553)	(0.493)	(0.386)
$\hat{\lambda}^F_{rt}$	0.339	1.875***	-1.536***	-1.430***	3.940	0.495	3.445	11.375
	(0.254)	(0.172)	(0.289)	(0.198)	(8.381)	(1.642)	(8.953)	(10.813)
IV								
Δ log emp	0.751***	-0.028	0.779***	0.823***	0.789***	-0.050	0.839***	0.837***
	(0.048)	(0.029)	(0.045)	(0.044)	(0.048)	(0.033)	(0.051)	(0.050)
Δ log emp * $\hat{\lambda}^F_{rt}$	0.928	5.975*	-5.047***	-8.370***	-1.039	3.667**	-4.705**	-6.027***
	(2.755)	(3.377)	(1.813)	(2.210)	(1.645)	(1.671)	(2.160)	(2.156)
Lagged log ER	0.314*	-0.217	0.530***	0.590***	0.492***	-0.059	0.552***	0.533***
	(0.183)	(0.216)	(0.137)	(0.158)	(0.093)	(0.041)	(0.085)	(0.081)
Lagged log ER * $\hat{\lambda}^F_{rt}$	3.757	9.871*	-6.114	-9.904**	-0.982	5.165**	-6.147*	-7.205**
	(5.558)	(5.704)	(3.869)	(4.466)	(3.744)	(2.014)	(3.600)	(3.279)
$\hat{\lambda}^F_{rt}$	1.504	4.368**	-2.864**	-3.728**	-16.279	2.187	-18.466	-9.620
	(2.063)	(2.114)	(1.433)	(1.670)	(11.073)	(2.805)	(11.599)	(12.629)
$\hat{\lambda}^F_{rt}$ * amenities	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

PANEL B: First stage

	Δ log emp	Δ log emp * $\hat{\lambda}^F_{rt}$	Lagged log ER	Lagged log ER * $\hat{\lambda}^F_{rt}$	Δ log emp	Δ log emp * $\hat{\lambda}^F_{rt}$	Lagged log ER	Lagged log ER * $\hat{\lambda}^F_{rt}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Current Bartik	**1.134*** **	-0.027***	-0.051	0.019***	**0.960*** **	-0.014*	0.044	0.009
	(0.100)	(0.007)	(0.072)	(0.005)	**(0.115)**	(0.008)	(0.113)	(0.007)
Current Bartik * $\hat{\lambda}^F_{rt}$	-4.996**	**1.766*** **	-0.287	-0.957***	9.035**	**2.021*** **	-6.766	-0.663*
	(2.515)	**(0.266)**	(1.161)	(0.118)	(4.266)	**(0.468)**	(5.519)	(0.369)
Lagged Bartik	0.140**	0.034***	**0.559*** **	-0.004	0.194**	0.025***	**0.551*** **	-0.008*
	(0.067)	(0.005)	**(0.068)**	(0.004)	(0.093)	(0.008)	**(0.079)**	(0.005)
Lagged Bartik * $\hat{\lambda}^F_{rt}$	-2.462	-1.321***	0.456	**1.014*** **	-7.408*	-1.264***	0.385	**1.131*** **
	(1.935)	(0.343)	(1.721)	**(0.232)**	(3.885)	(0.471)	(2.224)	**(0.274)**
$\hat{\lambda}^F_{rt}$	0.794***	0.126***	-0.142	-0.479***	-49.533**	-1.732***	29.715**	-0.262
	(0.245)	(0.045)	(0.192)	(0.033)	(19.669)	(0.543)	(13.328)	(0.298)
$\hat{\lambda}^F_{rt}$ * amenities	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

Panel A reports OLS and IV estimates of equation (25), across 722 CZs and five (decadal) time periods. Just as in Table 1 (see the associated table notes), I estimate this equation separately for overall local population growth (column 2) and the contributions of new migrants (column 3), other workers (column 4) and natives alone (column 5). All specifications control for the amenity variables described in the notes under Table 1, as well as for local migrant intensity, $\hat{\lambda}^F_{rt}$, as specified in equations (22) and (23). In addition, the remaining four columns (5-8) also control for interactions between all the amenity variables and the migrant intensity, $\hat{\lambda}^F_{rt}$. There are four endogenous variables: the change in log employment and the lagged log employment rate, and the same two variables interacted with local migrant intensity, $\hat{\lambda}^F_{rt}$. Panel B reports the first stage estimates for each endogenous variables, which use four corresponding instruments: the current and lagged Bartik shift-shares, both on their own and interacted with migrant intensity. I have marked in bold the effect of each instrument and its corresponding endogenous variable - that is, where one should theoretically expect to see significant positive effects. Errors are clustered by CZ, 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: Previous IV estimates of displacement using similar empirical specification and data

	Geographical variation (1)	Time variation (2)	Within-area variation? (3)	Longitudinal data? (4)	Estimate of δ_1 (5)
Card and DiNardo (2000)	119 MSAs	1980-1990	Yes: 3 imputed occupation groups	No	0.24 to 0.28
Card (2001)	175 MSAs	1985-1990	Yes: 6 imputed occupation groups	Yes	0.25 to 0.43
Cortes (2008)	30 MSAs	1980-2000	Yes: 2 educ groups (HSDs and all others)	No	-0.20 to 0.27
Card (2009*a*)	100 MSAs	1980-2000	No: aggregate-level	No	-0.8 to 0.5
Monras (2015*b*)	50 states + DC	1995-1996	Yes: 2 educ groups (College graduates and non-graduates)	No	-2.3*
Monras (2015*b*)	50 states + DC	1990-2000	Yes: 2 educ groups (College graduates and non-graduates)	No	-0.39 to -0.21*

This table reports previous IV estimates of displacement in the literature, based on similar empirical specifications to equation (27) and using similar data (decadal changes in the US census). Column 3 reports whether the paper studied aggregate-level geographical variation or exploited variation across skill groups within geographical units. In the latter case, I report the particular delineation of skill groups each paper uses. "Imputed occupation groups" describes a set-up where individuals are probabilistically assigned to occupation categories based on their demographic characteristics: see Section 6.3 for further details. Column 4 reports whether the paper studied decadal changes in census cross-sections or exploited the longitudinal aspect of the census, where individuals reported their residence five years ago. See Section 6 for further discussion. The final column reports the range of IV estimates of displacement, equivalent to my δ_1 coefficient, in each paper. *I report two results from Monras (2015b). The first is a short run effect (with the regressor lagged one year), based on his analysis of the Mexican Peso crisis of 1995. The -2.3 displacement estimate is imputed from column 8 of Table 5 in his paper. The second is based on a longer run decadal change between 1990 and 2000; the displacement estimates reported here are imputed from columns 6 and 8 from Table 7 in his paper. Note that, throughout, he focuses on displacement driven by Mexican migration specifically.

Table 4: Estimates of displacement across CZs

PANEL A: IV and OLS

	OLS			IV			IV with interacted instruments		
	Natives and old migrants		Natives only	Natives and old migrants		Natives only	Natives and old migrants		Natives only
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Basic specification									
New migs' contrib	-0.761***	-0.662***	-0.490***	-1.134***	-1.197***	-0.840***	-1.186***	-1.246***	-0.929***
	(0.143)	(0.178)	(0.142)	(0.128)	(0.129)	(0.107)	(0.128)	(0.131)	(0.110)
Lagged log ER	0.420***			0.609***			0.612***		
	(0.053)			(0.119)			(0.121)		
Current Bartik	0.716***	0.629***	0.611***	0.729***	0.698***	0.657***	0.742***	0.705***	0.668***
	(0.093)	(0.113)	(0.097)	(0.092)	(0.106)	(0.096)	(0.092)	(0.105)	(0.095)
Lagged Bartik		0.272***	0.241***		0.350***	0.292***		0.358***	0.305***
		(0.073)	(0.064)		(0.073)	(0.063)		(0.073)	(0.063)
FE specification									
New migs' contrib	-0.730***	-0.762***	-0.767***	-0.327	-1.034***	-0.448	-1.004***	-1.029***	-0.907***
	(0.154)	(0.155)	(0.157)	(0.554)	(0.304)	(0.303)	(0.216)	(0.191)	(0.196)
Lagged log ER	-0.236***			1.313***			0.211		
	(0.073)			(0.507)			(0.257)		
Current Bartik	0.783***	0.697***	0.609***	0.809***	0.675***	0.635***	0.764***	0.676***	0.598***
	(0.088)	(0.092)	(0.086)	(0.109)	(0.079)	(0.071)	(0.080)	(0.080)	(0.073)
Lagged Bartik		0.164***	0.137**		0.170***	0.131**		0.170***	0.140**
		(0.061)	(0.065)		(0.057)	(0.054)		(0.057)	(0.059)
Observations	3,610	3,610	3,610	3,610	3,610	3,610	3,610	3,610	3,610

PANEL B: First stage for new migrants' contribution

	Basic specification		FE specification	
	(1)	(2)	(3)	(4)
Current Bartik	0.066***	0.006	-0.007	-0.078***
	(0.019)	(0.023)	(0.018)	(0.020)
Current Bartik * $\hat{\lambda}^F_{rt}$		1.309*		1.885***
		(0.709)		(0.528)
Lagged Bartik	0.064***	0.033***	0.031**	-0.026**
	(0.013)	(0.013)	(0.015)	(0.011)
Lagged Bartik * $\hat{\lambda}^F_{rt}$		2.085***		2.481***
		(0.494)		(0.412)
$\hat{\lambda}^F_{rt}$	0.936***	0.408***	0.670***	0.063
	(0.045)	(0.121)	(0.042)	(0.115)
Observations	3,610	3,610	3,610	3,610

Panel A reports OLS and IV estimates of the displacement equations (26) and (27), across 722 CZs and five (decadal) time periods. In the first equation, estimated in columns 1, 4 and 7, there are two endogenous variables: the contribution of new migrants to local population growth, $\frac{L^F_{rt}}{L_{rt-1}}$, and the lagged log employment rate. In the second, estimated in the remaining columns, the lagged employment rate is replaced by the lagged Bartik shift share, so only one endogenous variable remains (the contribution of new migrants). In all IV specifications, I instrument the contribution of new migrants using the local migrant intensity, $\hat{\lambda}^F_{rt}$, as specified in equations (22) and (23); and I instrument the lagged employment rate using the lagged Bartik shift share. For the IV estimates in columns 7-9, I include two additional instruments - as suggested by equation (15) - namely interactions between the local migrant intensity $\hat{\lambda}^F_{rt}$ and the current and lagged Bartik shfit shares. All specifications include the full set of controls listed in the notes under Table 1. The bottom half of the table conditions further on CZ fixed effects, while the top half does not. Column 1, 2, 4, 5, 7 and 8 report estimates for the displacement of both natives and old migrants (who arrived in the US at least ten years previously), and the remaining columns report estimates for the displacement of natives alone. The first stage estimates are presented in Panel B, for both instrumenting strategies. Errors are clustered by CZ, 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: Robustness tests for IV displacement effects

	Basic specification						FEs
	1960s	1970s	1980s	1990s	2000s	All years	All years
	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Year effects	1.221	-0.843	-0.128	-0.952***	-0.590***	-0.580**	-1.619***
	(1.806)	(0.643)	(0.212)	(0.200)	(0.217)	(0.236)	(0.498)
+ Current and lagged Bartik	-0.683	-0.348	-0.418*	-1.432***	-0.664***	-0.719***	-1.266**
	(2.211)	(0.431)	(0.226)	(0.241)	(0.247)	(0.210)	(0.507)
+ Climate controls	-3.290*	-2.487***	-0.918***	-1.796***	-1.476***	-1.426***	-1.266**
	(1.912)	(0.630)	(0.245)	(0.216)	(0.183)	(0.130)	(0.507)
+ Coastline dummy	-3.421	-2.514***	-0.852***	-1.523***	-1.233***	-1.320***	-1.266**
	(2.090)	(0.713)	(0.264)	(0.182)	(0.172)	(0.158)	(0.507)
+ Log pop density 1900	-2.419**	-2.307***	-0.830***	-1.511***	-1.170***	-1.232***	-1.266**
	(1.020)	(0.454)	(0.162)	(0.179)	(0.194)	(0.166)	(0.507)
+ Log distance to closest CZ	-2.232**	-2.240***	-0.921***	-1.441***	-1.125***	-1.205***	-1.266**
	(0.948)	(0.441)	(0.178)	(0.177)	(0.188)	(0.159)	(0.507)
+ Amenities x year effects	-2.232**	-2.240***	-0.921***	-1.441***	-1.125***	-1.197***	-1.034***
	(0.948)	(0.441)	(0.178)	(0.177)	(0.188)	(0.129)	(0.304)
Observations	722	722	722	722	722	3,610	3,610

This table tests robustness of my IV estimates of displacement in column 5 of Table 4. These are based on the model of equation (27): the dependent variable is the contribution of natives and old migrants to local population growth, and the endogenous regressor is the contribution of new migrants (arriving in the last ten years), instrumented by local migrant intensity $\hat{\lambda}^F_{rt}$, as specified in equations (22) and (23). The first seven columns report estimates of δ_1 for the basic specification (without CZ fixed effects), separately for each decade and for all years together; and the final column looks at the fixed effects specification (for all years). Along the rows of the table, I show how estimates of δ_1 change as progressively more controls are included. The first row reports estimates when controlling for year effects alone; and the final row includes the full set of controls I use in Table 4. Errors are clustered by CZ, 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: IV effects of foreign inflows on local employment rates

	Basic emp rate			Composition-adjusted emp rate		
	All	Natives	Migrants	All	Natives	Migrants
	(1)	(2)	(3)	(4)	(5)	(6)
Basic specification						
New migs' contrib	-0.124***	-0.185***	-0.172***	-0.162***	-0.193***	-0.137***
	(0.025)	(0.022)	(0.043)	(0.020)	(0.020)	(0.044)
Current Bartik	0.384***	0.414***	0.269***	0.310***	0.304***	0.171**
	(0.039)	(0.037)	(0.096)	(0.035)	(0.034)	(0.084)
Lagged Bartik	-0.168***	-0.168***	-0.207***	-0.153***	-0.153***	-0.275***
	(0.023)	(0.024)	(0.074)	(0.022)	(0.021)	(0.075)
FE specification						
New migs' contrib	-0.16	-0.219*	0.161	-0.205*	-0.239**	-0.063
	(0.127)	(0.117)	(0.257)	(0.118)	(0.104)	(0.260)
Current Bartik	0.375***	0.416***	0.327***	0.304***	0.302***	0.151
	(0.052)	(0.045)	(0.122)	(0.045)	(0.044)	(0.106)
Lagged Bartik	-0.152***	-0.145***	-0.139	-0.125***	-0.128***	-0.260***
	(0.025)	(0.026)	(0.091)	(0.025)	(0.024)	(0.089)
Observations	3,610	3,610	3,610	3,610	3,610	3,601

This table reports IV estimates of the impact of inflows of new migrants on local employment rates, across 722 CZs and five (decadal) time periods. Specifically, I have replaced the dependent variable in equation (27) with the decadal change in the log employment rate. In all cases, the contribution of new migrants (to local population growth) is instrumented by local migrant intensity $\hat{\lambda}^F_{rt}$, as specified in equations (22) and (23). The first three columns report estimates for the basic (unconditional) employment rate, separately for the full sample of 16-64s, natives and migrants. In the final three columns, I repeat this exercise for employment rates adjusted for local demographic composition. The adjustment procedure is described in footnote 12 in Section 5.3. All specifications include the full set of controls listed in the notes under Table 1. The bottom half of the table conditions further on CZ fixed effects, while the top half does not. The corresponding first stage estimates can be found in columns 1 and 3 of Table 4. Errors are clustered by CZ, 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: Education composition of natives and migrants (2010)

	High school dropout	High school graduate	Some college	College graduate
Natives	0.118	0.364	0.249	0.269
Old migrants (> 10 years)	0.241	0.291	0.187	0.280
New migrants ($\leq$ 10 years)	0.273	0.281	0.153	0.293

This table reports education shares separately for three demographic groups: natives, old migrants (in the US for more than ten years) and new migrants (up to ten years). I denote those with less than 12 years of education as "high school dropouts"; "high school graduates" have twelve years; "some college" denotes individuals with 1-3 years of college study, and "college graduate" at least four years. The sample consists of individuals aged 16-64 in the American Community Survey of 2010.

Table 8: Education and migrant composition of imputed occupation groups (2010)

		Education shares				Migrant shares	
		HS dropout	HS grad	Some college	College grad	All migrants	New migrants
Card's (2001) scheme							
I	Laborers, low skilled service	0.307	0.425	0.217	0.051	0.246	0.099
II	Operative and craft	0.230	0.481	0.229	0.061	0.206	0.065
III	Clerical	0.083	0.383	0.321	0.212	0.130	0.038
IV	Sales	0.129	0.375	0.297	0.198	0.127	0.042
V	Managers	0.026	0.235	0.273	0.467	0.132	0.032
VI	Professional and technical	0.006	0.081	0.159	0.753	0.164	0.047
My scheme							
I	College share < 50%	0.204	0.427	0.259	0.110	0.187	0.065
II	College share > 50%	0.016	0.154	0.215	0.615	0.151	0.041

This table reports summary statistics on the "imputed" occupation groups I use in my analysis. Individuals are probabilistically assigned to broad occupation groups, based on their education and demographic characteristics, as described in Section 6.3. I study two such occupation classifications, one baesd on six broad occupation categories (following Card, 2001) and the other based on two groups: (i) all those two-digit occupations with less than 50 percent college share in 2010; and (ii) all those with more than 50 percent. The first four columns report education shares separately for each imputed occupation group: education categories are defined in the notes under Table 7. And the final two columns report shares of migrants and new migrants respectively: new migrants are those living in the US for less than ten years. The sample consists of individuals aged 16-64 in the American Community Survey of 2010.

Table 9: Within-area IV estimates of displacement

	First stage	Displacement		Observations
		Contrib of natives and old migrants	Contrib of natives alone	
	(1)	(2)	(3)	
Decadal cross-sections				
2 edu groups: CG/non	0.428***	1.190***	1.688**	7,220
	(0.100)	(0.450)	(0.695)	
2 edu groups: HSD/non	0.705***	0.604***	1.223***	7,220
	(0.052)	(0.137)	(0.234)	
4 educ groups	0.671***	0.828***	1.251***	14,440
	(0.046)	(0.175)	(0.288)	
2 occup groups	0.758***	0.109	0.702**	7,220
	(0.069)	(0.257)	(0.298)	
6 occup groups	0.816***	-0.086	0.244*	21,660
	(0.078)	(0.107)	(0.140)	
Five-year longitudinal differences				
2 edu groups: CG/non	0.472***	-3.056*	-2.362	4,332
	(0.137)	(1.782)	(1.534)	
2 edu groups: HSD/non	0.790***	-0.385***	-0.205**	4,332
	(0.041)	(0.077)	(0.088)	
4 educ groups	0.782***	-0.162	-0.008	8,664
	(0.039)	(0.101)	(0.109)	
2 occup groups	0.764***	-1.232***	-0.879***	4,332
	(0.051)	(0.211)	(0.206)	
6 occup groups	0.768***	-0.379***	-0.184***	12,996
	(0.036)	(0.048)	(0.058)	

This table reports IV estimates of the displacement effect (together with the first stage), exploiting variation across skill groups within CZ-year cells. Specifically, I regress the contribution of natives and old migrants (to local population growth) on the contribution of new migrants, with the latter instrumented using the migrant shift-share m_{srt}. The top half of the table reports estimates of equation (28), based on decadal differences between 1960 and 2010. And the bottom half reports estimates of (35), exploiting the longitudinal dimension of the 1980, 1990 and 2000 census microdata extracts (respondents were asked where they lived five years previously). Each row reports displacement effects for a different skill delineation. The first column presents the first stage effect (the coefficient on the migrant shift-share), and columns 2-3 report the IV estimates of δ_1: both the overall displacement effect (among both natives and old migrants) and for natives alone. All specifications control for the current and lagged skill-specific Bartik shocks, together with both CZ-year and skill-year interacted fixed effects. Errors are clustered by CZ, 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 10: State-level IV estimates of displacement across skill groups: decadal cross-sections

	First stage	Displacement		Observations
		State of residence	State of birth	
	(1)	(2)	(3)	
2 edu groups: CG/non	0.464***	1.213	0.819	490
	(0.115)	(0.847)	(0.854)	
2 edu groups: HSD/non	0.914***	0.675**	0.900***	490
	(0.033)	(0.341)	(0.331)	
4 educ groups	0.883***	0.897***	1.195***	980
	(0.032)	(0.263)	(0.321)	
2 occup groups	0.958***	0.349	1.041***	490
	(0.077)	(0.379)	(0.283)	
6 occup groups	1.067***	-0.021	0.540***	1,470
	(0.059)	(0.146)	(0.161)	

This table reports IV estimates of the displacement, together with the first stage, based on decadal differences between 1960 and 2010. Columns 1 and 2 replicate columns 1 and 2 of the top half of Table 9 (see notes under that table), using the specification of equation equation (28), but using variation across states rather than CZs. I include the 48 states of the Continental US plus the District of Columbia. Column 3 re-estimates equation (28), but replacing the dependent variable with $\frac{\Delta L_{sbt}}{L_{sbt-1}}$, where L_{sbt-1} is the population aged 16-64 at time $t-1$ with skill s and *born* in state b. Similarly, ΔL_{sbt} is the decadal change in the population aged 16-64 of skill s, among those born in state b. See Section 6.6 for further details. All specifications control for the current and lagged skill-specific Bartik shocks, together with both state-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.

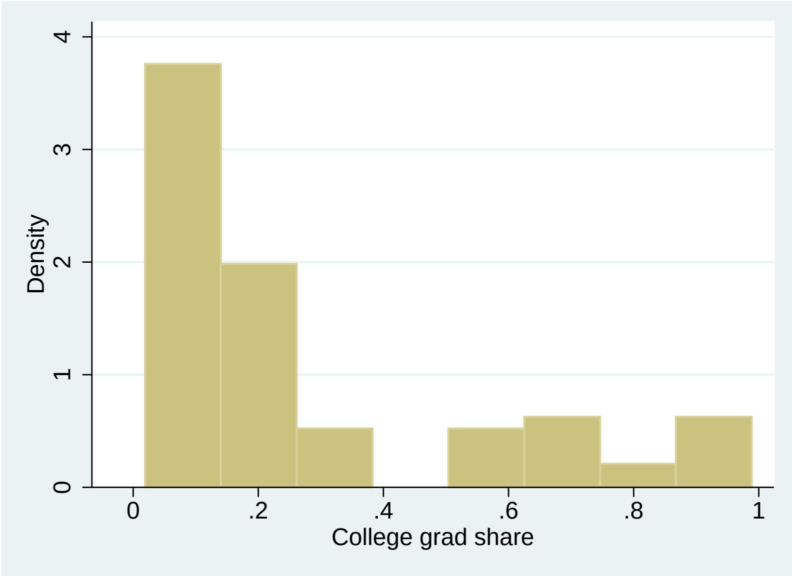

Figure 1: Histogram of college graduate share across occupations

Note: This data is based on the ACS of 2010 and covers 79 minor occupation categories (as described in Section 6.3).

Appendix

A Theoretical derivations

[TO BE COMPLETED]

B Replication of Card (2001) estimates

[TO BE COMPLETED]

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