The Contribution of Foreign Migration to Local Labor Market Adjustment

Michael Amior*

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PRELIMINARY AND INCOMPLETE

Abstract

The US suffers from large regional disparities in employment and labor force participation, which have persisted for many decades. It has often been argued that foreign migration offers a remedy: it "greases the wheels" of the labor market by accelerating the adjustment of local population, following shocks to demand. I confirm that foreign migration does indeed contribute disproportionately to local labor market adjustment and to the elimination of these regional disparities. But, I also find that foreign migration "crowds out" the native contribution to adjustment: so in regions better supplied by new migrants, census data suggests local population adjustment is no faster. This is fundamentally a story of geographical displacement, which can be tested more explicitly: using 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 (though there is reason to believe the census overstates these effects). These results differ markedly from much of the existing literature, and I identify the reasons why. *Keywords*: migration, geographical mobility, local labor markets, employment. *JEL*: J61, J64, R23.

*Hebrew University of Jerusalem, Mount Scopus, Jerusalem 91905, Israel; Centre for Economic Performance, LSE; Tel: +972(0)25883121, Email: michael.amior(at)mail.huji.ac.il. I am grateful to Alan Manning for his guidance and Christoph Albert, George Borjas, David Card and Jan Stuhler for helpful comments, as well as participants of the CEP (2015), RES (2016) and OECD-CEPII "Immigration in OECD Countries" (2017) conferences and seminars at IDC Herzliya, Bar Ilan, Hebrew University at Rehovot and Bank of Israel.

1 Introduction

The US suffers from large regional disparities in employment and labor force participation which have persisted for many decades (Kline and Moretti, 2013; Amior and Manning, forthcoming). Concern has grown about these inequities in recent years in light of the Great Recession and a secular decline in manufacturing employment (Kroft and Pope, 2014; Acemoglu et al., 2016), whose impact has been heavily concentrated geographically (Autor, Dorn and Hanson, 2013; Moretti, 2012) - with arguably important political consequences (Autor et al., 2016). In principle, these disparities should be eliminated by residential mobility, but long distance mobility has been in secular decline in recent decades (Molloy, Smith and Wozniak, 2011; Kaplan and Schulhofer-Wohl, 2017).

In the face of these challenges, it has famously been argued that foreign migration offers a remedy. Borjas (2001) claims that new immigrants "grease the wheels" of the labor market: given they have already incurred the fixed cost of moving, they are very responsive to regional differences in economic opportunity - and therefore accelerate the adjustment of local labor markets.[1] And Cadena and Kovak (2016) argue further that foreign-born workers (or at least low skilled migrants from Mexico) continue to "grease the wheels" even some years after arrival: migrants are a self-selected group with strong labor market attachment, and their mobility is also enhanced by long-distance co-patriot job networks. In this paper, I reexamine these claims using a large US dataset spanning 722 commuting zones (CZs) and five decades - and using an empirical model which explicitly accounts for dynamic adjustment. In the process, I offer new methodological insights on the identification of local immigration shocks in the context of these dynamics.

Table 1 offers some initial insights into migratory flows to US states. Between 2000 and 2016, 3.4 percent of individuals report living outside their current state of residence one year previously. The foreign-born account for 27 percent of these moves, which exceeds their 17 percent population share. This is not due to their mobility within the US (2.43 percent move annually between states, compared to 2.79 percent of natives), but rather because of large inflows from abroad.[2]

Of course, gross flows are not necessarily informative of population adjustment to local shocks. But exploiting decadal census data since 1960 across commuting zones (CZs), I

[1] Borjas (1999), Card and Lewis (2007), Jaeger (2007), Cadena (2013), Cadena (2014) offer additional evidence that new migrants' location decisions respond strongly to local economic conditions.

[2] These results reported here are consistent with Table 1 in Cadena and Kovak (2016). In Appendix B, I show the newest immigrants do in fact move more than natives, but the differential is eliminated within five years.

confirm that foreign migration does indeed contribute disproportionately to local population adjustment. Remarkably, on average, between 25 and 50 percent of the local population response can be explained by new arrivals from abroad (while the impact of longer term migrants is comparatively small). However, I also find that new migrants "crowd out" the native contribution to adjustment: so in regions better supplied by new migrants, the census data suggests local population adjustment is no faster. This is not to say that natives do not benefit from the contribution of foreign migration: moving is costly, and new foreign migrants save natives from having to incur these costs themselves. And furthermore, as I explain below, there is reason to believe the extent of crowding out may be somewhat overstated in the census data. But, the claim that migrants "grease the wheels" is not strongly supported by the evidence.

I underpin these results with a model of local labor market adjustment which builds on Amior and Manning (forthcoming). Local equilibrium is defined in a competitive Rosen-Roback framework (Rosen, 1979; Roback, 1982), which is supplemented with equations describing how population flows to areas offering higher utility - distinguishing between the contributions of foreign and internal migration. 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 does typically point to a relatively swift adjustment of local population: see e.g. Blanchard and Katz (1992); Beaudry, Green and Sand (2014); Amior and Manning (forthcoming). This suggests that large "crowding out" effects are theoretically plausible.

Following Amior and Manning (forthcoming), 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-population ratio (from here on, 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, the results show these dynamics matter even over the decadal intervals between census years.

Jaeger, Ruist and Stuhler (2017) have emphasized the importance of these dynamics in interpreting the local effects of immigration - and their solution is to control for lagged local immigration shocks. Controlling for the initial conditions (as summarized by the lagged employment rate) addresses the same concern, but it offers the advantage of encapsulating the entire history of both labor demand and supply shocks, whether observed or unobserved.

I then confirm that new foreign migrants contribute disproportionately to the population response. On average, they account for one quarter of the response to contemporaneous employment changes and, remarkably, over half the response to the lagged employment rate. This is partly due to the flexibility of new migrants' residential choices. But it also a consequence of the well-documented preference of new migrants to live among existing co-patriot communities. Given these communities are disproportionately located in areas with growing demand (a natural consequence of the persistence of local demand shocks: see Amior and Manning, forthcoming), this preference will accelerate the adjustment of local popuation.

However, this does not necessarily mean that new migrants "grease the wheels" - if their contribution 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.[3] 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 offset by a weaker native response. This result appears to contradict Cadena and Kovak (2016), who find a larger low skilled population response to employment shocks in the late 2000s in cities with initially large Mexican population shares. In Appendix D, I attempt to reconcile my findings with theirs: the omission of dynamics, right hand side controls and sample size appear to play an important role.[4]

This is fundamentally a story of geographical displacement. The question of displacement

[3]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).

[4]Cadena and Kovak (2016) find that low skilled natives make a negligible contribution to local adjustment - in which case one would expect negligible crowding out. But once I account for population dynamics (controlling for the initial employment rate) and observable amenity effects, I find a much larger response from natives. Applying my specification to their data, the evidence on crowding out appears mixed: using my preferred specification, I cannot reject the hypothesis of zero crowding out. But given the small sample (they study a single time difference between 2006 and 2010), the standard errors are large. So it is also difficult to exclude the possibility of a substantial displacement effect.

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". To name just a few, see Card (2001), Peri and Sparber (2009) and Monras (2015) on native wages and employment, Peri (2012) on total factor productivity, Cortes and Tessada (2011) on native labor supply, Saiz (2007) on housing prices, and Cortes (2008) on the prices of other non-tradables; and see Jaeger, Ruist and Stuhler (2017) for a much broader survey of this literature. But it is well known that the area approach may underestimate the aggregate-level impact of immigration in the presence of geographical displacement (see e.g. Borjas, Freeman and Katz, 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. And preliminary results (not yet finalized) suggest they are also robust to higher levels of spatial aggregation: I cannot reject one-for-one displacement across US states either. 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 in specifications without fixed effects, for both natives and migrants), largely manifested in changes in labor force participation - which is indicative of large but incomplete adjustment of local labor markets. See also Smith (2012), Edo and Rapoport (2017) and Gould (forthcoming), who identify adverse effects on native employment rates. 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, Freeman and Katz, 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.[5] See, for example, Card and DiNardo (2000), Card (2001, 2005,

[5] An interesting exception is Monras (2015), 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 (2017) exploit a policy allowing Czechs

2009*a*), Card and Lewis (2007), Cortes (2008), Boustan, Fishback and Kantor (2010), Wozniak and Murray (2012) and Edo and Rapoport (2017); 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) and Dustmann and Glitz (2015), for example, offer some evidence for this. But, this contradicts the spirit of Blanchard and Katz (1992), Hornbeck (2012), Beaudry, Green and Sand (2014) and Amior and Manning (forthcoming), 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), D'Amuri and Peri (2014) and Foged and Peri (2016) argue that natives have a comparative advantage in communication-intensive tasks. Of course, to the extent that imperfect substitutability shelters natives from migrant supply shocks, it will also limit the ability of migrants to "grease the wheels" of native markets.

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 (and the omission of dynamic effects), (ii) cohort effects and (iii) the delineation of skill groups. First, at the aggregate level, important drivers of local population (specifically climate, local demand shocks and initial employment conditions) 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 skill groups *within* geographical areas (see Card and DiNardo, 2000; Card, 2001, 2005; Borjas, 2006; Cortes, 2008; Monras, 2015); Dustmann, Schoenberg and Stuhler (2016) refer to this as the "mixture approach". These studies 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. First, 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

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.

census data[6] (following the example of Borjas, 2006, and Card, 2001) and using information on individuals' state of birth.

But there is a further problem with the within-area "mixture" approach: these estimates do not account for the impact that new migrants exert *outside* their own skill group (see Dustmann, Frattini and Preston 2012; Dustmann, Schoenberg and Stuhler 2016). 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 recent decline in cross-state mobility mentioned above: see Molloy, Smith and Wozniak (2017). A back-of-the envelope estimate suggests immigration might explain up to one third of the decline. To this extent, a reduction of internal mobility is not necessarily associated with slower regional population adjustment - as the residential choices of new migrants are compensating for this trend. 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 (forthcoming), but here distinguishing between the contributions of internal and foreign migration. To ease the exposition, I make no distinction between the labor supplied by natives and migrants in production. Of course, to the extent that these groups are imperfect substitutes in production, the model will overstate any effects of foreign migration on the labor outcomes of existing residents. But ultimately, these effects will be estimated empirically in

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

the analysis that follows. As it happens, I cannot reject one-for-one geographical displacement in the data - suggesting these assumptions may not be so unreasonable, at least in this aggregate-level framework.

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 online appendices of Amior and Manning (forthcoming), 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.[7] 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 (see Amior and Manning, forthcoming). 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:

[7] Equation (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.

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

Importantly, the real wage can be substituted using the labor supply curve (2) - so the employment rate can serve as a sufficient statistic for local employment conditions:

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

This result is fundamental to the analysis which follows. This interpretation of the aggregate employment rate (i.e. across all local workers) may be compromised if natives and migrants have different preferences for leisure (see e.g. Borjas, 2016). But I show in Appendix C that the empirical results are robust to adjusting local employment rates for demographic composition - controlling for age, education, gender and race, as well as nativity.

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

I now 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 (forthcoming), 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. Unfortunately, it is not possible to identify emigration in the data, but one might theoretically interpret λ_r^F as the *net* inflow from abroad to account for this.[8]

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

[8] The emigration decision may be particularly important for foreign-born workers: see e.g. Dustmann and Weiss (2007) for evidence on return migration. Of course, I do not observe foreign-born workers who both enter and leave the US between two consecutive census dates. And regarding those foreign-born workers who remain in the US for longer than one decade, I show below that they make a relatively small contribution to local population adjustment.

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

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 $\frac{\lambda_r^{Ii} - \hat{\lambda}_r^{Ii}}{\hat{\lambda}_r^{Ii}} = \gamma^{Ii} (\tilde{a}_r + n_r - l_r)$ and $\frac{\lambda_r^{Io} - \hat{\lambda}_r^{Io}}{\hat{\lambda}_r^{Io}} = -\gamma^{Io} (\tilde{a}_r + n_r - l_r)$. It then follows that

$\frac{\lambda_r^I}{L_r} = \frac{\hat{\lambda}_r^{Ii}}{L_r}\left(\gamma^{Ii} + \gamma^{Io}\right)(\tilde{a}_r + n_r - l_r)$. 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:

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

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 $\hat{\lambda}_r^F$ is constant within each discrete time unit. $\hat{\lambda}_{rt}^F$ is the total migrant intensity integrated between $t-1$ and t.

Equation (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 $\hat{\lambda}_{rt}^F$.

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

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

and

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

The migrant intensity $\hat{\lambda}_{rt}^{F}$ is the key parameter of interest. Notice that $\hat{\lambda}_{rt}^{F}$ enters (12) and (13) directly and also indirectly through changes in the aggregate population elasticity γ. The direct effect is simple to interpret: $\hat{\lambda}_{rt}^{F}$ has a 1-for-1 effect on foreign inflows λ_{rt}^{F} 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 $\hat{\lambda}_{rt}^{F}$ 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 $\hat{\lambda}_{rt}^{F} = 0$. As I show in Appendix A, this yields:

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

and

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

As the second term of (15) shows, a larger supply of foreign migrants (i.e. a larger $\hat{\lambda}_{rt}^{F}$) makes foreign inflows λ_{rt}^{F} more responsive to local employment shocks, both contemporaneous (Δn_{rt}) and historical ($n_{t-1} - l_{t-1}$). However, as (14) shows, a larger $\hat{\lambda}_{rt}^{F}$ also weakens the response of internal inflows to local shocks. Intuitively, in the presence of a larger $\hat{\lambda}_{rt}^{F}$, 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.

As noted above, I make no distinction here between the labor supplied by foreign migrants and native-born workers. To the extent that they are imperfect substitutes in production, this model will overstate any effect (whether direct or indirect) of migrant intensity $\hat{\lambda}^F_{rt}$ on existing residents. But I will ultimately estimate these effects empirically below.

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 overall response to $\hat{\lambda}^F_{rt}$ may be interpreted as a "reduced form" characterization. As a first step, I eliminate $\hat{\lambda}^F_{rt}$ in (12) using (13):

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

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 $(n_{t-1}-l_{t-1})$ 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:

$$\begin{aligned} \Delta\left(n_{rt}-l_{rt}\right) &= \frac{1-\eta}{1+(1-\eta)\,\gamma^I\left(\frac{1}{1-e^{-\gamma}}-\frac{1}{\gamma}\right)}\left(\Delta z^d_{rt}-\lambda^F_{rt}\right)+\frac{\eta}{1+(1-\eta)\,\gamma^I\left(\frac{1}{1-e^{-\gamma}}-\frac{1}{\gamma}\right)}\Delta z^s_{rt} \\ &\quad -\frac{(1-\eta)\,\gamma^I\left(\frac{1}{1-e^{-\gamma}}-\frac{1}{\gamma}\right)}{1+(1-\eta)\,\gamma^I\left(\frac{1}{1-e^{-\gamma}}-\frac{1}{\gamma}\right)}\Delta\tilde{a}_{rt}-\frac{\gamma^I}{1+(1-\eta)\,\gamma^I\left(\frac{1}{1-e^{-\gamma}}-\frac{1}{\gamma}\right)}\left(n_{t-1}-l_{t-1}+\tilde{a}_{rt-1}\right) \end{aligned} \tag{19}$$

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[9] on local population and employment across 722 Commuting Zone (CZ) in the Continental US since 1960.[10] CZs were originally developed as an approximation to local labor markets by Tolbert and Sizer (1996), based on county groups, and recently popularized by Autor and Dorn (2013) and Autor, Dorn and Hanson (2013).[11] Unless otherwise specified, the sample includes all individuals aged 16-64. See the appendices of Amior and Manning (forthcoming) 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.

[9] Where possible, I based the data on published county-level aggregates from the US census, extracted from the National Historical Geographic Information System (Manson et al., 2017). Not all demographic cells of interest are covered by these published results, so I 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., 2017).

[10] 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).

[11] Amior and Manning (forthcoming) 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.

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 take a first order approximation and study contributions to decadal population growth. 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 also 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 approach of Card and DiNardo (2000) and Card (2001), as recommended by Peri and Sparber (2011) and Card and Peri (2016)

3.3 Instruments

I identify changes in local demand using industry shift-shares (following Bartik, 1991), which are intended to 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; 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 (forthcoming), 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.

I predict the local migrant intensity $\hat{\lambda}_{rt}^F$ 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. Jaeger, Ruist and Stuhler (2017) offer a useful survey of the empirical literature. I construct the shift-share m_{rt} as follows:

$$m_{rt} = \frac{\sum_o \phi_{rt-1}^o L_{o(-r)t}^F}{L_{rt-1}} \tag{22}$$

where ϕ_{rt-1}^o is the share of population in area r at time $t-1$ which is native to origin o. $L_{o(-r)t}^F$ is the stock of new origin-specific migrants (excluding those living in area r) who arrived in the US between $t-1$ and t. 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. Similarly to the Bartik industry shift-shares, the exclusion of area r from $L_{o(-r)t}^F$ helps allay concerns over the endogeneity of m_{rt} to the dependent variable, local population growth. I construct this migrant shift-share variable using census and ACS micro-data from IPUMS, based on 79 origin countries.

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

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

where observations are weighted by the lagged local population share. The coefficient α_0 is estimated as 0.01, α_1 is 0.96, and the R squared is 76 percent.

3.4 Amenity controls

Aside from the Card shift-share, I control for a range of observable supply effects or amenities in my empirical specifications. The set of controls is identical to those in Amior and Manning (forthcoming). These consist of (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.

I 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. 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 migration

In this section, I study the average contribution of foreign migration 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), 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 2 here]

I set out estimates of (24) in column 1 of Table 2. 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 0.17 respectively. These cannot be interpreted causally: 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. To address these concerns, the IV specification instruments 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 0.39 respectively[12] (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 0.43 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 quarter of the overall

[12] These numbers are similar but not identical to the basic estimates of Amior and Manning (forthcoming). 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.

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 contribute little to the response to employment shocks.[13]

In the final four columns, I replicate columns 2-5, but now conditioning on local migrant intensity $\hat{\lambda}^F_{rt}$, 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 $\hat{\lambda}^F_{rt}$ 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 15 and 24 percent of the β_1 and β_2 response respectively (down from 25 and 55 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 (forthcoming). 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.[14]

Columns 7-9 also point to a direct displacement effect: a one point increase in the shift share raises the contribution of new migrants by 0.97 (column 7), but reduces the contribution of natives and old migrants by 0.92 (column 8). The effect on overall population growth is statistically insignificant (column 6). 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

[13]This finding appears to be at odds with Cadena and Kovak (2016): they find a negligible native response, at least among the low skilled. But I argue in Appendix D that our results can be reconciled by accounting for population dynamics and amenity controls in their specification.

[14]The fact that the overall population response in column 6 is unaffected hints at foreign migrants crowding out the internal response to employment shocks - which I explore in the following section.

effect is larger than might be expected: equation (14) above predicts a displacement effect equal to β_1, which takes a value of 0.64 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 foreign migrants do contribute disproportionately to local adjustment, and this is entirely due to new arrivals. But 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 $\hat{\lambda}^F_{rt}$ - as predicted by the migrant shift share (22). In Table 3, based on (14) and (15), I present estimates of the following equation:

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

where $\frac{X_{rt}}{L_{rt-1}}$ is the contribution of new migrants ($X_{rt} = L^F_{rt}$) or other workers ($X_{rt} = \Delta L_{rt} - L^F_{rt}$) 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 $\hat{\lambda}^F_{rt}$. Notice the model also suggests migrant intensity should be interacted with the vector of amenity controls $\tilde{A}_{rt}$ (i.e. coastline, climate indicators, historical population density and isolation). The first four columns of Panel A of Table 3 do not control for these $\hat{\lambda}^F_{rt}$-amenity interactions, and the latter four do.

[Table 3 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 $\hat{\lambda}^F_{rt}$. 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 $\hat{\lambda}^F_{rt}$. The contributions of new migrants to the Δn_{rt} and $(n_{rt-1} - l_{rt-1})$ responses are statistically insignificant at $\hat{\lambda}^F_{rt} = 0$ (as the model predicts); and they increase to 0.14 and 0.22 respectively at $\hat{\lambda}^F_{rt} = 0.1$, which is the 98th percentile of $\hat{\lambda}^F_{rt}$ (the maximum value is 0.31: the distribution is heavily skewed). But this larger contribution from new migrants 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 weaker for the lagged employment rate when I control for the $\hat{\lambda}^F_{rt}$-amenity interactions in columns 5-8, but foreign arrivals still add nothing to the overall population response to Δn_{rt} (column 5).

The bottom half of Table 3 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 $\hat{\lambda}^F_{rt}$ and the current and lagged Bartik shocks. The first stage estimates are reported in columns 1-4 of Panel B of Table 3. 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. Both columns 1 and 5 (without and including amenity interactions, respectively) shows the population response does not vary significantly with migrant intensity $\hat{\lambda}^F_{rt}$. The response of new migrants, however, is steeply increasing in $\hat{\lambda}^F_{rt}$ (columns 2 and 6) from a base of zero (though this effect is statistically insignificant in column 2 - without amenity interactions), and this is 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 0.45 and 0.71 respectively at $\hat{\lambda}^F_{rt} = 0.1$ (column 6), while the contributions of other workers decline to 0.37 (from 0.82 at $\hat{\lambda}^F_{rt} = 0$) and to 0.01 (from 0.52): see 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 that old migrants amplify the contribution of new migrants to adjustment - while natives account for the entire crowing out effect (offsetting the contributions of old and new migrants alike). The fact that old migrants amplify the contribution of new migrants 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 in these places.

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:

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

where $\frac{L_{rt}^F}{L_{rt-1}}$ is the contribution of new migrants to local population growth, and $\frac{\Delta L_{rt} - L_{rt}^F}{L_{rt-1}}$ 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}.

Controlling for initial conditions, as summarized by the initial employment rate, is new to the literature. It addresses the concern raised by Jaeger, Ruist and Stuhler (2017) that adjustment to local migration shocks is not instantaneous. Jaeger, Ruist and Stuhler suggest controlling for lagged migration shocks; but controlling for initial conditions offers the advantage of summarizing the entire history of both labor demand and supply shocks, whether observed or unobserved. Of course, this interpretation depends on the assumption that the local employment rate is a sufficient statistic for local labor market conditions. Furthermore, as Jaeger, Ruist and Stuhler show, it is difficult to separately identify the effects of current and lagged migration shocks, since the correlation between them is so tight.

With respect to identification, there are two endogenous variables: $\frac{L_{rt}^F}{L_{rt-1}}$ and $(n_{rt-1} - l_{rt-1})$, so two instruments are required. The simplest approach is to use the local migrant intensity $\hat{\lambda}_{rt}^F$, 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 $\hat{\lambda}_{rt}^F$ 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 $\frac{L_{rt}^F}{L_{rt-1}}$ is increasing in the local migrant intensity $\hat{\lambda}_{rt}^F$.

I present estimates of (18) both with and without CZ fixed effects. The fixed effects will absorb any time-invariant components of unobserved supply effects, $\Delta\tilde{a}_{rt}$. Identification with fixed effects relies on the fact that migrant inflows to different areas have grown at different speeds. This is similar in spirit to the double differencing methodology (comparing changes before and after 1970[15]) of Borjas, Freeman and Katz (1997). However, large serial correlation in local migration shocks (see e.g. Jaeger, Ruist and Stuhler, 2017) makes this an empirically demanding specification, especially given the short panel sutructure (just five periods) - and hence its absence (to my knowledge) in earlier work on displacement.

The question of gegographical displacement is certainly not a new one, and there are many existing estimates in the literature. 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) and Card and Peri (2016). 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.

In Table 4, I report a range of existing estimates of displacement which apply this specification. I restrict attention to IV estimates, which in all cases use a variant of the migrant enclave instrument. The displacement effects, analogous 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 I do in this section), 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), 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.

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

[Table 4 here]

5.2 Estimates of displacement

In contrast to the existing literature, almost all specifications in Panel A of Table 5 point to a substantial displacement effect. Column 1 offers OLS estimates of equation (18), with δ_1 taking a value of -0.78. That is, for each new migrant entering a given CZ, 0.78 natives or earlier migrants leave on net (relative to the initial population). The effect is somewhat smaller (-0.55) when I control for CZ fixed effects at the bottom of the table. 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.

[Table 5 here]

Of course, omitted labor supply and demand shocks make it difficult to interpret the OLS estimates. Column 3 of Panel A reports IV estimates of (26), using the migrant shift-share $\hat{\lambda}^F_{rt}$ as an instrument for the new migrant contribution and the lagged Bartik shift share b_{rt-1} as an instrument for the lagged employment rate. The first stage regression for the migrant contribution has 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 -1.11: i.e. exceeding (though insignificantly different from) 1-for-1 displacement. This effect is estimated resonably precisely, with a standard error of 0.13. The IV estimates are expected to be larger than OLS if we believe variation in the contribution of new migrants $\frac{L^F_{rt}}{L_{rt-1}}$ is conflated with unobserved local demand shocks. Similar to OLS, column 4 suggests that natives account for the bulk of the displacement effect.

When I control for fixed effects in column 4 however, the displacement effect drops to near zero, though the standard erorr balloons to 0.75. To address this apparent lack of power in the fixed effects specification, I include interactions between migrant intensity $\hat{\lambda}^F_{rt}$ and the current and lagged Bartik shift-shares as further instruments - as suggested by equation (15) in the model. The first stage estimates for the migrant contribution are reported in columns 2 and 4 of Panel B: the interaction effects are positive and (in most cases) statistically significant. The second stage estimates are presented in columns 8-9 of Panel A. The additional instruments make little difference to the basic specification. But the fixed effects estimates now sport much smaller standard errors, and the coefficients are very close to -1.

[Table 6 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 4). It seems this can be explained by choices of controls and sample years. In Table 6, I study the robustness of my IV estimate of δ_1^u in column 5 of Table 5 (without the interacted instruments) to these considerations. When I include no regression controls, the displacement effects vary greatly across decades. In particular, the results suggest little displacement before 1990 and significant displacement thereafter; and indeed, Card (2009*a*) finds something similar. But controlling for the current Bartik shift-share and the lagged employment rate (i.e. the initial conditions) moves the average displacement effect from -0.51 to -0.77 (see column 7); and once I control for the various amenity effects, I cannot reject a 1-for-1 displacement effect in any decade except the 2000s (and even there, the displacement effect is substantial: -0.63). In the final row of Table 6, I replace the lagged employment rate with the lagged Bartik shift-share control. The results looks very similar, except the fixed effects specification now also yields a substantial displacement effect (-1.25), even without the interacted instruments. To summarize, 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 4 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 surprising. As I noted above, the contribution of natives and old migrants to the population response to Δn_{rt} is estimated as 0.64 (see the IV estimate in column 8, Panel A, Table 2). And more importantly, 1-for-1 displacement sits uneasily with evidence on 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) demonstrates. But as I show below, local employment rates (among both natives and migrants) fall significantly in response to foreign inflows - though, at least in specifications without fixed effects, the effect is not large. See also Smith (2012), Edo and Rapoport (2017) and Gould (forthcoming), who identify 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 (see e.g. Nanos and Schluter, 2014; Albert, 2017; Amior, 2017*b*), or (ii) there is under-reporting of new migrants in the census (see the discussion in Section 3.1 above).

To study this further, I re-estimate (18), but this time replacing the dependent variable with the change in the local log employment rate, $\Delta \left(n_{rt} - l_{rt}\right)$. In Table 7, I present results for the employment rate change among the full sample of 16-64s, but also separately for natives and migrants. And just as in Table 5, I report estimates using both the "simple" IV strategy (with the migrant shift-share and lagged Bartik instruments) and including the additional interacted instruments.

[Table 7 here]

In the basic specification (without fixed effects), all estimates of δ_1 in Table 7 (i.e. the effect of migrant inflows) lie between -0.14 and -0.24, with standard errors between 0.05 and 0.07. It is worth emphasizing that the responses of the native and migrant employment rates are very similar in the basic specification. This suggests there is no great loss from my assumption in Section 2 that natives and migrants are perfect substitutes in production, at least in this particular context. However, the fixed effect results are much harder to interpret: using the simple IV strategy (columns 1-3), the δ_1 estimates appear unresonably large, reaching -1. The effects are smaller, but still very large when I use the interacted instruments: -0.3 for natives and -0.6 for migrants.

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. Building on (18), the following would be a typical empirical specification:

$$\frac{\Delta L_{srt} - L^F_{srt}}{L_{srt-1}} = \delta^s_0 + \delta^s_1 \frac{L^F_{srt}}{L_{srt-1}} + b_{srt} + b_{srt-1} + d_{rt} + d_{st} + \varepsilon_{srt} \tag{27}$$

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 (see Dustmann, Schoenberg and Stuhler, 2016). As Card (2001) shows, the importance of such effects will depend on the elasticity of substitution between skill groups. Consequently, estimates of δ^s_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:

$$Y_r = \theta_r \left(\sum_s \alpha_{sr} N^\sigma_{sr} \right)^{\frac{\rho}{\sigma}} \tag{28}$$

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:

$$w_{sr} - p = \log \alpha_{sr} + \log \rho + \frac{\sigma}{\rho} \log \theta_r + \frac{\rho - \sigma}{\rho} y_r - (1 - \sigma) n_{sr} \tag{29}$$

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:

$$n_{sr} = l_{sr} + \epsilon^s (w_{sr} - p_r) + z^s_{sr} \tag{30}$$

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:

$$\begin{aligned} \lambda^I_{srt} \quad = \quad & \frac{(1-\eta)\gamma^I \left(\frac{1}{1-e^{-\gamma}} - \frac{1}{\gamma}\right)}{1 + (1-\eta)\gamma^I \left(\frac{1}{1-e^{-\gamma}} - \frac{1}{\gamma}\right)} \cdot \frac{1}{1-\sigma} \left(\Delta \log \alpha_{srt} + \frac{\sigma}{\rho} \Delta \log \theta_{rt} + \frac{\rho - \sigma}{\rho} \Delta y_{rt}\right) \\ & + \frac{(1-\eta)\gamma^I \left(\frac{1}{1-e^{-\gamma}} - \frac{1}{\gamma}\right)}{1 + (1-\eta)\gamma^I \left(\frac{1}{1-e^{-\gamma}} - \frac{1}{\gamma}\right)} \left(\frac{\Delta \tilde{a}_{rt} + \eta \Delta z^s_{rt}}{1-\eta} - \lambda^F_{srt}\right) \\ & + \frac{\gamma^I}{1 + (1-\eta)\gamma^I \left(\frac{1}{1-e^{-\gamma}} - \frac{1}{\gamma}\right)} (n_{srt-1} - l_{srt-1} + \tilde{a}_{rt-1}) \end{aligned} \tag{31}$$

where, as before,

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

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

Now, consider again the empirical specification (27) in light of (31). The area-time 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^s in (27) will be equal to:

$$\delta_1^s = \frac{(1-\sigma)\,\epsilon^s \gamma^I \left(\frac{1}{1-e^{-\gamma}} - \frac{1}{\gamma}\right)}{1 + (1-\sigma)\,\epsilon^s \left[1 + \gamma^I \left(\frac{1}{1-e^{-\gamma}} - \frac{1}{\gamma}\right)\right]} \tag{32}$$

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 on 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^s 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^s 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 (29), is only true under the knife-edge condition $\sigma = \rho$. If σ is larger than ρ, the cross-elasticities are negative, and δ_1^s 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^s coefficient. And conversely, if σ is smaller than ρ, the cross-elasticities are positive, so δ_1^s 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 structure, with the elasticities of substitution varying across hierarchical nests, additive separability can never be satisfied - so δ_1^s can never equal the true displacement effect.

In practice, the delineation of skill groups is ultimately a choice made by the researcher. But this choice matters for estimates of δ_1^s, as δ_1^s 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 (32) shows, δ_1^s 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 be more attractive: Dustmann, Schoenberg and Stuhler (2016) make a similar argument. Even though the aggregate-level model does not accout for the interactions between different skill groups, 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^s vary across different skill delineations, and this is my focus for the remainder of the paper.

6.3 Skill delineation

Skill is typically identified in the literature by education, given it is relatively "exogenous" compared to occupation. Various education classifications have been applied in the displacement literature. Mechanically, finer classifications are likely to entail greater substitutability in production (i.e. larger σ) - and consequently lower estimates of δ_1^s. Finer classifications will also typically be associated more complex nesting structures, which make it harder to interpret estimates of δ_1^s. In what follows, I offer estimates for three education-based classifications: (i) college graduates v non-graduates; (ii) high school dropouts v all others (see e.g. Card, 2005; Cortes, 2008); (iii) four groups: dropouts, high school graduates, some college and college graduates (e.g. Borjas, 2006). Card (2009*a*) argues that a four-group classification may be too restrictive: it imposes a uniform substitution elasticity across all groups. The particular concern is that high school graduates and dropouts are very close substitutes (see Borjas, Grogger and Hanson, 2012, for an alternative view). If so, the dropout share (among non-college workers) should have no effect on native outcomes. This matters in the immigration context because migrants are much more likely to be dropouts than natives.[16] Having said that, this may also have implications for the interpretation of classification (ii).

Either way, classifications by education may not do justice in the particular context of immigration: there is evidence to suggest that similarly educated natives and migrants are not perfect substitutes (see Card, 2009*b*; Manacorda, Manning and Wadsworth, 2012; Ottaviano and Peri, 2012, though Borjas, Grogger and Hanson, 2012, dispute this). This may be a consequence of migrants working in lower skilled occupations than their schooling might otherwise warrant (Dustmann and Preston, 2012; Dustmann, Schoenberg and Stuhler, 2016). Card and DiNardo (2000) and Card (2001) offer a practical method to address this concern. They probabilistically assign individuals into broad occupation groups, conditional

[16] In the ACS sample of 2010, a similar fraction of migrants and natives have no college education: 57 and 48 percent respectively. But 27 percent of migrants are high school dropouts, compared to just 12 percent of natives.

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.

In what follows, I estimate displacement effects for two such probabilistic classifications. First, I use Card's (2001) six-group occupation classification: laborers and low skilled services; operative and craft; clerical; sales; managers; professional and technical. Given the number of groups, one might expect a somewhat complex production technology, with some groups being close substitutes. 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. As an alternative, I also study a 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.[17] I assign individuals probabilistically to these groups based on multinomial logit estimates using the 1990 census.

[Table 8 here]

6.4 Estimates of displacement: decadal cross-sections

I next estimate the empirical specification (27) separately for the three education classifications and the two imputed occupation classifications described above. The regressor of interest, the contribution of new migrants $\frac{L^F_{srt}}{L_{srt-1}}$ to the local skill s population, is presumably endogenous to cell-specific demand shocks; and 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:

$$m_{srt} = \frac{\sum_o \phi^o_{rt-1} L^F_{o(-r)st}}{L_{rst-1}} \tag{33}$$

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

[Table 9 here]

[17] As it happens, the occupational distribution in college share is strongly bipolar, and 50 percent is the natural dividing line.

In the top half of Table 9, I present IV estimates of the displacement effect δ_1^s from equation (27), 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 $\frac{L_{srt}^F}{L_{srt-1}}$. 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^s 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 5), 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^s 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) and Borjas (2006) use this data to test for displacement. I restrict attention to the period 1980-2000, since previous residence is only classified by state in 1970. 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 (27) using five year differences:

$$\frac{\left(L_{srt}-L_{srt}^{F}\right)-L_{srt-5}}{L_{srt-5}}=\delta_0^{s5}+\delta_1^{s5}\frac{L_{srt}^{F}}{L_{srt-5}}+\delta_2^{s5}b_{srt}+\delta_3^{s5}b_{srt-10}+d_{rt}+d_{st}+\varepsilon_{srt} \tag{34}$$

where t now denotes years (as opposed to decades), L_{srt}^{F} is the stock of "new" migrants (who arrived in the US less than five years previously), and $L_{srt}-L_{srt}^{F}$ is the local stock of workers who were living in the US for more than five years. Thus, the expression $\left(L_{srt}-L_{srt}^{F}\right)-L_{srt-5}$ 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^{s5} 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^{s5} 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^{s5} 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^{s5} estimates is substantial in each.

Using a similar set-up, Card (2001) finds no evidence of geographical displacement: see Table 4. 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 E, where I attempt a replication of Card's (2001) results. The difference can be explained by two additional factors. First, Card's restriction of the sample to the top 175 MSAs attenuates the effect. And second, he controls for a range of demographic means at time $t-5$ within the skill-area cells (age, education, migrants' years in US), which also attenuate the effect.

6.6 Estimates of cohort effects

These cohort effects can also 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 (27) 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^s, 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 (27), 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^s 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 might be 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 is mere speculation - and it warrants further investigation.

7 Conclusion

The US suffers from large and persistent regional disparities in employment and labor force participation, and it is often claimed that foreign migration may offer a remedy. Given that new migrants are more mobile geographically, they can help "grease the wheels" of the labor market and accelerate the adjustment of local outcomes (Borjas, 2001; Cadena and Kovak, 2016).

I confirm that new migrants do indeed contribute disproportionately to the adjustment of local population to demand shocks. However, the census data suggests 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 in the latter case, only after controlling for cohort effects and depeneding on how skill groups are delineated. These findings differ markedly from much of the existing the literature, and I have attempted to explain why.

Interestingly though, despite this one-for-one displacement estimate, foreign migration exerts a significant negative effect on local employment rates (with an elasticity of -0.1 to

-0.2), largely manifested in changes in labor force participation - which is indicative of incomplete adjustment. This may be reconciled with the displacement result if migrants are more productive than natives. Alternatively, the displacement effect may be slightly overestimated due to under-reporting of undocumented migrants in the census. In the latter case though, the magnitude of the employment rate response would suggest the true displacement effect is not much smaller: about -0.8 or -0.9 instead of -1.

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 (Molloy, Smith and Wozniak, 2017). 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 Current Population Survey, 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.[18] 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 (2017) point to a decline in the geographical specificity of returns to occupations, together with improving communications technology; and Molloy, Smith and Wozniak (2017) emphasize the declining rate of job transitions.

Appendix

A Theoretical derivations

A.1 Derivation of equation (11)

Here, I show how equation (9) can be discretized to yield (11), following similar steps to Amior and Manning (forthcoming). Notice first that (9) can be written as:

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

$$\frac{\partial e^{\gamma t} l_r(t)}{\partial t} = e^{\gamma t} \hat{\lambda}_r^F(t) + \gamma e^{\gamma t} \tilde{a}_r(t) + \gamma e^{\gamma t} n_r(t) \tag{A1}$$

which has as a solution:

$$e^{\gamma t} l_r(t) = l_r(0) + \int_0^t e^{\gamma s} \left[\hat{\lambda}_r^F(s) + \gamma n_r(s) + \gamma \tilde{a}_r(s) \right] ds \tag{A2}$$

which can be re-arranged to give:

$$\begin{aligned} l_r(t) - l_r(0) &= \int_0^t e^{\gamma(s-t)} \left[\hat{\lambda}_r^F(s) + \gamma n_r(s) - \gamma n_r(0) + \gamma \tilde{a}_r(s) \right] ds \\ &\quad + \left(1 - e^{-\gamma t}\right) \left[n_r(0) - l_r(0) \right] \end{aligned} \tag{A3}$$

which can be written as:

$$\begin{aligned} l_r(t) - l_r(0) &= \int_0^t e^{\gamma(s-t)} \hat{\lambda}_r^F(s)\, ds + n_r(t) - n_r(0) + \tilde{a}_r(t) - \tilde{a}_r(0) \\ &\quad - \int_0^t e^{\gamma(s-t)} \left[\dot{n}_r(s) + \dot{\tilde{a}}_r(s)\, ds \right] ds \\ &\quad + \left(1 - e^{-\gamma t}\right) \left[n_r(0) - l_r(0) + \tilde{a}_r(0) \right] \end{aligned} \tag{A4}$$

If $\hat{\lambda}_r^F(s)$ is constant between time 0 and t, and if employment n_r and the supply shifter $\tilde{a}_r$ change at a constant rate over the period, this gives:

$$\begin{aligned} l_r(t) - l_r(0) &= \hat{\lambda}_{rt}^F + \left[1 - \left(\frac{1 - e^{-\gamma t}}{\gamma t} \right) \right] \left[n_r(t) - n_r(0) + \tilde{a}_r(t) - \tilde{a}_r(0) - \hat{\lambda}_{rt}^F \right] \\ &\quad + \left(1 - e^{-\gamma t}\right) \left[n_r(0) - l_r(0) + \tilde{a}_r(0) \right] \end{aligned} \tag{A5}$$

where $\hat{\lambda}_{rt}^F = \int \hat{\lambda}_r^F(s)\, ds$ is the total migrant intensity integrated between 0 and t. (11) then follows from this equation.

A.2 Derivation of equations (14) and (15)

For clarity, it is useful to define two functions:

$$f_I\left(\hat{\lambda}^F_{rt}\right) = \frac{\gamma^I}{\gamma^I + \gamma^F \hat{\lambda}^F_r}\left[\left(1 - \frac{1 - e^{-\gamma^I - \gamma^F \hat{\lambda}^F_r}}{\gamma^I + \gamma^F \hat{\lambda}^F_r}\right)\left(\Delta n_{rt} + \Delta \tilde{a}_{rt} - \hat{\lambda}^F_{rt}\right) + \left(1 - e^{-\gamma^I - \gamma^F \hat{\lambda}^F_r}\right)(n_{t-1} - l_{t-1} + \tilde{a}_{rt-1})\right] \tag{A6}$$

and

$$f_F\left(\hat{\lambda}^F_{rt}\right) = \hat{\lambda}^F_{rt} + \frac{\gamma^F \hat{\lambda}^F_{rt}}{\gamma^I + \gamma^F \hat{\lambda}^F_r}\left[\left(1 - \frac{1 - e^{-\gamma^I - \gamma^F \hat{\lambda}^F_r}}{\gamma^I + \gamma^F \hat{\lambda}^F_r}\right)\left(\Delta n_{rt} + \Delta \tilde{a}_{rt} - \hat{\lambda}^F_{rt}\right) + \left(1 - e^{-\gamma^I - \gamma^F \hat{\lambda}^F_r}\right)(n_{t-1} - l_{t-1} + \tilde{a}_{rt-1})\right] \tag{A7}$$

which summarize the internal and foreign contributions to local population growth respectively, for given migrant intensity $\hat{\lambda}^F_{rt}$. These correspond to (12) and (13) respectively. Taking first order approximations of these functions around $\hat{\lambda}^F_{rt} = 0$:

$$f_I\left(\hat{\lambda}^F_{rt}\right) \approx f_I(0) + \hat{\lambda}^F_{rt} f_I'(0)$$

and

$$f_F\left(\hat{\lambda}^F_{rt}\right) \approx f_F(0) + \hat{\lambda}^F_{rt} f_F'(0)$$

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

A.3 Derivation of equations (18) and (19)

Using the labor supply and demand curves, (2) and (3), local employment can be expressed as:

$$n_{rt} = \eta\left(l_{rt} + z^s_{rt}\right) + (1 - \eta)\, z^d_{rt} \tag{A8}$$

for given local population l_{rt}, where

$$\eta = \frac{-\epsilon^d}{-\epsilon^d + \epsilon^s} \tag{A9}$$

is the ratio of the elasticity of labor demand to the sum of the supply and demand elasticities. Taking first differences:

$$\Delta n_{rt} = \eta\left(\lambda^I_{rt} + \lambda^F_{rt} + \Delta z^s_{rt}\right) + (1 - \eta)\, \Delta z^d_{rt} \tag{A10}$$

where local population growth Δl_{rt} has been disaggregated into the contributions from internal and foreign migration, λ^I_{rt} and λ^F_{rt}. Equation (19) can then be derived by substituting (A10) for Δn_{rt} in (17).

I next turn to the change in the local employment rate, $\Delta(n_{rt} - l_{rt})$. I first replace Δn_{rt} with (A10):

$$\Delta(n_{rt} - l_{rt}) = \eta \Delta z^s_{rt} + (1-\eta)\Delta z^d_{rt} - (1-\eta)\lambda^I_{rt} - \lambda^F_{rt} \tag{A11}$$

where Δl_{rt} has again been disaggregated into λ^I_{rt} and λ^F_{rt}. Equation (19) can then be derived by substituting (18) for λ^I_{rt}.

B Effect of years in US on cross-state mobility

Based on ACS samples between 2000 and 2016, Table 1 shows that foreign-born individuals are less likely to move between states (2.43 percent each year) than natives (2.79 percent). However, this masks some important heterogeneity by years in US. In this appendix, using the same data, I show that new immigrants are in fact more mobile between states than natives, but this differential is eliminated within five years.

To identify the effect of years in the US, it is important to control for entry cohort effects (Borjas, 1985) and observation year effects. To control for these, I estimate complementary log-log models for the annual incidence of cross-state migration (see Amior, 2017*a*).

Let $MigRate(X_i)$ denote the instantaneous cross-state migration rate conditional on a vector of individual characteristics X_i. The probability of moving before time t is then:

$$\Pr(Mig^\tau_i = 1, t < \tau) = 1 - \exp(-MigRate(X_i)\tau) \tag{A12}$$

This motivates the complementary log-log model:

$$\Pr(Mig^\tau_i = 1, t < \tau) = 1 - \exp(-\exp(\psi' X_i)\tau) \tag{A13}$$

where the ψ parameters can be interpreted as the elasticities of the instantaneous migration rate $MigRate(X_i)$ with respect to the components of X_i. An attractive feature of the complementary log-log model is that this interpretation is independent of the time horizon τ associated with the migration variable (assuming a constant hazard). I define an individual as a cross-state mover if he reports living in a different state 12 months previously - so I effectively normalize τ to one year. The X_i vector includes the following variables:

$$\psi' X_i = \sum_{k=1}^{20} \psi^{YRS}_k YrsUS_k + \sum_{k=1981}^{2015} \psi^{YRI}_k YrImmig_k + \sum_{k=2001}^{2016} \psi^{YRI}_k YrObs_k$$

The sample for this exercise consists of (1) all natives aged 16-64 (22.6m observations) and (2) all foreign-born individuals aged 16-64 with between 1 and 20 years in the US (2.2m). Thus, there are 21 demographic groups: natives, migrants with 1 years in US, migrants with 2 years, ..., migrants with 20 years. I include in the X_i vector binary indicators for the final 20, i.e. $YrsUS_k$ for k between 1 and 20, so natives are the omitted category. I also control for a full set of entry cohort effects $YrImmig_k$ (taking 0 for natives: the omitted category again) and a full set of observation year effects $YrObs_k$. I assume here that the observation year effects are common to natives and migrants.

Panel A of Figure A1 reports the basic coefficient estimates on the years in US dummies, together with the 95 percent confidence intervals. The estimates can be interpreted as the log point difference in cross-state mobility between migrants (with given years in US) and natives, controlling for entry cohort and observation year effects. Migrants are initially more mobile than natives: the deviation at the entry year is 93 log points. But this falls to zero by year 6 and becomes negative thereafter, dropping to -49 log points by year 20.

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

C Robustness to composition-adjusted employment rates

[TO BE COMPLETED]

D Reconciliation with Cadena and Kovak (2016)

[THIS SECTION IS PRELIMINARY AND INCOMPLETE]

Similarly to this paper, Cadena and Kovak (2016) study the contribution of (specifically Mexican) migrants to local labor market adjustment, exploiting variation in historical settlement patterns. But their results appear to diverge from mine in three ways. First, Cadena and Kovak find that natives contribute negligibly to local adjustment - in contrast to foreign-born workers. Second, they find that migrants respond heavily even after arriving in the US - while in my paper, the migrant response is entirely driven by new arrivals. And third, they find that migrants do not "crowd out" the native response - unsurprisingly, given they find that natives are immobile.

In this appendix, I attempt to reconcile my results with theirs. There are some important differences in empirical setting. They focus on the contribution of specifically Mexican-born migrants between 2006 and 2010 (during the Great Recession). And they find that Mexicans accelerate local adjustment specifically in the low skilled market (less than college): college-educated natives do respond strongly to local demand. In contrast, my focus is the overall contribution of all migrants to the aggregate labor market over a broader period: 1960-2010. Nevertheless, I show here that there are also differences in empirical specification between our papers which can help bridge much of the gap.

D.1 Average response to local demand shocks

Cadena and Kovak base their analysis on the following specification:

$$\Delta l_{gr} = \beta_0^{CK} + \beta_1^{CK} \Delta \tilde{n}_{gr} + X_{gr} \beta_X^{CK} + \varepsilon_{gr} \tag{A14}$$

where I have altered notation to match my own. The dependent variable Δl_r is the change in log local population in a given nativity group g (i.e. natives, Mexican migrants, non-Mexican migrants), and $\Delta \tilde{n}_{gr}$ represents the local employment shock experienced by that group. Specifically, this is the weighted average of industry-specific employment changes;

$$\Delta \tilde{n}_{gr} = \sum_i \phi_{gr}^i \Delta n_{irt} \tag{A15}$$

where the weights ϕ_{gr}^i are equal to group-specific shares of local employment in industry i. $\Delta \tilde{n}_{gr}$ is instrumented using a contemporaneous Bartik industry shift-share, akin to that described in equation (21) in the main text. The coefficient β_1^{CK} is then interpreted as the magnitude of the population response to a local group-specific demand shock. In certain specifications, two right-hand side controls are included in the vector X_{gr}: the Mexican population share in 2000 (which serves as an "enclave" instrument for Mexicans, akin to equation (22)) and indicators for MSAs in states that enacted anti-migrant employment legislation.

For the most part, Cadena and Kovak (2016) study local changes between 2006 and 2010 across 94 Metropolitan Statistical Areas (MSAs) in the US. Attention is restricted to MSAs with adult population exceeding 100,000, Mexican-born sample exceeding 60, and non-zero samples for all other studied demographic groups.

Compared to my specification in (24), there are five key differences. First, Cadena and Kovak (2016) study the response to a weighted industry employment shock $\Delta\tilde{n}$, rather than a simple change in log employment Δn. Second, they do not account for dynamics: in particular, they do not control for the lagged employment rate. In principle, these dynamics should be even more important for their short 2006-2010 interval than the decadal intervals in my own analysis. Third, they do not control for local amenity effects such as climate and coastline. And fourth, they exclude geographical areas with smaller aggregate and Mexican-born populations - while my Commuting Zone (CZ) sample is comprehensive of the continental US.

In Table A1, I offer estimates of (A14), relying on data and programs published alongside Cadena and Kovak's article. I restrict attention to low skilled workers (and specifically men) - who account for Cadena and Kovak's headline results. The first row of Table A1 replicates the first row of Table 4 in their paper. The response of low skilled natives to local demand shocks is negligble, while the Mexican-born population responds heavily (with a one-for-one effect). Interestingly, the response of non-Mexican migrants is large and negative, offsetting much of the Mexican response. The overall population response (column 1) is statistically insignificant.

In the next row, I replace the weighted industry employment shock $\Delta\tilde{n}_{gr}$ with a simple change in (group-specific) log employment Δn_{gr}. The estimates are mostly unchanged, except we now see a large positive response from non-Mexican migrants. In columns 5-8, I control additionally for the lagged employment rate (i.e. in 2006), which I instrument using a Bartik industry shift-share for 2000-6. The response among natives and the overall population are now substantially larger - and it is not possible to statistically reject complete adjustment over the period. The fit appears remarkably good, given the small sample of 94 MSAs. Intuitively, as Cadena and Kovak note, MSAs experiencing larger upturns before 2006 experienced larger downturns thereafter. Thus, the small native response in the first row of Table A1 may simply reflect a mixture between a (somewhat sluggish) response to a historic upturn and contemporaneous downturn.

In the third section of Table A1, I control for the local amenity effects described in Section 3 in the main text (using population allocations to map CZ data to MSAs): climate, coastline, historical population and isolation. In columns 1-4 (without the dynamics), there is now a strongly significant response from all demographic groups. This suggests that these amenity effects may be important omitted variables, correlated with local demand shocks. The responses become larger in magnitude in columns 5-8 (controlling for the lagged employment rate), though the standard errors are also much larger.

Of course, given the small sample of 94 MSAs, this is a demanding specification. In the final section of Table A1, I extend the sample of geographical areas. Specifically, I include the remaining 181 MSAs (based on Cadena and Kovak's scheme), and I also include 41 additional areas consisting of the non-metro areas in each state (so 316 areas in total). The latter modification ensures the area sample is comprehensive of the US, similarly to the Commuting Zones I use in the main text. The results are reported in the final section of Table A1, controlling for the amenity effects. The results look similar to before, but the standard errors are now much smaller in almost all cases. Native-born workers do exhibit a large population response, though not as large as Mexican-born migrants. The response of non-Mexican migrants is difficult to pin down, given large standard errors.

In the main text, I study the contribution of different nativity groups (natives, migrants, etc.) to overall population growth in the local area: see Table 2. I now replicate this approach, estimating:

$$\frac{\Delta L_{grt}}{L_{rt-1}} = \beta_0^{CK} + \beta_1^{CK} \Delta n_{rt} + \beta_2^{CK} \left(n_{rt-1} - l_{rt-1}\right) + X_{rt}\beta_X^{CK} + \varepsilon_{grt} \tag{A16}$$

This specification is identical to the final section of Table A1, but replacing the dependent variable with contributions (of group g) to population growth between 2006 and 2010 among low skilled men, $\frac{\Delta L_{grt}}{L_{rt-1}}$. Also, the employment shocks are no longer nativity-specific - and now correspond to all low skilled men. The vector X_{gr} contains the Mexican enclave, policy controls and also the amenity effects.

I report the results in Table A2. Native-born workers account for most of the response to the contemporaneous employment change, Δn_{rt}, and for the entire response to the lagged employment rate. "New" migrants (arriving in the country since 2006) explain the remainder the response - consistent with my findings in Table 2. The average contribution of old migrants (arriving before 2006) is statistically insignificant. Having said that, there is a significant response from "old" Mexicans (consistent with Cadena and Kovak's findings), but this is offset by a negative contribution from old non-Mexican migrants.

To summarize, once I account for population dynamics and amenity controls, the results look similar to my findings - despite important differences in the sample (low skilled men, as opposed to all individuals) and time period (2006-10, as opposed to 1960-2010).

D.2 Local heterogeneity

Table A2 confirms that foreign-born workers make a disproportionate contribution to local adjustment in Cadena and Kovak's data. I now assess the implications of a larger supply of migrants for overall adjustment: i.e. do migrants crowd out the contribution of natives? I address this question in the main text by exploiting local variation in the supply of migrants, and Cadena and Kovak do the same. Specifically, they rank the 94 MSAs according to the initial share of Mexican-born among the low skilled population: the median share is 0.147. And in Table 5 of their paper, they show that local employment rates respond more weakly to demand shocks in MSAs with Mexican share exceeding 0.147 than those with smaller shares.

In the main text, I study variation across the support of an aggregate migrant shift-share instrument - rather than initial Mexican share. However, unsurprisingly perhaps, the migrant shift-share and Mexican share are closely correlated, with an R squared of 41 percent in my 316 geographical area sample.

My approach here is to re-estimate equation (A16), with the endogenous variables (and their Bartik instruments) interacted with a dummy $MexHigh_{rt}$ which takes value 1 for an MSA with Mexican share exceeding 0.147:

$$\begin{aligned} \frac{\Delta L_{grt}}{L_{rt-1}} &= \beta_0^{CK} + \beta_1^{CK} \Delta n_{rt} + \beta_2^{CK} \left(n_{rt-1} - l_{rt-1}\right) + \beta_3^{CK} \Delta n_{rt} \cdot MexHigh_{rt} \qquad \text{(A17)} \\ &\quad + \beta_4^{CK} \left(n_{rt-1} - l_{rt-1}\right) \cdot MexHigh_{rt} + X_{rt} \beta_X^{CK} + \varepsilon_{grt} \end{aligned}$$

where the vector X_{rt} now contains both the policy controls and the $MexHigh_{rt}$ dummy.

I offer estimtaes of this equation in Table A3. The first section of the table reports estimates with a 94 MSA sample and excluding the amenity controls. Without accounting for dynamics (columns 1-4), there is no population response to local employment shocks in MSAs with low Mexican shares. But there is a large response in MSAs with high shares, largely driven by the contribution of Mexican-born workers. There is also no evidence of crowding out: the native response is negligible in MSAs with both high and low Mexican shares. This is all consistent with the results in Cadena and Kovak's Table 5. Once I control for the dynamics (columns 5-8), Mexicans continue to make a large contribution to the response to the contemporaneous shock Δn_{rt}, though not to the lagged employment rate.

In the second section of Table A3, I control for amenity effects. There is now some evidence of displacement of the native contribution. In low share MSAs, the native contribution is 0.36 (not accounting for dynamics), and this falls to 0.1 in high share MSAs - though the standard errors are large.

In the third section, I extend the sample to 316 geographical areas. Standard errors are now lower, and we see the same displacement effect in the first four columns: the overall response of population is insignificantly different in high and low share MSAs. However, once I account for dynamics (columns 5-8), it is no longer possible to reject the hypothesis of zero displacement. But again, the standard errors are large (especially on the native response: column 6) - so it also not possible to reject a substantial displacement effect. One might then conclude that, given the demand empirical specification, the sample is too small to make definitive statements on this question.

E Reconciliation with Card (2001)

A key reference in the geographical displacement literature is Card (2001). He avoids concerns about cohort effects by exploiting the longitudinal dimension of the US census - basing his estimates on respondents' reported places of residence five years previously. But despite this, he finds "negative displacement" effects - with each new foreign migrant to an area attracting (on net) 0.25 additional residents. In order to reconcile my results with his, this appendix explores the robustness of his results to various specification changes. I show the divergence of our estimates is explained by: (1) the delineation of skill groups, (2) the choice right hand side controls, and (3) the sample of geographical areas.

Card (2001) exploits variation across the 175 largest Metropolitan Statistical Areas (MSAs) in the 5 percent census extract of 1990 - in the contrast to the analysis in the main text, which is based on Commuting Zones. Similarly to the main analysis, I extract this data from the Integrated Public Use Microdata Series (Ruggles et al., 2017). The 1990 census extracts offers sub-state geographical identifiers known as Public Use Microdata Areas (PUMAs), and a concordance between PUMAs and MSAs can be found at: *https://usa.ipums.org/usa/volii/puma.shtml*. A number of PUMAs straddle MSA boundaries; and following Card (2001), I allocate the population of a given PUMA to a given MSA if at least half that PUMA's population resides in that MSA.

I construct the regression variables according to the details provided by Card (2001). The sample is restricted to individuals aged 16 to 68 with at least one year of potential experience. In constructing his sample, Card uses all foreign-born individuals in the census extract and a 25 percent random sample of the native-born. In contrast, I use the full sample of natives, and this may (at least partly) account for some small discrepancies between his estimates and my replication. Card delineates skill groups by probabilistically assigning individuals into six broad occupation groups, conditional on their education and demographic characteristics (as described in Section 6.3 above). This assignment is based on predictions from a multinomial logit model, estimated separately for native men, native women, migrant men and migrant women.

Card estimates a specification similar to (34) in the main text:

$$\frac{L_{sr,1990} - L_{sr,1985}}{L_{sr,1985}} = \delta_0^C + \delta_1^C \frac{L_{sr,1990}^F}{L_{sr,1985}} + \delta_2^{C\prime} x_{sr} + d_r^C + d_s^C + \varepsilon_{sr} \tag{B1}$$

where $L_{sr,1990}$ is the population in skill group s in area r in the census year, 1990; and $L_{sr,1985}$ is the local population five years previously, based on the sample of census respondents. $L_{sr,1990}^F$ is the number of migrants in the cell in 1990 who were living abroad in 1985. Thus, the dependent variable $\frac{L_{sr,1990}-L_{sr,1985}}{L_{sr,1985}}$ is the population growth in skill group s in area r (though not accounting for emigrants from the US), and the key independent variable $\frac{L_{sr,1990}^F}{L_{sr,1985}}$ is the contribution of foreign migration to that growth. x_{sr} is a vector of mean characteristics of individuals in the (s, r) cell. In line with Card, this consists of mean age, mean age squared, mean years of schooling and fraction black, separately for both natives and migrants in the cell, and (for migrants only) mean years in the US. Finally, d_r and d_s are full sets of area and skill fixed effects respectively.

In the main text however, my dependent variable is the contribution of natives and earlier (pre-1985) migrants to population growth (rather than overall population growth). To maintain consistency with the main text, I estimate the following specification:

$$\frac{\left(L_{sr,1990} - L_{sr,1990}^F\right) - L_{sr,1985}}{L_{sr,1985}} = \delta_0^{s5} + \delta_1^{s5} \frac{L_{sr,1990}^F}{L_{sr,1985}} + \delta_2^{s5\prime} x_{sr} + d_r + d_s + \varepsilon_{sr} \tag{B2}$$

While δ_1^C in (B1) describes the effect of an additional migrant to overall population growth within the cell, δ_1^{s5} in (B2) gives a within-cell "displacement effect".[19] In his baseline OLS specification (with 175 MSAs and observations weighted by cell population), Card estimates δ_1^C as 1.25 (with a standard error of 0.04), which implies a δ_1^{s5} of 0.25 - i.e. a "negative displacement" effect.[20] His equivalent specification (using the shift-share instrument described in the main text) gives the same number for δ_1^C, but with a standard error of 0.05. I record these estimates in columns 1 of Table A4.

[19]See Peri and Sparber (2011) for a discussion of this point.
[20]See Table 4 of Card (2001).

[Table A4 here]

I attempt to replicate these estimates in columns 2, and I achieve similar numbers for Card's six-group occupation scheme. In the remaining rows of these two columns, I re-estimate the model for the various skill delineations discussed in Section 6.3, but the δ_1^{s5} estimates are not significantly different. In column 3, I cluster the errors by MSA: the standard errors are now larger, but the broad conclusions are unaffected.

Much of the action comes in columns 4, when I exclude the mean demographic controls in x_{sr} from the right hand side. All the estimates of δ_1^{s5} are now negative, and they are statistically significant for both the graduate/non-graduate delineation and the two-group occupation scheme, with IV coefficients of -1.98 and -0.43 respectively. In principle, one should include these controls if they elicit a causal effect on the dependent variable. But to the extent that this is not the case, there may be concern that they are sapping the power of the instrument. Indeed, within skill-area cells, the demographic controls explain about half the variation in the migrant shift share instrument (for Card's six-group occupation scheme).[21] And given there does not appear to be a strong a priori reason to include the controls, one perhaps cannot reasonably reject the hypothesis of large geographical displacement.

Finally, column 5 extends the sample of geographical areas. The earlier columns restrict the sample to the 175 largest MSAs, following the example of Card; but I now include the remaining 145 MSAs sample (raising the total to 320), and I also include 49 additional areas consisting of the non-metro areas in each state (so 369 areas in total).[22] The latter modification ensures the area sample is comprehensive of the US, similarly to the Commuting Zones I use in the main text. The coefficient estimates in columns 5 are larger (more negative) for every skill delineation. In particular, the IV coefficients are now -2.54 and -0.78 for the graduate/non-graduate and two-group occupations schemes respectively. The estimates are closer to zero (though still for negative) for the remaining skill delineations, in line with the longitudinal estimates in Table 9 in the main text.

To summarise, Card's finding of no (or even negative) displacement is sensitive to three specification choices: (1) skill group delineation, (2) the inclusion of mean demographic controls and (3) the area sample. Table A4 shows it is possible to generate substantial

[21] A regression of the instrument on the d_r and d_s fixed effects yields an R squared of 0.849, and including the controls raises the R squared to 0.919. So within skill-area cells, the controls account for a fraction $\frac{0.919-0.848}{1-0.848} = 0.47$ of the remaining variation.

[22] Based on the allocation procedure described above, all of New Jersey is classified as part of an MSA.

displacement effects in the same data, but varying the specification in reasonable ways along these three dimensions.

Tables and figures

Table 1: Gross annual flows into US states

	All	Native-born	Foreign-born		
			All	In US last year	Abroad last year
	(1)	(2)	(3)	(4)	(5)
% living in a different US state last year	2.72	2.79	2.36	2.43	0
% living abroad last year	0.70	0.24	2.91	0	100
Gross annual inflows (total)	3.41	3.03	5.28	2.43	100
Contribution to gross annual inflows (%)	100	73.35	26.65	11.94	14.71

Data is based on individuals aged 16-64 in American Community Survey samples between 2000 and 2016, extracted from the Integrated Public Use Microdata Series (Ruggles et al., 2017). I break down the sample into native and foreign-born; and I break the latter down according to where they were living 12 months previously (in US or abroad). The first row give the percentage of individuals (in each group) who report living in a different US state 12 months previously, and the second row the percentage living abroad. The third row reports the sum of the first two rows. The final row reports the contribution of each demographic group to the total gross annual inflow (i.e. 3.41 percent).

Table 2: 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	0.803***	0.957***	0.039***	0.918***	0.869***	0.957***	0.045***	0.912***	0.865***
	(0.015)	(0.024)	(0.013)	(0.025)	(0.021)	(0.024)	(0.009)	(0.020)	(0.018)
Lagged log ER	0.174***	0.182***	0.102***	0.080**	0.047*	0.180***	0.076***	0.104***	0.062***
	(0.014)	(0.017)	(0.036)	(0.039)	(0.025)	(0.017)	(0.017)	(0.021)	(0.016)
$\hat{\lambda}^F_{rt}$						0.085*	0.971***	-0.886***	-0.552***
						(0.047)	(0.069)	(0.074)	(0.055)
IV									
Δ log emp	0.630***	0.761***	0.194**	0.567***	0.602***	0.757***	0.116***	0.641***	0.649***
	(0.038)	(0.051)	(0.090)	(0.097)	(0.066)	(0.049)	(0.044)	(0.062)	(0.052)
Lagged log ER	0.388***	0.429***	0.236***	0.193*	0.186**	0.422***	0.103**	0.319***	0.265***
	(0.056)	(0.065)	(0.068)	(0.100)	(0.083)	(0.066)	(0.044)	(0.083)	(0.073)
$\hat{\lambda}^F_{rt}$						0.051	0.968***	-0.917***	-0.581***
						(0.080)	(0.072)	(0.088)	(0.078)
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	0.894***	0.907***	-0.057	-0.056
	(0.117)	(0.112)	(0.079)	(0.073)
Lagged Bartik	0.101	0.119*	0.556***	0.558***
	(0.063)	(0.066)	(0.056)	(0.058)
$\hat{\lambda}^F_{rt}$		-0.208*		-0.017
		(0.106)		(0.166)
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 3: 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	0.966***	0.002	0.964***	0.971***	0.958***	-0.016	0.974***	0.972***
	(0.022)	(0.019)	(0.028)	(0.026)	(0.019)	(0.014)	(0.023)	(0.023)
Δ log emp * $\hat{\lambda}^F_{rt}$	-0.151	1.409***	-1.561***	-3.138***	0.023	1.763***	-1.740***	-3.112***
	(0.402)	(0.514)	(0.492)	(0.429)	(0.389)	(0.381)	(0.506)	(0.433)
Lagged log ER	0.152***	-0.007	0.159***	0.155***	0.152***	0.009	0.142***	0.147***
	(0.023)	(0.013)	(0.026)	(0.021)	(0.025)	(0.014)	(0.025)	(0.020)
Lagged log ER * $\hat{\lambda}^F_{rt}$	0.688	2.249***	-1.561**	-2.724***	1.449*	1.345*	0.103	-1.629***
	(0.613)	(0.664)	(0.737)	(0.433)	(0.862)	(0.709)	(0.726)	(0.478)
$\hat{\lambda}^F_{rt}$	0.392*	1.742***	-1.350***	-1.310***	1.511	1.017	0.494	0.759
	(0.237)	(0.222)	(0.277)	(0.173)	(1.583)	(1.484)	(1.067)	(0.906)
IV								
Δ log emp	0.746***	-0.030	0.775***	0.838***	0.800***	-0.023	0.823***	0.844***
	(0.057)	(0.048)	(0.057)	(0.052)	(0.041)	(0.029)	(0.044)	(0.047)
Δ log emp * $\hat{\lambda}^F_{rt}$	0.784	6.462	-5.678**	-7.901***	-0.030	4.493***	-4.523***	-6.953***
	(2.397)	(4.131)	(2.589)	(2.537)	(0.978)	(1.605)	(1.320)	(1.537)
Lagged log ER	0.345**	-0.223	0.568***	0.603***	0.428***	-0.095	0.523***	0.571***
	(0.141)	(0.243)	(0.161)	(0.151)	(0.090)	(0.072)	(0.098)	(0.100)
Lagged log ER * $\hat{\lambda}^F_{rt}$	2.403	10.303	-7.901**	-10.709***	2.010	7.144***	-5.134**	-9.542***
	(4.115)	(6.275)	(3.668)	(3.657)	(2.540)	(2.400)	(2.490)	(2.382)
$\hat{\lambda}^F_{rt}$	0.960	4.490**	-3.530***	-4.097***	2.461	6.051	-3.591	-5.710*
	(1.504)	(2.287)	(1.329)	(1.320)	(3.569)	(4.153)	(2.801)	(3.406)
$\hat{\lambda}^F_{rt}$ * 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	**1.128*** **	-0.021***	-0.062	0.018***	**1.148*** **	-0.007	-0.146**	0.002
	(0.105)	(0.007)	(0.078)	(0.006)	**(0.104)**	(0.006)	(0.064)	(0.005)
Current Bartik * $\hat{\lambda}^F_{rt}$	-5.520**	**1.489*** **	0.136	-0.826***	-5.666**	**1.219*** **	2.052**	-0.416***
	(2.701)	**(0.268)**	(1.137)	(0.119)	(2.870)	**(0.224)**	(0.976)	(0.108)
Lagged Bartik	0.127**	0.026***	**0.558*** **	-0.002	0.118*	0.021***	**0.474*** **	-0.005**
	(0.064)	(0.004)	**(0.068)**	(0.004)	(0.062)	(0.004)	**(0.056)**	(0.002)
Lagged Bartik * $\hat{\lambda}^F_{rt}$	-1.745	-0.878***	0.035	**0.826*** **	-0.987	-0.516***	0.734	**0.658*** **
	(1.315)	(0.243)	(1.757)	**(0.204)**	(1.545)	(0.190)	(1.084)	**(0.113)**
$\hat{\lambda}^F_{rt}$	0.734***	0.083**	-0.039	-0.456***	-0.868	0.008	-3.463	-1.159***
	(0.252)	(0.035)	(0.198)	(0.032)	(2.089)	(0.246)	(2.704)	(0.324)
$\hat{\lambda}^F_{rt}$ * 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 2 (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 2, 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 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 4: 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)	50 states + DC	1995-1996	Yes: 2 educ groups (College graduates and non-graduates)	No	-2.3*
Monras (2015)	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 (**??**) 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 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 5: Estimates of displacement across CZs

PANEL A: IV and OLS

	OLS		IV: simple		IV: 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)
Basic specification						
New migs' contrib	-0.782***	-0.573***	-1.110***	-0.755***	-1.167***	-0.861***
	(0.141)	(0.118)	(0.131)	(0.130)	(0.139)	(0.140)
Lagged log ER	0.427***	0.352***	0.598***	0.500***	0.605***	0.516***
	(0.054)	(0.048)	(0.122)	(0.109)	(0.122)	(0.108)
Current Bartik	0.687***	0.690***	0.707***	0.677***	0.721***	0.702***
	(0.093)	(0.083)	(0.095)	(0.088)	(0.094)	(0.086)
FE specification						
New migs' contrib	-0.553***	-0.706***	-0.317	0.141	-1.006***	-1.059***
	(0.169)	(0.166)	(0.751)	(0.666)	(0.319)	(0.272)
Lagged log ER	-0.258***	-0.346***	1.272***	0.993**	0.373	-0.458*
	(0.075)	(0.084)	(0.459)	(0.427)	(0.295)	(0.244)
Current Bartik	0.778***	0.696***	0.768***	0.715***	0.750***	0.682***
	(0.092)	(0.082)	(0.100)	(0.088)	(0.083)	(0.068)
Observations	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	0.100***	0.032	-0.006	-0.065***
	(0.029)	(0.031)	(0.018)	(0.024)
Current Bartik * $\hat{\lambda}^F_{rt}$		1.247		1.415**
		(0.858)		(0.566)
Lagged Bartik	0.071***	0.021	0.036**	-0.025**
	(0.020)	(0.020)	(0.017)	(0.011)
Lagged Bartik * $\hat{\lambda}^F_{rt}$		2.887***		2.710***
		(0.498)		(0.634)
$\hat{\lambda}^F_{rt}$	0.942***	0.319**	0.491***	-0.048
	(0.062)	(0.137)	(0.059)	(0.151)
Observations	3,610	3,610	3,610	3,610

Panel A reports OLS and IV estimates of the displacement equations (26) and (**??**), across 722 CZs and five (decadal) time periods. 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 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 5-6, 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 shift shares. All specifications include the full set of controls listed in the notes under Table 2. The bottom half of the table conditions further on CZ fixed effects, while the top half does not. Column 1, 3, and 5 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 6: Robustness tests for IV displacement effects: Basic specification

	Basic specification						FEs
	1960s	1970s	1980s	1990s	2000s	All years	All years
	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Year effects	0.319	-0.687	-0.048	-0.903***	-0.514**	-0.507**	-2.148**
	(0.922)	(0.579)	(0.208)	(0.203)	(0.221)	(0.231)	(0.934)
+ Current Bartik	-0.718	-0.276	-0.471*	-0.888***	-0.550**	-0.671***	-1.598*
	(1.032)	(0.385)	(0.257)	(0.239)	(0.220)	(0.196)	(0.862)
+ Lagged log ER (instrumented)	-0.656	-0.231	-1.656	0.392	-0.544**	-0.774***	-1.598*
	(1.082)	(0.326)	(3.819)	(0.610)	(0.213)	(0.232)	(0.862)
+ Climate controls	-2.090**	-2.391***	-1.315	-1.207***	-0.855***	-1.422***	-1.598*
	(0.958)	(0.623)	(1.042)	(0.375)	(0.139)	(0.138)	(0.862)
+ Coastline dummy	-2.153**	-2.414***	-1.222	-0.989***	-0.648***	-1.290***	-1.598*
	(1.029)	(0.724)	(1.179)	(0.358)	(0.168)	(0.172)	(0.862)
+ Log pop density 1900	-1.766***	-2.141***	-1.034	-0.984***	-0.581***	-1.149***	-1.598*
	(0.556)	(0.552)	(0.819)	(0.370)	(0.183)	(0.194)	(0.862)
+ Log distance to closest CZ	-1.705***	-2.168***	-1.058***	-1.096***	-0.630***	-1.153***	-1.598*
	(0.550)	(0.595)	(0.353)	(0.384)	(0.184)	(0.191)	(0.862)
+ Amenities x year effects	-1.705***	-2.168***	-1.058***	-1.096***	-0.630***	-1.110***	-0.317
	(0.550)	(0.595)	(0.353)	(0.384)	(0.184)	(0.131)	(0.751)
As above, but with lagged	-1.555***	-2.116***	-0.745***	-1.365***	-1.024***	-1.120***	-1.251***
Bartik replacing lagged ER	(0.525)	(0.536)	(0.174)	(0.181)	(0.190)	(0.136)	(0.433)
Observations	722	722	722	722	722	3,610	3,610

This table tests robustness of my IV estimates of displacement in column 3 of Table 5. These are based on the model of equation (26): 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^u 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^u change as progressively more controls are included. The first row reports estimates when controlling for year effects alone; the second row includes a current Bartik control; the third row includes the lagged employment rate (together with it's lagged Bartik instrument); and the various amenities are then progressively added - unil the penultimate row, which includes the full set of controls I use in Table 5. The final row replaces the lagged employment rate with a lagged Bartik control. 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: IV effects of foreign inflows on local employment rates

	IV: simple			IV: interacted instruments		
	All	Natives	Migrants	All	Natives	Migrants
	(1)	(2)	(3)	(4)	(5)	(6)
Basic specification						
New migs' contrib	-0.144**	-0.201***	-0.177***	-0.182***	-0.186***	-0.238***
	(0.059)	(0.058)	(0.064)	(0.066)	(0.066)	(0.064)
Lagged log ER	-0.282***	-0.279***	-0.356**	-0.276***	-0.282***	-0.346**
	(0.052)	(0.053)	(0.144)	(0.052)	(0.053)	(0.144)
Current Bartik	0.360***	0.338***	0.191**	0.368***	0.334***	0.205**
	(0.039)	(0.039)	(0.092)	(0.038)	(0.039)	(0.093)
FE specification						
New migs' contrib	-1.099***	-1.323***	-0.611	-0.613***	-0.311**	-0.615***
	(0.211)	(0.255)	(0.604)	(0.100)	(0.121)	(0.196)
Lagged log ER	-1.010***	-0.991***	-1.046	-0.455***	0.149	-1.008***
	(0.235)	(0.281)	(0.687)	(0.131)	(0.162)	(0.214)
Current Bartik	0.266***	0.218***	0.138	0.280***	0.247***	0.137
	(0.042)	(0.051)	(0.113)	(0.038)	(0.046)	(0.108)
Observations	3,610	3,610	3,610	3,610	3,610	3,610

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 replace the dependent variable in equation (26) with the decadal change in the log employment rate among (i) all individuals, (ii) natives and (iii) migrants, i.e. foreign-born. In the first three columns, the contribution of new migrants (to local population growth) is instrumented by local migrant intensity $\hat{\lambda}^F_{rt}$ and the lagged employment rate by the lagged Bartik shift-share. In the final three columns, I also include the interacted instrumented -as described in the notes under Table 5. All specifications include the full set of controls listed in the notes under Table 2, together with the current Bartik shift-share. The bottom half of the table conditions further on CZ fixed 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 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 **??**. 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 δ_1^s in equation (27), based on decadal differences between 1960 and 2010. And the bottom half reports estimates of δ_1^{s5} in (34), 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^s and δ_1^{s5}: 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 (27), 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 (27), 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.

Table A1: Robustness of average responses from Cadena and Kovak (2016): low skilled men

	All	Natives	Mexican migrants	Other migrants	All	Natives	Mexican migrants	Other migrants
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Baseline specification: equation (A14)								
Emp shock: group-specific	0.223	0.007	0.992**	-0.675**	-	-	-	-
	(0.166)	(0.090)	(0.468)	(0.278)				
(2) As above, but replace $\Delta\tilde{n}_{gt}$ with Δn_{gt}								
Δ log emp: group-specific	0.301*	0.013	0.771***	1.413***	0.654***	0.871**	0.380	1.470***
	(0.170)	(0.159)	(0.104)	(0.356)	(0.199)	(0.441)	(0.413)	(0.552)
Lagged log ER: group-specific					0.680**	0.745***	-2.429	-0.519
					(0.305)	(0.284)	(2.651)	(2.753)
(3) Include amenity controls								
Δ log emp: group-specific	0.540***	0.366***	0.839***	0.957**	0.598***	0.698	0.930***	0.798***
	(0.097)	(0.093)	(0.128)	(0.378)	(0.099)	(0.503)	(0.266)	(0.248)
Lagged log ER: group-specific					0.235	0.826	0.623	-0.669
					(0.304)	(0.969)	(2.257)	(1.017)
(4) Extend sample of geographical areas								
Δ log emp: group-specific	0.494***	0.373***	0.833***	0.955	0.518***	0.437***	0.910***	1.192
	(0.062)	(0.079)	(0.103)	(0.655)	(0.077)	(0.125)	(0.159)	(2.588)
Lagged log ER: group-specific					0.323***	0.420***	0.568	-2.086
					(0.118)	(0.113)	(1.258)	(8.780)
Observations: (1), (2), (3)	94	94	94	94	94	94	94	94
Observations: (4)	316	316	274	287	316	316	274	287

*** p<0.01, ** p<0.05, * p<0.1.

Table A2: Average contributions to local adjustment: Cadena and Kovak (2016) data, low skilled men

	All	Natives	All migrants		Mexican migrants		Other migrants	
			New	Old	New	Old	New	Old
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ log emp	0.514***	0.297***	0.130***	0.087	0.019	0.155***	0.111***	-0.069
	(0.077)	(0.093)	(0.040)	(0.098)	(0.013)	(0.055)	(0.039)	(0.077)
Lagged log ER	0.307***	0.381***	0.039	-0.114	0.035	-0.197**	0.004	0.084
	(0.117)	(0.113)	(0.059)	(0.108)	(0.023)	(0.078)	(0.058)	(0.060)
Observations	316	316	316	316	316	316	316	316

*** p<0.01, ** p<0.05, * p<0.1.

Table A3: Heterogeneity in contributions to adjustment: Cadena and Kovak (2016) data, low skilled men

	All	Natives	Mexican migrants	Other migrants	All	Natives	Mexican migrants	Other migrants
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Baseline specification: equation (A17)								
Δ log emp	0.006	0.073	0.107**	-0.174	0.299*	0.330	-0.009	-0.022
	(0.198)	(0.103)	(0.048)	(0.219)	(0.159)	(0.224)	(0.107)	(0.150)
Δ log emp * MexHigh	0.535**	0.017	0.311**	0.208	0.624**	0.059	0.417***	0.149
	(0.235)	(0.144)	(0.132)	(0.224)	(0.315)	(0.294)	(0.159)	(0.161)
Lagged log ER					0.563***	0.491*	-0.216	0.288**
					(0.200)	(0.293)	(0.140)	(0.137)
Lagged log ER * MexHigh					0.808*	0.581	0.18	0.047
					(0.473)	(0.464)	(0.233)	(0.186)
(2) Include amenity controls								
Δ log emp	0.393***	0.361***	0.106	-0.074	0.317*	0.314**	0.093	-0.090
	(0.103)	(0.117)	(0.073)	(0.146)	(0.166)	(0.135)	(0.073)	(0.147)
Δ log emp * MexHigh	0.164	-0.263*	0.317**	0.110	0.511*	-0.097	0.309**	0.298
	(0.166)	(0.139)	(0.137)	(0.160)	(0.261)	(0.208)	(0.144)	(0.197)
Lagged log ER					0.647	0.231	-0.125	0.541
					(0.464)	(0.380)	(0.207)	(0.383)
Lagged log ER * MexHigh					0.316	0.200	0.062	0.054
					(0.393)	(0.302)	(0.216)	(0.238)
(3) Extend sample of geographical areas								
Δ log emp	0.423***	0.357***	0.036	0.030	0.330**	0.291**	0.041	-0.001
	(0.074)	(0.084)	(0.041)	(0.071)	(0.153)	(0.136)	(0.042)	(0.076)
Δ log emp * MexHigh	0.158	-0.269**	0.411***	0.016	0.548*	0.010	0.391***	0.148
	(0.148)	(0.123)	(0.136)	(0.095)	(0.286)	(0.239)	(0.132)	(0.113)
Lagged log ER					0.485***	0.387***	-0.032	0.130
					(0.157)	(0.150)	(0.052)	(0.080)
Lagged log ER * MexHigh					0.507	0.327	-0.022	0.201
					(0.402)	(0.329)	(0.187)	(0.143)
Observations: (1), (2)	94	94	94	94	94	94	94	94
Observations: (3)	316	316	316	316	316	316	316	316

*** p<0.01, ** p<0.05, * p<0.1.

Table A4: Robustness of 1985-1990 within-area estimates from Card (2001)

	Card (2001): 175 MSAs, weighted	Replication	... with errors clustered by area	... excluding demog controls	... with full area sample
	(1)	(2)	(3)	(4)	(5)
OLS					
Coll grad v non-grad		-0.259	-0.259	-1.918***	-3.545***
		(0.439)	(0.741)	(0.555)	(0.767)
HSD v non-HSD		0.097	0.097	-0.081	-0.253
		(0.104)	(0.198)	(0.168)	(0.169)
4 educ groups		0.157	0.157	-0.115	-0.346**
		(0.106)	(0.144)	(0.133)	(0.154)
2 occup groups		0.028	0.028	-0.479**	-0.940***
		(0.178)	(0.305)	(0.213)	(0.297)
6 occup groups	0.25***	0.198***	0.198**	-0.069	-0.228***
	(0.04)	(0.045)	(0.084)	(0.072)	(0.083)
IV					
Coll grad v non-grad		0.697	0.697	-1.976***	-2.536***
		(0.915)	(1.575)	(0.674)	(0.838)
HSD v non-HSD		0.241***	0.241*	-0.046	-0.256**
		(0.082)	(0.145)	(0.117)	(0.127)
4 educ groups		0.447***	0.447***	-0.008	-0.159
		(0.117)	(0.153)	(0.123)	(0.126)
2 occup groups		0.160	0.160	-0.430***	-0.780***
		(0.134)	(0.248)	(0.141)	(0.171)
6 occup groups	0.25***	0.235***	0.235***	-0.043	-0.167**
	(0.05)	(0.045)	(0.081)	(0.062)	(0.068)

This table tests the robustness of Card's (2001) estimates of geographical displacement. Card's OLS and IV results (for his six-group occupation scheme) are presented in column 1. These are taken from Table 4 of his paper, based on the 175 largest MSAs of the 1990 census extract, with observations weighted by cell populations. (Card reports his estimates as the effect on population growth, but I substract one from his numbers to give a "displacement effect"; see Peri and Sparber, 2011.) I attempt to replicate his results in column 2. In columns 3, I cluster standard errors by MSA. Column 4 excludes the demographic controls from the regression. And column 5 extends the geographical sample to all identifiable MSAs (raising the total to 320), as well as 49 supplementary regions consisting of the non-metro areas in each state (so 369 areas in total). I present all results for both Card's six-group occupation scheme and also (in the remaining rows) the other skill delineations discussed in Section 6 in the main text. *** p<0.01, ** p<0.05, * p<0.1.

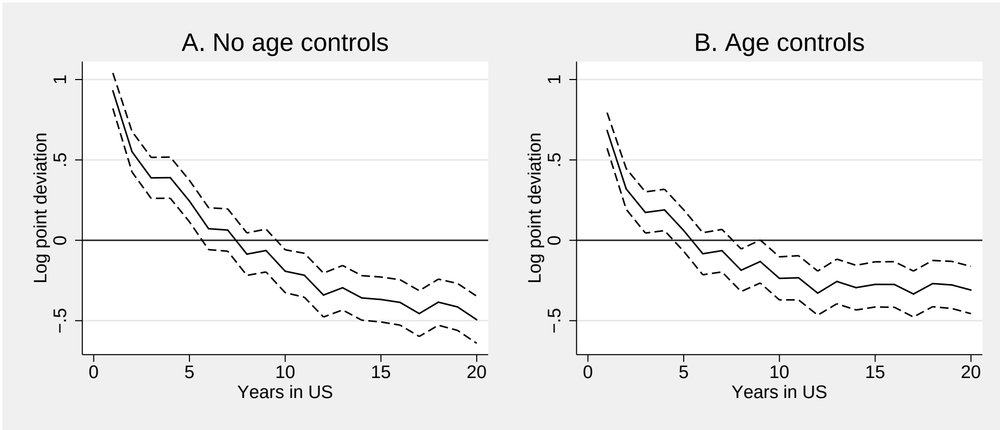

Figure A1: Effect of years in US on cross-state mobility

Note: This figure plots estimates of the log point difference in cross-state mobility between migrants (with given years in US) and natives. Estimates are based on complementary log-log models, controlling for a full set of entry cohort effects and observation year effects. In addition to these, the model in Panel B controls for a full set of age effects. Sample consists of individuals aged 16-64 in ACS waves between 2000 and 2016. See Appendix B for further details.

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