Monopsony and the Wage Effects of Migration

Michael Amior and Alan Manning*

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Abstract

In a generalization of the well-known "immigration surplus" result, we show that immigration which preserves the skill mix of migrants must always increase the average native worker's marginal product, in any long-run constant returns economy. But in a monopsonistic labor market, immigration may also affect native wages through the mark-downs imposed by firms. Using standard US census data, we reject the restrictions implied by the canonical competitive model. We attribute this rejection to an adverse mark-down effect, which quantitatively dominates the improvements in natives' marginal products. The capture of migrants' rents significantly expands the total surplus going to natives, but redistributes income among them (from workers to firms). Our estimates also suggest that policies which limit firms' market power over migrants can substantially benefit native labor.

1 Introduction

Much has been written on the impact of migration on native wages: see, for example, recent surveys by Borjas (2014), Card and Peri (2016) and Dustmann, Schoenberg and Stuhler (2016). This literature has traditionally studied these effects through the lens of a competitive labor market, where wages are equal to the marginal products of labor. In this paper, we assess the implications and robustness of this assumption.

We make three contributions to the literature. First, we offer new results on how immigration affects natives' marginal products. For any convex technology with constant

*Amior: Hebrew University of Jerusalem and Centre for Economic Performance, London School of Economics; michael.amior@mail.huji.ac.il. Manning: Centre for Economic Performance, London School of Economics; a.manning@lse.ac.uk. We are grateful to George Borjas, David Green, Barbara Petrongolo and Jan Stuhler for helpful comments, to seminar participants at UCL, LSE, Hebrew University, Haifa, Harvard, CREST, Edinburgh, the CEP Annual Conference, the CEPR/LSE Annual Symposium in Labour Economics and EALE-SOLE-AASLE. Amior acknowledges funding from the Israel Science Foundation under "The Labor Market Impact of Migration Under Monopsony" (grant no. 1548/18), and Manning from the ERC under project LPIGMANN. Asaf Abraham provided excellent research assistance. This paper subsumes much of the content of an earlier unpublished paper: "The Impact of Migration in a Monopsonistic Labor Market: Theoretical Insights" (Amior, 2017).

returns, we show a larger supply of migrants (keeping their skill mix constant) must *always* increase the marginal products of native-owned factors *on average*, as long as native and migrant workers have different skill mixes. And in the long run (if capital is supplied elastically), this surplus passes entirely to native labor. Borjas (1995) famously proves this "immigration surplus" result for a one-good economy with up to two labor types and capital; but we demonstrate it holds for any number of labor types, any number of (intermediate or final) goods, and any convex technology, as long as it is has constant returns. Although these are theoretical results, they do have empirical implications: any empirical model which imposes constant returns, convexity and perfect competition (as almost all existing "structural models" do, e.g. Borjas, Freeman and Katz, 1997; Borjas, 2003; Card, 2009; Manacorda, Manning and Wadsworth, 2012; Ottaviano and Peri, 2012; Burstein et al., 2020; Piyapromdee, forthcoming) can only ever conclude that immigration (keeping the skill mix of migrants constant) increases the average native wage in the long run (where capital is elastic), whatever data is used for estimation.[1] But this is a claim one may wish to test; and to allow for a different possibility, a more general model is needed.

Motivated by this insight, our second contribution is to reassess these results in a theoretical environment *without* perfect competition. We follow Bound and Johnson (1992) and Katz and Autor (1999) in allowing wages to differ from marginal products by a mark-down ϕ:

$$\log W = \log MP - \phi \tag{1}$$

and we consider the possibility that immigration affects mark-downs *as well as* marginal products. We justify this by reference to monopsony: if employers enjoy greater market power over migrants than natives, but cannot perfectly wage discriminate, they will exploit a larger migrant share by imposing larger mark-downs on natives and migrants alike. The introduction of monopsony will also affect natives' total income gains from immigration (and not just their wages), to the extent that firms accrue larger rents by employing migrants. There are a number of other papers which consider the impact of immigration in non-competitive settings: Malchow-Moller, Munch and Skaksen (2012), Chassamboulli and Palivos (2013, 2014), Chassamboulli and Peri (2015), Naidu, Nyarko and Wang (2016), Battisti et al. (2017), Amior (2017) and Albert (forthcoming) set out various search, bargaining or monopsonistic models.[2] But as Borjas (2013) has noted,

[1] Borjas (2013) also emphasizes that factor demand theory imposes strong constraints on the impact of migration on the average wage of *all* workers. Our contribution here is to develop the implications for *natives* specifically.

[2] Using Danish data, Malchow-Moller, Munch and Skaksen (2012) find that migrant employees depress native wages within firms; and they attribute this to differential outside options. Naidu, Nyarko and Wang (2016) study a UAE reform which relaxed restrictions on employer transitions for migrant workers,

the literature is surprisingly sparse, given the ubiquity of imperfect competition in other parts of labor economics.

Our third contribution is to develop an estimable model, to test whether mark-downs depend on the migrant share (and if so, how), using skill-based variation in wages and employment from the US census (as analyzed by Borjas, 2003, and Ottaviano and Peri, 2012, among others). We rely on the canonical structural model with nested CES technology (from Card, 2009; Manacorda, Manning and Wadsworth, 2012; Ottaviano and Peri, 2012), but relax the assumption of perfect competition. Wages of each labor type depend on both the cell-specific marginal product *and* mark-down, where cells are defined by education and experience. The marginal products are determined by cell-level employment stocks, according to a functional form set by the technology. Conditional on these stocks, our model predicts that the mark-down effects are identified by the wage response to a cell's *composition* (and specifically its migrant share). Though this prediction comes out of our monopsony model, it can be motivated by other non-competitive frameworks.

We test (and reject) the null hypothesis that the native and migrant mark-downs are equal and independent of the migrant share (of which perfect competition is a special case). For a native-migrant substitution elasticity similar to Ottaviano and Peri (2012), our estimates suggest a 1 pp increase in a cell's migrant share allows firms to mark down native wages by 0.4-0.6% more; and the effect is similar for migrants. The model cannot be fully point-identified; but it is set-identified, and an analysis of alternative calibrations suggests this native mark-down effect is a lower bound. The mark-down effect more than offsets the small (positive) gains to native wages which arise from predicted changes in marginal products. The direction of the mark-down effect suggests that migrants supply labor to firms less elastically than natives.

Our results suggest the existence of monopsony power may significantly expand the "immigration surplus" (the total income gains of natives), which is typically found to be small in competitive models (Borjas, 1995). This is because native-owned firms capture rents from new immigrants (who earn less than their marginal product), even in a "long run" scenario where capital is elastically supplied. But just as the aggregate native surplus is larger, so too are the distributional effects: if mark-downs expand, rents are transferred from workers to firms.

These mark-down effects should not be interpreted as simply supporting a story of "cheap" migrant labor undercutting native wages. Any such effects may be offset through policies which constrain monopsony power over migrant labor (such as minimum wages, as in e.g. Edo and Rapoport, 2019, or amnesties, as in Monras, Vázquez-Grenno and Elias, 2020), rather than by restricting migration itself. In fact, these objectives may

though they focus on the implications for incumbent migrants rather than natives.

come into conflict: for example, limitations on access to permanent residency (designed to deter migration) may deliver more market power to firms, and natives may ultimately suffer. Indeed, we present evidence that the mark-down effects we estimate are driven specifically by non-citizens, which matches similar evidence from France (Edo, 2015). Consistent with this, we also find the wage elasticity of job separations is substantially lower for non-citizens, suggesting a highly inelastic supply of labor to firms. With this in mind, we then simulate a policy which transforms a portion of non-citizens to citizens, which might be interpreted as a regularization program: based on our estimated mark-down effects, both native and migrant labor (and especially the low skilled) stand to benefit substantially, at the expense of firms.

Given our rejection of the canonical model, one may choose to abandon structural estimation of wage effects altogether, in favor of more empirical reduced-form strategies. Dustmann, Schoenberg and Stuhler (2016) recommend such an approach, though for different reasons, namely the difficulty of correctly allocating migrants to skill cells (if migrants do not compete with equally skilled natives). But, there are advantages to the structural approach. First, reduced form studies typically cannot estimate the impact of any given type of migrant on any given type of native. If there are A native types and B migrant types, one would need to include $A \times B$ interactions in a fully specified reduced-form model, almost certainly more than can be estimated from the data. Though natural experiments may offer remarkably clean identification (see e.g. Dustmann, Schoenberg and Stuhler, 2017; Edo, forthcoming; Monras, 2020), they are typically restricted to studying the impact of particular migration events (which bring particular skill mixes); and it may be difficult to extrapolate to other scenarios. Second, the existence of mark-downs effects has important implications for policy design, and it may be difficult to identify these effects in the absence of structural assumptions. Our paper offers an approach to embedding more flexible assumptions on labor market competition within a tractable structural framework.

In the next section, we set out our theoretical results on the effects of immigration on marginal products. Section 3 extends our framework to allow for monopsonistic firms, and Section 4 describes our identification and empirical strategy. In Section 5, we describe our data; and Section 6 presents our basic estimates, which reject the canonical model. In Section 7, we offer evidence that this rejection reflects the presence of mark-down effects. And finally, Section 8 quantifies the aggregate-level implications of an immigration shock and naturalization policy for native and migrant wages, the immigration surplus and distribution. We also offer Online Appendices with proofs, theoretical extensions and supplementary empirical estimates.

2 Immigration surplus and native marginal products

In a competitive market, the wages of native labor are fully determined by their marginal products (MPs). In this section, we offer a set of results which describe how immigration affects these MPs in a closed economy.[3] Underpinning our results are the assumptions of constant returns to scale (CRS) and convex technology (which implies diminishing returns to individual factors). Under perfect competition, these results will be sufficient for an analysis of the "immigration surplus" (i.e. the income gains of natives). But to the extent that native-owned firms enjoy monopsony power, the total surplus will also depend on any changes in their rents - and we return to this point in Section 8 below.

Consider the following production function:

$$Y = F(\mathbf{K}, \mathbf{L}) \tag{2}$$

where $\mathbf{K} = (K_1, K_2, ...K_I)$ is a vector of perfectly elastic factor inputs, and $\mathbf{L} = (L_1, L_2, ...L_J)$ is a vector of inputs which are treated as fixed (either because they are inelastically supplied, or simply for analytical convenience). Each input may be owned by natives or migrants, or a combination of the two. Without loss of generality, we refer to the fixed inputs with labor and the elastic ones with capital. This approach follows the precedent of the migration literature, which traditionally equates an elastic supply of capital with a "long run" scenario. We consider more general scenarios at the end of this section, as well as the case of factor inputs in imperfectly elastic supply.

Under the assumption of CRS, we can simplify the analysis with the following claim:

Proposition 1. *We can summarize total revenue net of the costs of the (elastic)* $\mathbf{K}$ *inputs using a "long run" production function* $\tilde{F}(\mathbf{L})$*, where* $\tilde{F}$ *has constant returns in the (fixed)* $\mathbf{L}$ *inputs, and where the derivatives of each* $\mathbf{L}$ *input equal their MPs.*

Proof. See Appendix A, and see also Dustmann, Frattini and Preston (2012). □

This proposition allows us to abstract away from the elastic "capital" inputs. In what follows, we will begin with the simplest possible model, and we will consider the implications for the immigration surplus as we progressively add more features.

2.1 Homogeneous natives and migrants

Suppose there are two fixed labor inputs, natives and migrants: $\mathbf{L} = (N, M)$; so long run output (net of the costs of elastic inputs) is $\widetilde{F}(N, M)$. Each group is homogeneous,

[3] See Borjas (2013) for an open economy model, which shows the wage effects of immigration will depend on the extent to which natives and migrants consume imported goods.

though they may differ from each other. The two-input case was originally analyzed[4] by Borjas (1995); but as we show, it provides a useful foundation for more general results:

Proposition 2. *Given CRS and convex technology, a larger supply of homogeneous migrants M must strictly increase the MP of homogeneous natives N, unless natives and migrants are perfect substitutes - in which case there is no effect.*

Proof. If there are two factor inputs with CRS and convex technology, they must be Q-complements: i.e. $\frac{\partial^2 \widetilde{F}(N,M)}{\partial N \partial M} \geq 0$, and with equality only if N and M are perfect substitutes. Intuitively, convexity ensures diminishing returns to migrant labor (if natives and migrants are imperfect substitutes); and since CRS ensures that factor payments exhaust output, the surplus from immigration must go to the other factor (i.e. native labor). It immediately follows that the native MP is increasing in migrant supply M, unless the two inputs are perfect substitutes. □

2.2 Heterogeneous skills

Proposition 1 is well-known: see e.g. Borjas (2014, p. 65). But perhaps it is specific to the extreme case of two inputs. Suppose instead there are J skill-defined labor inputs, characterized by arbitrary patterns of substitutability and complementarity. And for each labor type j, suppose $L_j = N_j + M_j$, where N_j and M_j are the native and migrant components. Let $\eta_j \equiv \frac{N_j}{N}$ denote the share of natives who are type-j, and $\mu_j \equiv \frac{M_j}{M}$ the share of migrants. This set-up allows the possibility that any or all types are exclusively native or migrant, which would imply $\eta_j \mu_j = 0$ for some j. Long run output (net of the elastic inputs' costs) is then:

$$\tilde{Y} = \tilde{F}\left(L_1, .., L_J\right) \tag{3}$$

And under the assumptions of CRS and convexity, we can make the following claim:

Proposition 3. *Suppose natives are divided into an arbitrary number of skill groups, and similarly for migrants. Given CRS and convexity, a larger supply of migrants M (holding their skill mix fixed) raises the average MP of natives, unless the skill mixes of natives and migrants are identical - in which case there is no effect.*

Proof. Write the production function in (3) as:

$$\tilde{Y} = \tilde{F}\left(\eta_1 N + \mu_1 M, .., \eta_J N + \mu_J M\right) = Z\left(N, M\right) \tag{4}$$

i.e. output can be expressed as a function Z of the total number of natives N and migrants M, where the skill mix of these groups is subsumed in Z. The function $Z\left(N, M\right)$ must

[4] To be more precise, Borjas' (1995) two inputs are capital and labor, where immigration contributes to the latter only. But the implications are the same.

have CRS if $\tilde{F}(L_1,..,L_J)$ does. And the partial derivative of $Z(N,M)$ with respect to N can be written as:

$$\frac{\partial Z(N,M)}{\partial N} = \sum_j \eta_j \frac{\partial \tilde{F}(L_1,..,L_J)}{\partial L_j} \tag{5}$$

which is the average native MP (or, under perfect competition, the average native wage). Similarly, the partial derivative of $Z(N,M)$ with respect to M is equal to the average migrant MP. In this way, we have reduced a production function with arbitrarily many labor types to one with only two composite inputs, N and M, whose partial derivatives equal natives' and migrants' *average* MPs. Since Z has CRS and convexity, it follows (from Proposition 2) that a larger migrant stock M increases the average MP of natives. This effect is strict if natives' and migrants' skill mixes differ. If the skill mixes are identical, then $Z(N,M) = k(N+M)$ for some constant k; and migration has no effect on natives' MPs, because they are effectively perfect substitutes (at the aggregate level). □

Note that Proposition 3 applies only to the *average* native MP: there may be negative effects on particular skill types. For example, if all migrants were unskilled, a larger M would compress the MPs of unskilled natives.

It is not entirely clear how well-known Proposition 3 is in the literature. Dustmann, Frattini and Preston (2012) study a CES production function and conclude: "For *small* levels of immigration, we should ... expect to find mean native wages rising if capital is perfectly mobile. Indeed, there can be a positive surplus for labor if capital is mobile and immigrant labor *sufficiently* different to native labor [emphasis added]". This result is similar to the one proved here, but we impose no restriction on technology beyond CRS and convexity (so CES is not required), no requirement that immigration be "small", and no requirement that native and migrant skill mixes be "sufficiently" different: we show that any difference will generate a surplus for natives, though its size will depend on the amount of immigration and the extent of skill differences between natives and migrants.

2.3 Changing the skill mix of immigration

Propositions 1-3 focus on how CRS and convexity constrain the response of natives' MPs to immigration, holding the skill mix of migrants constant. However, these assumptions also constrain the possible response of natives' MPs to changes in the skill mix of migrants. Denote the vector of natives' skill shares $(\eta_1, \eta_2, ..., \eta_J)$ by η, and suppose the skill mix of migrants can be written as:

$$\mu(\zeta) = \eta + \zeta(\mu - \eta) \tag{6}$$

where ζ describes the extent to which the skill mixes of natives and migrants differ. If $\zeta = 0$, the two groups are identical, while $\zeta = 1$ corresponds to the case analyzed so far.

It can then be shown that natives benefit from greater skill differences:

Proposition 4. *An increase in ζ increases the average native MP.*

Proof. See Appendix B. $\square$

Borjas (1995) makes a similar point, that the immigration surplus is increasing in native-migrant skill differences. But our result generalizes this claim to an economy with an arbitrary number of skill types.

2.4 Multiple goods

Until now, we have restricted attention to a single-good economy. But can allowing for multiple goods overturn the surplus result? In this more general environment, the marginal *revenue* products are affected by relative prices and not just technology. To obtain the welfare implications of immigration, we must therefore account for these price changes; and this necessitates an assumption about price determination (which we did not require before). It turns out that if both product and labor markets are perfectly competitive, and if preferences are homothetic (so there is a single price index for all consumers, native and migrant alike), the surplus result continues to hold:

Proposition 5. *In a perfectly competitive economy with multiple (intermediate or final) goods, in which all sectors have CRS and convex technology, and where all consumers have the same homothetic preferences, a larger supply of migrants (holding their skill mix constant) must increase the average utility of natives, unless the skill mixes of natives and migrants are identical (in which case there is no effect).*

Proof. See Appendix C. $\square$

Intuitively, one can think of all goods as being produced, directly or indirectly, by labor inputs. So, consumption of goods can be interpreted as demand for different types of labor. When M increases, the relative price of goods which are intensive users of migrant labor (in the sense of supply minus demand) must fall, and this must be to the advantage of natives. Note that Proposition 4 (that the immigration surplus is increasing in native-migrant skill differences) also applies to the multiple good case.

2.5 Robustness of conclusions

To summarize, any closed economy model, theoretical or empirical, which imposes CRS, convexity and perfectly elastic capital, must *always* predict that immigration (holding migrants' skill mix constant) increases the average MP of native labor, irrespective of the data used for estimation - unless natives and migrants have identical skill mixes.

We have assumed that the labor inputs in the **L** vector are fixed, but allowing for an imperfect elasticity of labor supply would not change the nature of these results. It would still be the case that, holding the migrant skill mix fixed, immigration generates an outward-shift of the labor demand curve for the average native. Whether this shift manifests in higher wages or employment will depend on the elasticity of the supply of natives to the labor market. We return to this question in the empirical analysis below. But either way, the shift in MPs for fixed labor inputs is informative about whether labor market opportunities are improving for natives.

Above, we have identified the fixed inputs in **L** with labor. But one may also consider "short run" scenarios where some capital inputs are fixed. In this more general case, the results above will apply to the average MP of *all* fixed native-owned factors in **L**, whether labor or capital; and native labor may lose out on average. But if capital is elastic in the "long run", the entire surplus will ultimately pass to native labor. Certainly, there are objections to this scenario: persistent immigration may depress wages if capital cannot accumulate fast enough (Borjas, 2019), though immigration may also yield increasing returns if there are human capital externalities. Still, Ottaviano and Peri (2012) argue that long run macroeconomic trends are consistent with CRS and elastic capital.

Under perfect competition, the predicted increase in native labor's average MP will necessarily translate to larger average wages. However, we now show that an imperfectly competitive model can admit the possibility of *negative* wage effects (even if MPs increase), if immigration increases the monopsony power of firms. To the extent that firms accrue rents by employing migrants, imperfect competition will also have implications for the *total* native surplus (of firms and workers combined) - as we discuss below.

3 Modeling imperfect competition

3.1 Existing literature

There is a small literature which models the impact of migration under imperfect competition. Most studies (Chassamboulli and Palivos, 2013, 2014; Chassamboulli and Peri, 2015; Battisti et al., 2017) assume wages are bargained individually (due to random matching), which rules out direct competition between natives and migrants. As a result, natives unambiguously benefit from low migrant wage demands: immigration stimulates the creation of new vacancies, which improves natives' outside options and wage bargains. In contrast, Malchow-Moller, Munch and Skaksen (2012), Amior (2017) and Albert (forthcoming) do allow for direct competition; but they all take marginal products as given, which rules out wage effects through traditional competitive channels. In this paper, we will offer a simple estimable framework which can account for both.

3.2 Monopsony model for labor market j

In this section, we illustrate how immigration may affect the mark-downs imposed by firms. We offer a stylized model of an individual firm operating in the market for skill type j labor. To focus on the mark-down effect, we turn off the marginal product effect for now: we assume type j natives and migrants have the same marginal product, denoted by MP_j, which does not depend on the level of employment. But when we move to the empirical model in Section 4, we relate MP_j to the long run technology in equation (3).

Suppose the supply of native labor to the firm takes the form proposed by Card et al. (2018):

$$N = N_0 \left(W - R_N\right)^{\epsilon_N} \tag{7}$$

where N_0 will depend on the wages offered by other firms and the number of natives in the market. R_N functions as a reservation wage, below which natives will not work; and the supply curve is iso-elastic in wages in excess of R_N. Card et al. (2018) motivate this upward-sloping curve (the source of firms' market power) by workers having idiosyncratic preferences over firms, but one might alternatively motivate it by search frictions. The supply of migrants takes the same form, but with possibly different reservation R_M and elasticity ϵ_M:

$$M = M_0 \left(W - R_M\right)^{\epsilon_M} \tag{8}$$

There are various reasons why migrants' reservations may lie below those of natives, i.e. $R_M < R_N$. Migrants may base their reference points on their country of origin (Constant et al., 2017; Akay, Bargain and Zimmermann, 2017), whether for psychological reasons or because of remittances (Albert and Monras, 2018; Dustmann, Ku and Surovtseva, 2019). They may discount their time in the host country more heavily, perhaps because they intend to only work there for a limited period (Dustmann and Weiss, 2007), or because of binding visa time limits or deportation risk. And they may face more restricted access to out-of-work benefits. Using a structural model, Nanos and Schluter (2014) conclude that migrants do indeed demand lower wages (for given productivity). Also, Albert (forthcoming) shows that undocumented migrants transition much more quickly from unemployment to employment than other workers, which is consistent with lower reservation wages.

Natives and migrants may also differ in their elasticity parameter ϵ. Migrants may be less efficient in job search, due to lack of information, language barriers, exclusion from social networks, undocumented status (Kossoudji and Cobb-Clark, 2002; Orrenius and Zavodny, 2009; Hotchkiss and Quispe-Agnoli, 2013), the E-Verify program (which compels employers to authenticate legal status: see e.g. Borjas and Cassidy, 2019, on wage effects), or visa-related restrictions on labor mobility (see e.g. Matloff, 2003; Depew, Norlander and Sørensen, 2017; Hunt and Xie, 2019; Wang, forthcoming on the H-1B and L-1; see Gibbons et al., 2019, on other US guest worker programs; and see Naidu, Nyarko and Wang, 2016, on the UAE). These arguments suggest $\epsilon_M < \epsilon_N$; and indeed, Hirsch and Jahn (2015) find that migrants' job separations in Germany are less sensitive to wages than natives'.[5] In Appendix H.12, we offer similar evidence for the US (see also Biblarsh and De-Shalit, 2021), and show further that these native-migrant differences are largely driven by very low separation elasticities among non-citizens (and especially low-educated non-citizens). There are some reasons why one might expect the reverse. Cadena and Kovak (2016) argue that foreign-born workers are relatively mobile geographically, though this speaks to the elasticity of labor supply to *regions* and not to *individual employers* (which is what matters for monopsony power); also, see Amior (2020) for a dissenting view.

3.3 Optimal wage offers

The firm sets wages of type j natives and migrants (W_{Nj} and W_{Mj}) to maximize profit, subject to the labor supply curves (7) and (8). Since we are assuming that natives and migrants have the same (fixed) marginal product MP_j, profits can be written as:

$$\max_{W_{Nj}, W_{Mj}} \pi\left(W_{Nj}, W_{Mj}\right) = \left(MP_j - W_{Nj}\right) N\left(W_{Nj}\right) + \left(MP_j - W_{Mj}\right) M\left(W_{Mj}\right) \qquad (9)$$

We will consider two wage-setting assumptions: (i) perfect wage discrimination, where the firm is free to set distinct native and migrant wages, and (ii) zero discrimination, where the firm must offer the same wage to all type j workers (i.e. $W_{Nj} = W_{Mj} = W_j$).

We begin with the discriminating case. The labor supply curves (7) and (8) imply the following marginal cost functions for native and migrant labor:

$$MC_Q\left(W\right) = W + \frac{W - R_Q}{\epsilon_Q}, \quad Q = \{N, M\} \qquad (10)$$

The second term in (10) is decreasing in the reservation wage R_Q and the supply elasticity ϵ_Q (above the reservation). For illustration, we plot the MC curves for natives and

[5] Borjas (2017) shows similar patterns in market-level labor supply elasticities, which we confirm below: these will contribute to the firm-level elasticities (which determine monopsony power), though of course they are not the same.

migrants against wages W in Figure 1, under the assumption that $R_M < R_N$ and $\epsilon_M < \epsilon_N$. Notice MC_M lies above MC_N: intuitively, since migrants supply labor less elastically (whether because of a small R_M or ϵ_M), the cost of raising wages for the infra-marginals (per new worker is hired) is more prohibitive. Equating these marginal costs with the marginal product MP_j, the optimal migrant wage W_M will lie below the native wage W_N. Relative to the marginal product MP_j, the optimal native and migrant mark-downs (ϕ_{Nj} and ϕ_{Mj}) can be written as:

$$\phi_{Qj} = \log \frac{MP_j}{W_j} = \log \left(\frac{\epsilon_Q + 1}{\epsilon_Q + \frac{R_Q}{MP_j}} \right), \quad Q = \{N, M\} \tag{11}$$

The mark-down is decreasing in the reservation wage $\frac{R_Q}{MP_j}$ (relative to the marginal product) and the supply elasticity ϵ_Q (above the reservation). But crucially, the mark-down is independent of the number of migrants: this is because perfect discrimination ensures the native and migrant markets are fully segregated. The same implication arises from the individual bargaining models of Chassamboulli and Palivos (2013, 2014), Chassamboulli and Peri (2015) and Battisti et al. (2017).

[Figure 1 here]

However, if the firm cannot discriminate (such that $W_{Nj} = W_{Mj}$), natives and migrants will compete directly; and the mark-downs will depend on the migrant share. To see why, notice the firm now faces a marginal cost curve which lies between MC_N and MC_M (the dotted line in Figure 1). This curve tends towards MC_N as the wage rises (since in this example, natives supply labor more elastically, so they will comprise an ever larger share of the firm's labor pool); and similarly, it tends towards MC_M as the wage declines (and eventually touches MC_M, when the wage falls below the native reservation R_N). There is no simple closed-form expression for the mark-down in this case, but the optimal wage will lie between what a discriminating monopsonist pays to natives and migrants. As the migrant share increases, the marginal cost curve shifts towards MC_M; and in the case of Figure 1 (where $R_M < R_N$ and $\epsilon_M < \epsilon_N$), the optimal wage will fall. Intuitively, since the firm enjoys more market power over migrant labor, it can exploit immigration by extracting greater rents from natives and migrants alike. See Appendix D.2 for a more formal exposition.

Notice the migrant share has no effect if $R_M = R_N$ and $\epsilon_M = \epsilon_N$: since natives and migrants supply labor identically, the degree of market power is immune to immigration. And given the model's symmetry, the migrant share will have the opposite effect (and diminish mark-downs) if $R_M > R_N$ and $\epsilon_M > \epsilon_N$.

This simple model is consistent with a range of evidence. The model predicts that more productive firms should pay higher wages and hire relatively fewer migrants (if they supply labor less elastically); and indeed, De Matos (2017), Dostie et al. (2020) and Arellano-Bover and San (2020) find that migrant-native wage differentials are partly driven by firm effects. The model can also explain why *individual* employers spend heavily on foreign recruitment (whether through political lobbying to influence visa rules, payment of visa fees, or use of foreign employment agencies: see e.g. Rodriguez, 2004; Fellini, Ferro and Fullin, 2007; Facchini, Mayda and Mishra, 2011), which is difficult to explain if wages are equal to marginal products. Indeed, Doran, Gelber and Isen (2014) find that firms reduce average pay and take larger profits after winning H-1B lotteries. See also Gibbons et al. (2019) on the substantial costs which US firms pay to recruit migrants through guest worker programs. Finally, Brown, Hotchkiss and Quispe-Agnoli (2013) show the employment of undocumented workers significantly enhances firms' survival prospects.

3.4 Implications for immigration surplus

The existence of monopsony power has important implications for the immigration surplus. In Section 2, we showed that natives must benefit on average from immigration, under very general assumptions. If the labor market is competitive, this surplus will be entirely captured by native labor in the "long run" scenario where capital is elastically supplied. However, the mere existence of non-zero mark-ups will generate a surplus for firms also - as they will take a cut on the marginal products of new immigrants. And furthermore, if immigration allows firms to impose larger mark-downs on the existing workforce, they may capture more of the surplus for themselves - at the expense of native labor. The impact of immigration on the mark-downs may be larger if migrants compete more closely with natives whereas the reverse is true for the marginal products (Borjas, 1995). Ultimately, whether native labor or firms benefit is an empirical question; and we will quantify these effects in Section 8 below.

4 Empirical model

The model of the previous section illustrates why the migrant share might affect mark-downs, but it is too stylized to apply directly to data. We now turn to our empirical model. We begin by discussing identification of the mark-down effects, and we then set out our estimation strategy.

4.1 Production technology and wages

Our empirical application, following a long-standing empirical literature beginning with Borjas (2003), is to exploit variation across education-experience cells - though our strategy could also be applied if the labor market were segmented in some other way, e.g. by geography or occupation. We model the education-experience cells as the lowest (observable) level of a nested CES structure. In the long run, output $\tilde{Y}_t$ at time t (net of the elastic inputs' costs) depends on the composite labor inputs, L_{et}, of education groups e:

$$\tilde{Y}_t = \left(\sum_e \alpha_{et} L_{et}^{\sigma_E} \right)^{\frac{1}{\sigma_E}} \tag{12}$$

where the α_{et} are education-specific productivity shifters (which may vary with time), and $\frac{1}{1-\sigma^E}$ is the elasticity of substitution between education groups. In turn, the education inputs L_{et} will depend on (education-specific) experience inputs L_{ext}:

$$L_{et} = \left(\sum_x \alpha_{ext} L_{ext}^{\sigma_X} \right)^{\frac{1}{\sigma_X}} \tag{13}$$

where the α_{ext} encapsulate the relative efficiency of the experience inputs within each education group e. Finally, in line with Card (2009), Manacorda, Manning and Wadsworth (2012), Ottaviano and Peri (2012) and Piyapromdee (forthcoming), we allow for distinct native and migrant labor inputs (within education-experience cells) which are imperfect substitutes:

$$L_{ext} = Z_{ext} \left(N_{ext}, M_{ext} \right) \tag{14}$$

We will ultimately impose a CES structure on the Z_{ext} function also; but for now, we assume only constant returns and convexity. We can then write equations for log native and migrant wages in education-experience cells as the log marginal product minus a mark-down:

$$\log W_{Next} = \log \left\{ A_{ext} \left[Z_{ext} \left(N_{ext}, M_{ext} \right) \right]^{\sigma_X - 1} \frac{\partial Z_{ext} \left(N_{ext}, M_{ext} \right)}{\partial N_{ext}} \right\} - \phi_{Next} \left(\frac{M_{ext}}{N_{ext}} \right) \tag{15}$$

$$\log W_{Mext} = \log \left\{ A_{ext} \left[Z_{ext} \left(N_{ext}, M_{ext} \right) \right]^{\sigma_X - 1} \frac{\partial Z_{ext} \left(N_{ext}, M_{ext} \right)}{\partial M_{ext}} \right\} - \phi_{Mext} \left(\frac{M_{ext}}{N_{ext}} \right) \tag{16}$$

where A_{ext} is a cell-level productivity shifter:

$$A_{ext} = \alpha_{et} \alpha_{ext} \left(\frac{\tilde{Y}_t}{L_{et}} \right)^{1-\sigma_E} L_{et}^{1-\sigma_X} \tag{17}$$

which summarizes the impact of all other labor market cells, as well as the general level of productivity. The wage equations in (15) and (16) allow for the presence of native and migrant mark-downs which (i) potentially differ from one another *and* (ii) may depend on the cell-level migrant share.

One may rationalize (i) and (ii) by a model where *some* firms can discriminate (which ensures native and migrant mark-downs differ to some extent) and *others* cannot (which generates some dependence on the migrant share). But in Appendix D, we show it can also be rationalized by a model with *no* discriminating firms, as long as natives and migrants differ in their skill distribution *within* education-experience cells. Drawing on a long-standing literature on production functions (Houthakker, 1955; Levhari, 1968; Jones, 2005; Growiec, 2008), the observable education-experience cell Z can be interpreted as an aggregation of many *unobservable* skill-defined labor markets j (corresponding to those described in Section 3): see also the transformation in equation (4). In each market j, natives and migrants are productively identical and perfect substitutes; and in the absence of discrimination, they receive identical wages, with mark-downs varying with the migrant share. But at the level of (observable) education-experience cells, natives and migrants will be imperfect substitutes, as long as the migrant share varies across the constituent markets j. Furthermore, the *average* native and migrant mark-downs (at the cell level) may differ from one another, as migrants will be over-represented in (unobservable) markets j with larger migrant shares (and potentially different mark-downs). The idea that natives and migrants may have different skill specializations *within* education-experience cells has some precedent in the literature: e.g. Peri and Sparber (2009) emphasize comparative advantage in communication or manual tasks.

4.2 Identification

In principle, we would like to estimate the cell-level wage equations (15) and (16). However, it turns out we cannot separately identify (i) the cell aggregator Z in the lowest observable nest and (ii) the mark-down functions (ϕ_N, ϕ_M), using standard wage and employment data. Nevertheless, we can test the joint hypothesis that the native and migrant mark-downs are equal and independent of the cell-level migrant share, of which perfect competition is a special case (where both mark-downs are fixed at zero).

In Appendix E, we show how this joint hypothesis can be tested for *any* constant returns technology Z, and for mark-down functions ϕ_N and ϕ_M with any functional form. In practice though, we do impose more structure on the technology and mark-downs; and this section describes our identification strategy under these restrictions. However, we do exploit the more general model in Appendix E to explore the possibility of misspecification of technology: this will be important for the interpretation of our results.

In line with the canonical model (Card, 2009; Manacorda, Manning and Wadsworth, 2012; Ottaviano and Peri, 2012), we assume Z has CES form:

$$Z_{ext}\left(N_{ext}, M_{ext}\right) = \left(N_{ext}^{\sigma_Z} + \alpha_{Zext} M_{ext}^{\sigma_Z}\right)^{\frac{1}{\sigma_Z}} \tag{18}$$

where α_{Zext} is a migrant-specific productivity shifter (which is permitted to vary across cells and over time), and $\frac{1}{1-\sigma^Z}$ is the elasticity of substitution between natives and migrants (within education-experience cells). We also assume the mark-downs ϕ_{Next} and ϕ_{Mext} can be written as log-linear functions of $\frac{M_{ext}}{N_{ext}}$:

$$\begin{aligned} \phi_{Next}\left(\frac{M}{N}\right) &= \phi_{0Next} + \phi_{1N} \log \frac{M}{N} && (19) \\ \phi_{Mext}\left(\frac{M}{N}\right) &= \phi_{0Next} + \Delta\phi_{0ext} + \left(\phi_{1N} + \Delta\phi_1\right) \log \frac{M}{N} && (20) \end{aligned}$$

where we permit the two mark-downs to have different (cell and time-varying) intercepts and different sensitivity to $\frac{M}{N}$. Though we express ϕ_N and ϕ_M as functions of $\log \frac{M}{N}$, there are theoretical reasons to prefer a specification in terms of the migrant share, $\frac{M}{N+M}$: equal absolute changes are more likely to have the same impact on mark-downs than equal proportionate changes. We make this point more formally in Appendix D.5. But as we now show, we can better illustrate the identification problem by formulating (19) and (20) in terms of $\log \frac{M}{N}$.[6]

Applying (18)-(20), the wage equations (15) and (16) can then be expressed as:

$$\log W_{Next} = \log A_{ext} - \phi_{0Next} - (1-\sigma_X)\log N_{ext} - (\sigma_Z - \sigma_X)\log\left[1 + \alpha_{Zext}\left(\frac{M_{ext}}{N_{ext}}\right)^{\sigma_Z}\right]^{\frac{1}{\sigma_Z}} - \phi_{1N}\log\frac{M_{ext}}{N_{ext}} \tag{21}$$

$$\begin{aligned} \log W_{Mext} = {} & \log A_{ext} + \log \alpha_{Zext} - \phi_{0Next} - \Delta\phi_{0ext} - (1-\sigma_X)\log N_{ext} \\ & - (\sigma_Z - \sigma_X)\log\left[1 + \alpha_{Zext}\left(\frac{M_{ext}}{N_{ext}}\right)^{\sigma_Z}\right]^{\frac{1}{\sigma_Z}} - (1 - \sigma_Z + \phi_{1N} + \Delta\phi_1)\log\left(\frac{M_{ext}}{N_{ext}}\right) \end{aligned} \tag{22}$$

where σ_X represents the substitutability between experience groups, σ_Z between natives and migrants (within education-experience cells), and A_{ext} is the cell-level productivity shifter defined by (17).

Clearly, it is impossible to separately identify the productivity shifter A from the mark-down intercept ϕ_{0N}. Intuitively, the observed wage in some cell can be rationalized by one (A, ϕ_{0N}) combination, but also by a larger A and ϕ_{0N}.[7] One may be able to

[6] If we write (19) and (20) in terms of $\frac{M}{N+M}$, we could in principle rely on functional form for identification. But we prefer not to pursue this strategy.

[7] There may also be a price mark-up if the goods market is imperfectly competitive. Any such mark-up is unlikely to depend on the migrant share in the workforce, so we subsume this in the constant.

separately identify these parameters using data on output and labor shares, but we do not pursue this line of inquiry here.

Of greater concern for our purposes, we also cannot identify the effect of the migrant share on the mark-downs (i.e. ϕ_{1N} for natives), if this effect is different for natives and migrants (i.e. if $\Delta\phi_1 \neq 0$). To see this, suppose one observes a large number of labor market cells, differing only in the total number of natives N and the ratio $\frac{M}{N}$. Then, using (21) and (22), one can identify σ_X by observing how wages vary with N, holding the ratio $\frac{M}{N}$ constant (which fixes the final two terms in each equation). However, holding N constant and observing how wages vary with $\frac{M}{N}$, it is not possible to separately identify the three parameters $(\sigma_Z, \phi_{1N}, \Delta\phi_1)$, as we only have two equations.

4.3 Empirical strategy

While the most general model is not identified, there are interesting models which can be estimated and tested. It is useful to consider two distinct hypotheses:

1. $H1$ **(Equal mark-downs)**: Natives face the same mark-downs as migrants within labor market cells: $\phi_{Next}\left(\frac{M}{N}\right) = \phi_{Mext}\left(\frac{M}{N}\right)$. In terms of (19) and (20), this is equivalent to: $\Delta\phi_{0ext} = \Delta\phi_1 = 0$.

2. $H2$ **(Independent mark-downs)**: Natives' mark-downs are independent of migrant share, i.e. $\phi'_{Next}\left(\frac{M}{N}\right) = 0$. Or in terms of (19), $\phi_{1N} = 0$.

Of course, $H1$ and $H2$ jointly imply that migrants' mark-downs are also independent of migrant share, i.e. $\phi'_{Mext}\left(\frac{M}{N}\right) = 0$. Perfect competition is a special case of the joint hypothesis of $H1$ and $H2$, with both mark-downs equal to zero. More generally, both $H1$ and $H2$ follow from the case of $R_M = R_N$ and $\epsilon_M = \epsilon_N$ in our model above, where natives and migrants supply labor to firms identically; but our tests of these claims will have validity irrespective of the underlying theory of imperfect competition.

Though we cannot test $H1$ and $H2$ in isolation, it turns out we can test the joint hypothesis of $H1$ and $H2$. This is because $H1$ implies restrictions which make $H2$ testable. Our strategy consists of two steps:

Step 1: Estimate the relative wage equation

Take differences between (21) and (22), which yields the following expression for log relative wages:

$$\log \frac{W_{Mext}}{W_{Next}} = \log \alpha_{Zext} - \Delta\phi_{0ext} - (1 - \sigma_Z + \Delta\phi_1) \log \frac{M_{ext}}{N_{ext}} \tag{23}$$

which we estimate by regressing $\log \frac{W_{Mext}}{W_{Next}}$ on $\log \frac{M_{ext}}{N_{ext}}$, exploiting variation across skill cells and over time. Equation (23) shows the identification problem: the intercepts cannot disentangle α_{Zext} from $\Delta\phi_{0ext}$; and the slope coefficient cannot disentangle σ_Z from $\Delta\phi_1$. But conditional on $H1$ (i.e. $\Delta\phi_{0ext} = \Delta\phi_1 = 0$), we can identify the technology parameters α_{Zext} and σ_Z. Indeed, this is the implicit assumption imposed by Card (2009), Manacorda, Manning and Wadsworth (2012), Ottaviano and Peri (2012).

Step 2: Conditional on $H1$, estimate the native wage equation

Rearranging (21), write the native wage equation as:

$$\log W_{Next} + (1-\sigma_Z)\log N_{ext} = \log A_{ext} - \phi_{0Next} - (\sigma_Z - \sigma_X)\log\left(N_{ext}^{\sigma_Z} + \alpha_{Zext}M_{ext}^{\sigma_Z}\right)^{\frac{1}{\sigma_Z}} - \phi_{1N}\log\frac{M_{ext}}{N_{ext}} \tag{24}$$

Using our $(\alpha_{Zext}, \sigma_Z)$ estimates from Step 1 (i.e. conditional on $H1$), we can compute (i) the left-hand side expression (a weighted average of log native wages and employment)[8] and (ii) the cell "Armington" aggregator $\left(N_{ext}^{\sigma_Z} + \alpha_{Zext}M_{ext}^{\sigma_Z}\right)^{\frac{1}{\sigma_Z}}$. We can then estimate (24) by regressing $[\log W_{Next} + (1-\sigma_Z)\log N_{ext}]$ on $\log\left(N_{ext}^{\sigma_Z} + \alpha_{Zext}M_{ext}^{\sigma_Z}\right)^{\frac{1}{\sigma_Z}}$ and $\log \frac{M_{Ext}}{N_{ext}}$; and the coefficient on $\log \frac{M_{ext}}{N_{ext}}$ will identify ϕ_{1N}. Intuitively, the effect of immigration on the marginal products must enter through the cell aggregator; so conditional on this, the cell composition $\log \frac{M}{N}$ will pick up the mark-down effect. Conditional on $H1$, a rejection of $\phi_{1N} = 0$ (i.e. independent native mark-downs, $H2$) would then imply a rejection of the joint hypothesis of $H1$ and $H2$. More generally, notice that for any given set of $(\alpha_{Zext}, \sigma_Z)$ values, equation (24) can identify the mark-down effect ϕ_{1N}: as we show below, this permits a form of set-identification of the key parameters.

We have framed this test using the native wage equation (24), but one may alternatively derive an equivalent equation for migrant wages. However, this would add no information beyond the combination of the relative wage equation (23) and the native levels equation (24). We now describe the data we use to estimate the model.

5 Data

5.1 Samples and variable definitions

As in Borjas (2003; 2014) and Ottaviano and Peri (2012), we exploit variation across education-experience cells in US census data to estimate our wage equations. One might

[8] This type of measure has precedent in the literature on technical change (Berman, Bound and Griliches, 1994). E.g. if the lower nest Z is Cobb-Douglas (so $\sigma_Z = 0$), the left-hand side becomes the log native wage bill.

alternatively rely on geographical variation; but this would raise pertinent questions about adjustment through internal mobility (see e.g. Borjas, Freeman and Katz, 1997; Amior, 2020; Piyapromdee, forthcoming), which would distract from our agenda. We construct our data in a similar way to these earlier studies, but we extend the time horizon: we use IPUMS census extracts of 1960, 1970, 1980, 1990 and 2000, and American Community Survey (ACS) samples of 2010 and 2019 (Ruggles et al., 2017).[9] Throughout, we exclude under-18s and those living in group quarters.

Following Borjas (2003) and Ottaviano and Peri (2012), we group individuals into four education groups in our main specifications: (i) high school dropouts, (ii) high school graduates, (iii) some college education and (iv) college graduates.[10] But we also consider specifications with two education groups: college and high-school equivalents. Following Borjas (2003; 2014) and Ottaviano and Peri (2012), we divide each education group into eight categories of potential labor market experience[11], based on 5-year intervals between 1 and 40 years - though we also estimate specifications with four 10-year categories.

We identify employment stocks with hours worked, and wages with log weekly earnings of full-time civilian employees (at least 35 hours per week, and 40 weeks per year), weighted by weeks worked - though we study robustness to using hourly wages. Following Borjas (2003, 2014), we exclude enrolled students from the wage sample. For each wage variable, we exclude the top and bottom 1% of observations in each cross-section.

5.2 Composition-adjusted wages

Ruist (2013) argues that Ottaviano and Peri's (2012) estimates of the elasticity of relative migrant-native wages (within education-experience cells) may be conflated with changes in the composition of the migrant workforce (by country of origin). To address this issue (and related concerns about composition effects), we adjust wages for observable changes in demographic composition over time in our main specifications.

We begin by pooling census and ACS microdata from all our observation years. Separately for each of our 32 education-experience cells, and separately for men and women, we regress log wages on a quadratic in age, a postgraduate education indicator (for col-

[9]The 1960 census does not report migrants' year of arrival or citizenship status, but we require this information for various parts of the analysis. In particular, we need to know (i) the employment stock of migrants living in the US for no more than ten years and (ii) the employment stock of citizens, both by education-experience cell. We impute (i) using information on the same migrant cohorts (by year of arrival and citizenship status) 10 years later. And we then impute (ii) using citizen shares of old and new migrant stocks across education-experience cells in 1970. See Appendix G.1 for further details.

[10]Borjas (2014) further divides college graduates into undergraduate and postgraduate degree-holders. We choose not to account for this distinction, as there are very few postgraduates early in our sample.

[11]To predict experience, we assume high school dropouts begin work at 17, high school graduates at 19, those with some college at 21, and college graduates at 23.

lege graduate cells only), race indicators (Hispanic, Asian, black), and a full set of year effects. We then predict the mean male and female wage for each year, for a distribution of worker characteristics identical to the multi-year pooled sample (within education-experience cells). And finally, we compute a composition-adjusted native wage in each cell-year by taking weighted averages of the predicted male and female wages (using the gender ratios in the pooled sample as weights). We repeat the same exercise for migrants, but replacing the race indicators with dummies covering 12 regions of origin[12], and also including an indicator for recent arrivals[13].

5.3 Instruments

One may be concerned that both native and migrant employment, by education-experience cell, are endogenous to wages. Unobserved cell-specific demand shocks may affect the human capital choices of natives (Hunt, 2017; Llull, 2018*b*) and foreign-born residents, as well as the skill mix of new migrants from abroad (Llull, 2018*a*; Monras, 2020). These shocks may also affect individuals' labor supply choices, even conditional on their education and experience. To address these concerns, we construct instruments (by demographic cell) for each of three worker types: (i) natives, (ii) "old" migrants (living in the US for more than ten years) and (iii) "new" migrants (up to ten years), which are intended to exclude cell-specific innovations to labor demand. Our strategy is to predict the population of each cell based on the mechanical aging of cohorts (by education) over time, both in the US and abroad. We discuss each of the three instruments in turn.

(i) Natives. The mechanical aging of native cohorts generates predictable changes in cell population stocks over time, as younger (and better educated) cohorts replace older ones (as in Card and Lemieux, 2001). For natives aged over 33, we predict cell populations using cohort sizes (by education) ten years previously, separately by single-year age. For example, the stock of native college graduates aged 50 in 1980 is predicted using the population of 40-year-old native graduates in 1970. This is not feasible for 18-33s: given our assumptions on graduation dates, some of them will not have reached their final education status. In these cases, we allocate the *total* cohort population (by single-year age) to education groups using the same shares as the preceding cohort (i.e. from ten years earlier). Having constructed historical cohort population stocks (ten years before observation year t) by single-year age and education, we then aggregate to 5-year experience groups. We denote our instrument as $\tilde{N}_{ext}$, for each of 32 education-experience

[12]Specifically: North America, Mexico, Other Central America, South America, Western Europe, Eastern Europe and former USSR, Middle East and North Africa, Sub-Saharan Africa, South Asia, Southeast Asia, East Asia, Oceania.

[13]Specifically, we include a dummy for arriving in the US in the previous five years: this category is observable in all census years, including 1960.

cells (e, x) and 7 observation years t (between 1960 and 2019).

(ii) Old migrants. We construct our instrument for "old" migrants $\tilde{M}^{old}_{ext}$ (with more than ten years in the US) in an identical way. Specifically, for over-33s, we use foreign-born cell populations within education cohorts ten years previously; and for 18-33s, we allocate total historical cohort populations to education groups according to the education choices of earlier cohorts.

(iii) New migrants. Analogously to our approach for existing US residents, we predict "new" migrant inflows using historical cohort sizes (by education) in *origin countries.*[14] This is motivated by Hanson, Liu and McIntosh (2017), who relate the rise and fall of US low skilled immigration to changing fertility patterns in Latin America. For each education-experience cell (e, x) and year t, we predict the population of "new" immigrants (with up to ten years in the US) as a weighted aggregate of historical cohort sizes in origin countries (ten years before t), using data from Barro and Lee (2013). The weights are based on origin-specific emigration propensities (since demographic shifts in certain global regions matter more for immigration to the US) and a time-invariant cell-specific index of geographical mobility (varying by education and experience). In practice, our weights are the coefficient estimates from a regression of log population of new migrants (by origin, education, experience and time) on origin region fixed effects and the mobility index. See Appendix G.2 for further details. We denote the predicted new migrant stocks (aggregated to cell-level) as $\tilde{M}^{new}_{ext}$. Combining this with the old migrant instrument, we can now predict the *total* migrant stock as $\tilde{M}_{ext} = \tilde{M}^{old}_{ext} + \tilde{M}^{new}_{ext}$.

It is important to stress that these instruments are *not* simply lags in a panel of education-experience cells. Rather, for US residents (natives and old migrants), we are tracking populations within *birth cohorts* (and not within education-experience cells); and for new immigrants, we are exploiting information on cohort sizes *abroad*. For US residents, variation in the instrument is driven by the replacement of older cohorts with younger and better educated ones (as in Card and Lemieux, 2001). And among new immigrants, the instrument predicts the replacement of older Europeans with lower educated cohorts from Latin America (see Table 1 below). Reassuringly, as we show in Appendix H.4 and H.5, the instruments have sufficient power to disentangle contemporaneous immigration shocks from those which occurred one period (i.e. ten years) earlier, and to disentangle variation in new and old migrant shares.

[14] Llull (2018*a*) and Monras (2020) offer alternative instruments for cell-specific inflows of new migrants: Monras exploits a natural experiment (the Mexican Peso crisis), while Llull bases his instrument on interactions of origin-specific push factors, distance and skill-cell dummies. But for consistency with our approach for existing residents, we instead exploit data on historical cohort sizes.

5.4 Descriptive statistics

Table 1 sets out a range of descriptive statistics, across our 32 education-experience cells. The average migrant employment share, $\frac{M_{ext}}{N_{ext}+M_{ext}}$, was just 5% in 1960 (Panel A), but reached 24% by 2019. This expansion was disproportionately driven by high school dropouts (Panel B). In Panel C, we predict changes in migrant share using our instruments: specifically, we report changes in $\frac{\tilde{M}_{ext}}{\tilde{N}_{ext}+\tilde{M}_{ext}}$, where $\tilde{M}_{ext} = \tilde{M}_{ext}^{old} + \tilde{M}_{ext}^{new}$. These changes closely resemble the patterns in Panel B, though the instruments do underpredict the increase in migrant share among young college graduates. In Appendix Table A2, we break down these predicted changes into contributions from new and old migrants: both match the observed data reasonably well. The strong performance of the instruments suggests that much of the variation in migrant share can be predicted from demographic factors alone (i.e. historical cohort sizes, both in the US and abroad).

[Table 1 here]

The remaining panels report variation in wages, adjusted for changes in demographic composition. Panel D shows that wages have declined most among the young and low educated (these changes are normalized to have mean zero across all groups).

Panel E sets out the mean migrant-native wage differentials in each cell, averaged over all sample years. In almost all cells, migrants earn less than natives, with wage penalties varying from 0 to 15%, typically larger among high school workers and the middle-aged. In the context of our model, these penalties may reflect differences in within-cell marginal products or alternatively differential monopsony power. Either way, this can be interpreted as "downgrading", in the sense that migrants receive "lower returns to the same measured skills than natives" (Dustmann, Schoenberg and Stuhler, 2016).

6 Estimates of wage effects

We now turn to our empirical estimates. We begin by estimating the relative wage equation (23). On imposing $H1$, we are able to identify $(\alpha_{Zext}, \sigma_Z)$, and this allows us to test the joint hypothesis of $H1$ and $H2$ by estimating the native wage equation (24). As it happens, we reject this joint hypothesis; and we then explore set identification of the key parameters by exploiting the model's various restrictions.

6.1 Estimates of relative wage equation

We initially parameterize the differential migrant productivity/mark-down effect in (23) as:

$$\log \alpha_{Zext} - \Delta\phi_{0ext} = \log \bar{\alpha}_Z - \bar{\Delta\phi}_0 + u_{ext} \tag{25}$$

for education e, experience x and time t, where $\log \bar{\alpha}_Z$ and $\bar{\Delta\phi}_0$ are means across education-experience cells, and the deviations u_{ext} have mean zero. (25) yields the following specification:

$$\log \frac{W_{Mext}}{W_{Next}} = \beta_0 + \beta_1 \log \frac{M_{ext}}{N_{ext}} + u_{ext} \tag{26}$$

where β_0 identifies $\log \bar{\alpha}_Z - \bar{\Delta\phi}_0$, and β_1 identifies $-(1 - \sigma_Z + \Delta\phi_1)$.

We report estimates of (26) in Table 2.[15] In line with Ottaviano and Peri (2012), we cluster our standard errors by the 32 education-experience cells. And following the recommendation of Cameron and Miller (2015), we apply a small-sample correction to the cluster-robust standard errors (in this case, scaling them by $\sqrt{\frac{G}{G-1} \cdot \frac{N-1}{N-K}}$) and using $T(G-1)$ critical values, where G is the number of clusters, and K the number of regressors and fixed effects. We apply these adjustments both for OLS and IV. The relevant 95% critical value of the T distribution (with 31 degrees of freedom) is 2.04.[16]

[Table 2 here]

In column 1, we present OLS estimates for "raw" wages (i.e. not adjusted for changes in demographic composition): β_0 takes a value of -0.13, and β_1 is -0.029. These numbers are comparable to Ottaviano and Peri (2012).[17] Under the hypothesis of equal mark-downs $H1$ (i.e. $\Delta\phi_{0ext} = \Delta\phi_1 = 0$), β_0 identifies the mean within-cell productivity differential $\log \bar{\alpha}_Z$, and β_1 identifies $-(1 - \sigma_Z)$, implying a large elasticity of substitution of $\frac{1}{1-\sigma_Z} = 34$ between natives and migrants. But in general, these parameters cannot be separately identified from differentials in the mark-downs: a negative β_0 may reflect larger migrant mark-downs ($\bar{\Delta\phi}_0 > 0$), and a negative β_1 a greater sensitivity of migrant mark-downs to immigration ($\Delta\phi_1 > 0$).

Our β_1 estimate varies little with specification. In some columns, it is significantly different from zero (as in Ottaviano and Peri, 2012), and in others not (as in Borjas,

[15] Borjas, Grogger and Hanson (2012) find the β_1 coefficient is sensitive to the choice of regression weights: they recommend using the inverse sampling variance, rather than Ottaviano and Peri's total employment. In light of this controversy, we have chosen instead to focus on unweighted estimates.

[16] As Cameron and Miller (2015) emphasize, these adjustments do not entirely eliminate the bias. But even when we reduce the number of clusters to 16, bootstrapped estimates suggest the bias is small in this data: see Appendix H.9.

[17] For full-time wages of men and women combined, with no fixed effects, Ottaviano and Peri estimate a β_1 of -0.044: see column 4 of their Table 2. The small difference is partly due to our extended year sample (we include 2010 and 2019) and restricted wage sample (like Borjas, 2003, we exclude students).

Grogger and Hanson, 2012). But the differences are quantitatively small: under $H1$, natives and migrants are either perfect substitutes (if $\beta_1 = 0$) or very close substitutes (if e.g. $\beta_1 = -0.029$); and as we show below, this variation makes little difference to our estimates of the native wage equation.

With this in mind, we now go into the specifics. Adjusting wages for composition in column 2 attenuates our β_1 estimate towards zero, which reflects Ruist's (2013) findings on migrant cohort effects. Following Ottaviano and Peri, we also respecify α_{Zext} to include interacted education-experience and year fixed effects:

$$\alpha_{Zext} = \alpha_{Zex} + \alpha_{Zt} + u_{ext} \tag{27}$$

which enter our empirical specification in columns 4-5. Instead of a constant, we now report the mean β_0 intercept across all observations (averaging the fixed effects). β_1 turns small and negative in column 4, and the mean β_0 expands. In column 6, we estimate the model in first differences, i.e. regressing $\Delta \log \frac{W_{Mext}}{W_{Next}}$ on $\Delta \log \frac{M_{ext}}{N_{ext}}$: β_1 now expands to -0.04. But once we include year effects (column 8), β_1 goes down to zero.

One may be concerned that the relative migrant supply, $\frac{M_{ext}}{N_{ext}}$, is endogenous to within-cell relative (migrant/native) demand shocks in the error, u_{ext}. It is not possible to sign the resulting bias. To the extent that employment responds positively to cell-specific demand, we may expect our OLS estimates to be positively biased. On the other hand, if native and migrant labor supply elasticities differ (as our estimates in Section H.6 suggest), a balanced cell-level demand shock could generate a negative correlation between relative wages and employment - which would bias the OLS estimates negatively.

In columns 3, 5, 7 and 9, we instrument $\log \frac{M_{ext}}{N_{ext}}$ with $\log \frac{\tilde{M}_{ext}}{\tilde{N}_{ext}}$, where $\tilde{M}_{ext} = \tilde{M}^{new}_{ext} + \tilde{M}^{old}_{ext}$ is the total predicted migrant employment (described above), and $\tilde{N}_{ext}$ is predicted native employment.[18] In each case, the first stage has considerable power: see Panel B. But our estimates change little. Under fixed effects, they do become more negative (reaching -0.029 in column 5); though the difference is quantitatively small. To summarize, our mean β_0 varies from -0.09 to -0.15, and β_1 from zero to -0.045.

6.2 Native wage equation: Test of null hypothesis

We now test the null hypothesis of equal and independent mark-downs (i.e. the combination of $H1$ and $H2$), of which perfect competition is a special case. To this end, we turn to the equation for native wages (24). We parameterize the cell-level productivity shifter A_{ext} in (17) as:

$$\log A_{ext} = d_{ex} + d_{et} + d_{xt} + v_{ext} \tag{28}$$

[18] In columns 7 and 9, the instrument is differenced - like the endogenous variable.

where the d_{ex} are education-experience interacted fixed effects, the d_{et} are education-year effects, and the d_{xt} experience-year effects. Comparing to (17), notice the d_{et} pick up productivity shocks α_{et} and labor supply effects at the education nest level (i.e. L_{et}); and the d_{ex} and d_{xt} account for components of the education-specific experience effects α_{ext}. Any remaining variation in the α_{ext} (at the triple interaction) falls into the idiosyncratic v_{ext} term. Our native wage equation (24) can then be estimated using:

$$\begin{aligned}[\log W_{Next} + (1-\sigma_Z)\log N_{ext}] &= \gamma_0 + \gamma_1 \left[\log\left(N_{ext}^{\sigma_Z} + \alpha_{Zext} M_{ext}^{\sigma_Z}\right)^{\frac{1}{\sigma_Z}}\right] \\ &\quad + \gamma_2 \log \frac{M_{ext}}{N_{ext}} + d_{ex} + d_{et} + d_{xt} + v_{ext}\end{aligned} \tag{29}$$

Based on (24), γ_1 will identify $(\sigma_X - \sigma_Z)$, where σ_X measures the substitutability between experience groups and σ_Z between natives and migrants (within education-experience cells). In turn, γ_2 will identify $-\phi_{1N}$, the impact of migrant composition on native wage mark-downs. In some specifications, we replace the relative supply variable $\log \frac{M_{ext}}{N_{ext}}$ with the migrant share $\frac{M_{ext}}{N_{ext}+M_{ext}}$: as we argue above, the latter should better represent the mark-down effects. We also estimate first differenced versions of (29), where all variables of interest (and instruments) are differenced and the d_{ex} fixed effects eliminated.

As we have explained above, under equal mark-downs ($H1$), equation (26) identifies the technology parameters $(\alpha_{Zext}, \sigma_Z)$. We use our β_1 estimate in column 5 of Table 2, which implies $\sigma_Z = 1 - 0.029$; and we back out the α_{Zext} in each labor market cell as the residual, i.e. $\log \alpha_{Zext} = \log \frac{W_{Mext}}{W_{Next}} - \beta_1 \log \frac{M_{ext}}{N_{ext}}$. These allow us to construct the two bracketed terms (the augmented wage variable and cell aggregator) in (29) and estimate the equation linearly. The joint null of equal and independent mark-downs ($H1$ and $H2$) requires that $\gamma_2 = 0$, and this can be tested. The functional form of the cell aggregator depends on our assumption of CES technology in the lower nest; but our analysis of the data in Appendix H.7 suggests the implicit restrictions are reasonable.

The two right hand side variables in (29) rely on different sources of variation: native employment N_{ext} increases the aggregator $\log\left(N_{ext}^{\sigma_Z} + \alpha_{Zext} M_{ext}^{\sigma_Z}\right)^{\frac{1}{\sigma_Z}}$ but diminishes the migrant composition $\log \frac{M_{ext}}{N_{ext}}$; whereas migrant employment M_{ext} increases both. However, there are a number of concerns about their exogeneity. First, omitted demand shocks at the interaction of education, experience and time (in v_{ext} in (28)) may generate unwanted selection: through the arrival of new immigrants (see Llull, 2018*a*, Monras, 2020), the human capital choices of existing US residents (Hunt, 2017; Llull, 2018*b*), and the labor supply choices of all workers. Second, native employment N_{ext} appears on both the left and right hand sides; so any measurement error in N_{ext} or misspecification of the technology will mechanically threaten identification. The direction of the bias is unclear: measurement error or misspecification should bias OLS estimates of γ_1 positively and γ_2

negatively; but we cannot sign the implications of omitted demand shocks (it depends whether native or migrant employment is more responsive). To address these challenges, we construct instruments for the two right hand side variables by combining our predicted native and migrant stocks, $\tilde{N}_{ext}$ and $\tilde{M}_{ext}$: we instrument $\log \frac{M_{ext}}{N_{ext}}$ using $\log \frac{\tilde{M}_{ext}}{\tilde{N}_{ext}}$, and $\log \left(N_{ext}^{\sigma_Z} + \alpha_{Zext} M_{ext}^{\sigma_Z}\right)^{\frac{1}{\sigma_Z}}$ using $\log \left(\tilde{N}_{ext} + \tilde{M}_{ext}\right)$.[19]

[Tables 3 and 4 here]

In Panel A of Table 3, we present our first stage estimates for equation (29), imposing the hypothesis of equal mark-downs ($H1$). Each instrument drives its corresponding endogenous variable with considerable power: the Sanderson and Windmeijer (2016) conditional F-statistics, which account for multiple endogenous variables, all exceed 50.[20]

Panel A of Table 4 presents the second stage results (we return to Panel B below). Our estimates of γ_1 are mostly positive (which would imply $\sigma_X > \sigma_Z$) but close to zero. If σ_Z is close to 1 (as Table 2 suggests, at least under $H1$), these γ_1 estimates would then imply $\sigma_X \approx 1$, i.e. experience groups are (approximately) perfect substitutes within education nests. This appears to contradict the prevailing view in the literature; but as we show below, our estimates closely match those of Card and Lemieux (2001), the seminal work on this subject, when we use broader education groups.

The effect of migrant cell composition, γ_2, is universally negative. Its statistical significance leads us to reject the null of independent native mark-downs ($H2$), conditional on $H1$. Adjusting native wages for compositional changes (columns 3-4) approximately doubles our γ_2 coefficient. When we control for the relative supply $\log \frac{M_{ext}}{N_{ext}}$ and migrant share $\frac{M_{ext}}{N_{ext}+M_{ext}}$ simultaneously (in column 5), the latter picks up the entire effect: this suggests $\frac{M_{ext}}{N_{ext}+M_{ext}}$ is the more appropriate functional form for the mark-down effect, which is consistent with our monopsony story. Using IV instead of OLS makes little difference, which suggests selection is not a significant problem in this particular specification.[21] For illustration, identifying cell composition with the migrant share, our IV estimate of γ_2 is -0.61 (column 7 of Panel A), with a standard error of just 0.07. That is, conditional on $H1$, a 1 pp expansion of the migrant share allows firms to mark down native wages by 0.61% more. The first differenced estimates are similar: the equivalent specification yields a γ_2 of -0.48 (in column 9), with a similar standard error.

To summarize, the fact that γ_2 differs significantly from zero allows us to reject the null hypothesis of equal and independent mark-downs (i.e. the joint hypothesis of $H1$ and

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[19] One might alternatively use $\log \left(\tilde{N}_{ext}^{\sigma_Z} + \alpha_{Zext} \tilde{M}_{ext}^{\sigma_Z}\right)^{\frac{1}{\sigma_Z}}$ as an instrument in the latter case; but we prefer not to, since the α_{Zext} are themselves estimated functions of wages (our dependent variable).

[20] These can be assessed against standard Stock and Yogo (2005) weak instrument critical values.

[21] In contrast, Llull's (2018*a*) IV estimate of the migrant share effect is more than twice his OLS estimate - though as we have explained above, he uses a different instrument.

$H2$), which includes perfect competition. And conditional on $H1$ (equal mark-downs), the negative coefficient on γ_2 implies that a larger migrant share in an education-experience cell expands the native mark-down. This is consistent with the view that firms have greater monopsony power over migrants than natives, whether because migrants have lower reservation wages or supply labor to firms less elastically.

6.3 Set identification of key parameters

Importantly, the estimates of γ_2 reported above are conditional on the veracity of $H1$ (that natives and migrants face equal mark-downs). However, we are unable to test $H1$ in isolation. If it is not satisfied in reality, the true mark-down effect may be entirely different: conceivably, even its sign may be incorrect.

Though the full model is not identified, it does imply restrictions on sets of parameters; and this allows us to explore the robustness of our conclusions. For any given α_Z and σ_Z, we can use the native wage equation (29) to point identify the mark-down effect, ϕ_{1N}. (And for given α_Z and σ_Z, we can also identify $\Delta\phi_0$ and $\Delta\phi_1$ using our estimates of the relative wage equation.) Our strategy is therefore to study how our ϕ_{1N} estimate varies across a broad range of α_Z and σ_Z values. This approach offers a form of set identification, in the sense that only some combinations of parameters are consistent with the data.

We begin by considering a specification where, in line with e.g. Borjas (2003), natives and migrants contribute identically to output within education-experience cells: i.e. $\alpha_{Zext} = \sigma_Z = 1$. In this environment, we would attribute any deviation of β_0 and β_1 from zero (in the relative wage equation) to the differential mark-down effects, $\Delta\phi_{0ext}$ and $\Delta\phi_1$. Moving to the native wage equation (29), the left hand side collapses to the log native wage $\log W_{Next}$, and the cell aggregator collapses to total employment $\log(N_{ext} + M_{ext})$. We offer first and second stage estimates for this specification in Panel B of Tables 3 and 4. Unsurprisingly perhaps, the results are similar to Panel A: this is because the α_{Zext} and σ_Z values implied by $H1$ are themselves close to 1. In the fixed effect IV specification (column 7 of Table 4), the coefficient γ_2 on the migrant share (which identifies ϕ_{1N}) drops from -0.61 to -0.56; and in first differences (column 9), it drops from -0.48 to -0.42.

[Figure 2 here]

In Figure 2, we now study how our estimate of ϕ_{1N}, the effect of migrant share on the native mark-down, varies across a broader range of (α_Z, σ_Z) calibrations.[22] In Panel A, we focus on the IV fixed effect specification (comparable with column 7 of Table 4), with native wages adjusted for composition, and with the mark-down effect written in

[22]Unlike in Panel A of Tables 3 and 4, we impose equal α_Z values in every labor market cell.

terms of the migrant share $\frac{M_{ext}}{N_{ext}+M_{ext}}$; and Panel B repeats the exercise for first differences (comparable with column 9 of Table 4). We offer more complete regression tables for a selection of (α_Z, σ_Z) values in Appendix Table A3.

Compared with other (α_Z, σ_Z) values, our ϕ_{1N} estimates in Table 4 (which hover around 0.5) represent a lower bound. As σ_Z decreases from 1, ϕ_{1N} becomes larger. Intuitively, for a lower σ_Z, we are treating natives and migrants as more complementary in technology. This would imply that immigration is more beneficial for native marginal products (as in Proposition 4 above); and consequently, to rationalize the observable wage variation, we require a more adverse mark-down effect. Notice the effect of σ_Z diminishes as α_Z declines: if migrants contribute little to output, they will have less influence on native marginal products, so the value of σ_Z becomes moot. In the limit, when α_Z reaches zero, the cell aggregator collapses to the native stock; so σ_Z has no influence.

6.4 Comparison with existing empirical literature

We are not the first to estimate a native wage equation across education-experience cells. But equation (29) is distinctive in controlling simultaneously for *both* cell size (the Armington aggregator) *and* cell composition (the migrant share); whereas other studies just include one or the other.

Borjas (2003; 2014) and Ottaviano and Peri (2012) study a specification with the cell aggregator alone, to estimate the substitutability σ_X between experience groups within education nests (building on Card and Lemieux, 2001). Borjas (2003) estimates a coefficient γ_1 of -0.29 on the cell aggregator (implying an elasticity of substitution of 3.4, assuming $\sigma_Z = 1$), and Ottaviano and Peri's preferred estimate is -0.16; while our estimates of γ_1 are close to zero. However, both Borjas and Ottaviano and Peri instrument the cell aggregator $Z(N, M)$ using total migrant labor hours. This instrument will violate the exclusion restriction if, as our model suggests, migrant composition enters wages independently (through the mark-down effect). In contrast, we identify distinct effects of the cell aggregator and cell composition, using two distinct instruments.

Borjas (2003) also estimates a version of equation (29) which excludes the cell aggregator $Z(N, M)$, implicitly imposing $\gamma_1 = 0$. His motivation is to generate descriptive estimates (i.e. without imposing theoretical structure) of the effect of immigration, using skill-cell variation. The effect of migrant share varies from -0.5 or -0.6, very similar to our own estimates of γ_2. His empirical specification has latterly been criticized by Peri and Sparber (2011) and Card and Peri (2016): they note that native employment appears in the denominator of the migrant share $\frac{M_{ext}}{N_{ext}+M_{ext}}$, in which case unobserved cell-specific demand shocks (which raise wages and draw in natives) may generate a spurious negative relationship between wages and migrant share. We address these endogeneity concerns by using instruments.

To summarize, relative to this empirical literature, our contributions are (i) to simultaneously account for the effects of *both* cell size (which determines the impact of marginal products) *and* cell mix, (ii) offer a novel interpretation to the latter (namely the mark-down effect), and (iii) identify the effect of each using distinct instruments.

6.5 Robustness of wage effects

We now consider the robustness of our estimates of the migrant share effect, γ_2, in the native wage equation (29) to: (i) outliers, (ii) wage definition and weighting, (iii) instrument specification, (iv) new and old migrant instruments, (v) accounting for dynamics, and (vi) selection into employment. We discuss each point briefly here, and we offer greater detail and regression tables in the marked appendices. For simplicity, we impose $\alpha_{Zext} = \sigma_Z = 1$ throughout, so the dependent variable in the native wage equation (29) collapses to log native wages and the cell aggregator to log total employment, $\log(N_{ext} + M_{ext})$: recall from Table 4 that this makes little difference to the results.

(i) Outliers. First, one may be concerned that our γ_2 estimates are driven by outliers. To address this, Figure 3 graphically illustrates our OLS and IV estimates of γ_2, both for fixed effects and first differences, based on columns 4, 7, 8 and 9 of Panel B in Table 4. These plots partial out the effects of the controls (i.e. log total employment and the various fixed effects) from both native wages (on the y-axis) and migrant share (on the x-axis).[23] By inspection of the plots, it is clear the slope coefficients (which identify the γ_2 estimates of Table 4) are not driven by outliers.

[Figure 3 here]

(ii) Wage definition and weighting (Appendix H.2). In Appendix Table A4, we show our IV estimates of γ_2 are robust to the choice of wage variable and weighting. We study the wages of native men and women separately, and hourly wages instead of full-time weekly wages; and we experiment with weighting observations by total cell employment. But the effect of the migrant share is little affected.

(iii) Instrument specification (Appendix H.3). One possible concern is that our predictor for the migrant stock, $\tilde{M}_{ext}$, is largely noise; in which case, the first stage might be driven by the correlation between native employment N_{ext} and its predictor $\tilde{N}_{ext}$ (which appear in the denominators of the migrant share $\frac{M_{ext}}{N_{ext}+M_{ext}}$ and its instrument $\frac{\tilde{M}_{ext}}{\tilde{N}_{ext}+\tilde{M}_{ext}}$). See Clemens and Hunt (2019) for a related criticism. Reassuringly though,

[23] For IV, we first replace both (i) log total employment and (ii) migrant share with their linear projections on the instruments and fixed effects; and we then follow the same procedure as for OLS.

our IV estimates of γ_2 remain large and significant (though somewhat smaller in fixed effects) after replacing the migrant share instrument $\frac{\tilde{M}_{ext}}{\tilde{N}_{ext}+\tilde{M}_{ext}}$ with its numerator $\tilde{M}_{ext}$: see Appendix Table A5.

(iv) New and old migrant instruments (Appendix H.4). Recall that our migrant share instrument aggregates distinct components for new migrants (up to ten years in the US) and old migrants (more than ten years). Reassuringly, it turns out each component does indeed individually elicit the migrants we intend; and we have sufficient power in the first stage to identify the wage effects of each group separately (at least in fixed effects), after breaking the instrument into two. We explore this more formally in Appendix Tables A6 and A7. As it happens, both new and old migrants have large and negative effects on native wages: we return to the significance of this below.

(v) Dynamics (Appendix H.5). Another possible issue is serial correlation in the migrant share, conditional on the various fixed effects. If wages adjust sluggishly to immigration shocks, the lagged migrant share will be an omitted variable; and in the presence of serial correlation, our γ_2 estimate may be biased (Jaeger, Ruist and Stuhler, 2018). However, our instruments have sufficient power to disentangle the effect of contemporaneous and lagged shocks (despite the presence of serial correlation); and at least in IV, we find these dynamics are statistically insignificant (i.e. past shocks have no influence on current wages).

(vi) Labor supply responses (Appendix H.6). As Dustmann, Schoenberg and Stuhler (2016) stress, immigration may affect the labor market through employment rates and not just wages. But if so, any estimated native wage effects may potentially reflect unobservable changes in the *composition* of the native employment pool (Bratsberg and Raaum, 2012; Borjas and Edo, 2021): adjusting for observables (as we do) may be insufficient. In Appendix Table A10, we replace the left-hand side of the native wage equation with the native employment rate (defined as log average hours per individual, adjusted for observable changes in composition). Consistent with Borjas (2003) and Monras (2020), who study similar skill-cell variation, we find that migrant share (suitably instrumented) does indeed reduce native employment rates. It turns out this response is entirely driven by native women, which matches the findings of Borjas and Edo (2021) in France.[24] But despite this, the wage effects are very similar for men and women (see Appendix Table A4): this suggests the wage effects are not conflated with selection, at least in this context. The results also show the labor supply responses are smaller for migrants than natives (though note this is supply to the *market*, rather than to individual

[24] Quantitatively, the elasticity of female employment to migrant share is approximately double the wage effect. In the absence of job creation effects (see below), this implies a substantial female labor supply elasticity of about 2 (and a male elasticity of zero). The female elasticity is larger than many estimates in the micro literature, but more reminiscent of macro-level estimates.

firms), consistent with Borjas (2017).

It is worth stressing that the employment rate effect is entirely driven by migrant share, and does not respond to total cell employment. Based on our model, we conclude that these effects are elicited by changes in *mark-downs* rather than marginal products. This is theoretically significant: in non-competitive models, the larger profits associated with larger mark-downs may stimulate job creation, and employment may in principle *grow* (if this effect dominates the labor supply response).[25] However, the job creation effect appears to be relatively weak in our context.

7 Interpretation of migrant share effects

Above, we reject the overidentifying restrictions of the canonical model, and we offer a theory (of imperfect competition) which can account for this rejection. However, this rejection may in principle also reflect a misspecification of the production technology. In this section, we first show that plausible alternative technologies cannot rationalize our results. And we then offer positive evidence for our monopsony story.

7.1 Sensitivity to specification of technology

In what follows, we consider the sensitivity of our estimates to five features of the production technology: (i) CES functional form, (ii) cross-cell heterogeneity in σ_Z, (iii) broad education groups, (iv) broad experience groups, and (v) the allocation of migrants to native cells. As in the previous section, we discuss each point briefly here, and we offer greater detail and regression tables in the marked appendices.

(i) Assumption of CES technology (Appendix H.7). To estimate the native wage equation (29), we need to construct an aggregator $Z(N, M)$ over native and migrant employment within education-experience cells. In line with the existing literature (Card, 2009; Manacorda, Manning and Wadsworth, 2012; Ottaviano and Peri, 2012), we have assumed Z has CES form. But in principle, our identification strategy can be generalized to any Z with constant returns. Under constant returns, we show in Appendix E that the log relative wage (of migrants to natives) must depend only on the log relative supply of migrants, $\frac{M}{N}$: see equation (A41). The assumption of CES imposes that this relationship is *linear*: see equation (23). Therefore, to check the validity of the CES assumption (conditional on constant returns), we need only consider the linearity of the relationship between log relative wages and log relative supply. In Appendix Figure A2, we plot this

[25] In particular, Chassamboulli and Palivos (2013), Chassamboulli and Peri (2015), Amior (2017) and Albert (forthcoming) argue that migrants' low wage demands may stimulate job creation (for a given marginal product of labor).

relationship for our preferred IV specification (after partialing out the fixed effects). We consider separately the first stage relationship (the log relative supply on its instrument) and the reduced form (the log relative wage on the same instrument): in each case, linearity appears a reasonable description of the data.

(ii) Cross-cell heterogeneity in σ_Z (Appendix H.8). In our relative wage model (equation (26)), we implicitly assume that σ_Z (the within-cell substitutability between natives and migrants) is identical across education-experience cells. But one may be concerned that there may be important heterogeneity: this would imply the Z aggregator should be constructed differently (on the right-hand side of the native wage equation), and this may cause us to incorrectly estimate the mark-down effect. In Appendix Table A11, we test for heterogeneity in the relative wage effect across college/non-college cells and high/low experience cells. Reassuringly, the interactions are quantitatively small in all specifications.

(iii) Broad education groups (Appendix H.9). Our results are also robust to a specification with two education groups (college and high school "equivalents"[26]), instead of four. As Card (2009) notes, a four-group scheme implicitly constrains the elasticity of substitution between any two groups to be identical; but there is evidence that high-school graduates and dropouts are closer substitutes with each other than with college graduates. Similar to Table 4, we report estimates of the native wage equation both under the assumption of equal mark-downs ($\Delta\phi_{0ext} = \Delta\phi_1 = 0$) and under $\alpha_{Zext} = \sigma_Z = 1$. In the former case, we impose a σ_Z of 0.907, as estimated from an IV relative wage equation with education-experience and year effects (which we do not report here).[27] The γ_2 estimates (on migrant share) in the native wage equation are larger than before, exceeding -1 under fixed effects, and ranging from -0.6 to -1.3 in first differences (Appendix Table A13). Interestingly, γ_1 (the elasticity to total cell employment) is now consistently negative in the $\alpha_{Zext} = \sigma_Z = 1$ specification, taking a value of -0.1 under fixed effects: this matches the findings of Card and Lemieux (2001), who use a similar two-group education classification.[28] This implies an elasticity of substitution between experience groups (within education nests) of 10.

(iv) Broad experience groups (Appendix H.9). There may also be concerns

[26]"College-equivalents" consist of all college graduates, plus 0.8 times half the some-college stock; and "high-school equivalents" consist of all high-school graduates, plus 0.7 times the dropout stock, plus 1.2 times half the some-college stock. The weights, borrowed from Card (2009), have an efficiency unit interpretation. This leaves us with just 16 clusters (since we cluster by labor market cell); but at least in this data, the bias to the standard errors appears to be small: see Appendix H.9.

[27]This implies a native-migrant elasticity of substitution of 11 (within education-experience cells): this is still large, but noticeably smaller than in our baseline specification (where the elasticity is over 30: see Section 6.1).

[28]In their main specification, they estimate an elasticity of substitution of 5 across age (rather than experience) groups; but they also offer estimates across experience groups which are similar to ours.

over the independence of the detailed 5-year experience-education clusters in the baseline specification (which may bias the standard errors). To address this, we re-estimate our model in Appendix Table A13 using four 10-year experience groups (rather than eight 5-year groups), while keeping the original four-group education classification. Reassuringly, this makes little difference to our coefficient estimates and standard errors.

(v) Allocation of migrants to native cells (Appendix H.10). In this paper, we allocate migrants to native labor market cells according to their education and experience, following the example of Borjas (2003), Ottaviano and Peri (2012) and others. But to the extent that migrants "downgrade" occupation (Dustmann, Schoenberg and Stuhler, 2016) and compete with natives of lower education or experience, this would generate measurement error in the cell-specific migrant stocks. While one might expect measurement error to attenuate our (negative) migrant share effects, Dustmann, Schoenberg and Stuhler (2016) show that particular patterns of downgrading may also artificially inflate the effects. In Appendix H.10, in the spirit of Card (2001) and Sharpe and Bollinger (2020), we probabilistically allocate migrants (of given education and experience) to native cells according to their occupational distribution. Again, we continue to see a large effect of migrant share, in both the $\Delta\phi_{0ext} = \Delta\phi_1 = 0$ and $\alpha_{Zext} = \sigma_Z = 1$ specifications, and under both fixed effects and first differences: see Appendix Tables A14 and A15.

7.2 Heterogeneity by citizenship status

Above, we have argued the migrant share effect in the native wage equation cannot plausibly be attributed to a misspecification of technology. We now offer positive evidence that it instead reflects larger mark-downs. Based on our model, such a mark-down effect will arise if firms enjoy greater market power over migrants than natives, whether because migrants supply labor less elastically (to individual firms) or demand lower reservations. As we argue in Section 3.2, this may be rationalized in different ways, but the common thread is a migrant labor force which lacks credible outside options. If so, we should expect some heterogeneity in the mark-down effects, if migrants vary in access to employment opportunities.

One natural indicator of the degree of access is citizenship status. In our sample, about half of migrants lack citizenship; and this reaches 70% for migrants without a high school degree: see Table 5. In the same table, we also show that non-citizens account for almost the entire wage differential (within education-experience cells) between natives and migrants. Bratsberg, Ragan and Nasir (2002) argue that naturalization removes barriers to public sector, white collar and union jobs, and brings an acceleration in individual wage growth; and Mazzolari (2009) identifies significant effects of naturalization on employment, based on quasi experimental variation. Crucially also, close to half of non-citizens are undocumented (Passel and Cohn, 2011): this may severely limit access to employment, whether because of deportation risk for workers or legal risk of firms (see e.g. Kossoudji and Cobb-Clark, 2002; Orrenius and Zavodny, 2009; Borjas and Cassidy, 2019).

[Table 5 here]

In what follows, we first show that the migrant share effect on native wages is driven specifically by non-citizens (at least in IV). This reflects similar evidence from France (Edo, 2015). These results are difficult to reconcile with a competitive model. But they are consistent with a monopsony model, where non-citizens enhance the market power of firms. We also offer evidence on job separation elasticities which supports this story.

To separately estimate the wage effects of citizen and non-citizen migrants, we require two distinct instruments. One approach might be to use the predicted stocks of new and old migrants, given the latter are more likely to be naturalized. In practice though, these do not offer sufficient power to disentangle citizen from non-citizen stocks. Instead, to predict the cell-specific stock of non-citizen employment, we take the sum of (i) all predicted new migrants *and* (ii) predicted old migrants of specifically Mexican origin[29] (Mexicans are known to have an unusually low naturalization rate: see e.g. Gonzalez-Barrera, 2017). We denote the total predicted non-citizen stock as $\tilde{M}_{ext}^{cit}$, and we then predict the stock of naturalized migrants as the residual: $\tilde{M}_{ext}^{cit} \equiv \tilde{M}_{ext} - \tilde{M}_{ext}^{noncit}$. Our two instruments are then the respective shares of $\tilde{M}_{ext}^{cit}$ and $\tilde{M}_{ext}^{noncit}$ of the total predicted cell stock, i.e. $\frac{\tilde{M}_{ext}^{cit}}{\tilde{N}_{ext}+\tilde{M}_{ext}}$ and $\frac{\tilde{M}_{ext}^{noncit}}{\tilde{N}_{ext}+\tilde{M}_{ext}}$. Table 6 shows that these instruments perform remarkably well: the citizen share instrument has a large positive effect on its corresponding endogenous variable and no significant effect on the non-citizen share; and vice versa.

[Tables 6 and 7 here]

In Table 7, we re-estimate the native wage equation (29), but breaking down the overall migrant employment share $\frac{M_{ext}}{N_{ext}+M_{ext}}$ into (i) the migrant citizen share of the cell $\frac{M_{ext}^{cit}}{N_{ext}+M_{ext}}$ and (ii) the non-citizen share $\frac{M_{ext}^{noncit}}{N_{ext}+M_{ext}}$. For simplicity, we impose $\alpha_{Zext} = \sigma_Z = 1$ throughout, so the left-hand side variable is simply the log native wage. In the OLS specifications (columns 1 and 3), the effect of the citizen and non-citizen shares are similar; but there may be important concerns here about selection into citizenship (beyond any concerns, listed above, about selection into cells and employment). In columns 2 and 4, we apply our instruments. In both the fixed effect and first differenced specifications, the

[29]We construct this by following the procedure for old migrants described in Section 5.3, but restricting the sample to Mexicans.

non-citizen share picks up the entire effect. The standard errors on the citizen share effect are large (0.4 or 0.5); but we can at least conclude that the entire IV effect in the baseline specifications (in Table 4) is driven by non-citizens. In contrast to this stark result, we find no evidence that the mark-down effects from immigration differ substantially between new and old migrants (see Appendix Table A7): this suggests the distinctive effects of non-citizens are not merely driven by years in the US.

The dominant role of non-citizens is difficult to reconcile with a competitive model, since (higher-earning) naturalized migrants should (if anything) compete *more* efficiently with similarly skilled natives (and so, should erode their marginal products more significantly). But it is entirely consistent with our mark-down interpretation. In Appendix H.12 (and the accompanying Table A17), similar to Hotchkiss and Quispe-Agnoli (2013), Hirsch and Jahn (2015) and Biblarsh and De-Shalit (2021), we estimate job separation elasticities (to initial wages) for natives and migrant, using the Survey of Income and Program Participation. These estimates speak to the elasticity of labor supply to individual firms, as Manning (2003) shows more formally. We show the elasticities are similar for natives and naturalized migrants, but much smaller for non-citizens. This effect is driven by low-educated non-citizens (many of whom are undocumented), whose separation elasticity is less than 20% of similarly educated natives. In the final column of Appendix Table A17, we also show the remarkably low separation elasticities of non-citizens cannot be statistically explained by years in the US or Central American origin. Of course, these are merely observational relationships; but the comparisons across migrant status are suggestive.

8 Quantifying the immigration surplus

Borjas (1995) famously shows that immigration generates a surplus for natives (and our results in Section 2 suggests this is a robust result under perfect competition), though he predicts this surplus is small. In this section, we discuss how the introduction of monopsony affects the immigration surplus, both its size and distribution - and we quantify these effects, based on our estimates above.

We consider two counterfactuals. The first is an immigration shock equal to 1% of total employment in 2019[30], holding migrants' skill mix fixed. And the second, motivated by the discussion above, is a "naturalization" policy which transforms a portion of non-citizens (equal to 1% of total employment, or 11% of non-citizen employment) to citizens, within education-experience cells.

[30]Our predictions can only be interpreted as first-order approximations, as they rely on mark-down effects estimated from linearized equations: see equations (19) and (20).

We simulate these counterfactuals in a "long run" scenario (where capital inputs are supplied elastically) and assuming that workers supply labor inelastically (so the welfare effects can be summarized by changes in wages). This exercise requires a calibration of the entire nested CES production technology. We restrict attention to our baseline structure, with four education groups and eight experience groups. Our estimates above focus only on the lowest nest, at the level of education-experience cells. For comparability, we calibrate the upper nests using Ottaviano and Peri's (2012) estimates (based on their "Model A"): we set σ^E (the substitutability between composite education inputs, L_e) in equation (12) to 0.7, and σ^X (between experience inputs, L_{ex}) to 0.84.[31] We explain exactly how we process these counterfactuals in Appendix F. For simplicity, for the immigration shock counterfactual, we ignore any differences between citizen and non-citizen migrants, and rely instead on our baseline IV mark-down effects from Table 4.

8.1 Immigration shock counterfactual: Perfect competition

We begin with the 1% immigration shock: Table 8 presents our results. The first column reports estimates under the assumption of perfect competition, the conventional case. We set the mark-downs to zero; and under this assumption, the substitutability between natives and migrants (σ_Z) and the relative productivity of migrants (α_{Zex}) within education-experience cells are identified by the relative wage equation (26). Using these parameter estimates, we predict the change in native and migrants wages (Panels A and B) and the change in output and immigration surplus (Panel C), following the hypothesized immigration shock. Appendix F provides details on how these effects are computed: they account for the effect of immigration in each cell on every other cell.

[Table 8 here]

Under perfect competition (column 1), the average native wage rises in response to the immigration shock - as Proposition 3 requires. The average effect is small (0.04%), but this hides large distributional effects. In particular, we predict the wage of native high-school dropouts declines by 0.5%, though this is offset by wage increases in other education groups. This is a consequence of the concentration of migrants in the dropout category, so a larger number of migrants (holding their skill mix constant) increases the

[31] Blau and Mackie (2017) report a similar exercise for several different scenarios reflecting different assumptions about the elasticity of substitution (under perfect competition): see e.g. footnote 32. But since the focus of our paper is the implications of monopsony power, we restrict attention to one set of upper-nest elasticities. Importantly, the mark-down effects are independent of these assumptions.

relative supply of dropouts in the economy.[32] For migrants, wages are predicted to fall for all groups (and especially among dropouts): this is because natives and migrants are treated as imperfect substitutes within education-experience cells.

Panel C predicts the % change in long run "net output" (i.e. net of the costs of the elastic capital inputs), and decomposes this change into contributions from native wage income, migrant wage income and monopsony rents. Net output rises because the labor force expands; but the increase is a little less than 1%, due to diminishing returns to individual factors and migrants' over-representation in low-wage cells. With perfect competition and CRS, net output is fully exhausted by wage income. Total migrant wage income rises, but by less than proportionally to the 1% immigration shock (as their wages fall). And total native wage income expands because their wages grow on average.

8.2 Immigration shock counterfactual: Monopsony

Column 2 now introduces monopsony. We begin with the simple case where mark-downs are equal for natives and migrants (i.e. $\Delta\phi_{0Nex} = \Delta\phi_{1N} = 0$) and do not depend on the cell's migrant share (so $\phi_{1N} = 0$). A crucial parameter in this exercise is the baseline level of the mark-down (and monopsony rents). As we explain above, the mark-down *level* is not identified by our model; and there is no commonly accepted estimate in the literature. For illustrative purposes, we assume the baseline share of monopsony rents is 10%: i.e. $\phi_{0N} = 0.1$ in equation (19). This seems a reasonable value, perhaps a bit on the conservative side: e.g. Lamadon, Mogstad and Setzler (2019) estimate an average US mark-down of 15%, and Kroft et al. (2020) find mark-downs of 20% in the construction sector. Since mark-downs are equal for natives and migrants in this specification, the σ_Z and α_{Zex} technology parameters are again identified by the relative wage equation.

Column 2 shows the predicted wage effects are exactly the same as under perfect competition (column 1). Intuitively, a constant mark-down implies that immigration only affects wages via the marginal products (which adjust in the same way as in the competitive case). Similarly, the response of net output is identical, since this depends only on the technological interaction between natives and migrants. However, immigration now increases monopsony rents (commensurate with the baseline mark-down level), as firms take a cut from the new migrants' marginal product. Following the convention that capital is owned by natives (e.g. Borjas, 1995), we assume all firms are native-

[32] Card (2009), Ottaviano and Peri (2012) and Blau and Mackie (2017) emphasize that these distributional effects are much smaller if high school dropouts and graduates are treated as close substitutes. In this case, wage effects will only materialize to the extent that natives and migrants differ in college share - but differences in college share are known to be small. Our purpose in this paper is not to revisit this debate, but rather to study the implications of monopsony power.

owned.[33] The total native surplus then expands to 0.12% of net long run output, the bulk of which goes to employers as monopsony rents. In this way, monopsony power greatly expands the surplus to natives from immigration; and this expansion is built on the exploitation of migrants who are paid less than their marginal products.[34]

In column 3, we now allow mark-downs to vary with migrant share $\frac{M}{M+N}$, but we continue to assume they are the same for natives and migrants (i.e. $\Delta\phi_{0Nex} = \Delta\phi_{1N} = 0$). We calibrate the native mark-down response to 0.614 (based on column 7 of Table 4), while maintaining a 10% share of monopsony rents at baseline. We now see universally negative effects on native wages, averaging -0.4%. The mark-down effect is larger in cells with larger migrant shares at baseline (so dropouts suffer especially). Overall, column 3 suggests the negative mark-down effects on native wages dominate the small positive response arising from shifts in marginal products. This has important distributional implications: while workers are worse off, the flip-side is larger growth of monopsony rents, which we calibrate to 0.52% of net output. The total native surplus (0.20%) is larger than in column 2, as firms are now capturing even greater rents from migrant labor.

In column 4, we allow the native and migrant mark-downs to differ: in particular, we impose $\alpha_{Zex} = \sigma_Z = 1$ (so natives and migrants are productively identical within cells); and we allow the relative wage equation to identify the differential mark-down effects. This requires us to slightly modify the mark-down response, according to the specification of Panel B in Table 4 (as opposed to Panel A). The net output response is now somewhat larger, since migrants are no longer less productive than natives (within cells). But overall, the results change little.

Overall, our results suggest monopsony power has important implications for the impact of immigration. On the one hand, it may significantly expand the total surplus going to natives: native-owned firms take a cut from new migrants' marginal products and capture additional rents from the existing migrant workforce. But the distributional effects may also be larger, with employers gaining and native labor losing (from larger mark-downs). Indeed, our estimates suggest the entire surplus goes to monopsonistic firms, even in a "long run" scenario with elastic capital; and this may help account for the large investment of individual firms in foreign recruitment, cited above. In principle, it may also help account for the aggregate decline in labor's income share (e.g. Karabarbounis and Neiman, 2014; Stansbury and Summers, 2020).

In this counterfactual, we have assumed the same mark-down effect (estimated in Table 4) applies to all immigration. But, if mark-down effects vary across migrant types

[33] One might expect part of these profits to go to migrants, especially if migrants often work for migrant-owned firms. But since we lack information on this, we do not explore it further.

[34] Though these migrants may still be earning more than in their country of origin.

(as we have suggested is the case for citizens and non-citizens), our basic IV mark-down estimate will apply specifically to those migrants elicited by the migrant share instrument $\frac{\tilde{M}_{ext}}{\tilde{N}_{ext}+\tilde{M}_{ext}}$ (i.e. the "compliers"). In Appendix H.11 and Table A16, we show that the compliers consist almost entirely of non-citizens.[35] Therefore, our 1% immigration shock counterfactual may be more accurately interpreted as an inflow of specifically *non-citizens*, whose skill mix matches the existing migrant population.

8.3 Naturalization counterfactual

The results above suggest the effects of immigration depend heavily on firms' market power over migrants. This suggests that policies which directly target this market power may help protect native workers from any adverse effects. With this in mind, we now turn to our second counterfactual: a "naturalization" policy which transforms a portion of non-citizens (equal to 1% of total employment, or 11% of non-citizen employment) into citizens, within education-experience cells. Non-citizens in every skill group are transformed with equal probability. Though we call this a "naturalization" counterfactual, it may better represent a "regularization" policy (if the mark-down effects are mostly driven by undocumented migrants). However, we are unable to identify undocumented migrants in our data, and the citizen/non-citizen distinction comes closest.

For the purposes of this exercise, we assume that all workers (natives, migrant citizens and non-citizens) within education-experience cells are perfect substitutes (i.e. $\sigma_Z = 1$).[36] However, we permit productive differences between these workers. Specifically, we write the cell-level input L_{ex} as: $L_{ex} = N_{ex} + \alpha^{cit}_{Zex} M^{cit}_{ex} + \alpha^{noncit}_{Zex} M^{noncit}_{ex}$, where M^{cit}_{ex} is the employment stock of migrant citizens, M^{noncit}_{ex} is the stock of non-citizens, and α^{cit}_{Zex} and α^{noncit}_{Zex} are the relative efficiencies of each migrant type (compared to natives).

[Table 9 here]

We present our results in Table 9. We begin in column 1 by assuming the labor market is fully competitive: mark-downs are fixed at zero for all workers. Any wage differentials between natives, migrant citizens and non-citizens (within education-experience cells) are attributed entirely to productive differences (in the α^{cit}_{Zex} and α^{noncit}_{Zex} parameters); so the

[35] This can explain why the IV coefficients on the *non-citizen* share in Table 7 (-0.66 in fixed effects, and -0.57 in first differences) are similar to the effect of *overall* migrant share in Table 4 (-0.56 in column 7, -0.42 in column 9), despite non-citizens accounting for just half of migrant employment in our sample (Table 5).

[36] Recall from the exercise above that the limited amount of imperfect substitutability suggested by the data makes little difference to the broad conclusions.

economic impact of the naturalization policy derives from an increase in the productivity of former non-citizens.[37] This generates a 0.1% increase in net output, the bulk of which goes to the migrants themselves. Natives do benefit on average (the effect is very small), but there are distributional effects: the wages of native dropouts contract by 0.2%, because this is where the newly naturalized migrants are concentrated (and where the increase in quality-adjusted labor supply is largest).

In column 2, we now introduce monopsony rents which depend on the cell-specific employment share of non-citizens (but not on the citizen share). We calibrate the mark-down effect of the non-citizen share to 0.657, based on column 2 of Table 7. We continue to assume equal mark-downs for all workers, so within-cell wage differentials are again driven by α_{Zex}^{cit} and α_{Zex}^{noncit}. The policy now has two effects: a change in migrant productivity (as in column 1) and also a reduction in monopsony rents (as firms have less market power following naturalization). Comparing columns 1 and 2, it is clear that the latter effect dominates in the wage response. Native wages now increase substantially across all cells, especially among dropouts. Since the mark-downs do not matter for net output, these wage increases are absorbed by a contraction of monopsony rents (equal to 0.5% of net output).

Finally, in column 3, we maintain the mark-down response of column 2, but now assume no within-cell productivity difference between citizens and non-citizen migrants (i.e. we impose $\alpha_{Zex}^{cit} = \alpha_{Zex}^{noncit} = 1$); and we instead attribute the within-cell wage differential to differences in mark-downs. In this case, the policy has no effect on net output, since productivity is unchanged; but the effects on wages and monopsony rents are similar to column 2. Migrants continue to benefit disproportionately, but now through access to lower mark-downs rather than higher productivity.

9 Conclusion

For any convex technology with constant returns, we show that a larger supply of migrants (keeping their skill mix constant) must *always* increase the marginal products of native-owned factors on average, unless natives and migrants have identical skill mixes. And in the long run (if capital is supplied elastically), this surplus passes entirely to native labor. This extends Borjas' (1995) "immigration surplus" result to a wide class of models with many types of labor and goods. But in a monopsonistic labor market, wages will also depend on any mark-downs imposed by firms. If migrants demand lower wages or supply

[37]Our assumption here is that the wage differential between citizens and non-citizens represents the causal impact of citizenship on productivity. If, instead, the wage differential purely reflects unobserved heterogeneity, the policy would have no effect on productivity - and therefore no economic effect at all under perfect competition.

labor to firms less elastically than natives (and there is evidence to support this claim), firms can exploit immigration by imposing larger mark-downs on the wages of natives and migrants alike.

We develop a test of the hypothesis that native and migrant mark-downs are equal and unaffected by immigration, of which perfect competition is a special case; and we reject this hypothesis using standard US data on employment and wages. Under an alternative framework with imperfect competition, our estimates suggest that immigration may in fact depress mean native wages overall - even in a "long-run" setting with perfectly elastic capital. Empirically, these mark-down effects are entirely driven by non-citizens (many of whom may be undocumented), rather than naturalized migrants. Though native labor loses out from larger mark-downs, the capture of migrants' rents (by firms) will significantly expand the *total* surplus going to natives. However, a policy which transforms all non-citizens to citizens (within education-experience cells) will have the opposite effect: native and migrant labor benefit substantially, at the expense of firms.

Crucially, one cannot conclude that immigration is generally harmful for native workers. If policy interventions (such as minimum wages or amnesties) can limit monopsony power over migrant labor, immigration would only have the surplus-raising feature for native labor. On the other hand, interventions ostensibly designed to protect native wages by deterring immigration (such as limitations on access to permanent residency) may be self-defeating, if they make the labor market less competitive. Whether the impact of immigration is affected by labor market institutions may be a fruitful topic for further investigation.

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Appendices: For Online Publication

A Long run production function

Suppose the production function can be written as $F(\mathbf{L}, \mathbf{K})$, where $\mathbf{L}$ is a vector of inputs that are treated as fixed (perhaps because they are in inelastic supply, or simply for analytical convenience) and $\mathbf{K}$ a vector of inputs that are in perfectly elastic supply at prices $\mathbf{p_K}$. Assume the production function has constant returns to scale in all its inputs. For given $\mathbf{L}$, let Π represent the profits net of the cost of elastic inputs:

$$\Pi(\mathbf{L}, \mathbf{p_K}) = \max_{\mathbf{K}} \{F(\mathbf{L}, \mathbf{K}) - \mathbf{p}'_{\mathbf{K}}\mathbf{K}\} \tag{A1}$$

The purpose of this appendix is to show that Π can be treated as a "long run" production function with constant returns in the $\mathbf{L}$ inputs, and whose derivatives equal their marginal products.

Notice first that the first-order conditions for profit maximization can be written as:

$$\mathbf{F_K}(\mathbf{L}, \mathbf{K}) = \mathbf{p_K} \tag{A2}$$

These first-order conditions can be solved to write the optimal choice of inputs as a function $\mathbf{K}(\mathbf{L}, \mathbf{p_K})$ of $\mathbf{L}$ and input prices. From the assumption of constant returns, $\mathbf{K}(\mathbf{L}, \mathbf{p_K})$ must be Hod1 in $\mathbf{L}$. Substituting this for $\mathbf{K}$ in (A1) gives:

$$\Pi(\mathbf{L}, \mathbf{p_K}) = F(\mathbf{L}, \mathbf{K}(\mathbf{L}, \mathbf{p_K})) - \mathbf{p_K}'\mathbf{K}(\mathbf{L}, \mathbf{p_K}) \tag{A3}$$

which is a function of $\mathbf{L}$ and $\mathbf{p_K}$ alone. Since $\mathbf{K}(\mathbf{L}, \mathbf{p_K})$ is Hod1 in $\mathbf{L}$, the net profit function $\Pi(\mathbf{L}, \mathbf{p_K})$ must have constant returns in $\mathbf{L}$. Also, the derivatives of the net profit function must equal the marginal products of the respective $\mathbf{L}$ inputs. To see this, notice that:

$$\Pi_{\mathbf{L}}(\mathbf{L}, \mathbf{p_K}) = F_{\mathbf{L}}(\mathbf{L}, \mathbf{K}(\mathbf{L}, \mathbf{p_K})) + [\mathbf{F_K} - \mathbf{p_K}]' \frac{\partial \mathbf{K}(\mathbf{L}, \mathbf{p_K})}{\partial \mathbf{L}} = F_{\mathbf{L}}(\mathbf{L}, \mathbf{K}(\mathbf{L}, \mathbf{p_K})) \tag{A4}$$

where the second equality follows from (A2).

Therefore, assuming the $\mathbf{K}$ inputs are elastically supplied, we can write the long-run production function as $\tilde{F}(\mathbf{L}) = \Pi(\mathbf{L}, \mathbf{p_K})$ in the main body of the paper, where we suppress the dependence on $\mathbf{p_K}$ for notational convenience.

B Proof of Proposition 4

Proposition 4 follows from Proposition 3 with the following modification. Instead of defining natives and migrants as the two distinct groups, define the groups as those with skill mix vector η and those with skill mix μ. Let $\tilde{\mathbf{N}}$ be the first group's vector of employment stocks (across skill types), and $\tilde{\mathbf{M}}$ the second group's vector. Based on (6), the $\tilde{\mathbf{N}}$ group consists of all natives and a fraction $1 - \zeta$ of migrants:

$$\tilde{\mathbf{N}} = \mathbf{N} + (1 - \zeta)\,\mathbf{M} \tag{A5}$$

and the $\tilde{\mathbf{M}}$ group consists of the remaining migrants:

$$\tilde{\mathbf{M}} = \zeta \mathbf{M} \tag{A6}$$

An increase in ζ diminishes the first group but expands the second. From Proposition 3, we know this must increase the average wage of the first group. This group is not exclusively composed of natives. But the natives and migrants in this group have, by construction, the same skill mix; so the average wage must be the same for both these components of the group. Hence, the average wage of natives must rise. Note that the average wage of migrants may also rise, because a change in the skill mix may shift the group composition towards skills that yield higher wages in equilibrium.

C Proof of Proposition 5

C.1 Production

Suppose there are K industries in a closed economy, all of which produce goods with the J different types of labor (and possibly the K goods as intermediate inputs) using a convex and constant returns to scale production function. If the goods market is competitive, the price of each good will equal its unit cost function:

$$\mathbf{p} = \widetilde{c}\,(\mathbf{w}, \mathbf{p}) \tag{A7}$$

where $\mathbf{p}$ is the $K \times 1$ vector of prices, and the cost function $\tilde{c}$ will depend on the $J \times 1$ vector of wages $\mathbf{w}$ and (if there are intermediate or capital good inputs) the vector of goods prices.[38] From standard theory, $\tilde{c}$ will be homogenous of degree 1 in its arguments, increasing and concave. One can solve (A7) to give a "reduced form" cost function:

$$\mathbf{p} = c(\mathbf{w}) \tag{A8}$$

This cost function c must also be homogeneous of degree 1 in its arguments.

Let $a_{kj}(\mathbf{w})$ denote the quantity of factor j demanded for producing one unit of good k (both directly and indirectly through the intermediate inputs), and let $\mathbf{A}(\mathbf{w})$ denote the $K \times J$ matrix of these factor demands. By Shephard's lemma, the vector $\mathbf{A}(\mathbf{w})$ can be obtained by differentiating the cost function c with respect to wages:

$$c_w(\mathbf{w}) = \mathbf{A}(\mathbf{w}) \tag{A9}$$

C.2 Consumption

Now consider the consumer side. To keep things simple, we assume every consumer, native and migrant, has the same homothetic utility function; so the expenditure function can be written as $\widetilde{e}(\mathbf{p})\,u$, where $\mathbf{p}$ is the price vector and the level of utility is u. It will be convenient to write this expenditure function not (as is usual) in terms of prices, but rather in terms of wages - using (A8). Per utility expenditure can be written as:

$$e(\mathbf{w}) = \widetilde{e}(c(\mathbf{w})) \tag{A10}$$

where $e(\mathbf{w})$ will be an increasing, concave function of its arguments and homogeneous of degree 1. That is, it will behave identically to a normal expenditure function. It is useful to imagine consumers as demanding different types of labor (which produce the goods they consume), rather than demanding the goods directly. These derived demands for labor can be written as:

$$\mathbf{L}(\mathbf{w}, u) = e_w(\mathbf{w})\,u \tag{A11}$$

To see how, notice that differentiating (A10) with respect to wages yields:

$$e_w(\mathbf{w}) = \widetilde{e}_p(c(\mathbf{w}))\,c_w(\mathbf{w}) = \mathbf{X}(c(\mathbf{w}))\,\mathbf{A}(\mathbf{w}) \tag{A12}$$

[38] As Caselli and Manning (2019) note, the rental price of capital should equal the user cost - which is $(r+\delta)$ times the purchase price of the relevant intermediate good, where r and δ are the rates of interest and depreciation respectively.

where $\mathbf{X}(\mathbf{p})$ is the per utility demands for goods. And consequently, the product of $\mathbf{X}$ and $\mathbf{A}$ is equal to the factor demands for unit utility - from which (A11) follows.

C.3 Introducing natives and migrants

Suppose there are N natives and M migrants in total. Natives and migrants differ in their per capita factor supplies: denote the skill mix of natives by η and migrants by μ. The vector of total labor supply can then be written as:

$$\mathbf{L} = N\eta + M\mu \tag{A13}$$

Since natives and migrants differ in skill mix, they may have different levels of utility in equilibrium. Let u^n denote the average utility of natives, and u^m the average utility of migrants.[39] As total income must equal total expenditure for natives and migrants alike, we must have:

$$\eta\mathbf{w} = e(\mathbf{w})\, u^n \tag{A14}$$

and

$$\mu\mathbf{w} = e(\mathbf{w})\, u^m \tag{A15}$$

Finally, supply must equal demand in each of the labor markets. This equilibrium condition can be written as:

$$N\eta + M\mu = e_w(\mathbf{w})\left[Nu^n + Mu^m\right] \tag{A16}$$

where the left-hand side is supplies of labor, and the right-hand side the derived demand of different types of labor from native and migrant consumers, using (A11). (A16) can conveniently be rewritten as:

$$N\left[\eta - e_w(\mathbf{w})\, u^n\right] + M\left[\mu - e_w(\mathbf{w})\, u^m\right] = 0 \tag{A17}$$

The terms in square brackets represent a "balance of payments condition": the difference between the factors supplied by each group (natives or migrants) and the factors they demand. If factor supplies are identical for natives and migrants, these terms must both be zero. But if natives and migrants differ in skill mix, this will not be the case.

(A14), (A15) and (A17) appear to consist of $J+2$ equations in $J+2$ unknowns $(\mathbf{w}, u_n, u_m)$. But, one of the factor demands is redundant, and equilibrium wages are only determined up to a common factor - so they must be normalized in some way.

[39] Because of the homotheticity assumption, we can focus on the average level of utility - and we do not have to worry about the distribution of utility

C.4 Assessing the impact of immigration

We want to know what happens when the number of migrants M increases, holding constant their skill mix μ. Differentiating (A14) leads, after some rearrangement, to:

$$e(\mathbf{w})\,du^n = [\eta - u^n e_w(\mathbf{w})]\,d\mathbf{w} \tag{A18}$$

That is, native utility grows (on average) if wages increase more for the types of labor they supply than the implied labor in the goods they buy. And differentiating (A14) leads to a similar equation for migrant utility (in the host country):

$$e(\mathbf{w})\,du^m = [\mu - ue_w^m(\mathbf{w})]\,d\mathbf{w} \tag{A19}$$

Multiplying (A18) by N and (A19) by M, and using (A17), then leads to:

$$Mdu^m = -Ndu^n \tag{A20}$$

which implies that average native and migrant utility must move in opposite directions, if there is any change at all. But this does not tell us who gains and who loses.[40] This would require an expression for the change in wages. Differentiating (A17) leads to:

$$dM[\mu - e_w(w)\,u^m] = d\mathbf{w}'e_{ww}(\mathbf{w})\,[Nu^n + Mu^m] + e_w(\mathbf{w})\,[Ndu^n + Mdu^m] \tag{A21}$$

Using (A20), the final term must equal zero. Multiplying both sides by $d\mathbf{w}$ then gives:

$$dM[\mu - e_w(\mathbf{w})\,u^m]\,d\mathbf{w} = [Nu^n + Mu^m]\,d\mathbf{w}'e_{ww}(\mathbf{w})\,d\mathbf{w} \tag{A22}$$

and substituting (A19) into the left-hand side:

$$dMe(\mathbf{w})\,du^m = [Nu^n + Mu^m]\,d\mathbf{w}'e_{ww}(\mathbf{w})\,d\mathbf{w} \tag{A23}$$

The right-hand side of (A23) is negative, because it contains a quadratic form in which the middle matrix is negative semi-definite (from concavity of the expenditure function). This means that migrant utility (in the host country) must fall, or at least not rise; and from (A20), it then follows that native utility must rise, or at least not fall. The effect will be zero if the factor content of the goods demanded by migrants is identical to the factors which they supply: in this case, we would have $d\mathbf{w} = 0$, as can be seen from (A18) or (A19).

[40]Note that this is migrant utility in the host country: it says nothing about whether there are gains from migration as a whole.

D Justifying our empirical mark-down model

In our empirical model, we allow for the average native and migrant mark-downs within education-experience cells to (i) differ from one another and (ii) vary with the cell-specific migrant share. One may rationalize (i) and (ii) by a model where *some* firms can discriminate (which ensures native and migrant mark-downs will differ to some extent) and *other* firms cannot (which generates some dependence on the migrant share). But in this appendix, we show (i) with (ii) can also be rationalized by a model with *no* discriminating firms, as long as natives and migrants differ in their skill distribution *within* education-experience cells.

D.1 Relationship between skill-defined markets j and education-experience cells

The central idea is that each education-experience cell observed by the researcher consists of a large number of *unobservable* labor markets, which we denote j. These markets j are defined by skill; and we define them sufficiently narrowly such that all constituent workers (whether native or migrants) are productively identical and perfect substitutes. Crucially, natives and migrants may be allocated differently across these markets j, *within* observable education-experience cells. The idea that natives and migrants of identical education-experience may have different skill specializations has some precedent in the literature: e.g. Peri and Sparber (2009) emphasize comparative advantage in communication or manual tasks. In the extreme case, there will be perfect segregation (with natives and migrants competing in entirely different markets); but more generally, there will be some cross-over.

We will now show more formally how labor can be aggregated across multiple markets j. For simplicity, we will consider aggregation across *all* markets in the economy. But this procedure can equally be applied to any *subset* of markets - in particular, within a given (observable) education-experience cell. Suppose there are M migrants (at the aggregate level or within a given observable cell), of whom a fraction μ_j have skill j; and there are N natives, of whom a fraction η_j have skill j. Recall from equation (3) that long run output (net of the costs of elastic inputs) is aggregated according to the function $\tilde{F}(L_j, .., L_J)$, which we assume to be homogeneous of degree 1. Using equation (4) and Proposition 3, we can define an aggregate production function in terms of N and M as:

$$Z(N, M) = \tilde{F}((\eta_1 N + \mu_1 M), .., (\eta_J N + \mu_J M)) \tag{A24}$$

The partial derivative of Z with respect to N is:

$$\frac{\partial Z(N,M)}{\partial N} = \sum_j \eta_j \frac{\partial \tilde{F}(L_1,..,L_J)}{\partial L_j} \tag{A25}$$

which is the mean marginal product of natives. Similarly, the partial derivative with respect to M is:

$$\frac{\partial Z(N,M)}{\partial M} = \sum_j \mu_j \frac{\partial \tilde{F}(L_1,..,L_J)}{\partial L_j} \tag{A26}$$

which is the mean marginal product of migrants. In this way, we have reduced $\tilde{F}$ to an aggregated production function over two composite inputs (N and M), whose marginal products are equal to those of the average native and migrant. Our approach here builds on a long-standing literature on the aggregation of production functions (Houthakker, 1955; Levhari, 1968; Jones, 2005; Growiec, 2008). This literature offers a range of methods to achieve this where the two inputs are capital and labor, rather than natives and migrants. Levhari (1968) in particular shows how one can construct an underlying $\tilde{F}$ from a desired Z, using as an example the case where Z is CES.

D.2 Wage-setting in market j

We now elaborate on the market j wage-setting problem, described in Section 3; and in the following section, we consider how the resulting mark-downs can be averaged across multiple markets. For the purposes of this appendix, we assume firms cannot discriminate: they offer identical wages to all natives and migrants of skill type j. That is, firms choose a wage W_j to maximize profits, under the constraint that $W_{Nj} = W_{Mj} = W_j$. The marginal cost of labor facing such a firm is given by:

$$\begin{aligned} MC(W_j) &= W_j + \frac{N(W)+M(W)}{N'(W)+M'(W)} \qquad \text{(A27)} \\ &= W_j + \left[\frac{N(W_j)}{N(W_j)+M(W_j)}\left(\frac{\epsilon_N}{W_j - R_N}\right) + \frac{M(W_j)}{N(W_j)+M(W_j)}\left(\frac{\epsilon_M}{W_j - R_M}\right)\right]^{-1} \end{aligned}$$

where $N(W_j)$ and $M(W_j)$ are respectively the supply of native and migrant labor to the firm, as defined by (7) and (8). As illustrated by Figure 1, this marginal cost curve (the dotted line) will lie between the native and migrant MC curves of the discriminating firm. The optimal wage will equate the marginal cost with the marginal product, so $MC(W_j) = MP_j$, where the market j marginal product is equal to $\frac{\partial \tilde{F}}{\partial L_j}$. Rearranging this gives:

$$\frac{N_j}{N_j+M_j}\epsilon_N\left(e^{-\phi_j}-\frac{R_N}{MP_j}\right)^{-1}+\frac{M_j}{N_j+M_j}\epsilon_M\left(e^{-\phi_j}-\frac{R_M}{MP_j}\right)^{-1}=\left(1-e^{-\phi_j}\right)^{-1} \quad \text{(A28)}$$

where $\phi_j = \log\frac{MP_j}{W_j}$ is the mark-down, as defined by equation (1). (A28) implicitly solves for the mark-down ϕ_j in market j, as a function of (i) the native and migrant reservations (relative to the marginal product), $\frac{R_N}{MP_j}$ and $\frac{R_M}{MP_j}$, (ii) the native and migrant supply elasticities (in excess of the reservations), ϵ_N and ϵ_M, and (iii) the migrant share $\frac{M_j}{N_j+M_j}$ in market j. If migrants supply labor to firms less elastically (for which $R_M < R_N$ and $\epsilon_M < \epsilon_N$ is a sufficient condition), the mark-down ϕ_j will be increasing in the migrant share. Intuitively, if firms have greater market power over migrant labor, they will exploit immigration by extracting greater rents from natives and migrants alike.

D.3 Averaging mark-downs and wages across markets j

We now show how one can compute average native and migrant wages, aggregating over multiple markets j (perhaps within a given education-experience cell). In the absence of discrimination, the market j wage is identical for natives and migrants, and can be written as:

$$\log W_j = \log MP_j - \phi\left(\frac{\mu_j M}{\eta_j N}\right) \quad \text{(A29)}$$

where MP_j is the marginal product of skill type j labor, equal to $\frac{\partial \tilde{F}}{\partial L_j}$; and $\phi\left(\frac{\mu_j M}{\eta_j N}\right)$ is the mark-down, which depends on the relative supply of migrants, $\frac{\mu_j M}{\eta_j N}$. As equation (A28) shows, the mark-down ϕ will be increasing in the migrant share if migrants supply labor to firms relatively inelastically.

Now, let W_{Nex} be the average native wage. This will be a weighted average of wages (A29) across markets j, with weights equal to η_j:

$$\log W_N = \log\frac{\partial Z(N,M)}{\partial N} - \phi_N\left(\frac{M}{N}\right) \quad \text{(A30)}$$

where $\frac{\partial Z(N,M)}{\partial N}$ is the mean marginal product of natives (as in (A25)), and ϕ_N is their aggregate mark-down:

$$\phi_N\left(\frac{M}{N}\right) = \log\frac{\sum_j \eta_j MP_j}{\sum_j \eta_j MP_j \exp\left(-\phi\left(\frac{\mu_j M}{\eta_j N}\right)\right)} \quad \text{(A31)}$$

which is a function of the aggregate-level migrant share. Similarly, the mean migrant wage is:

$$\log W_M = \log \frac{\partial Z(N, M)}{\partial M} - \phi_M\left(\frac{M}{N}\right) \tag{A32}$$

where ϕ_M is the migrant aggregate mark-down:

$$\phi_M\left(\frac{M}{N}\right) = \log \frac{\sum_j \mu_j MP_j}{\sum_j \mu_j MP_j \exp\left(-\phi\left(\frac{\mu_j M}{\eta_j N}\right)\right)} \tag{A33}$$

In general, the aggregate mark-downs will (i) differ for natives and migrants and (ii) depend on the migrant share. We discuss the likely properties of the aggregate mark-down functions in the following section.

D.4 Properties of aggregate mark-down functions

We now explore the properties of the aggregate mark-down functions, $\phi_N\left(\frac{M}{N}\right)$ and $\phi_M\left(\frac{M}{N}\right)$. First, consider the special case where the markets j are completely segregated: i.e. each is entirely composed of either natives or migrants, so $\mu_j\eta_j = 0$ for all j. Based on (A28), this implies that $\phi_j = \log\left(\frac{\epsilon_N+1}{\epsilon_N+\frac{R_N}{MP_j}}\right)$ in all native markets (where $\eta_j > 0$); so the aggregate native mark-down $\phi_N\left(\frac{N}{M}\right)$ depends *only* on the native reservation R_N and supply elasticity ϵ_N. Similarly, complete segregation implies that $\phi_j = \log\left(\frac{\epsilon_M+1}{\epsilon_M+\frac{R_M}{MP_j}}\right)$ in all migrant markets (where $\mu_j > 0$), so the migrant mark-down $\phi_M\left(\frac{M}{N}\right)$ depends only on the migrant reservation and elasticity. Thus, the mark-downs are identical to those generated by the discriminating firm described in Section 3.

However, if there is any overlap of natives and migrants across markets j, the aggregate mark-downs will in general depend on the migrant share. The one exception is the extreme case where the supply parameters are equal ($R_M = R_N$ and $\epsilon_M = \epsilon_N$), so natives and migrants supply labor to firms identically. In this case, (A28) shows the market j mark-downs ϕ_j will be independent of migrant share and invariant with market j (if the reservations are fixed as shares of the marginal products, MP_j); so natives will face the same aggregate mark-downs as migrants ($\phi_N = \phi_M$), and both will be independent of migrant share. We illustrate ϕ_N and ϕ_M as functions of $\frac{M}{N}$ in Appendix Figure A1a, for the case where $R_M = R_N$ and $\epsilon_M = \epsilon_N$.

[Appendix Figure A1 here]

In Figure A1b, we consider the case where migrants supply labor less elastically to firms (e.g. if $R_M < R_N$ and $\epsilon_M < \epsilon_N$), as the evidence discussed in Section 3 might suggest. Migrants must necessarily be concentrated in markets j with larger migrant shares and larger mark-downs; and therefore, $\phi_M \geq \phi_N$. However, as (A28) shows, ϕ_M and ϕ_N must converge to equality as $\frac{M}{N} \to 0$ or $\frac{M}{N} \to \infty$. Intuitively, as the labor force becomes exclusively native or migrant, the elasticity facing firms converges to the pure native or migrant one (identical to those of the discriminating case), in which case all workers will face the same mark-down. For intermediate values of $\frac{M}{N}$, both ϕ_N and ϕ_M must be increasing in $\frac{M}{N}$, as firms can exploit the less elastic supply of migrants by cutting wages. Given the symmetry of the model, the results will be reversed if migrants supply labor to firms *more* elastically than natives.

To conclude, we now derive a more formal expression for the differential between the aggregate migrant and native mark-downs, ϕ_M and ϕ_N. Define $\tilde{\eta}_j = \frac{\eta_j MP_j}{\sum_j \eta_j MP_j}$ and $\tilde{\mu}_j = \frac{\mu_j MP_j}{\sum_j \mu_j MP_j}$. From (A31) and (A33), we then have:

$$\begin{aligned}
\exp(-\phi_M) - \exp(-\phi_N) &= \sum_j \tilde{\mu}_j \exp(-\phi_j) - \sum_j \tilde{\eta}_j \exp(-\phi_j) \qquad \text{(A34)} \\
&= \sum_j \tilde{\eta}_j \left(\frac{\tilde{\mu}_j}{\tilde{\eta}_j}\right) \exp(-\phi_j) - \sum_j \tilde{\eta}_j \exp(-\phi_j) \\
&= E_\eta \left[\frac{\tilde{\mu}_j}{\tilde{\eta}_j} \exp(-\phi_j)\right] - E_\eta \left[\frac{\tilde{\mu}_j}{\tilde{\eta}_j}\right] E_\eta \left[\exp(-\phi_j)\right] \\
&= Cov_\eta \left[\frac{\tilde{\mu}_j}{\tilde{\eta}_j}, \exp(-\phi_j)\right]
\end{aligned}$$

where the expectation E_η is taken with respect to the distribution $\tilde{\eta}_j$, and we are using the fact that $E_\eta \left[\frac{\tilde{\mu}_j}{\tilde{\eta}_j}\right] = 1$. If natives supply labor to firms more elastically than migrants (for which $R_M < R_N$ and $\epsilon_M < \epsilon_N$ is a sufficient condition), the market j mark-down $\phi_j = \phi\left(\frac{\mu_j M}{\eta_j N}\right)$ will be an increasing function of the ratio $\frac{\tilde{\mu}_j}{\tilde{\eta}_j}$; so the covariance in the final line of (A34) will be negative, and the aggregate mark-down will be larger for migrants. Intuitively, migrants will be disproportionately located in migrant-intensive markets (which are less competitive and have larger mark-downs).

D.5 Functional form of mark-down effects

In this section, we argue the mark-down function ϕ_j can be better approximated as a linear function of the migrant share, $\frac{M_j}{N_j+M_j}$, than of the log relative migrant supply, $\log \frac{M_j}{N_j}$. To keep things simple, suppose the reservations of natives and migrants are the same (i.e. $R_M = R_N = R$), but the labor supply elasticities (above the reservations) may differ (i.e. $\epsilon_M \neq \epsilon_N$). The optimal mark-down equation (A28) for a non-discriminating firm in market j then collapses to:

$$\left[\epsilon_N + \frac{M_j}{N_j + M_j}\Delta\epsilon\right]\left(1 - e^{-\phi_j}\right) = e^{-\phi_j} - \frac{R}{MP_j} \tag{A35}$$

where $\frac{M_j}{N_j+M_j}$ is the migrant share in the market, ϵ_N is the native elasticity, and $\Delta\epsilon \equiv \epsilon_M - \epsilon_N$ is the difference between the migrant and native elasticities. The derivative of the mark-down ϕ_j with respect to the migrant share is:

$$\frac{d\phi_j}{d\left(\frac{M_j}{N_j+M_j}\right)} = -\frac{\left(1 - e^{-\phi_j}\right)^2}{\left(1 - \frac{R}{MP_j}\right)e^{-\phi_j}}\Delta\epsilon \tag{A36}$$

Notice the migrant share $\frac{M_j}{N_j+M_j}$ has no effect on the mark-down if the elasticity difference is zero ($\Delta\epsilon = 0$), but a positive effect if migrants supply labor less elastically ($\Delta\epsilon < 0$), and vice versa. Crucially, this is true irrespective of the size of the migrant share.

However, this is not the case for the relationship between ϕ_j and $\log\left(\frac{M_j}{N_j}\right)$. The derivative can be written as:

$$\frac{d\phi_j}{d\log\left(\frac{M_j}{N_j}\right)} = \frac{d\phi_j}{d\frac{M_j}{N_j+M_j}} \cdot \frac{d\frac{M_j}{N_j+M_j}}{d\log\left(\frac{M_j}{N_j}\right)} = -\frac{\left(1 - e^{-\phi_j}\right)^2}{\left(1 - \frac{R}{MP_j}\right)e^{-\phi_j}} \cdot \frac{M_j}{N_j + M_j}\left(1 - \frac{M_j}{N_j + M_j}\right)\Delta\epsilon \tag{A37}$$

This goes to zero as the migrant share becomes small, even for a non-zero elasticity difference $\Delta\epsilon$. Intuitively, a very small rise in the migrant share can lead to a very large rise in $\log\left(\frac{M_j}{N_j}\right)$ if the initial migrant share is small; but such a rise would be expected to have only a small impact on the labor supply elasticity (and the mark-down ϕ_j) overall. Given this, a linear relationship between ϕ_j and $\log\left(\frac{M_j}{N_j}\right)$ would offer a relatively poor approximation of the true relationship, especially for small migrant share $\frac{M_j}{N_j+M_j}$.

E Identification for general Z, ϕ_N and ϕ_M

In Sections 4.2 and 4.3, we describe the identification problem and explain how we test the joint hypothesis of equal and independent mark-downs, under the assumption that Z is CES and the mark-down functions ϕ_N and ϕ_M are log-linear. In this appendix, we show how the joint hypothesis can be tested for any technology Z with constant returns to scale, and for mark-down functions ϕ_N and ϕ_M with any functional form.

Assuming the cell aggregator Z has constant returns, and suppressing the *ext* (education-experience-time) subscripts, it can be written as:

$$Z\left(N,M\right)=Nz\left(\frac{M}{N}\right) \tag{A38}$$

for some single-argument function z. Using (A38), the wage equations (15) and (16) can then be expressed as:

$$\begin{aligned}
\log W_N &= \log A-\left(1-\sigma_X\right)\log N+\log\left[\frac{z\left(\frac{M}{N}\right)-\frac{M}{N}z'\left(\frac{M}{N}\right)}{z\left(\frac{M}{N}\right)^{1-\sigma_X}}\right]-\phi_N\left(\frac{M}{N}\right) &\text{(A39)}\\
\log W_M &= \log A-\left(1-\sigma_X\right)\log N+\log\left[\frac{z'\left(\frac{M}{N}\right)}{z\left(\frac{M}{N}\right)^{1-\sigma_X}}\right]-\phi_M\left(\frac{M}{N}\right) &\text{(A40)}
\end{aligned}$$

where σ_X represents the substitutability between experience groups, and A is the cell-level productivity shifter defined by (17).

Just as in Section 4.2, we cannot identify the relationship between the mark-downs and the migrant share, if this relationship is different for natives and migrants. To see why, suppose one observes a large number of labor market cells, differing only in the total number of natives N and the ratio $\frac{M}{N}$. Then, using (A39) and (A40), one can identify σ_X by observing how wages vary with N, holding the ratio $\frac{M}{N}$ constant (which fixes the final two terms in each equation). However, holding N constant and observing how wages vary with $\frac{M}{N}$, it is not possible to separately identify the three functions (z,ϕ_N,ϕ_M), as we only have two equations.[41]

In the main text, we discuss two hypotheses of interest: $H1$ is $\phi_N\left(\frac{M}{N}\right)=\phi_M\left(\frac{M}{N}\right)$, i.e. equal mark-downs; and $H2$ is $\phi_N'\left(\frac{M}{N}\right)=0$, i.e. independent native mark-downs. While it is not possible to test $H1$ and $H2$ individually, it is possible to test the joint hypothesis of $H1$ and $H2$ (of which perfect competition is a special case).

In Section 4.3, we show how this test can be performed in two steps, for a Z of CES form and log-linear mark-down functions. But the same principle applies for more general functional forms. The basic idea is that $H1$ implies restrictions which make $H2$ testable. Conditional on equal mark-downs ($H1$), the difference between (A39) and (A40) collapses to:

$$\log\frac{W_M}{W_N}=\log\left[\frac{z'\left(\frac{M}{N}\right)}{z\left(\frac{M}{N}\right)-\frac{M}{N}z'\left(\frac{M}{N}\right)}\right] \tag{A41}$$

[41] Identification may be feasible if we assume the difference between ϕ_N and ϕ_M converges to zero as $\frac{M}{N}\to 0$ or $\frac{M}{N}\to\infty$, as our model in Appendix D.4 predicts. Then, taking differences between (A39) and (A40), we can identify Z (at least at the limits); and given Z, we can back out the mark-down functions. However, we do not pursue this strategy: "identification at infinity" may be feasible asymptotically, but it will be unreliable in small samples.

Using the relative wage equation (A41), variation in $\frac{M}{N}$ can then identify $z\left(\frac{M}{N}\right)$ up to a constant (this is analogous to "Step 1" in Section 4.3). And using the native wage equation (A39), knowledge of z then allows us to identify the native mark-down function $\phi_N\left(\frac{M}{N}\right)$ up to a constant (analogous to "Step 2"). Intuitively, knowledge of $z\left(\frac{M}{N}\right)$ allows us to predict how the native marginal product varies with $\frac{M}{N}$; so we can attribute the remaining effect of $\frac{M}{N}$ on wages to the mark-down. So conditional on equal mark-downs ($H1$), we are able to test whether the native mark-down is independent of the migrant share ($H2$). A rejection of $H2$ would then imply rejection of the combination of $H1$ and $H2$ (i.e. the null hypothesis of equal and independent mark-downs), of which perfect competition is a special case.

F Computing effects on wages, surplus and distribution

In this appendix, we describe how we compute the impact of the two counterfactuals in Section 8. The first is an immigration shock equal to 1% of total employment in 2019 (or 11% of non-citizen employment), holding migrants' skill mix fixed. And the second is a "naturalization" policy which grants citizenship to 1% of the total workforce, with non-citizens in every skill group naturalized with equal probability.

In Sections F.1-F.5, we first describe how we derive the impact of the immigration shock (ignoring distinctions between citizens and non-citizens). The procedure is similar for the naturalization counterfactual, but not identical: in Section F.6, we describe what exactly is different.

F.1 Immigration shock: Wage equations

We begin by setting out the wage equations. Imposing CES technology on the lowest-level education-experience nest Z (in line with (18)), and replacing the productivity shifter A with (17), the wage equations (15) and (16) can be written as:

$$W_{Nex} = \exp\left(-\phi_{Nex}\right)\alpha_e\left(\frac{L_e}{\tilde{Y}}\right)^{\sigma_E-1}\alpha_{ex}\left(\frac{L_{ex}}{L_e}\right)^{\sigma_X-1}\left(\frac{N_{ex}}{L_{ex}}\right)^{\sigma_Z-1} \tag{A42}$$

$$W_{Mex} = \exp\left(-\phi_{Mex}\right)\alpha_e\left(\frac{L_e}{\tilde{Y}}\right)^{\sigma_E-1}\alpha_{ex}\left(\frac{L_{ex}}{L_e}\right)^{\sigma_X-1}\alpha_Z\left(\frac{M_{ex}}{L_{ex}}\right)^{\sigma_Z-1} \tag{A43}$$

where $\tilde{Y}$ is long-run output, net of the costs of elastic inputs (i.e. capital). Taking logs:

$$\log W_{Nex} = \log\left(\alpha_e\alpha_{ex}\right) + \left(1-\sigma_E\right)\log\tilde{Y} + \left(\sigma_E-\sigma_X\right)\log L_e \tag{A44}$$

$$
\begin{aligned}
& + (\sigma_X - \sigma_Z) \log L_{ex} + (\sigma_Z - 1) \log N_{ex} - \phi_{Nex} \\
\log W_{Mex} \quad = \quad & \log (\alpha_e \alpha_{ex} \alpha_{Zex}) + (1 - \sigma_E) \log \tilde{Y} + (\sigma_E - \sigma_X) \log L_e \qquad \text{(A45)} \\
& + (\sigma_X - \sigma_Z) \log L_{ex} + (\sigma_Z - 1) \log M_{ex} - \phi_{Mex}
\end{aligned}
$$

Consider an immigration shock equal to 1% of total employment, holding the skill mix of migrants fixed. Using (A44) and (A45), we can assess the impact on native and migrant wages in each labor market cell. To this end, it is necessary to consider the effect of immigration in any given cell (e, x) on wages in every other cell (e', x'). For $e' \neq e$, we need only consider the impact on net output, $\log \tilde{Y}$. For $e' = e$ and $x' \neq x$, we must also consider the impact on the education aggregator, $\log L_e$. For wages in the same cell (i.e. $e' = e$ and $x' = x$), we must also consider the impact on the education-experience aggregator, $\log L_{ex}$; and for migrant wages in the same cell, we must also consider the effect via the $\log M_{ex}$ term in (A45). Finally, workers in the same cell ($e' = e$ and $x' = x$) will be subject to mark-down effects via ϕ_{Nex} and ϕ_{Mex}.

F.2 Immigration shock: Components of wage equations

How does the immigration shock affect the various components of (A44) and (A45)? Let $N \equiv \sum_{e,x} N_{ex}$ denote the aggregate native stock, and $M \equiv \sum_{e,x} M_{ex}$ the aggregate migrant stock. Notice first that, holding the native stock and migrant skill mixed fixed, a 1% increase in the aggregate migrant stock M (relative to total employment, $M + N$), i.e. $\frac{dM}{M+N}$, will cause the log migrant stock M_{ex} in each cell (e, x) to expand by:

$$
d \log M_{ex} = 0.01 \cdot \frac{N + M}{M} \tag{A46}
$$

For a given change in M_{ex}, the education-experience aggregator L_{ex} will increase by:

$$
\frac{d \log L_{ex}}{d \log M_{ex}} = \frac{\alpha_{Zex} M_{ex}^{\sigma_Z}}{N_{ex}^{\sigma_Z} + \alpha_{Zex} M_{ex}^{\sigma_Z}} = \frac{\tilde{F}_{Mex} M_{ex}}{\tilde{F}_{Mex} M_{ex} + \tilde{F}_{Nex} N_{ex}} \tag{A47}
$$

where the second equality follows from (18), and where:

$$
\begin{aligned}
\tilde{F}_{Nex} &= \exp (\phi_{Nex}) W_{Nex} && \text{(A48)} \\
\tilde{F}_{Mex} &= \exp (\phi_{Mex}) W_{Mex} && \text{(A49)}
\end{aligned}
$$

are the (long-run) cell-specific marginal products of native and migrant labor respectively. Notice that, under perfect competition (i.e. $\phi_{Nex} = \phi_{Mex} = 0$), $\frac{\tilde{F}_{Mex} M_{ex}}{\tilde{F}_{Mex} M_{ex} + \tilde{F}_{Nex} N_{ex}}$ will equal the migrant wage bill share (within the labor market cell).

For a given change in L_{ex} in some experience group x, the education aggregator L_e

increases by:

$$\frac{d\log L_e}{d\log L_{ex}} = \frac{\alpha_{ex}L_{ex}}{\sum_{x'}\alpha_{ex'}L_{ex'}} = \frac{\tilde{F}_{Mex}M_{ex}+\tilde{F}_{Nex}N_{ex}}{\sum_{x'}\left(\tilde{F}_{Mex'}M_{ex'}+\tilde{F}_{Nex'}N_{ex'}\right)} \tag{A50}$$

where the second equality follows from (13), and where $\frac{\tilde{F}_{Mex}M_{ex}+\tilde{F}_{Nex}N_{ex}}{\sum_{x'}\left(\tilde{F}_{Mex'}M_{ex'}+\tilde{F}_{Nex'}N_{ex'}\right)}$ will equal the wage bill share of experience group x (within education group e) under perfect competition.

And finally, for a given change in L_e in some education group e, net output $\tilde{Y}$ increases by:

$$\frac{d\log\tilde{Y}}{d\log L_e} = \frac{\alpha_e L_e}{\sum_{e'}\alpha_{e'}L_{e'}} = \frac{\sum_{x'}\left(\tilde{F}_{Mex'}M_{ex'}+\tilde{F}_{Nex'}N_{ex'}\right)}{\sum_{e',x'}\left(\tilde{F}_{Me'x'}M_{e'x'}+\tilde{F}_{Ne'x'}N_{e'x'}\right)} \tag{A51}$$

where the second equality follows from (12), and where $\frac{\sum_{x'}\left(\tilde{F}_{Mex'}M_{ex'}+\tilde{F}_{Nex'}N_{ex'}\right)}{\sum_{e',x'}\left(\tilde{F}_{Me'x'}M_{e'x'}+\tilde{F}_{Ne'x'}N_{e'x'}\right)}$ will equal the wage bill share of education group e under perfect competition.

F.3 Immigration shock: Mark-down effects

Finally, consider the mark-down effects, which fall on workers in the same cell (i.e. $e' = e$ and $x' = x$). In equations (19) and (20), we specify the mark-down functions in terms of the log relative supply of migrant to native employment, i.e. $\log\frac{M_{ex}}{N_{ex}}$. But for the purposes of this analysis (consistent with our empirical specifications), we respecify these as functions of the cell-specific migrant share $\frac{M_{ex}}{M_{ex}+N_{ex}}$:

$$\phi_{Nex} = \phi_{0Nex} + \phi_{1N}\frac{M_{ex}}{M_{ex}+N_{ex}} \tag{A52}$$

$$\phi_{Mex} = \phi_{0Nex} + \Delta\phi_{0ex} + \left(\phi_{1N}+\Delta\phi_1\right)\frac{M_{ex}}{M_{ex}+N_{ex}} \tag{A53}$$

Taking derivatives with respect to $\log M_{ex}$, while holding native employment stocks fixed, then gives:

$$\frac{d\phi_{Nex}}{d\log M_{ex}} = \phi_{1N}\frac{d\left(\frac{M_{ex}}{M_{ex}+N_{ex}}\right)}{d\log M_{ex}} = \phi_{1N}\frac{N_{ex}M_{ex}}{\left(N_{ex}+M_{ex}\right)^2} \tag{A54}$$

$$\frac{d\phi_{Mex}}{d\log M_{ex}} = \left(\phi_{1N}+\Delta\phi_1\right) = \left(\phi_{1N}+\Delta\phi_1\right)\frac{N_{ex}M_{ex}}{\left(N_{ex}+M_{ex}\right)^2} \tag{A55}$$

F.4 Immigration shock: Aggregation of wage change components

The equations above describe the effect of immigration in any given cell (e,x) on the various aggregators (L_{ex}, L_e and $\tilde{Y}$), as well as the mark-downs (ϕ_{Nex} and ϕ_{Mex}). To compute the overall response of wages in some education-experience cell, accounting for immigration $d\log M_{ex}$ across the full distribution of cells (e,x), we simply aggregate over all these effects. Using (A44) and (A45), we have:

$$\begin{aligned} d\log W_{Nex} \quad = \quad & (1-\sigma_E)\sum_{e',x'}\frac{d\log\tilde{Y}}{d\log L_{e'}}\cdot\frac{d\log L_{e'}}{d\log L_{e'x'}}\cdot\frac{d\log L_{e'x'}}{d\log M_{e'x'}}\cdot d\log M_{e'x'} \\ & +(\sigma_E-\sigma_X)\sum_{e,x'}\frac{d\log L_e}{d\log L_{ex'}}\cdot\frac{d\log L_{ex'}}{d\log M_{ex'}}\cdot d\log M_{ex'} \\ & +(\sigma_X-\sigma_Z)\frac{d\log L_{ex}}{d\log M_{ex}}\cdot d\log M_{ex}-d\phi_{Nex} \end{aligned} \tag{A56}$$

and

$$\begin{aligned} d\log W_{Mex} \quad = \quad & (1-\sigma_E)\sum_{e',x'}\frac{d\log\tilde{Y}}{d\log L_{e'}}\cdot\frac{d\log L_{e'}}{d\log L_{e'x'}}\cdot\frac{d\log L_{e'x'}}{d\log M_{e'x'}}\cdot d\log M_{e'x'} \\ & +(\sigma_E-\sigma_X)\sum_{e,x'}\frac{d\log L_e}{d\log L_{ex'}}\cdot\frac{d\log L_{ex'}}{d\log M_{ex'}}\cdot d\log M_{ex'} \\ & +(\sigma_X-\sigma_Z)\frac{d\log L_{ex}}{d\log M_{ex}}\cdot d\log M_{ex}-(1-\sigma_Z)\,d\log M_{ex}-d\phi_{Mex} \end{aligned} \tag{A57}$$

F.5 Immigration shock: Distributional effects and surplus

We now turn to Panel C of Table 8. The first row of Panel C reports the impact on total migrant wage income, relative to net output. To derive this, we first compute the change in migrant wage income in each labor market cell (e,x):

$$d\left(W_{Mex}M_{ex}\right)=W_{Mex}M_{ex}\left(d\log W_{Mex}+d\log M_{ex}\right) \tag{A58}$$

Similarly, the change in native wage income in cell (e,x) can be written as:

$$d\left(W_{Nex}N_{ex}\right)=W_{Mex}N_{ex}\cdot d\log W_{Nex} \tag{A59}$$

To compute the total change in the migrant and native wage bills, we sum (A58) and (A59) over labor market cells (e,x). And we express these changes relative to net output

$\tilde{Y}$, where $\tilde{Y}$ can be written as:

$$\tilde{Y} = \sum_{e,x} \left(\tilde{F}_{Mex} M_{ex} + \tilde{F}_{Nex} N_{ex} \right) \tag{A60}$$

given our assumption that production has constant returns. The change in monopsony rents R (relative to $\tilde{Y}$) can be expressed as a residual, after subtracting changes in total wage income from total income growth:

$$\frac{dR}{\tilde{Y}} = d \log \tilde{Y} - \sum_{e,x} \frac{d \left(W_{Nex} N_{ex} \right)}{\tilde{Y}} - \sum_{e,x} \frac{d \left(W_{Mex} M_{ex} \right)}{\tilde{Y}} \tag{A61}$$

Finally, if we assume that all monopsony rents go to natives, we can write the immigration surplus S (relative to net output) as:

$$\frac{S}{\tilde{Y}} = \frac{dR}{\tilde{Y}} + \sum_{e,x} \frac{d \left(W_{Nex} N_{ex} \right)}{\tilde{Y}} \tag{A62}$$

F.6 Naturalization counterfactual

Above, we have described how we estimate the impact of the immigration shock counterfactual. The procedure for the naturalization counterfactual is similar, but not identical. In this section, we describe what exactly is different. We begin by disaggregating the cell-specific migrant employment stock, M_{ex}, into citizen and non-citizen components:

$$M_{ex} \equiv M_{ex}^{cit} + M_{ex}^{noncit} \tag{A63}$$

Let π_{ex} be the fraction of migrants employment in cell (e, x) which is attributed to non-citizens:

$$\pi_{ex} \equiv \frac{M_{ex}^{noncit}}{M_{ex}} \tag{A64}$$

In the naturalization counterfactual, we consider the impact of transforming a small (and proportionately equal) number of non-citizens in every education-experience cell to citizens. That is, we consider a small (and equal) decrease in $\log \pi_{ex}$ in every cell. For a policy which naturalizes 1% of the total workforce (which we consider in Table 9), $\log \pi_{ex}$ decreases in every (e, x) cell by:

$$d \log \pi_{ex} = 0.01 \cdot \frac{N + M}{M^{noncit}} \tag{A65}$$

For the purposes of this exercise, we assume that all workers (natives, migrant citizens and non-citizens) within education-experience cells are perfect substitutes: i.e. $\sigma_Z = 1$.

However, we permit productive differences between these workers. In place of (18), we therefore write the cell-level input L_{ex} as:

$$L_{ex} = N_{ex} + \alpha_{Zex}^{cit} M_{ex}^{cit} + \alpha_{Zex}^{noncit} M_{ex}^{noncit} \tag{A66}$$

where α_{Zex}^{cit} and α_{Zex}^{noncit} are the relative efficiencies of each migrant type. The production technology at higher nests is identical to before: i.e. (13) and (12) are unchanged.

In place of (A45), we now have distinct wage equations migrant citizens and non-citizens:

$$\begin{aligned}
\log W_{Mex}^{cit} &= \log\left(\alpha_e \alpha_{ex} \alpha_{Zex}^{cit}\right) + (1-\sigma_E)\log \tilde{Y} + (\sigma_E - \sigma_X)\log L_e \qquad \text{(A67)} \\
&\quad - (1-\sigma_Z)\log L_{ex} - \phi_{Mex}^{cit} \\
\log W_{Mex}^{noncit} &= \log\left(\alpha_e \alpha_{ex} \alpha_{Zex}^{noncit}\right) + (1-\sigma_E)\log \tilde{Y} + (\sigma_E - \sigma_X)\log L_e \qquad \text{(A68)} \\
&\quad - (1-\sigma_Z)\log L_{ex} - \phi_{Mex}^{noncit}
\end{aligned}$$

where ϕ_{Mex}^{cit} and ϕ_{Mex}^{noncit} are the cell-specific mark-downs of migrant citizens and non-citizens respectively.

Using (A66), we begin by consider the impact of a change in $d\log \pi_{ex}$ on $\log L_{ex}$ in a given cell, in place of equation (A47) above:

$$\frac{d\log L_{ex}}{d\log \pi_{ex}} = \frac{\left(\tilde{F}_{Mex}^{noncit} - \tilde{F}_{Mex}^{cit}\right) M_{ex}^{noncit}}{\tilde{F}_{Mex}^{cit} M_{ex}^{cit} + \tilde{F}_{Mex}^{noncit} M_{ex}^{noncit} + \tilde{F}_{Nex} N_{ex}} \tag{A69}$$

where

$$\begin{aligned}
\tilde{F}_{Nex} &= \exp\left(\phi_{Nex}\right) W_{Nex} && \text{(A70)} \\
\tilde{F}_{Mex}^{cit} &= \exp\left(\phi_{Mex}^{cit}\right) W_{Mex}^{cit} && \text{(A71)} \\
\tilde{F}_{Mex}^{noncit} &= \exp\left(\phi_{Mex}^{noncit}\right) W_{Mex}^{noncit} && \text{(A72)}
\end{aligned}$$

are the cell-specific marginal products. Similarly to equations (A50) and (A51) above, we can then derive the changes in the education-level aggregator $d\log L_e$ and net output $d\log \tilde{Y}$, but simply replacing all occurrences of $\left\{\tilde{F}_{Mex} M_{ex}\right\}$ with $\left\{\tilde{F}_{Mex}^{cit} M_{ex}^{cit} + \tilde{F}_{Mex}^{noncit} M_{ex}^{noncit}\right\}$.

We now turn to the mark-down responses. Motivated by our empirical estimates, we suppose the mark-downs respond only to the *non-citizen* share of cell-specific employment (and not to the share of migrant citizens). For simplicity, we also assume this response is identical (within cells) for natives, citizens and non-citizens alike. Using the same functional form as (A52) and (A53), we can therefore write the three mark-down functions as:

$$
\begin{aligned}
\phi_{Nex} &= \phi_{0Nex} + \phi_{1N} \frac{M_{ex}^{noncit}}{M_{ex} + N_{ex}} && \text{(A73)} \\
\phi_{Mex}^{cit} &= \phi_{0Nex} + \Delta\phi_{0ex}^{cit} + \phi_{1N} \frac{M_{ex}^{noncit}}{M_{ex} + N_{ex}} && \text{(A74)} \\
\phi_{Mex}^{noncit} &= \phi_{0Nex} + \Delta\phi_{0ex}^{noncit} + \phi_{1N} \frac{M_{ex}^{noncit}}{M_{ex} + N_{ex}} && \text{(A75)}
\end{aligned}
$$

Holding native and total migrant employment stocks fixed, the derivatives of the mark-downs with respect to $\log \pi_{ex}$ are identical for all workers within education-experience cells:

$$
\begin{aligned}
\frac{d\phi_{Nex}}{d\log \pi_{ex}} = \frac{d\phi_{Mex}^{cit}}{d\log \pi_{ex}} = \frac{d\phi_{Mex}^{noncit}}{d\log \pi_{ex}} &= \phi_{1N} \frac{d\left(\frac{M_{ex}^{noncit}}{M_{ex}+N_{ex}}\right)}{d\log \pi_{ex}} && \text{(A76)} \\
&= \phi_{1N} \frac{M_{ex}^{noncit}}{M_{ex} + N_{ex}}
\end{aligned}
$$

Using the various equations above, we can then aggregate over the components of the wage equation, to derive wage changes in every education-experience cell, just as we do in equations (A56) and (A57) for the immigration shock. Since we assume the mark-down response is identical for all workers within cells, and that all workers are perfect substitutes within cells, the wage response is identical across natives and migrants. Specifically:

$$
\begin{aligned}
d\log W_{ex} &= (1-\sigma_E) \sum_{e',x'} \frac{d\log \tilde{Y}}{d\log L_{e'}} \cdot \frac{d\log L_{e'}}{d\log L_{e'x'}} \cdot \frac{d\log L_{e'x'}}{d\log \pi_{e'x'}} \cdot d\log \pi_{e'x'} && \text{(A77)} \\
&+ (\sigma_E - \sigma_X) \sum_{e,x'} \frac{d\log L_e}{d\log L_{ex'}} \cdot \frac{d\log L_{ex'}}{d\log \pi_{ex'}} \cdot d\log \pi_{ex'} \\
&+ (\sigma_X - \sigma_Z) \frac{d\log L_{ex}}{d\log M_{ex}} \cdot d\log \pi_{ex} - d\phi_{Nex}
\end{aligned}
$$

Using (A77), can then compute the distributional effects, in the same way as outlined in Section F.5. The only difference is the cell-specific migrant wage bill change in equation (A58), which we now replace with:

$$
\begin{aligned}
d\left(W_{Mex} M_{ex}\right) &= d\left(W_{Mex}^{cit} M_{ex}^{cit} + W_{Mex}^{noncit} M_{ex}^{noncit}\right) && \text{(A78)} \\
&= \left(W_{Mex}^{noncit} - W_{Mex}^{cit}\right) M_{ex}^{noncit} d\log \pi_{ex} \\
&+ \left(W_{Mex}^{cit} M_{ex}^{cit} + W_{Mex}^{noncit} M_{ex}^{noncit}\right) d\log W_{ex}
\end{aligned}
$$

G Further details on data

G.1 Disaggregation of migrant stocks in 1960 census

The 1960 census does not report migrants' year of arrival or citizenship status, but we require this information for various parts of the analysis (specifically in Section 7.2). In particular, we need to know (i) the employment stock of "old" migrants (i.e. living in the US for more than ten years) and (ii) the employment stock of citizens, both by education-experience cell. We impute (i) using information on the same migrant cohorts (by year of arrival and citizenship status) ten years later. And we then impute (ii) using citizen shares of old and new migrant stocks across education-experience cells in 1970.

We begin by describing the imputation of old migrant stocks. There are three steps:

1. For each education-experience stock of old migrants in 1960 (i.e. with more than ten years in the US), predict the size of the same cohort in 1970 (i.e. among migrants with more than *twenty* years in the US). For the purposes of this exercise, we assume prospective high school graduates leave education at 19, those with some college at 21, and college graduates at 23. Under these assumptions, we can assign every immigrant in 1970 to a 1960 labor market cell.

2. Account for emigration. To the extent foreign-born residents leave the US, the cohort size in 1970 should be smaller than in 1960. To account for this phenomenon, we repeat step (1) for the 1970 and 1980 census years; and we regress the log predicted cohort size (based on census data in 1980) on the log actual size (in 1970). We then use the regression estimates to predict the 1960 stocks of old migrants, based on the 1970 cohort size. The regression coefficient in 1.11, which suggests about 10% of immigrants leave the country each decade, which is consistent with estimates from Ahmed and Robinson (1994).

3. Convert from population to employment. Step (2) yields estimates of the old migrant population in every education-experience cell in 1960. For our analysis though, we require estimates of employment stocks. Our approach is to compute employment rates for the total migrant population in each 1960 education-experience cell, and then to apply these rates to the old migrant stocks. (Note the population and employment stocks of "new" migrants can be computed as the difference between the total cell-specific migrants stocks and imputed old migrant stocks.)

Using our estimates of new and old migrant employment stocks in 1960, we now predict migrant citizen/non-citizen employment in that year. There are two steps:

1. For each education-experience cell in 1970, compute the citizen share of both new migrant employment (with up to ten years in the US) and old migrant employment (more than ten years).

2. To predict 1960 citizen employment stocks, apply these 1970 shares to the new/old 1960 migrant employment stocks (as imputed above).

G.2 Instrument for new immigrant stocks

In this section, we describe in greater detail how we construct the instrument for new immigrant stocks, $\tilde{M}^{new}_{ext}$. As we explain in Section 5.3 in the main text, this is a weighted aggregate of historical cohort sizes in origin countries. We construct this weighted average using the coefficient estimates of the following linear regression:

$$\log M^{new}_{oext} = \lambda^{Mnew}_0 + \lambda^{Mnew}_1 \log HistoricalCohortSize_{oext} + \lambda^{Mnew}_2 Mobility_{ex} + Region_o + \varepsilon^{Mnew}_{oext} \tag{A79}$$

where the dependent variable, M^{new}_{oext}, is the US population of new migrants (with up to ten years in the US) at each observation year t, for each of 164 origin countries o and 32 education-experience cells (e, x). We take this information from our ACS and census samples. $HistoricalCohortSize_{oext}$ is the historical size of the relevant education cohort at origin o, ten years before t, which we take from Barro and Lee (2013) and the UN World Population Prospects database.[42] Of course, we cannot observe the historical sizes of education cohorts aged 18-33 in year t, since many of them will not have reached their final education status ten years previously: we assign these individuals to education groups in the same way as we do for US natives (as described in Section 5.3), based on the education choices of the previous cohort (in the relevant origin country). Conditional on cohort size, one might expect more emigration to the US from more mobile demographic groups - especially the young. To account for this, we control in (A79) for a time-invariant index of cell-specific residential mobility, $Mobility_{ex}$, which we describe in the following section (Appendix G.3). And finally, we control for a set of 12 region of origin effects[43], $Region_o$, which account for the fact that demographic shifts in certain regions matter

[42]The Barro-Lee data offer population counts by country, education and 5-year age category for individuals aged 15 or over. We identify Barro and Lee's "complete tertiary" education category with college graduates, "incomplete tertiary" with some college, "secondary complete" with high school graduates, and all remaining categories with high school dropouts. We impute single-year age counts by dividing the 5-year stocks equally across their single-year components. To predict historical cohort sizes of the youngest groups, we also require counts of under-15s; and we take this information from the UN World Population Prospects database: *https://population.un.org/wpp/*.

[43]Specifically: North America, Mexico, Other Central America, South America, Western Europe, Eastern Europe and former USSR, Middle East and North Africa, Sub-Saharan Africa, South Asia, Southeast Asia, East Asia, Oceania.

more for emigration to the US. As it turns out, origin cohort size delivers substantial predictive power: we estimate a λ_1^{Mnew} of 0.475 (with a standard error of 0.03, clustered by education-experience cells).

Using our estimates of (A79), we then predict $\log M_{oext}^{new}$ for every origin o, education-experience cell (e, x) and observation year t. And to generate our instrument $\tilde{M}_{ext}^{new}$ for the cell-level (e, x) stock of new migrants, we sum the predicted M_{oext}^{new} over origins o:

$$\tilde{M}_{ext}^{new} = \sum_o \exp\left(\hat{\lambda}_0^{Mnew} + \hat{\lambda}_2^{Mnew} Mobility_{ex} + Region_o\right) \cdot HistoricalCohortSize_{oext}^{\hat{\lambda}_1^{Mnew}} \tag{A80}$$

Effectively, this is a weighted aggregate of historical cohort sizes in origin countries (ten years before t), where the weights depend on time-invariant origin-specific migration propensities (as picked up by the $Region_o$ effects) and cell-specific mobility (as picked up by the $Mobility_{ex}$ index). Notice we do not rely on e, x or t fixed effects in our predictive regression (A79), as these may pick up employment responses to unobserved cell-level demand shocks; and the entire purpose of this instrument is to exclude such variation.

G.3 Mobility index for predicting new immigrant stocks

In this section, we describe our education-experience index of residential mobility $Mobility_{ex}$, which we use to predict new migrant stocks in equation (A79). One might choose to measure mobility using cell-level (e, x) shares of new immigrants in the US population. But of course, this may pick up demand effects at the education-experience cell level, which we are attempting to exclude (as US cells with stronger demand may attract more immigrants). Instead, we proxy mobility with cross-state migration *within* the US rather than *international* migration.

More specifically, our chosen index is the log rate of cross-state migration, based on the 1960 census. We use the log rate to match the log migrant inflow on the left hand side of (A79). The census reports place of residence *five* years previously. But our dependent variable is the stock of new immigrants who arrived in the last *ten* years. These differences may matter, given we are studying mobility within fine 5-year experience cells. To address this inconsistency, we take the following approach. The first step is to compute internal mobility shares (i.e. the probability of living in a different state five years previously) by education and 5-year experience cell, using the 1960 census. Denote these shares as $ShareDiffState5yr_{ex}$. For each education-experience cell (e, x), we then compute the mobility index as:

$$Mobility_{ex} = \log\left[\frac{1}{2}\left(ShareDiffState5yr_{ex} + ShareDiffState5yr_{ex-1}\right)\right] \tag{A81}$$

i.e. the log average of internal mobility shares of cells (e, x) and $(e, x-1)$, where the latter predicts the mobility of the same education cohort five years previously. For example, the mobility index of college graduates in experience group 8 (i.e. with 36-40 years of experience) is computed as the log average of graduates' 5-year mobility shares in experience groups 8 (36-40 years of experience) and 7 (31-35 years).

The computation of $Mobility_{ex}$ for experience group 1 (1-5 years of experience) is more challenging: we require a value of $ShareDiffState5yr_{ex}$ for a hypothetical pre-career experience group "0" (between -4 and 0 years of experience). We apply the following strategy. For college graduates (who we assume leave school at age 23), we compute $ShareDiffState5yr_{ex}$ for experience group "0" as the migration probability of students aged 19-23. Similarly, for the "some college" group in experience group 0, we use the migration probability of students aged 17-21. For high school graduates, we use students aged 15-19s; and for high school dropouts, we use students aged 13-17.

[Appendix Table A1 here]

We set out the resulting mobility index $Mobility_{ex}$ in Table A1. As is well known, cross-state mobility is highest among the young and highly educated.

G.4 Predicted changes in old and new migrant shares

In Panel B of Table 1 in the main text, we set out changes over 1960-2019 in migrant employment share $\frac{M_{ext}}{N_{ext}+M_{ext}}$ across the 32 education-experience cells; and in Panel C, we predict these changes using our instruments (i.e. we report changes in $\frac{\tilde{M}_{ext}}{\tilde{N}_{ext}+\tilde{M}_{ext}}$, where $\tilde{M}_{ext} = \tilde{M}^{old}_{ext} + \tilde{M}^{new}_{ext}$).

In Appendix Table A2, we now decompose these changes into the contributions of "new" migrants (with up to ten years in the US) and "old" migrants (more than ten years). In Panel A, we report changes over 1960-2019 in old migrants' share of employment hours, i.e. $\frac{M^{old}_{ext}}{N_{ext}+M_{ext}}$. In Panel B, we predict this change with our instruments: i.e. we report changes in $\frac{\tilde{M}^{old}_{ext}}{\tilde{N}_{ext}+\tilde{M}_{ext}}$. Similarly, Panel C reports changes in the new migrants share, $\frac{M^{new}_{ext}}{N_{ext}+M_{ext}}$; and Panel D predicts these using changes in $\frac{\tilde{M}^{new}_{ext}}{\tilde{N}_{ext}+\tilde{M}_{ext}}$.

[Appendix Table A2 here]

For both new and old migrants, the instruments appear to predict changes in employment shares reasonably well. In the discussion of Table 1 in the main text, we noted that the instruments do underpredict the increase in migrant share among young college graduates. Looking at Appendix Table A2, it is clear that this underprediction stems from the instrument for new (rather than for old) migrants.

H Supplementary empirical analysis

H.1 Regression tables corresponding to Figure 2

In Appendix Table A3, we set out IV estimates of the native wage equation (29), corresponding to a selection of (α_Z, σ_Z) values in Figure 2. Notice that column 2 (with $\alpha_Z = \sigma_Z = 1$) is identical to columns 7 and 9 in Panel B of Table 4.

[Appendix Table A3 here]

H.2 Robustness to wage definition and weighting

In Appendix Table A4, we confirm that our IV estimates of the native wage equation (29) are robust to the choice of wage variable and weighting.

[Appendix Table A4 here]

In each specification, the right hand side is identical to columns 7 and 9 of Table 4 (Panel B), and we also use the same instruments. The only difference is the left hand side variable and the choice of weighting. Odd columns study the wages of native men, and even columns those of native women. Columns 1-2 and 5-6 study weekly wages of full-time workers (as in the main text), and the remaining columns hourly wages of all workers. All wage variables are adjusted for changes in demographic composition, in line with the method described in Section 5.2. The estimates in Panel A are unweighted (as in Table 4); while in Panel B, we weight observations by total cell employment. It turns out the estimates are similar across specifications.

H.3 Alternative specification for instrument

One may be concerned that our predictor for the migrant stock, $\tilde{M}_{ext}$, is largely noise; and that the first stage of our native wage equation is driven instead by the correlation between native employment N_{ext} and its predictor $\tilde{N}_{ext}$ (which appear in the denominators of the migrant share, $\frac{M_{ext}}{N_{ext}+M_{ext}}$, and its instrument, $\frac{\tilde{M}_{ext}}{\tilde{N}_{ext}+\tilde{M}_{ext}}$). See Clemens and Hunt (2019) for a related criticism.

However, in Appendix Table A5, we show the IV estimates are robust to replacing the migrant share instrument $\frac{\tilde{M}_{ext}}{\tilde{N}_{ext}+\tilde{M}_{ext}}$ with its numerator $\tilde{M}_{ext}$. In practice, we scale $\tilde{M}_{ext}$ by 10^{-6} to make the coefficients visible in the table. Columns 1-4 are otherwise identical to columns 3-6 in Table 3 (Panel B), and columns 5-6 are comparable to columns 7 and 9 in Table 4 (Panel B).

[Appendix Table A5 here]

The instruments take the correct sign in the first stage: in particular, the migrant share is decreasing in $\log\left(\tilde{N}_{ext} + \tilde{M}_{ext}\right)$ but increasing in $\tilde{M}_{ext}$; and the associated F-statistics are large, especially in first differences. Comparing the second stage estimates to Table 4, the migrant share coefficients are somewhat smaller: the fixed effect estimate is -0.34 (down from -0.56), and the first differenced estimate is -0.38 (down from -0.42). Though the standard errors are now unsurprisingly larger, both estimates remain statistically significant.

H.4 Heterogeneous effects of new and old migrants

In this section, we study whether mark-downs are more responsive to "new" migrants (in the US for up to new years) or "old" migrants (more than ten years). Our approach is to control separately for the shares of new migrants $\frac{M_{ext}^{new}}{N_{ext}+M_{ext}}$ and old migrants $\frac{M_{ext}^{old}}{N_{ext}+M_{ext}}$ in the native wage equation (29). We construct distinct instruments for each, i.e. $\frac{\tilde{M}_{ext}^{new}}{\tilde{N}_{ext}+\tilde{M}_{ext}}$ and $\frac{\tilde{M}_{ext}^{old}}{\tilde{N}_{ext}+\tilde{M}_{ext}}$. Table A6 reports first stage estimates: our instruments perform remarkably well in fixed effects, but offer limited power in first differences (F-statistics are all below 10).

[Appendix Tables A6 and A7 here]

Appendix Table A7 presents our OLS and IV estimates. Both the new and old migrant shares command large and negative effects. In OLS, the effects of old migrants are somewhat larger (columns 1 and 3); but they are very similar in the IV fixed effect specification (column 2). In the first differenced IV specification, the standard error on the new immigrant share is too large to make definitive claims.

H.5 Dynamic wage adjustment

One possible concern is serial correlation in the migrant share, conditional on the various fixed effects. If wages adjust sluggishly to immigration shocks, the lagged migrant share will be an omitted variable; and in the presence of serial correlation, our γ_2 estimate in the native wage equation (29) may be biased (Jaeger, Ruist and Stuhler, 2018). However, as we now show, our instruments have sufficient power to disentangle the effect of contemporaneous and lagged shocks (despite the presence of serial correlation); and at least in IV, we find these dynamics are statistically insignificant (i.e. past shocks have no influence on current wages).

We take the native wage equation (29) as a point of departure, but now control additionally for the 1-period lagged cell aggregator (in this case, total employment) and migrant share. The lag is 10 years at all observation years except for 2019 (where the lagged outcome corresponds to 2010). For IV, this requires two additional instruments; and we use the lags of our existing instruments.

[Appendix Tables A8 and A9 here]

We present our first stage estimates in Appendix Table A8, and our OLS and IV estimates in Appendix Table A9. Since we include lagged observations, we necessarily lose one period of data; so for comparison, we report estimates of the basic specification (without lags) using the shorter sample: see the odd-numbered columns in Table A9. These look very similar to the full-sample estimates in Table 4 in the main text.

Next, consider the dynamic specification. Looking at the dynamic first stage estimates (columns 2, 3, 5 and 6 of Appendix Table A8), each instrument has a large positive effect on its corresponding endogenous variable; and the F-statistics are universally large. This suggests the instruments offer sufficient power to disentangle the effects of contemporaneous and lagged immigration shocks.

What are the implications for the wage responses? Columns 2 and 6 of Appendix Table A9 report dynamic OLS estimates, for fixed effects and first differences respectively. In each case, the lagged migrant share picks up about half the negative wage effect. This suggests there is large serial correlation (even in the presence of the various fixed effects); and at least in OLS, it appears that wages adjust sluggishly to immigration shocks. However, once we apply the instruments in columns 4 and 8, the entire effect is picked up by the contemporaneous shocks: the lagged shocks become small and statistically insignificant. That is, once we use sources of variation which are more plausibly exogenous to cell-specific demand, we find no evidence of sluggish wage adjustment.

H.6 Labor supply responses

In Appendix Table A10, we replace the left-hand side of the native wage equation with the native employment rate (defined as log average hours per individual). Just as in our wage sample (and like Borjas, 2003), we exclude enrolled students when computing employment rates; and we also adjust employment rates for changes in demographic composition[44] (as we do for wages). We report IV estimates for both fixed effect and first

[44]Our motivation for adjusting employment rates is the same as for wages: changes in either outcome may be conflated with observable demographic shifts (within education-experience cells). We follow identical steps to those described in Section 5.2; but this time, we estimate linear regressions for annual employment hours (including zeroes for individuals who do not work) rather than log wages.

differenced specifications, separately for the employment rates of men and women, and natives and migrants.

[Appendix Table A10 here]

Consistent with Borjas (2003) and Monras (2020), who study similar skill-cell variation, we find that migrant share (suitably instrumented) does indeed reduce native employment rates. It turns out this response is entirely driven by native women, which matches the findings of Borjas and Edo (2021) in France. But despite this, the wage effects are very similar for men and women (see Appendix Table A4): this suggests the wage effects are not conflated with selection, at least in this context.

H.7 Empirical robustness of CES assumption

To estimate the native wage equation (29), we need to construct an aggregator $Z(N, M)$ over native and migrant employment within education-experience cells. In line with the existing literature (Card, 2009; Manacorda, Manning and Wadsworth, 2012; Ottaviano and Peri, 2012), we assume Z has CES form. But in principle, our identification strategy can be generalized to any Z with constant returns. Under constant returns, we show in Appendix E that the log relative wage (of migrants to natives) must depend only on the log relative supply of migrants, $\log \frac{M}{N}$: see equation (A41). The assumption of CES imposes that this relationship is *linear*: see equation (23). Therefore, to check the validity of the CES assumption (conditional on constant returns), we need only consider the linearity of the relationship between log relative wages and log relative supply.

[Appendix Figure A2 here]

To study the shape of this relationship, we present scatter-plots which illustrate our preferred IV specification of the relative wage equation (26): specifically, column 5 of Table 2 (which controls for education-experience effects and year effects). In Panel A of Figure **??**, we plot the first stage relationship corresponding to this specification (i.e. the log relative supply on its instrument), after partialing the fixed effects from both the left and right-hand side variables. And in Panel B, we do the same for the reduced form (i.e. the log relative wage directly on the instrument). In each case, by inspection, linearity appears a reasonable description of the data.

H.8 Cross-cell heterogeneity in σ_Z

In our relative wage model (equation (26)), we implicitly assume that σ_Z (the within-cell substitutability between natives and migrants) is identical across education-experience cells. But one may be concerned that there may be important heterogeneity: this would imply the Z aggregator should be constructed differently (on the right-hand side of the native wage equation), and this may cause us to incorrectly estimate the mark-down effect.

[Appendix Table A11 here]

In Table A11, we test for heterogeneity in IV estimates of the relative wage effect, across college/non-college cells and high/low experience cells. In the odd-numbered columns, we report estimates without heterogeneity: these replicate the baseline estimates of Table 2. In the even-numbered columns, we include interactions between log relative employment and (i) a college dummy and (ii) a high-experience (more than 20 years) dummy. Our instruments are the interactions between the predicted log relative employment and the respective dummies. The F-statistics show the first stage is strong in each case. However, in the second stage, the interactions are quantitatively small in all specifications. This suggests heterogeneity in σ_Z across education-experience cells will not affect our conclusions.

H.9 Broad education and experience groups

We next study alternative specifications with two (instead of four) education groups, and four (instead of eight) experience groups. We begin with the two-group education specification. We divide workers into "college-equivalents" (which include all college graduates, plus 0.8 times half of the some-college stock) and "high-school equivalents" (high school graduates, plus 0.7 times the dropout stock, plus 1.2 times half of the some-college stock): the weights, borrowed from Card (2009), have an efficiency unit interpretation. This leaves us with just 16 clusters (since we cluster by labor market cell); but at least in this data, the bias to the standard errors appears to be small.[45]

Similar to Table 4, we report estimates of the native wage equation both under the assumption of equal mark-downs ($\Delta\phi_{0ext} = \Delta\phi_1 = 0$) and under $\alpha_{Zext} = \sigma_Z = 1$. In

[45] For example, consider the OLS coefficient on $\frac{M}{N+M}$ in column 1 of Table A13. Since we have 16 clusters, we apply the 95% critical value of the $T(15)$ distribution (as recommended by Cameron and Miller, 2015), which is 2.13. The standard error in column 1 then implies a confidence interval of $[-1.302, -0.639]$. But the wild bootstrap recommended by Cameron, Gelbach and Miller (2008), which we implement with Roodman et al.'s (2019) "boottest" command, delivers a very similar interval of $[-1.251, -0.588]$.

the former case, we impose a σ_Z of 0.907. This is estimated from an IV relative wage equation with education-experience and year fixed effects (which we do not report in full here).[46]

We report first stage estimates in Table A12, and OLS and IV estimates in columns 1-4 of Table A13. Notice that γ_1 (the elasticity to total cell employment) is now consistently negative in the $\alpha_{Zext} = \sigma_Z = 1$ specification, taking a value of -0.1 under fixed effects. This implies an elasticity of substitution between experience groups (within education nests) of 10. The OLS estimate of γ_1 in column 1 is similar to that of Card and Lemieux (2001), who use an equivalent two-group education classification.[47] The γ_2 estimate (on migrant share) now exceeds -1 under fixed effects (columns 1-2). In first differences (columns 3-4), it ranges from -0.6 to -1.3.

[Appendix Tables A12 and A13 here]

In columns 5-8 of Table A13, we also re-estimate our model using four 10-year experience groups (rather than eight 5-year groups), while keeping the original four-group education classification. This makes little difference to our baseline estimates in Table 4. This result can also help address concerns over the independence of the detailed 5-year education-experience clusters in the baseline specification: Table A13 shows the estimates (and standard errors) are little affected after aggregating to larger 10-year groups.

H.10 Occupation-imputed migrant stocks

In this paper, we have chosen to allocate migrants to native labor market cells according to their education and experience, following the example of Borjas (2003), Ottaviano and Peri (2012) and others. One important concern is that migrants may "downgrade" occupation and compete with natives of lower education or experience. As a result, the true migrant stocks in native cells would be measured with error. In principle, this may attenuate our (negative) estimates of the impact of migrant share. But importantly, Dustmann, Schoenberg and Stuhler (2016) show it may also artificially inflate the effects, depending on the particular pattern of downgrading.

To address this concern, we study what happens if we probabilistically allocate migrants (of given education and experience) to native cells according to their occupational distribution. Our strategy here is similar in spirit to Card (2001) and Sharpe and Bollinger (2020). Suppose there are O occupations, denoted o, and EX education-experience cells,

[46]The β_1 estimate in (26) is -0.093, with a standard error of 0.039.

[47]In their main specification, they estimate an elasticity of substitution of 5 across age (rather than experience) groups; but they also offer estimates across experience groups which are similar to ours.

denoted ex. Let $\mathbf{\Pi}^M_{O\times EX}$ be a matrix, with O rows and EX columns, which allocates migrant education-experience cells to occupations, where the (o, ex) element is the share of education-experience ex migrant labor which is employed in occupation o (so the columns of $\mathbf{\Pi}^M_{O\times EX}$ sum to 1). We base these shares on averages across all sample years. Similarly, let $\mathbf{\Pi}^N_{EX\times O}$ be an $EX \times O$ matrix which allocates occupations to native education-experience cells, where the (ex, o) element is the share of occupation o native labor which has education-experience ex (so the columns of $\mathbf{\Pi}^N_{EX\times O}$ sum to 1). Using these matrices, we can probabilistically allocate migrant education-experience cells to native education-experience cells, according to their occupational distribution:

$$\mathbf{M}^{occ}_{EX\times T} = \mathbf{\Pi}^N_{EX\times O}\mathbf{\Pi}^M_{O\times EX}\mathbf{M}_{EX\times T} \tag{A82}$$

where $\mathbf{M}_{EX\times T}$ is the matrix of *actual* migrant employment stocks by education-experience cell and time, and $\mathbf{M}^{occ}_{EX\times T}$ is the *imputed* allocation of migrants to native cells (based on the occupational distributions). In practice, we rely on the time-consistent IPUMS classification of occupations (based on the 1990 census scheme), aggregated to the 2-digit level (with 81 codes). We use an identical strategy to construct instruments for the occupation-imputed migrant stock:

$$\tilde{\mathbf{M}}^{occ}_{EX\times T} = \mathbf{\Pi}^N_{EX\times O}\mathbf{\Pi}^M_{O\times EX}\tilde{\mathbf{M}}_{EX\times T} \tag{A83}$$

where $\tilde{\mathbf{M}}^{occ}_{EX\times T}$ is our instruments for immigrant stocks by education and experience, as described in Section 5.3.

Using this data, we now re-estimate the native wage equation (29), but replacing education-experience migrant stocks M_{ext} with occupation-imputed stocks M^{occ}_{ext} (and replacing the instruments accordingly). Similar to Table 4, we report estimates of the native wage equation both under the assumption of equal mark-downs ($\Delta\phi_{0ext} = \Delta\phi_1 = 0$) and under $\alpha_{Zext} = \sigma_Z = 1$. In the former case, we impose a σ_Z of 0.979. This is estimated from an IV relative wage equation with education-experience and year fixed effects (which we do not report in full here), based on the occupation-imputed stocks.[48] Appendix Table A14 suggests the instruments work well for the occupation-imputed stocks.

[Appendix Tables A14 and A15]

We present OLS and IV estimates in Appendix Table A15. The OLS effects of migrant share (columns 1 and 5) are very similar to our baseline specifications in the main text

[48]The β_1 estimate in (26) is -0.021, with a standard error of 0.006.

(compare to Table 4). The IV effects are much larger, with migrant share effects hovering around -1.5 in fixed effects and -0.9 in first differences. However, the standard errors are also large: about 0.5 in fixed effects and 0.3 in first differences. This appears to stem from a collinearity problem: once we drop the cell aggregator (whose coefficient is always insignificant) in columns 4 and 8, the IV effects of migrant share are smaller (ranging from -0.6 to -1) and more precise (with standard errors between 0.1 and 0.2). This suggests our estimates are robust to concerns about occupational downgrading.

H.11 Heterogeneity in migrants elicited by instrument

In this section, we consider to what extent our basic instrument for the migrant share, i.e. $\frac{\tilde{M}}{\tilde{M}+\tilde{N}}$, elicits a representative draw of migrants. We present our estimates in Table A16, separately for fixed effects in Panel A and first differences in Panel B.

[Appendix Table A16]

As our point of departure, in column 1, we reproduce the first stage estimates for the overall migrant share $\frac{M}{M+N}$ (this is identical to columns 4 and 6 of Table 3). In columns 2 and 3, we then replace the dependent variable with (i) the share of old migrants in total cell employment and (ii) the share of new migrants respectively. By construction, the coefficients in columns 2 and 3 sum to the coefficients in column 1. The estimates show that migrant share instrument mostly elicits variation in old (rather than new) migrants. In columns 4 and 5, we repeat this exercise for the citizen and non-citizen share; and in columns 5 and 6, we repeat it for Mexicans and non-Mexicans. The results show the power of the instrument is almost exclusively driven by Mexican-born non-citizens. These are *not* representative of the migrant population: in our sample, only half of migrants are non-citizens, and only 20% of Mexican-born.

H.12 Separation elasticities

In this appendix, we offer estimates of job separation elasticities across workers with different migrant status and education, based on the Survey of Income and Program Participation (SIPP). As is well known, the separation elasticity offers a useful (and easily estimable) proxy for the elasticity of labor supply to a firm. Since the flow of separations from a firm must equal the flow of recruits in equilibrium, the overall elasticity of labor supply to the firm should be double the separation elasticity (Manning, 2003). We are not the first to compare separation elasticities by migrant status: see Hotchkiss and Quispe-Agnoli (2013), Hirsch and Jahn (2015) and Biblarsh and De-Shalit (2021).

The SIPP is a longitudinal dataset with large samples and frequent waves, just four months apart. We rely on SIPP panels beginning 1996, 2001, 2004 and 2008 (which cover the period 1996-2013). Our sample consists of individuals aged at least 18, with 1-40 years of potential labor market experience and no business income. Unusually, the SIPP records both citizenship status and whether respondents have legal permanent residency (i.e. a green card). For an individual in employment at the end of wave $t-1$, a separation occurs (by our definition) if that individual leaves their "primary" job[49] by the end of wave t.

Like Manning (2003), we estimate separation elasticities using a complementary log-log model. Suppose the instantaneous separation rate for individual i is fixed within the time interval $t-1$ to t, and denote this separation rate as s_{it}. The probability of separating within this interval is:

$$\Pr\left(Sep_{it}=1\right)=1-\exp\left(-s_{it}\right) \tag{A84}$$

where Sep_{it} is a binary variable taking 1 if the individual separates between $t-1$ and t. This motivates our complementary log-log model:

$$\Pr\left(Sep_{it}=1\right)=1-\exp\left(-\exp\left(\beta_W\log W_{it-1}+\beta_X'X_{it}+\beta_t\right)\right) \tag{A85}$$

where we write s_{it} as a function of the initial wave W_{it-1}, human capital and demographic indicators[50] X_{it}, and a full set of wave effects β_t. The coefficient of interest β_W (which we expect to be negative) can then be interpreted as the elasticity of the instantaneous separation rate with respect to W_{it-1}. Assuming a constant hazard, this interpretation is independent of the time interval between waves.

The purpose of the X_{it} is to purge, as much as possible, variation across individuals in productivity. This would allow us to interpret β_W as the separation elasticity with respect to W_{it-1} for individuals of fixed marginal product: that is, the elasticity of the separation rate to wage mark-downs. Of course, unobservable heterogeneity in individual productivity may confound this interpretation; but comparisons of separation elasticities across demographic groups can still be informative.

[49] Respondents report up to two jobs in each wave. If an individual repots two jobs in $t-1$, the primary job is the one which occupies the most weekly hours. Where both jobs have the same hours, we define the primary job as the first one reported in the survey.

[50] Specifically: experience and experience squared; four education indicators (high school graduate, some college, undergraduate and postgraduate), each interacted with a quadratic in experience; immigration status indicators (foreign-born, non-citizen, non-permanent status), each interacted with education and the experience quadratic; Central American origin and recent immigrant (arriving in last ten years), each interacted with education and the experience quadratic; and a gender dummy, interacted with education, the experience quadratic, immigration status, Central American origin and recent immigrant.

[Appendix Table A17 here]

In Table A17, we present our estimates of the separation elasticity β_W by immigration status. Crucially, all variables which are interacted with the lag logged wage are included individually on the right-hand side (among the demographic controls). In column 1, we include both the lagged wage and an interaction with a foreign-born dummy: on average, migrants have significantly lower separation elasticities than natives: -0.30 compared to -0.45. Biblarsh and De-Shalit (2021) reach similar conclusions using the US Current Population Survey. In column 2, we replace the foreign-born interaction with distinct citizen migrant and non-citizen categories (the omitted category continues to be natives) this shows the native-migrant differential in separation elasticities is mostly driven by non-citizens.

In column 3-6, we repeat this exercise separately for college-educated and non-college workers. Notice first that the native separation elasticities vary little by education. However, the entire native-migrant differential in separation elasticities appears is driven by the low educated; and again, non-citizens account for the bulk of the effect (column 6). In fact, the non-citizen elasticity (-0.07) is under 20% of the native elasticity (-0.42). Column 7 shows the low non-citizen elasticity (among non-college workers) is mostly due to non-permanent residents, many of whom are undocumented. In fact, the separation elasticity for this group is slightly positive - though insignificantly different from zero.

One might wonder whether the low separation elasticities of non-citizens are a *consequence* of their legal status, or due to immutable characteristics which are merely *correlated* with citizenship. Two such characteristics are length of stay in the US and country of origin, both of which are predictive of legal status. In column 8, we include interactions between the lagged wage and dummies for a “new” migrant (up to 10 years in the US) and Central American origin. However, these do not dent the effects of legal status. This suggests that legal status itself may be playing an important role.

Tables and figures

Table 1: Descriptive statistics

	Experience groups							
	1-5	6-10	11-15	16-20	21-25	26-30	31-35	36-40
Panel A: Migrant share of employment hours, 1960								
HS dropouts	0.035	0.037	0.040	0.045	0.045	0.053	0.083	0.127
HS graduates	0.016	0.017	0.024	0.031	0.030	0.046	0.074	0.115
Some college	0.027	0.033	0.041	0.045	0.042	0.058	0.073	0.094
College graduates	0.031	0.038	0.045	0.048	0.058	0.064	0.092	0.111
Panel B: Change in migrant share of employment hours, 1960-2019								
HS dropouts	0.138	0.283	0.418	0.509	0.559	0.585	0.532	0.425
HS graduates	0.077	0.110	0.152	0.184	0.204	0.185	0.124	0.042
Some college	0.058	0.059	0.073	0.083	0.100	0.083	0.058	0.020
College graduates	0.082	0.117	0.137	0.155	0.142	0.118	0.078	0.038
Panel C: Predicted change in migrant share, 1960-2019								
HS dropouts	0.147	0.358	0.431	0.477	0.501	0.541	0.478	0.371
HS graduates	0.115	0.176	0.184	0.207	0.214	0.192	0.123	0.027
Some college	0.032	0.048	0.083	0.094	0.100	0.089	0.067	0.034
College graduates	-0.001	0.038	0.088	0.143	0.148	0.112	0.089	0.037
Panel D: Change in log native wages, 1960-2019								
HS dropouts	-0.053	-0.115	-0.125	-0.137	-0.052	-0.067	-0.030	-0.016
HS graduates	-0.232	-0.218	-0.214	-0.134	-0.100	-0.044	-0.022	-0.007
Some college	-0.209	-0.179	-0.112	-0.049	0.013	0.069	0.106	0.133
College graduates	0.060	0.116	0.177	0.229	0.273	0.293	0.326	0.323
Panel E: Mean log migrant-native wage differential								
HS dropouts	-0.032	-0.113	-0.136	-0.134	-0.140	-0.140	-0.121	-0.088
HS graduates	-0.049	-0.112	-0.123	-0.143	-0.139	-0.145	-0.145	-0.130
Some college	-0.038	-0.075	-0.091	-0.095	-0.105	-0.121	-0.105	-0.080
College graduates	0.016	-0.036	-0.059	-0.074	-0.102	-0.132	-0.142	-0.133

Panel A reports the migrant employment share $\frac{M}{N+M}$ in 1960, across the four education and eight experience groups; and Panel B reports changes in this share over 1960-2019. Panel C predicts changes in the migrant share using our instruments: i.e. we report changes in $\frac{\tilde{M}}{\tilde{N}+\tilde{M}}$. Panel D reports changes over 1960-2019 in composition-adjusted log native (weekly) wages, normalized to mean zero across all groups. Panel E reports the mean composition-adjusted log migrant-native wage differential, averaged over 1960-2019, in education-experience cells. The wage sample consists of full-time workers who are not enrolled as students. Wages are adjusted for cell-level changes in demographic composition, according to the procedure described in Section 5.2.

Table 2: Model for log relative migrant-native wages

	Basic estimates			Fixed effects: Edu*Exp, Year		First differences		First diff + Year effects	
	Raw wages	Composition-adjusted		Composition-adjusted		Composition-adjusted		Composition-adjusted	
	OLS	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: OLS and IV estimates									
$\log \frac{M}{N}$	-0.029***	0.003	0.007	-0.016**	-0.029***	-0.042***	-0.045***	-0.006	-0.003
	(0.003)	(0.004)	(0.006)	(0.007)	(0.010)	(0.007)	(0.008)	(0.006)	(0.006)
Constant (or	-0.134***	-0.094***	-0.086***	-0.126***	-0.154***	-	-	-	-
mean intercept)	(0.011)	(0.013)	(0.018)	(0.013)	(0.020)				
Panel B: First stage estimates									
$\log \frac{\tilde{M}}{\tilde{N}}$	-	-	1.083***	-	1.103***	-	1.003***	-	1.046***
	-	-	(0.049)	-	(0.071)	-	(0.053)	-	(0.048)
Observations	224	224	224	224	224	192	192	192	192

Panel A reports estimates of equation (26), across 32 education-experience cells and 7 time observations (over 1960-2019). Columns 1-3 include no fixed effects, while columns 4-5 control for interacted education-experience and year fixed effects. The "constant" row in columns 4-5 reports the mean β_0 intercept (accounting for the fixed effects) across all observations. Columns 6-9 are estimated in first differences, with columns 8-9 controlling additionally for year effects. Panel B reports first stage coefficients for the IV estimates, where the instrument is the log ratio of the predicted migrant to native employment. Robust standard errors, clustered by 32 education-experience cells, are in parentheses. We adjust these for degrees of freedom, scaling them by $\sqrt{\frac{G}{G-1} \cdot \frac{N-1}{N-K}}$ for both OLS and IV, where G is the number of clusters, and K the number of regressors and fixed effects. The relevant 95% critical value for the T distribution (with $G-1=31$ degrees of freedom) is 2.04. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Model for native wages: First stage

	Fixed effects				First differences	
	$\log Z(N,M)$	$\log \frac{M}{N}$	$\log Z(N,M)$	$\frac{M}{N+M}$	$\log Z(N,M)$	$\frac{M}{N+M}$
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Imposing equal mark-downs (H1), $\Delta\phi_{0ext} = \Delta\phi_1 = 0$						
$\log\left(\tilde{N}+\tilde{M}\right)$	1.068***	0.044	1.102***	0.029	0.880***	0.046***
	(0.082)	(0.103)	(0.073)	(0.018)	(0.091)	(0.015)
$\log \frac{\tilde{M}}{\tilde{N}}$	0.054	0.944***				
	(0.060)	(0.116)				
$\frac{\tilde{M}}{\tilde{N}+\tilde{M}}$			0.707**	1.093***	1.134***	1.000***
			(0.283)	(0.073)	(0.329)	(0.110)
Panel B: Imposing $\alpha_{Zext} = \sigma_Z = 1$						
$\log\left(\tilde{N}+\tilde{M}\right)$	1.091***	0.044	1.121***	0.029	0.883***	0.046***
	(0.085)	(0.103)	(0.074)	(0.018)	(0.091)	(0.015)
$\log \frac{\tilde{M}}{\tilde{N}}$	0.07	0.944***				
	(0.061)	(0.116)				
$\frac{\tilde{M}}{\tilde{N}+\tilde{M}}$			0.800***	1.093***	1.149***	1.000***
			(0.265)	(0.073)	(0.319)	(0.110)
SW F-stat: Panel A	123.12	57.98	230.26	201.15	98.50	82.40
SW F-stat: Panel B	126.20	58.39	254.83	210.22	98.56	82.54
Observations	224	224	224	224	192	192

This table presents first stage estimates for the native wage equation (29), across 32 education-experience cells and 7 time observations (over 1960-2019). There are two endogenous variables: the cell aggregator $\log Z(N,M) = \log\left(N^{\sigma_Z} + \alpha_{Zext} M^{\sigma_Z}\right)^{\frac{1}{\sigma_Z}}$ and the cell composition. We consider two specifications for the cell aggregator: in Panel A, we identify α_{Zext} and σ_Z using the estimates from column 5 of Table 2, under the hypothesis of equal mark-downs ($H1$: $\Delta\phi_{0ext} = \Delta\phi_1 = 0$); and in Panel B, we impose that $\alpha_{Zext} = \sigma_Z = 1$, so $Z(N,M)$ collapses to total employment, $N+M$. We also consider two specifications for the cell composition: columns 1-2 use the log relative migrant-native ratio $\log \frac{M}{N}$, while columns 3-6 use the migrant share $\frac{M}{N+M}$. Our instrument for cell composition is constructed using the identical functional form over the predicted native and migrant employment, i.e. $\tilde{N}$ and $\tilde{M}$. And our instrument for the cell aggregator is $\log\left(\tilde{N}+\tilde{M}\right)$ in both panels. Columns 1-4 control for interacted education-year, experience-year and education-experience fixed effects; and columns 5-6 are estimated in first differences, controlling for the interacted education-year and experience-year effects. Sanderson-Windmeijer F-statistics account for multiple endogenous variables. Robust standard errors, clustered by 32 education-experience cells, are in parentheses. We apply the same small-sample corrections as detailed in Table 2. The relevant 95% critical value for the T distribution (with $G-1=31$ degrees of freedom, where G is the number of clusters) is 2.04. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Model for native wages: OLS and IV

	Fixed effects							First differences	
	Raw wages		Comp-adjusted					Comp-adjusted	
	OLS	OLS	OLS	OLS	OLS	IV	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Imposing equal mark-downs (H1), $\Delta\phi_{0ext} = \Delta\phi_1 = 0$									
$\log Z(N, M)$	0.064***	0.079***	0.026	0.059***	0.064***	0.029	0.054***	0.038***	0.050***
	(0.015)	(0.014)	(0.016)	(0.012)	(0.021)	(0.026)	(0.015)	(0.010)	(0.018)
$\log \frac{M}{N}$	-0.059***		-0.105***		0.014	-0.105***			
	(0.019)		(0.014)		(0.031)	(0.028)			
$\frac{M}{N+M}$		-0.392***		-0.563***	-0.620***		-0.614***	-0.424***	-0.476***
		(0.051)		(0.039)	(0.133)		(0.065)	(0.044)	(0.081)
Panel B: Imposing $\alpha_{Zext} = \sigma_Z = 1$									
$\log(N + M)$	0.039**	0.051***	0.000	0.031**	0.035	0.002	0.025*	0.012	0.023
	(0.014)	(0.013)	(0.015)	(0.012)	(0.021)	(0.025)	(0.015)	(0.010)	(0.018)
$\log \frac{M}{N}$	-0.050***		-0.096***		0.011	-0.097***			
	(0.018)		(0.014)		(0.031)	(0.027)			
$\frac{M}{N+M}$		-0.342***		-0.512***	-0.561***		-0.564***	-0.372***	-0.422***
		(0.052)		(0.039)	(0.135)		(0.065)	(0.044)	(0.080)
Observations	224	224	224	224	224	224	224	192	192

Panels A and B present OLS and IV estimates of the native wage equation (29), across 32 education-experience cells and 7 time observations (over 1960-2019). The dependent variable is $[\log W_N + (1 - \sigma_Z)\log N]$, where we use either raw mean or composition-adjusted wages. The two regressors of interest are the cell aggregator $\log Z(N, M) = \log(N^{\sigma_Z} + \alpha_{Zext} M^{\sigma_Z})^{\frac{1}{\sigma_Z}}$ and cell composition. In Panel A, we identify α_{Zext} and σ_Z using the estimates from column 5 of Table 2, under the hypothesis of equal mark-downs ($H1$: $\Delta\phi_{0ext} = \Delta\phi_1 = 0$); and in Panel B, we impose that $\alpha_{Zext} = \sigma_Z = 1$, so the dependent variable collapses to the log native wage, and $Z(N, M)$ collapses to total employment, $N + M$. We also consider two specifications for the cell composition: the log relative migrant-native ratio $\log \frac{M}{N}$ and the migrant share $\frac{M}{N+M}$. Columns 1-7 control for interacted education-year, experience-year and education-experience fixed effects; and columns 8-9 are estimated in first differences, controlling for the interacted education-year and experience-year effects. We report the corresponding first stage estimates in Table 3. Robust standard errors, clustered by 32 education-experience cells, are in parentheses. We apply the same small-sample corrections as detailed in Table 2. The relevant 95% critical value for the T distribution (with $G - 1 = 31$ degrees of freedom, where G is the number of clusters) is 2.04. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Mean employment and wages of migrant citizens and non-citizens

	HS dropouts	HS grads	Some coll	Coll grads	Average
Citizen share of migrant employment	0.321	0.492	0.586	0.585	0.491
Wage differentials:					
Migrant citizens v natives	-0.040	-0.055	-0.036	-0.028	-0.036
Non-citizens v natives	-0.182	-0.193	-0.170	-0.156	-0.168

This table reports descriptive statistics on migrant citizens and non-citizens. The top row reports the citizen share of migrant employment, by education and overall, averaged over the full sample (1960-2019). The second row reports differentials in log wages between migrant citizens and natives, and the third row repeats for non-citizens. These wage differentials are computed within education-experience cells, and then averaged over the period 1970-2019 (citizenship status is not reported in the 1960 microdata). Wages are adjusted for cell-level changes in demographic composition, separately for natives, migrant citizens and non-citizens, according to the procedure described in Section 5.2.

Table 6: Effects of citizen and non-citizen migrants: First stage

	Fixed effects			First differences		
	$\log(N+M)$	$\frac{M^{cit}}{N+M}$	$\frac{M^{noncit}}{N+M}$	$\log(N+M)$	$\frac{M^{cit}}{N+M}$	$\frac{M^{noncit}}{N+M}$
	(1)	(2)	(3)	(4)	(5)	(6)
$\log\left(\tilde{N}+\tilde{M}\right)$	0.899***	-0.050***	0.081***	0.726***	-0.022**	0.057***
	(0.075)	(0.016)	(0.016)	(0.099)	(0.008)	(0.016)
$\frac{\tilde{M}^{cit}}{\tilde{N}+\tilde{M}}$	-3.828***	0.908***	0.219	-3.247***	0.809***	-0.112
	(1.038)	(0.128)	(0.230)	(0.955)	(0.078)	(0.217)
$\frac{\tilde{M}^{noncit}}{\tilde{N}+\tilde{M}}$	0.663**	0.099*	0.995***	1.367***	0.115	0.900***
	(0.261)	(0.053)	(0.080)	(0.280)	(0.071)	(0.099)
SW F-stat	11.11	12.90	19.28	10.32	16.19	14.02
Observations	224	224	224	192	192	192

This table presents first stage estimates for the native wage equation (29), but this time accounting separately for the employment shares of migrant citizens $\frac{M^{cit}}{N+M}$ and non-citizens $\frac{M^{noncit}}{N+M}$. These estimates correspond to the IV specifications of Table 7. We impose that $\alpha_{Zext} = \sigma_Z = 1$, so the cell aggregator collapses (the third endogenous variable) to $\log(N+M)$. Our three instruments are (i) log total predicted population $\log\left(\tilde{N}+\tilde{M}\right)$, (ii) the predicted migrant citizen share $\frac{\tilde{M}^{cit}}{\tilde{N}+\tilde{M}}$, and (iii) predicted non-citizen share $\frac{\tilde{M}^{noncit}}{\tilde{N}+\tilde{M}}$: we describe the latter two in Section 7.2. Columns 1-3 control for interacted education-year, experience-year and education-experience fixed effects; and columns 4-6 are estimated in first differences, controlling for the interacted education-year and experience-year effects. Sanderson-Windmeijer F-statistics account for multiple endogenous variables. Robust standard errors, clustered by 32 education-experience cells, are in parentheses. We apply the same small-sample corrections as detailed in Table 2. The relevant 95% critical value for the T distribution (with $G-1=31$ degrees of freedom, where G is the number of clusters) is 2.04. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Effects of citizen and non-citizen migrants

	Fixed effects		First differences	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
$\log(N+M)$	0.022	0.086	0.001	0.065
	(0.019)	(0.056)	(0.013)	(0.047)
$\frac{M^{cit}}{N+M}$	-0.618***	0.060	-0.577***	0.096
	(0.137)	(0.504)	(0.102)	(0.424)
$\frac{M^{noncit}}{N+M}$	-0.492***	-0.657***	-0.337***	-0.569***
	(0.068)	(0.095)	(0.051)	(0.155)
Observations	224	224	192	192

This table presents OLS and IV estimates of the native wage equation (29), but this time accounting separately for the effects of the employment shares of migrant citizens $\frac{M^{cit}}{N+M}$ and non-citizens $\frac{M^{noncit}}{N+M}$. We impose that $\alpha_{Zext} = \sigma_Z = 1$, so the dependent variable collapses to the log native wage (which we adjust for composition in all specifications), and the cell aggregator on the right hand side collapses to $\log(N+M)$. Columns 1-2 control for interacted education-year, experience-year and education-experience fixed effects; and columns 3-4 are estimated in first differences, controlling for the interacted education-year and experience-year effects. We report the corresponding first stage estimates in Appendix Table A6. Robust standard errors, clustered by 32 education-experience cells, are in parentheses. We apply the same small-sample corrections as detailed in Table 2. The relevant 95% critical value for the T distribution (with $G-1=31$ degrees of freedom, where G is the number of clusters) is 2.04. *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Simulation of 1% immigration shock

	(1)	(2)	(3)	(4)
Impose equal mark-downs ($H1$)?	Yes	Yes	Yes	No
Impose $\alpha_{Zex} = \sigma_Z = 1$?	No	No	No	Yes
Baseline native mark-down	0	0.1	0.1	0.1
Native mark-down response to migrant share	0	0	0.614	0.564
Panel A: Native wages (% changes)				
HS dropouts	-0.484	-0.484	-1.281	-1.321
HS graduates	0.035	0.035	-0.473	-0.477
Some college	0.115	0.115	-0.250	-0.242
College graduates	0.022	0.022	-0.471	-0.449
Average	0.038	0.038	-0.429	-0.417
Panel B: Migrant wages (% changes)				
HS dropouts	-0.688	-0.688	-1.512	-1.560
HS graduates	-0.136	-0.136	-0.669	-0.675
Some college	-0.051	-0.051	-0.424	-0.416
College graduates	-0.145	-0.145	-0.649	-0.626
Average	-0.186	-0.186	-0.708	-0.700
Panel C: Net long run output and distribution of gains				
% change in net output	0.962	0.962	0.962	0.991
Decomposition:				
(i) Δ Migrant wage income (% net output)	0.930	0.842	0.761	0.758
(ii) Δ Native wage income (% net output)	0.032	0.029	-0.322	-0.311
(iii) Δ Monopsony rents (% net output)	0	0.092	0.523	0.544
Total native surplus (% net output) = (ii) + (iii)	0.032	0.120	0.201	0.233

This table quantifies the impact of immigration on native and migrant wages, monopsony rents and "net output" (i.e. long-run output net of the costs of elastic inputs). In particular, we consider the effect of an immigration shock equal to 1% of total employment in 2019, holding migrants' skill mix fixed. For consistency with Ottaviano and Peri (2012), we impose their estimates of the elasticities in the upper nests of the CES technology: specifically, we set σ_E in equation (12) to 0.7, and σ_X in equation (13) to 0.84 (based on their "Model A"). Column 1 describes the perfect competition case (with zero mark-downs), column 2 imposes a fixed mark-down of 0.1 for all workers, and columns 3-4 permit mark-downs to respond to migrant share (in line with our estimates in Table 4). See Section 8 for further details on the various model specifications. Panels A and B predict changes in native and migrant wages (in % terms), by education and overall. Panel C predicts the % change in net output, and decomposes this into contributions from migrant wage income, native wage income and monopsony rents. The native surplus is the sum of changes in native wage income and monopsony rents, as a % of net output (i.e. we assume that all monopsony rents go to native-owned firms).

Table 9: Simulation of naturalization counterfactual

	(1)		(2)		(3)	
Impose equal mark-downs ($H1$)?	Yes		Yes		No	
Impose $\alpha^{cit}_{Zex} = \alpha^{noncit}_{Zex} = 1$?	No		No		Yes	
Baseline native mark-down	0		0.1		0.1	
Mark-down response to non-citizen share	0		0.657		0.657	
Panel A: Wage effects (% changes)	*Natives*	*Migrants*	*Natives*	*Migrants*	*Natives*	*Migrants*
HS dropouts	-0.207	1.386	2.692	4.541	2.899	4.770
HS graduates	-0.015	0.860	0.722	1.636	0.737	1.653
Some college	0.011	0.525	0.337	0.852	0.326	0.842
College graduates	0.014	0.297	0.500	0.798	0.486	0.785
Average	0.004	0.543	0.540	1.338	0.536	1.356
Panel B: Net long run output and distribution of gains						
% change in net output	0.095		0.095		0	
Decomposition:						
(i) Δ Migrant wage income (% net output)	0.092		0.205		0.206	
(ii) Δ Native wage income (% net output)	0.003		0.406		0.400	
(iii) Δ Monopsony rents (% net output)	0		-0.516		-0.605	
Total native surplus (% net output) = (ii) + (iii)	0.003		-0.110		-0.206	

This table quantifies the impact of a "naturalization" policy which transforms a portion of the non-citizen workforce (equal to 1% of total employment) into citizens, within education-experience cells. For consistency with Ottaviano and Peri (2012), we impose their estimates of the elasticities in the upper nests of the CES technology: specifically, we set σ_E in equation (12) to 0.7, and σ_X in equation (13) to 0.84 (based on their "Model A"). Within education-experience cells, we assume that all workers (natives, migrant citizens and non-citizens) are perfect substitutes (i.e. $\sigma_Z = 1$); but we permit productive differences between these workers. Specifically, we write the cell-level input L_{ex} as: $L_{ex} = N_{ex} + \alpha^{cit}_{Zex} M^{cit}_{ex} + \alpha^{noncit}_{Zex} M^{noncit}_{ex}$, where M^{cit}_{ex} is the employment stock of citizens, M^{noncit}_{ex} is the stock of non-citizens, and α^{cit}_{Zex} and α^{noncit}_{Zex} are the relative efficiencies of each migrant type. Column 1 describes the perfect competition case (with zero mark-downs), and with all within-cell wage differentials attributed to α^{cit}_{Zex} and α^{noncit}_{Zex}. Column 2 imposes a baseline native mark-down of 0.1, and permits mark-downs to respond to the non-citizen (but not citizen) cell employment share, in line with our estimates in Table 7. And column 3 maintains the mark-down response, but attributes within-cell wage differentials entirely to differential mark-downs (rather than productivity). See Section 8.3 for further details on the various model specifications. Panels A and B predict changes in native and migrant wages (in % terms), by education and overall. Panel C predicts the % change in net output, and decomposes this into contributions from migrant wage income, native wage income and monopsony rents. The native surplus is the sum of changes in native wage income and monopsony rents, as a % of net output (i.e. we assume that all monopsony rents go to native-owned firms).

Table A1: Residential mobility index

	Experience groups							
	1-5	6-10	11-15	16-20	21-25	26-30	31-35	36-40
HS dropouts	-2.431	-2.064	-2.092	-2.399	-2.686	-2.938	-3.140	-3.263
HS graduates	-2.219	-1.842	-2.007	-2.315	-2.520	-2.730	-2.888	-2.974
Some college	-1.864	-1.480	-1.718	-1.985	-2.191	-2.466	-2.704	-2.843
College graduates	-1.418	-1.138	-1.448	-1.764	-2.073	-2.392	-2.625	-2.752

This table sets out values of the residential mobility index, $Mobility_{ex}$, described in Appendix G.3. This index is essentially the log rate of cross-state mobility (within the US), based on the 1960 census.

Table A2: Actual and predicted changes in old/new migrant shares

	Experience groups							
	1-5	6-10	11-15	16-20	21-25	26-30	31-35	36-40
Panel A: Change in old migrant share of employment hours, 1960-2019								
HS dropouts	0.029	0.092	0.265	0.404	0.473	0.524	0.489	0.402
HS graduates	0.035	0.059	0.107	0.140	0.168	0.161	0.116	0.051
Some college	0.037	0.048	0.065	0.076	0.095	0.094	0.074	0.05
College graduates	0.037	0.055	0.082	0.123	0.135	0.120	0.102	0.081
Panel B: Predicted change in old migrant share, 1960-2019								
HS dropouts	0.054	0.123	0.192	0.296	0.376	0.440	0.398	0.307
HS graduates	0.041	0.055	0.088	0.133	0.158	0.155	0.102	0.018
Some college	0.029	0.035	0.064	0.074	0.087	0.085	0.066	0.037
College graduates	0.038	0.075	0.090	0.145	0.150	0.118	0.097	0.049
Panel C: Change in new migrant share of employment hours, 1960-2019								
HS dropouts	0.109	0.190	0.153	0.105	0.086	0.061	0.043	0.023
HS graduates	0.043	0.051	0.045	0.043	0.036	0.024	0.008	-0.009
Some college	0.021	0.012	0.007	0.007	0.005	-0.011	-0.017	-0.030
College graduates	0.045	0.063	0.056	0.032	0.007	-0.002	-0.024	-0.043
Panel D: Predicted change in new migrant share, 1960-2019								
HS dropouts	0.094	0.234	0.239	0.181	0.124	0.101	0.081	0.064
HS graduates	0.073	0.121	0.096	0.074	0.056	0.037	0.021	0.008
Some college	0.003	0.013	0.019	0.020	0.014	0.005	0.000	-0.004
College graduates	-0.039	-0.037	-0.002	-0.002	-0.001	-0.006	-0.008	-0.012

"Old" migrants are those with over ten years in the US, and "new" migrants are those with up to ten. Panels A reports observed changes (over 1960-2019) in old migrants' share of employment hours, i.e. $\frac{M^{old}_{ext}}{N_{ext}+M_{ext}}$, across the four education and eight experience groups. Panel B predicts these changes using our instruments: i.e. we report changes in $\frac{\tilde{M}^{old}_{ext}}{\tilde{N}_{ext}+\tilde{M}_{ext}}$ Panels C and D repeat this exercise for new migrants, reporting changes in $\frac{M^{new}_{ext}}{N_{ext}+M_{ext}}$ and $\frac{\tilde{M}^{new}_{ext}}{\tilde{N}_{ext}+\tilde{M}_{ext}}$ respectively.

Table A3: IV estimates of native wage equation for selection of (α_Z, σ_Z) values

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Fixed effects (N = 224)									
$\log Z(N,M)$	0.026	0.025*	0.025*	0.526***	0.541***	0.558***	1.026***	1.101***	1.019***
	(0.016)	(0.015)	(0.015)	(0.016)	(0.018)	(0.022)	(0.016)	(0.063)	(0.099)
$\frac{M}{N+M}$	-0.519***	-0.564***	-0.582***	-0.519***	-1.566***	-1.985***	-0.519***	-3.039***	-3.990***
	(0.086)	(0.065)	(0.061)	(0.086)	(0.066)	(0.065)	(0.086)	(0.217)	(0.240)
Panel B: First differences (N = 192)									
$\log Z(N,M)$	0.023	0.023	0.023	0.523***	0.542***	0.566***	1.023***	1.137***	1.071***
	(0.020)	(0.018)	(0.018)	(0.020)	(0.023)	(0.028)	(0.020)	(0.068)	(0.082)
$\frac{M}{N+M}$	-0.379***	-0.422***	-0.438***	-0.379***	-1.452***	-1.894***	-0.379***	-2.985***	-3.962***
	(0.079)	(0.080)	(0.085)	(0.079)	(0.086)	(0.096)	(0.079)	(0.253)	(0.319)
σ_Z	1	1	1	0.5	0.5	0.5	0	0	0
α_Z	0	1	2	0	1	2	0	1	2

In this table, we offer complete regression tables (i.e. IV estimates of the native wage equation (29)) corresponding to a selection of (α_Z, σ_Z) values in Figure 2. These replicate the exercises of columns 7 and 9 of Table 4 (with the same instruments), but for different (α_Z, σ_Z) values. See the notes accompanying that table for further details. *** p<0.01, ** p<0.05, * p<0.1.

Table A4: Robustness of native IV estimates to wage variable and weighting

	Fixed effects				First differences			
	FT weekly wages		Hourly wages		FT weekly wages		Hourly wages	
	Men	Women	Men	Women	Men	Women	Men	Women
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Unweighted estimates								
$\log(N+M)$	0.020	0.045**	0.017	0.023	0.003	0.049***	0.001	0.043**
	(0.013)	(0.017)	(0.014)	(0.022)	(0.021)	(0.017)	(0.024)	(0.021)
$\frac{M}{N+M}$	-0.478***	-0.589***	-0.434***	-0.583***	-0.405***	-0.378***	-0.360***	-0.369***
	(0.056)	(0.083)	(0.063)	(0.086)	(0.089)	(0.111)	(0.077)	(0.087)
Panel B: Weighted by cell employment								
$\log(N+M)$	0.024	0.056**	0.018	0.033	-0.014	0.050*	-0.016	0.042
	(0.018)	(0.022)	(0.018)	(0.027)	(0.029)	(0.028)	(0.033)	(0.027)
$\frac{M}{N+M}$	-0.486***	-0.543***	-0.430***	-0.550***	-0.473***	-0.359**	-0.415***	-0.339***
	(0.056)	(0.104)	(0.066)	(0.102)	(0.121)	(0.149)	(0.112)	(0.118)
Observations	224	224	224	224	192	192	192	192

In this table, we study the robustness of our IV estimates of the native wage equation (29) to the wage definition and choice of weighting. Throughout, the right hand side is identical to columns 7 and 9 of Table 4 (Panel B), and we also use the same instruments. Odd columns estimate the impact on the wages of native men, and even columns the wages of native women. Columns 1-2 and 5-6 study weekly wages of full-time workers (as in the main text), and the remaining columns hourly wages of all workers. All wage variables are adjusted for demographic composition, in line with the method described in Section 5.2. The estimates in Panel A are unweighted (as in Table 4); while in Panel B, we weight observations by total cell employment. Robust standard errors, clustered by 32 education-experience cells, are in parentheses. We apply the same small-sample corrections as detailed in Table 2. The relevant 95% critical value for the T distribution (with $G-1=31$ degrees of freedom, where G is the number of clusters) is 2.13. *** p<0.01, ** p<0.05, * p<0.1.

Table A5: Alternative instrument specification for native wage equation

	First stage				Second stage	
	Fixed effects (FE)		First differences (FD)		FE	FD
	$\log(N+M)$	$\frac{M}{N+M}$	$\log(N+M)$	$\frac{M}{N+M}$	$\log W_N$	$\log W_N$
	(1)	(2)	(3)	(4)	(5)	(6)
$\log\left(\tilde{N}+\tilde{M}\right)$	-0.154***	0.192***	-0.313***	0.166***		
	(0.055)	(0.025)	(0.084)	(0.013)		
$\tilde{M}\times 10^{-6}$	0.988***	-0.097***	0.761***	-0.047***		
	(0.067)	(0.034)	(0.095)	(0.012)		
$\log(N+M)$					0.048*	0.025
					(0.025)	(0.024)
$\frac{M}{N+M}$					-0.343**	-0.376***
					(0.126)	(0.130)
SW F-stat	29.01	17.43	64.42	54.66	-	-
Observations	224	224	192	192	224	192

This table replicates the first and second stage estimates of the native wage equation (29) in Tables 3 and 4, but using an alternative instrument for migrant share. In the main text, our two instruments are $\log\left(\tilde{N}+\tilde{M}\right)$ and $\frac{\tilde{M}}{\tilde{N}+\tilde{M}}$; but here, we replace $\frac{\tilde{M}}{\tilde{N}+\tilde{M}}$ with $\tilde{M}\times 10^{-6}$, the predicted migrant employment *level* (which we have scaled to make the coefficients visible). Columns 1-4 are otherwise identical to columns 3-6 in Table 3, and columns 5-6 are otherwise identical to columns 7 and 9 in Panel B of Table 4. See the notes under Tables 3 and 4 for additional details. *** p<0.01, ** p<0.05, * p<0.1.

Table A6: Impact of new and old migrant shares: First stage

	Fixed effects			First differences		
	$\log(N+M)$	$\frac{M^{old}}{N+M}$	$\frac{M^{new}}{N+M}$	$\log(N+M)$	$\frac{M^{old}}{N+M}$	$\frac{M^{new}}{N+M}$
	(1)	(2)	(3)	(4)	(5)	(6)
$\log\left(\tilde{N}+\tilde{M}\right)$	1.029***	0.005	0.046***	0.893***	-0.009	0.052***
	(0.073)	(0.011)	(0.014)	(0.088)	(0.008)	(0.014)
$\frac{\tilde{M}^{old}}{\tilde{N}+\tilde{M}}$	0.008	1.390***	-0.100	0.399	1.091***	0.151
	(0.266)	(0.079)	(0.078)	(0.483)	(0.092)	(0.097)
$\frac{\tilde{M}^{new}}{\tilde{N}+\tilde{M}}$	2.208***	0.100	0.641***	2.506***	0.115	0.446**
	(0.426)	(0.110)	(0.192)	(0.521)	(0.139)	(0.174)
SW F-stat	94.95	433.13	17.16	4.32	9.32	2.56
Observations	224	224	224	192	192	192

This table presents first stage estimates for the native wage equation (29), but this time accounting separately for the effect of the new migrant share $\frac{M^{new}}{N+M}$ (i.e. up to ten years in the US) and the old migrant share $\frac{M^{old}}{N+M}$ (more than ten years). These estimates correspond to the IV specifications of Table A7. We impose that $\alpha_{Zext} = \sigma_Z = 1$, so the cell aggregator collapses to $\log(N+M)$. As always, we construct corresponding instruments by applying the same functional forms over the predicted native employment and (in this case) new and old migrant employment separately. Columns 1-3 control for interacted education-year, experience-year and education-experience fixed effects; and columns 4-6 are estimated in first differences, controlling for the interacted education-year and experience-year effects. Sanderson-Windmeijer F-statistics account for multiple endogenous variables. Robust standard errors, clustered by 32 education-experience cells, are in parentheses. We apply the same small-sample corrections as detailed in Table 2. The relevant 95% critical value for the T distribution (with $G-1=31$ degrees of freedom, where G is the number of clusters) is 2.04. *** p<0.01, ** p<0.05, * p<0.1.

Table A7: Impact of new and old migrants: OLS and IV

	Fixed effects		First differences	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
$\log(N+M)$	0.013	0.029	0.006	0.030
	(0.014)	(0.022)	(0.011)	(0.044)
$\frac{M^{old}}{N+M}$	-0.548***	-0.558***	-0.426***	-0.391***
	(0.041)	(0.050)	(0.053)	(0.117)
$\frac{M^{new}}{N+M}$	-0.309**	-0.616**	-0.281**	-0.544
	(0.116)	(0.297)	(0.111)	(0.657)
Observations	224	224	192	192

This table presents OLS and IV estimates of the native wage equation (29), but this time, accounting separately for the effect of the new migrant share $\frac{M^{new}}{N+M}$ (i.e. up to ten years in the US) and the old migrant share $\frac{M^{old}}{N+M}$ (more than ten years). We impose that $\alpha_{Zext} = \sigma_Z = 1$, so the dependent variable collapses to the log native wage (which we adjust for composition in all specifications), and the cell aggregator on the right hand side collapses to $\log(N+M)$. Columns 1-2 control for interacted education-year, experience-year and education-experience fixed effects; and columns 3-4 are estimated in first differences, controlling for the interacted education-year and experience-year effects. We report the corresponding first stage estimates in Appendix Table A6. Robust standard errors, clustered by 32 education-experience cells, are in parentheses. We apply the same small-sample corrections as detailed in Table 2. The relevant 95% critical value for the T distribution (with $G-1=31$ degrees of freedom, where G is the number of clusters) is 2.04. *** p<0.01, ** p<0.05, * p<0.1.

Table A8: Robustness of native wage effects to dynamics: First stage

	$\log(N+M)$		$\log\left(\tilde{N}+\tilde{M}\right)$: Lagged	$\frac{M}{N+M}$		$\frac{\tilde{M}}{\tilde{N}+\tilde{M}}$: Lagged
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: First stage for fixed effect estimates (N = 192)						
$\log\left(\tilde{N}+\tilde{M}\right)$	1.124***	0.891***	0.275***	0.034	0.022	0.018
	(0.100)	(0.103)	(0.093)	(0.022)	(0.017)	(0.013)
$\log\left(\tilde{N}+\tilde{M}\right)$: Lagged		0.124	0.849***		-0.024	0.018**
		(0.074)	(0.096)		(0.018)	(0.008)
$\frac{\tilde{M}}{\tilde{N}+\tilde{M}}$	1.022***	-0.507	-1.893***	1.153***	0.972***	0.076
	(0.311)	(0.599)	(0.592)	(0.082)	(0.112)	(0.073)
$\frac{\tilde{M}}{\tilde{N}+\tilde{M}}$: Lagged		2.255***	1.147*		0.163	0.816***
		(0.608)	(0.645)		(0.116)	(0.078)
Panel B: First stage for fixed differenced estimates (N = 160)						
$\log\left(\tilde{N}+\tilde{M}\right)$	0.927***	0.781***	0.438***	0.057***	0.036**	0.003
	(0.106)	(0.094)	(0.103)	(0.018)	(0.017)	(0.011)
$\log\left(\tilde{N}+\tilde{M}\right)$: Lagged		0.094	0.880***		0.030	0.014
		(0.084)	(0.100)		(0.022)	(0.009)
$\frac{\tilde{M}}{\tilde{N}+\tilde{M}}$	1.473***	0.791**	-0.479	1.065***	0.960***	-0.008
	(0.299)	(0.344)	(0.433)	(0.118)	(0.132)	(0.065)
$\frac{\tilde{M}}{\tilde{N}+\tilde{M}}$: Lagged		2.302***	0.390		0.422**	0.862***
		(0.601)	(0.445)		(0.163)	(0.077)
SW F-stat: Panel A	149.39	60.50	43.22	179.43	18.64	32.04
SW F-stat: Panel B	76.85	30.77	113.87	80.99	43.42	30.77

This table presents first stage estimates for the native wage equation (29), but this time controlling additionally for the 1-period lagged cell aggregator and migrant share. These estimates correspond to the IV specifications of Appendix Table A9. Since we include lagged observations, we necessarily lose one period of data. The first stage estimates for the dynamic specification are reported in columns 2, 3, 5 and 6: these require two additional instruments, and we use lags of our existing instruments. Columns 1 and 4 report the first stage of our basic specification (without lags); for comparison, we use the shorter sample of our dynamic specification. We impose that $\alpha_{Zext} = \sigma_Z = 1$, so the cell aggregator collapses to $\log(N+M)$. As always, we construct corresponding instruments (both current and lagged) by applying the same functional forms over the predicted native and migrant employment. Panel A reports fixed effect estimates, controlling for interacted education-year, experience-year and education-experience fixed effects; and Panel B reports first differenced estimates, controlling for the interacted education-year and experience-year effects. Sanderson-Windmeijer F-statistics account for multiple endogenous variables. Robust standard errors, clustered by 32 education-experience cells, are in parentheses. We apply the same small-sample corrections as detailed in Table 2. The relevant 95% critical value for the T distribution (with $G-1=31$ degrees of freedom, where G is the number of clusters) is 2.04. *** p<0.01, ** p<0.05, * p<0.1.

Table A9: Robustness of native wage effects to dynamics: OLS and IV

	Fixed effects				First differences			
	OLS	OLS	IV	IV	OLS	OLS	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\log\left(N+M\right)$	0.036**	0.047***	0.025*	0.026	0.012	0.033**	0.021	0.025
	(0.014)	(0.012)	(0.014)	(0.019)	(0.013)	(0.014)	(0.018)	(0.019)
$\log\left(\tilde{N}+\tilde{M}\right)$: Lagged		0.015		0.015		0.000		0.032**
		(0.010)		(0.015)		(0.000)		(0.014)
$\frac{M}{N+M}$	-0.501***	-0.352***	-0.566***	-0.458***	-0.380***	-0.318***	-0.458***	-0.363***
	(0.030)	(0.055)	(0.037)	(0.078)	(0.044)	(0.061)	(0.063)	(0.077)
$\frac{M}{N+M}$: Lagged		-0.239**		-0.118		-0.310***		-0.187
		(0.101)		(0.097)		(0.104)		(0.132)
Observations	192	192	192	192	160	160	160	160

This table presents OLS and IV estimates of the native wage equation (29); but in even-numbered columns, we control additionally for the 1-period lagged cell aggregator and migrant share. The lag is 10 years at all observation years except for 2019 (where the lagged outcome corresponds to 2010). For IV, this requires two additional instruments; and we use the lags of our existing instruments. Since we include lagged observations, we necessarily lose one period of data; so for comparison, in odd-numberd columns, we report estimates of the basic specification (without lags) using the shorter sample. We impose that $\alpha_{Zext} = \sigma_Z = 1$, so the dependent variable collapses to the log native wage (which we adjust for composition in all specifications), and the cell aggregator on the right hand side (both current and lagged) collapses to $\log\left(N+M\right)$. Columns 1-4 control for interacted education-year, experience-year and education-experience fixed effects; and columns 5-8 are estimated in first differences, controlling for the interacted education-year and experience-year effects. We report the corresponding first stage estimates in Appendix Table A8. Robust standard errors, clustered by 32 education-experience cells, are in parentheses. We apply the same small-sample corrections as detailed in Table 2. The relevant 95% critical value for the T distribution (with $G-1=31$ degrees of freedom, where G is the number of clusters) is 2.04. *** p<0.01, ** p<0.05, * p<0.1.

Table A10: IV employment rate responses

	Native employment rate				Migrant employment rate			
	Men		Women		Men		Women	
	FE	FD	FE	FD	FE	FD	FE	FD
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\log(N+M)$	0.037*	0.033	0.039	0.064*	0.010	0.040	-0.122**	-0.062
	(0.018)	(0.034)	(0.030)	(0.036)	(0.021)	(0.027)	(0.049)	(0.046)
$\frac{M}{N+M}$	-0.111	-0.036	-1.162***	-0.724***	-0.077	0.081	-0.030	-0.495**
	(0.142)	(0.133)	(0.175)	(0.203)	(0.089)	(0.114)	(0.286)	(0.207)
Observations	224	192	224	192	224	192	224	192

This table estimates the IV response of native and migrant employment rates, by gender, to total cell employment and migrant share. We rely on the native wage equation (29), but replace the left-hand side variable with the employment rates of various subgroups (defined as log average hours per individual, adjusted for observable changes in composition). See Appendix H.6 for further details. The right-hand side of all specifications are identical to column 7 of Table 4 (Panel B), with the same instruments, and with the cell aggregator expressed as log total employment (i.e. under the assumption that $\alpha_{Zext} = \sigma_Z = 1$). The fixed effect (FE) specifications control for interacted education-year, experience-year and education-experience fixed effects; and the first differenced (FD) specifications control only for the interacted education-year and experience-year effects. Robust standard errors, clustered by 32 education-experience cells, are in parentheses. We apply the same small-sample corrections as detailed in Table 2. The relevant 95% critical value for the T distribution (with $G-1=31$ degrees of freedom, where G is the number of clusters) is 2.04. *** p<0.01, ** p<0.05, * p<0.1.

Table A11: Heterogeneity in relative wage estimates

	Basic estimates		Fixed effects: Edu*Exp, Year		First diff		First diff + Year effects	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\log \frac{M}{N}$	0.007	-0.001	-0.029***	-0.010	-0.045***	-0.057***	-0.003	-0.004
	(0.006)	(0.006)	(0.010)	(0.010)	(0.008)	(0.010)	(0.006)	(0.009)
$\log \frac{M}{N}$ * Coll		-0.010**		0.046**		0.016		0.047**
		(0.004)		(0.018)		(0.014)		(0.018)
$\log \frac{M}{N}$ * (Exp $\geq$ 20)		0.017***		-0.004		0.014		-0.001
		(0.004)		(0.006)		(0.010)		(0.009)
SW F-Stat: $\log \frac{M}{N}$	491.89	854.15	238.58	70.34	356.20	226.73	475.61	252.04
SW F-Stat: $\log \frac{M}{N}$ * Coll		2673.18		148.62		1773.79		1062.71
SW F-Stat: $\log \frac{M}{N}$ * (Exp $\geq$ 20)		5025.87		3001.42		828.97		540.28
Observations	224	224	224	224	192	192	192	192

This table tests for heterogeneity in our IV estimates of the relative wage equation (26), across college/non-college cells and high/low experience cells. See Section H.8 for further details. In the odd-numbered columns, we report estimates without heterogeneity: these replicate the baseline estimates of Table 2. In the even-numbered columns, we include interactions between log relative employment and (i) a college dummy and (ii) a high-experience (more than 20 years) dummy. Our instruments are the interactions between the predicted log relative employment and the respective dummies. Columns 1-2 include no fixed effects, while columns 3-4 control for interacted education-experience and year fixed effects. Columns 5-8 are estimated in first differences, with columns 7-8 controlling additionally for year effects. In all specifications, wages are adjusted for changes in observable demographic composition. Sanderson-Windmeijer F-statistics account for multiple endogenous variables. Robust standard errors, clustered by 32 education-experience cells, are in parentheses. We apply the same small-sample corrections as detailed in Table 2. The relevant 95% critical value for the T distribution (with $G-1=31$ degrees of freedom, where G is the number of clusters) is 2.04. *** p<0.01, ** p<0.05, * p<0.1.

Table A12: Broad education and experience groups: First stage

	Two education groups				Four experience groups			
	Fixed effects		First differences		Fixed effects		First differences	
	$\log Z(N,M)$	$\frac{M}{N+M}$	$\log Z(N,M)$	$\frac{M}{N+M}$	$\log Z(N,M)$	$\frac{M}{N+M}$	$\log Z(N,M)$	$\frac{M}{N+M}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Imposing equal mark-downs (H1), $\Delta\phi_{0ext} = \Delta\phi_1 = 0$								
$\log\left(\tilde{N}+\tilde{M}\right)$	0.919***	-0.012	0.742**	0.023*	1.144***	0.040	0.942***	0.064**
	(0.084)	(0.007)	(0.270)	(0.012)	(0.113)	(0.031)	(0.125)	(0.026)
$\frac{\tilde{M}}{\tilde{N}+\tilde{M}}$	3.163**	0.551***	1.847	0.697***	0.594	1.029***	1.337***	0.850***
	(1.197)	(0.147)	(1.617)	(0.181)	(0.357)	(0.112)	(0.450)	(0.174)
Panel B: Imposing $\alpha_{Zext} = \sigma_Z = 1$								
$\log\left(\tilde{N}+\tilde{M}\right)$	0.945***	-0.012	0.751**	0.023*	1.168***	0.040	0.951***	0.064**
	(0.086)	(0.007)	(0.269)	(0.012)	(0.112)	(0.031)	(0.122)	(0.026)
$\frac{\tilde{M}}{\tilde{N}+\tilde{M}}$	3.294**	0.551***	1.857	0.697***	0.699*	1.029***	1.383***	0.850***
	(1.179)	(0.147)	(1.591)	(0.181)	(0.332)	(0.112)	(0.442)	(0.174)
SW F-stat: Panel A	115.60	22.33	8.85	18.35	76.39	78.68	72.71	24.30
SW F-stat: Panel B	117.21	22.24	9.20	18.15	85.83	83.01	74.53	23.56
Observations	112	112	96	96	112	112	96	96

This table presents first stage estimates for the native wage equation (29), but this time across broader labor market cells. These estimates correspond to the IV specifications in Table A13. In columns 1-4, we use 2 broad education groups (college and high school equivalents) and the 8 original experience groups. And in columns 5-8, we use the original 4 education groups, but this time 4 broad experience groups (1-10, 11-20, 21-30, 31-40 years). See Section H.9 for further details on these groupings. Similar to Table 3, we consider two specifications for the cell aggregator. In Panel A, we impose equal mark-downs (and set σ_Z to 0.907, based on IV estimates of the relative wage equation: see Section H.9). And in Panel B, we impose that $\alpha_{Zext} = \sigma_Z = 1$, so $Z(N,M)$ collapses to total employment, $N+M$. Instruments are identical to Table 3. The fixed effect specifications control for interacted education-year, experience-year and education-experience fixed effects; and the differenced specifications control only for the interacted education-year and experience-year effects. Sanderson-Windmeijer F-statistics account for multiple endogenous variables. Robust standard errors, clustered by 16 education-experience cells, are in parentheses. We apply the same small-sample corrections as detailed in Table 2. The relevant 95% critical value for the T distribution (with $G-1=15$ degrees of freedom, where G is the number of clusters) is 2.13. *** p<0.01, ** p<0.05, * p<0.1.

Table A13: Broad education and experience groups: OLS and IV

	2 education groups				4 experience groups			
	Fixed effects		First differences		Fixed effects		First differences	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Imposing equal mark-downs (H1), $\Delta\phi_{0ext} = \Delta\phi_1 = 0$								
$\log Z\,(N, M)$	-0.001	-0.021	0.039	0.047	0.052***	0.056***	0.042**	0.068***
	(0.033)	(0.051)	(0.027)	(0.055)	(0.014)	(0.018)	(0.015)	(0.022)
$\frac{M}{N+M}$	-1.085***	-1.654***	-0.724***	-1.343*	-0.550***	-0.574***	-0.497***	-0.584***
	(0.153)	(0.465)	(0.144)	(0.649)	(0.043)	(0.079)	(0.079)	(0.093)
Panel B: Imposing $\alpha_{Zext} = \sigma_Z = 1$								
$\log\,(N + M)$	-0.092**	-0.112**	-0.049*	-0.045	0.021	0.025	0.014	0.038
	(0.033)	(0.050)	(0.027)	(0.054)	(0.014)	(0.018)	(0.014)	(0.022)
$\frac{M}{N+M}$	-0.971***	-1.543***	-0.605***	-1.233*	-0.494***	-0.519***	-0.443***	-0.526***
	(0.155)	(0.467)	(0.144)	(0.645)	(0.043)	(0.079)	(0.077)	(0.092)
Observations	112	112	96	96	112	112	96	96

This table presents OLS and IV estimates of the native wage equation (29), but this time across broader labor market cells. In columns 1-4, we use 2 broad education groups (college and high school equivalents) and the 8 original experience groups. And in columns 5-8, we use the original 4 education groups, but this time 4 broad experience groups (1-10, 11-20, 21-30, 31-40 years). See Section H.9 for further details on these groupings. Similar to Table 4, we report estimates of the native wage equation both under the assumption of equal mark-downs (Panel A) and under $\alpha_{Zext} = \sigma_Z = 1$ (Panel B). In the former case, we impose a σ_Z of 0.907, based on IV estimates of the relative wage equation (26): see Section H.9. The fixed effect specifications control for interacted education-year, experience-year and education-experience fixed effects; and the differenced specifications control only for the interacted education-year and experience-year effects. We report the corresponding first stage estimates in Appendix Table A12. Robust standard errors, clustered by 16 education-experience cells, are in parentheses. We apply the same small-sample corrections as detailed in Table 2. The relevant 95% critical value for the T distribution (with $G - 1 = 15$ degrees of freedom, where G is the number of clusters) is 2.13. *** p<0.01, ** p<0.05, * p<0.1.

Table A14: Occupation-imputed migrant stocks: First stage

	Fixed effects			First differences		
	$\log\left(N+M^{occ}\right)$	$\frac{M^{occ}}{N+M^{occ}}$	$\frac{M^{occ}}{N+M^{occ}}$	$\log\left(N+M^{occ}\right)$	$\frac{M^{occ}}{N+M^{occ}}$	$\frac{M^{occ}}{N+M^{occ}}$
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Imposing equal mark-downs (H1), $\Delta\phi_{0ext}=\Delta\phi_1=0$						
$\log\left(\tilde{N}+\tilde{M}^{occ}\right)$	0.575***	-0.013		0.374**	0.027	
	(0.180)	(0.024)		(0.151)	(0.017)	
$\frac{\tilde{M}^{occ}}{\tilde{N}+\tilde{M}^{occ}}$	-2.030***	0.598***	0.639***	-2.173***	0.746***	0.630***
	(0.689)	(0.118)	(0.068)	(0.498)	(0.116)	(0.064)
Panel B: Imposing $\alpha_{Zext}=\sigma_Z=1$						
$\log\left(\tilde{N}+\tilde{M}^{occ}\right)$	0.592***	-0.013		0.384**	0.027	
	(0.179)	(0.024)		(0.149)	(0.017)	
$\frac{\tilde{M}^{occ}}{\tilde{N}+\tilde{M}^{occ}}$	-1.949***	0.598***	0.639***	-2.105***	0.746***	0.630***
	(0.704)	(0.118)	(0.068)	(0.494)	(0.116)	(0.064)
SW F-stat: Panel A	21.35	20.14	88.39	10.88	12.89	96.67
SW F-stat: Panel B	25.42	23.17	88.39	11.24	14.30	96.67
Observations	224	224	224	192	192	192

This table presents first stage estimates for the native wage equation (29), but this time replacing education-experience migrant stocks, M_{ext}, with occupation-imputed stocks, M_{ext}^{occ}. Similarly, we replace our migrant stock instruments, $\tilde{M}_{ext}$, with occupation-imputed equivalents, $\tilde{M}_{ext}^{occ}$. See Section H.10 for further details. These estimates correspond to the IV specifications in columns 3-4 and 7-8 of Table A15. As before, we consider two specifications for the cell aggregator. In Panel A, we impose equal mark-downs (and set σ_Z to 0.979, based on IV estimates of the relative wage equation: see Section H.10). And in Panel B, we impose that $\alpha_{Zext}=\sigma_Z=1$, so $Z(N,M)$ collapses to total employment, $N+M$. Columns 1-3 control for interacted education-year, experience-year and education-experience fixed effects; and columns 4-6 are estimated in first differences, controlling for the interacted education-year and experience-year effects. Sanderson-Windmeijer F-statistics account for multiple endogenous variables. Robust standard errors, clustered by 32 education-experience cells, are in parentheses. We apply the same small-sample corrections as detailed in Table 2. The relevant 95% critical value for the T distribution (with $G-1=31$ degrees of freedom, where G is the number of clusters) is 2.04. *** p<0.01, ** p<0.05, * p<0.1.

Table A15: Occupation-imputed migrant stocks: OLS and IV

	Fixed effects				First differences			
	OLS	OLS	IV	IV	OLS	OLS	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Imposing equal mark-downs (H1), $\Delta\phi_{0ext} = \Delta\phi_1 = 0$								
$\log Z\left(N, M^{occ}\right)$	0.036		-0.093		0.017		-0.026	
	(0.024)		(0.074)		(0.016)		(0.057)	
$\frac{M^{occ}}{N+M^{occ}}$	-0.565***	-0.776***	-1.538***	-0.987***	-0.345***	-0.440***	-0.902**	-0.745***
	(0.167)	(0.152)	(0.525)	(0.171)	(0.113)	(0.080)	(0.343)	(0.117)
Panel B: Imposing $\alpha_{Zext} = \sigma_Z = 1$								
$\log\left(N + M^{occ}\right)$	0.015		-0.109		0.003		-0.045	
	(0.022)		(0.071)		(0.015)		(0.056)	
$\frac{M}{N+M}$	-0.537***	-0.623***	-1.469***	-0.833***	-0.279**	-0.295***	-0.856**	-0.590***
	(0.172)	(0.150)	(0.498)	(0.172)	(0.112)	(0.084)	(0.333)	(0.123)
Observations	224	224	224	224	192	192	192	192

This table presents OLS and IV estimates of the native wage equation (29), but this time replacing education-experience migrant stocks, M_{ext}, with occupation-imputed stocks, M_{ext}^{occ}. Similarly, we replace our migrant stock instruments, $\tilde{M}_{ext}$, with occupation-imputed equivalents, $\tilde{M}_{ext}^{occ}$. See Section H.10 for further details. We report estimates both under the assumption of equal mark-downs (Panel A) and under $\alpha_{Zext} = \sigma_Z = 1$ (Panel B). In the former case, we impose a σ_Z of 0.979, based on IV estimates of the relative wage equation (26): see Section H.10. Columns 1-4 control for interacted education-year, experience-year and education-experience fixed effects; and columns 5-8 are estimated in first differences, controlling for the interacted education-year and experience-year effects. We report the corresponding first stage estimates in Appendix Table A14. Robust standard errors, clustered by 32 education-experience cells, are in parentheses. We apply the same small-sample corrections as detailed in Table 2. The relevant 95% critical value for the T distribution (with $G-1=31$ degrees of freedom, where G is the number of clusters) is 2.04. *** p<0.01, ** p<0.05, * p<0.1.

Table A16: Heterogeneity in migrants elicited by instrument

	All migrants (1)	Old migrants (2)	New migrants (3)	Citizens (4)	Non-citizens (5)	Mexicans (6)	Non-Mexicans (7)
Panel A: Fixed effects							
$\log\left(\tilde{N}+\tilde{M}\right)$	0.029	-0.048*	0.077***	-0.090***	0.119***	0.075***	-0.047***
	(0.018)	(0.027)	(0.020)	(0.018)	(0.017)	(0.018)	(0.008)
$\frac{\tilde{M}}{\tilde{N}+\tilde{M}}$	1.093***	0.926***	0.167*	0.074	1.018***	1.024***	0.069**
	(0.073)	(0.096)	(0.082)	(0.054)	(0.075)	(0.075)	(0.032)
Panel B: First differences							
$\log\left(\tilde{N}+\tilde{M}\right)$	0.046***	-0.005	0.051***	-0.046***	0.092***	0.085***	-0.039***
	(0.015)	(0.009)	(0.014)	(0.011)	(0.018)	(0.017)	(0.008)
$\frac{\tilde{M}}{\tilde{N}+\tilde{M}}$	1.000***	0.744***	0.256***	0.148*	0.852***	0.893***	0.106*
	(0.110)	(0.078)	(0.070)	(0.083)	(0.102)	(0.109)	(0.060)
Observations: Panel A	224	224	224	224	224	224	224
Observations: Panel B	192	192	192	192	192	192	192

This table studies the composition of migrants elicited by our basic instrument for the migrant share, $\frac{\tilde{M}}{\tilde{N}+\tilde{M}}$. As our point of departure, in column 1, we reproduce the first stage estimates for the overall migrant share $\frac{M}{N+M}$ (this is identical to columns 4 and 6 of Table 3). In columns 2 and 3, we then replace the dependent variable with (i) the share of old migrants in total cell employment and (ii) the share of new migrants respectively. By construction, the coefficients in columns 2 and 3 sum to the coefficients in column 1. In columns 4 and 5, we repeat this exercise for the citizen and non-citizen share; and in columns 5 and 6, we repeat it for Mexicans and non-Mexicans. Panel A controls for interacted education-year, experience-year and education-experience fixed effects; and Panel B is estimated in first differences, controlling for the interacted education-year and experience-year effects. Robust standard errors, clustered by 32 education-experience cells, are in parentheses. We apply the same small-sample corrections as detailed in Table 2. The relevant 95% critical value for the T distribution (with $G-1=31$ degrees of freedom, where G is the number of clusters) is 2.04. *** p<0.01, ** p<0.05, * p<0.1.

Table A17: Separation elasticities

	All edu groups		College		Non-college			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lagged log wage	-0.452***	-0.452***	-0.459***	-0.459***	-0.424***	-0.424***	-0.424***	-0.424***
	(0.013)	(0.013)	(0.015)	(0.015)	(0.028)	(0.028)	(0.028)	(0.028)
Lagged log wage * Foreign-born: any	0.149***		0.065		0.275***			
	(0.036)		(0.041)		(0.066)			
Lagged log wage * Foreign-born: citizen		0.092*		0.075		0.123	0.123	0.194*
		(0.048)		(0.056)		(0.093)	(0.093)	(0.107)
Lagged log wage * Foreign-born: non-citizen		0.199***		0.055		0.353***		
		(0.049)		(0.054)		(0.083)		
Lagged log wage * Non-citizen: permanent							0.276***	0.392***
							(0.092)	(0.126)
Lagged log wage * Non-citizen: non-permanent							0.511***	0.664***
							(0.151)	(0.186)
Lagged log wage * New immigrant								0.013
								(0.126)
Lagged log wage * Central American								-0.191
								(0.121)
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	893,919	893,919	573,080	573,080	320,839	320,839	320,839	320,839

This table reports estimates of the elasticity of job separation to initial wages, based on the complementary log-log specification in equation (A85). We rely on SIPP panels beginning 1996, 2001, 2004 and 2008 (which cover the period 1996-2013), whose waves are four months apart. See Appendix H.12 for further details on data, sample and empirical specification. All specifications control for a range of demographic controls, including education, experience, gender, immigration status (foreign-born, non-citizen, no permanent status), Central American origin, recent immigrant indicator, and various interactions: see the appendix for details. Crucially, all variables which are interacted with the lag logged wage are included individually on the right-hand side. Columns 1-2 are estimated for the full sample, columns 3-4 for individuals with at least some college education, and columns 5-8 for those without. Robust standard errors, clustered by individual, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

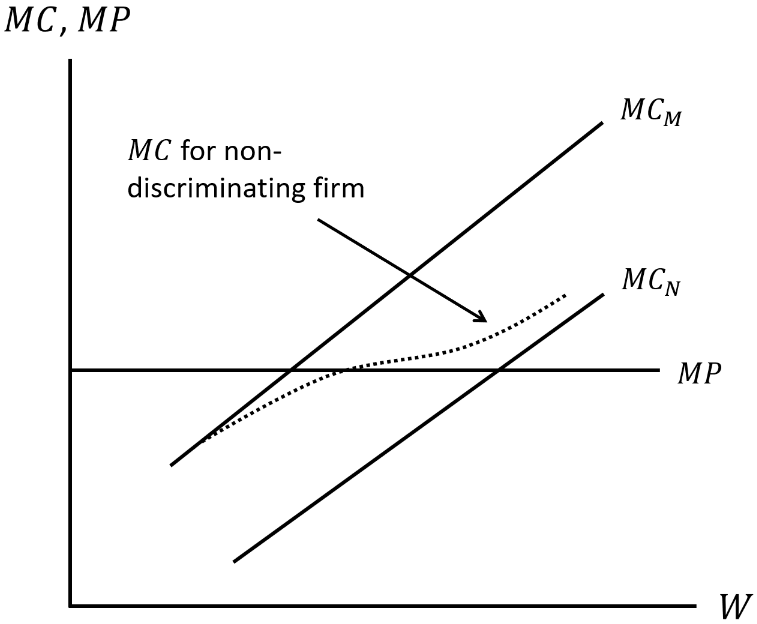


Figure 1: Optimal wages for discriminating and non-discriminating firms

This figure illustrates the wage-setting problem for a firm operating in the market for workers of some skill type j, for the case where $R_M < R_N$ and $\epsilon_M < \epsilon_N$. Natives and migrants in this market deliver the same marginal product (MP), which is fixed at $\frac{\partial \tilde{F}}{\partial L_j}$. For a discriminating firm (which can offer distinct wages to natives and migrants), the marginal cost of native and migrant labor are represented by MC_N and MC_M respectively; and the optimal wages will satisfy $MC_N = MP$ and $MC_M = MP$. For a non-discriminating firm, the marginal cost of labor is represented by the dotted line; and the optimal wage will equate this dotted line with the marginal product.

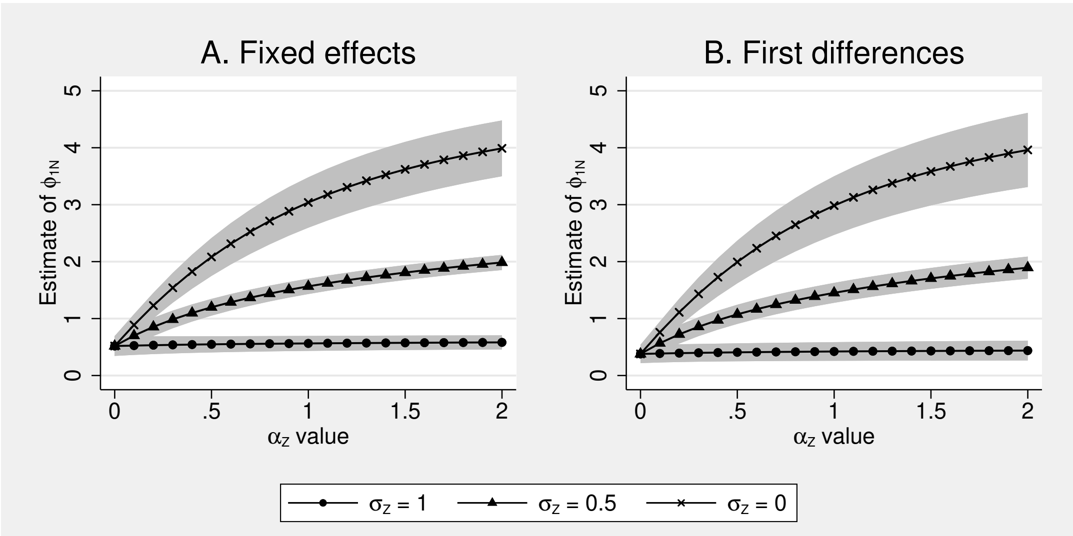


Figure 2: Native mark-down response ϕ_{1N} for different (α_Z, σ_Z)

This figure reports IV estimates of the response of the native mark-down to the migrant share $\frac{M}{N+M}$ (i.e. ϕ_{1N}), for a range of (α_Z, σ_Z) values. This is identified as the negative of γ_2, the coefficient on migrant share in the native wage equation (29). The estimates for $\alpha_Z = \sigma_Z = 1$ are identical to columns 7 and 9 of Panel B of Table 4. Other plotted values replicate the exercise of these columns, but for different (α_Z, σ_Z) values. See the notes accompanying Table 4 for further details. The shaded areas are 95% confidence intervals on our γ_2 estimates. We offer formal regression tables for a selection of (α_Z, σ_Z) values in Appendix Table A3.

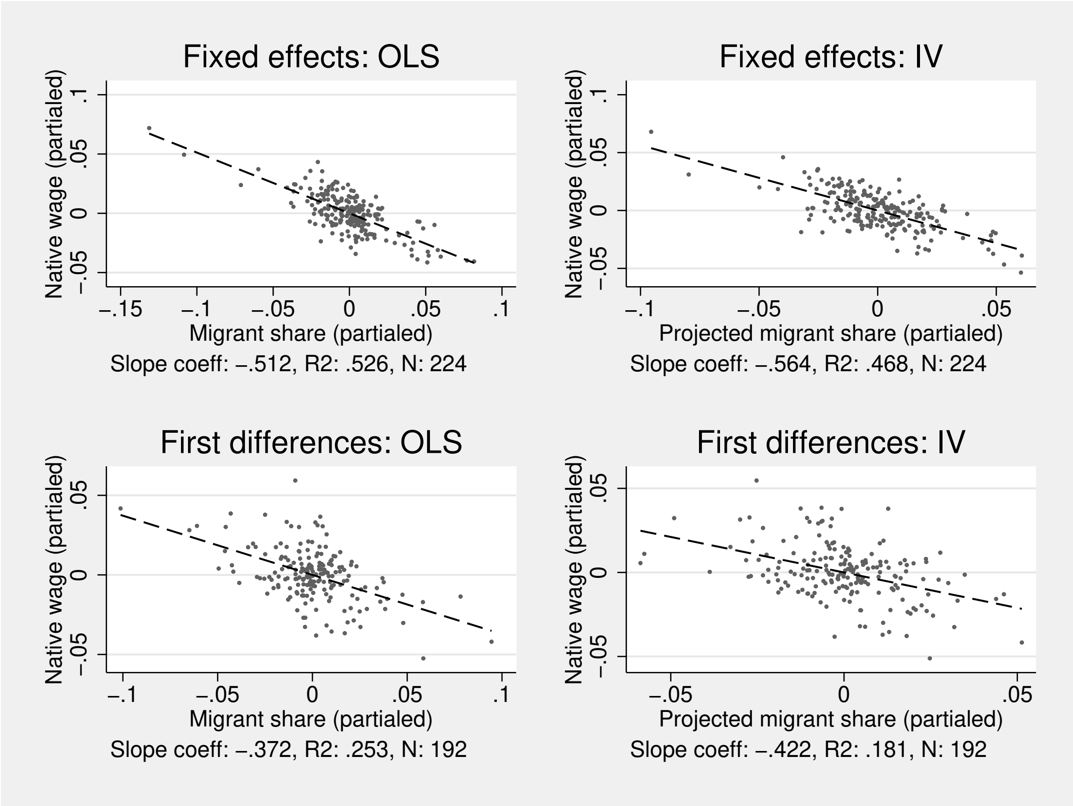
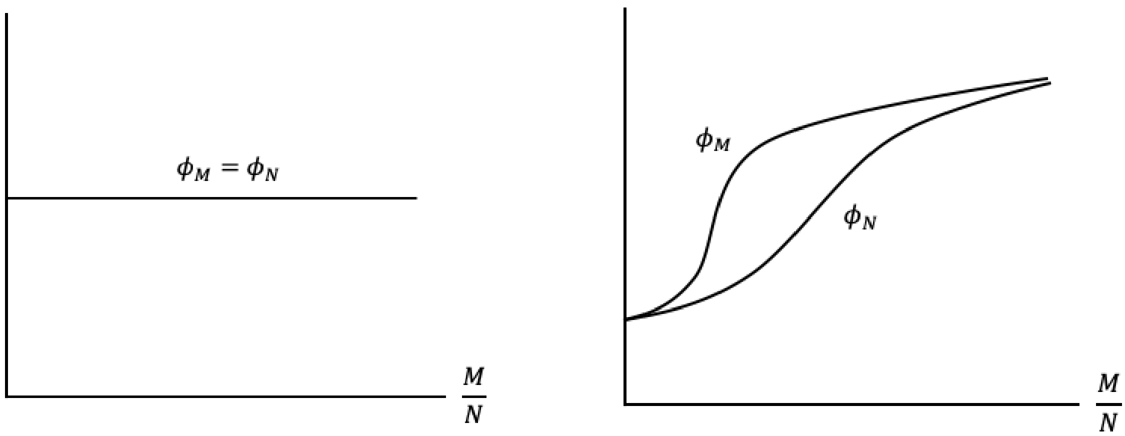


Figure 3: Visualization of native wage responses to migrant share

This figure graphically illustrates the OLS and IV effects of migrant employment share, $\frac{M}{N+M}$, on native composition-adjusted wages, based on columns 4, 7, 8 and 9 of Panel B in Table 4. For the OLS plot, we partial out the effect of the controls (i.e. log total employment and the various fixed effects) from both the composition-adjusted log native wage (on the y-axis) and the migrant employment share (on the x-axis). For IV, we first replace both (i) the log total employment and (ii) the migrant employment share with their linear projections on the instruments and fixed effects; and we then follow the same procedure as for OLS. In the fixed effect specifications, we control for interacted education-year, experience-year and education-experience fixed effects; and in first differences, we control for the interacted education-year and experience-year effects only.



(a) $R_M = R_N$ and $\epsilon_M = \epsilon_N$ (b) $R_M < R_N$ and $\epsilon_M < \epsilon_N$

Figure A1: Aggregate mark-down functions

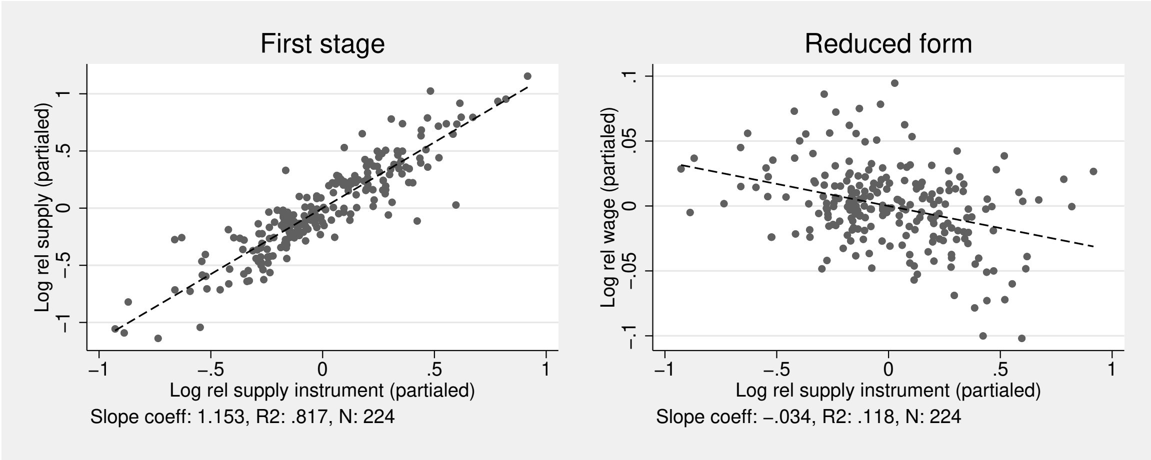


Figure A2: Visualization of relative wage equation estimates

This figure graphically illustrates our preferred IV specification of the relative wage equation (26), i.e. the log relative migrant-native wage, $\log \frac{w_M}{w_N}$, on log relative supply, $\log \frac{M}{N}$. We focus on the specification of column 5 of Table 2, which controls for education-experience effects and year effects. In Panel A of Figure **??**, we plot the first stage relationship corresponding to this specification (i.e. the log relative supply on its instrument), after partialing the fixed effects from both the left and right-hand side variables. And in Panel B, we do the same for the reduced form (i.e. the log relative wage directly on the instrument).