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Monopsony and the Wage Effects of Migration

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Abstract

In a generalization of the well-known “immigration surplus” result, we show immigration 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 traditional competitive model. We find that immigration increases mark-downs, and this effect 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).

Key words: Migration, wages, monopsony

JEL Codes: J31; J42; J61

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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 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 has constant returns. This does not mean that the marginal products of *all* native workers will increase: there may be large distributional effects. Although these are theoretical results, they do have empirical implications: any empirical model which imposes constant returns, convexity and perfect competition (as 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) 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.

Our approach (and second contribution) is to relax the assumption of perfect competition and then revisit these questions. 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 the mark-downs *as well as* the 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

¹Borjas (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.

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 rents by employing migrants. There are a number of other papers which consider the impact of immigration in non-competitive settings: Chassamboulli and Palivos (2013, 2014), Chassamboulli and Peri (2015), Battisti et al. (2017), Amior (2017) and Albert (forthcoming) offer theoretical discussions or calibrations of search or monopsonistic models; and Malchow-Moller, Munch and Skaksen (2012) and Edo (2015) offer suggestive evidence for mark-down effects.² But as Borjas (2013) has noted, the literature is surprisingly sparse, given the ubiquity of imperfectly competitive models 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; Ottaviano and Peri, 2012, among others). We use a standard 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.

²Using Danish data, Malchow-Moller, Munch and Skaksen (2012) find that migrant employees depress native wages within firms; and they cite lower reservation wages as a possible explanation. Edo (2015) finds that non-naturalized migrants in France reduce native employment rates, while naturalized migrants have no effect; and he too relates this to reservation wages. Also, Naidu, Nyarko and Wang (2016) study a UAE reform which relaxed restrictions on employer transitions for migrant workers (and improved their outside options), though they focus on the implications for incumbent migrants rather than natives.

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. Consistent with this interpretation, we show that natives’ employment rates are more responsive to cell-specific wage changes (identified by immigration shocks) than those of migrants.

Given the restrictions imposed by the assumption of perfect competition, 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 contribution of mark-downs to wage effects has important implications for policy design (see below), and this contribution may be difficult to identify 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.

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 (such as minimum wages: see Edo and Rapoport, 2019, for evidence), rather than by restricting migration itself. In fact, these objectives may come into conflict: for example, limitations on migrant access to welfare benefits or visa restrictions (designed to deter migration) may deliver more market power to firms, and natives may ultimately suffer.

In the next section, we set out our theoretical results on the effects of immigration on marginal products, under the assumptions of constant returns and convexity. 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, which are based on the classic studies of Borjas (2003) and Ottaviano and Peri (2012). Section 6 presents our basic estimates, and we offer various empirical extensions in Section 7. Finally, Section 8 quantifies the aggregate-level implications for native and migrant wages, the immigration surplus and distribution. We also offer Online Appendices with various 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.

³See 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.

Consider the following production function:

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

where $\mathbf{K} = (K_1, K_2, \dots, K_I)$ is a vector of perfectly elastic factor inputs, and $\mathbf{L} = (L_1, L_2, \dots, L_J)$ 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 $\tilde{F}(N, M)$. Each group is homogeneous, though they may differ from each other. The two-input case was originally analyzed⁴ 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.*

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

Proof. If there are two factor inputs with CRS and convex technology, they must be Q-complements: i.e. $\frac{\partial^2 \tilde{F}(N, M)}{\partial N \partial M} \geq 0$, 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. \square

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:

$$\tilde{Y} = \tilde{F}(L_1, \dots, L_J) \quad (3)$$

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:

$$\tilde{Y} = \tilde{F}(\eta_1 N + \mu_1 M, \dots, \eta_J N + \mu_J M) = Z(N, M) \quad (4)$$

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

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

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). \square

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 $(\eta_1, \eta_2, \dots, \eta_J)$ 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. □

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 \mathbf{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 \mathbf{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 \mathbf{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, Amior (2017) and Albert (forthcoming) do allow for direct competition; but both assume marginal products are fixed, 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):

$$N = N_0 (W - R_N)^{\epsilon_N} \quad (7)$$

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 :

$$M = M_0 (W - R_M)^{\epsilon_M} \quad (8)$$

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).

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 (Hotchkiss and Quispe-Agnoli, 2013; Albert, forthcoming) 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; and see Naidu, Nyarko and Wang, 2016, on the UAE). These arguments suggest $\epsilon_M < \epsilon_N$; and indeed, the evidence shows that migrants' job separations are less sensitive to wages than natives' (Hirsch and Jahn, 2015), and undocumented migrants' even less (Hotchkiss and Quispe-Agnoli, 2009).⁵ Still, there are reasons why one might expect the reverse. Cadena and Kovak (2016) argue that foreign-born workers are relatively mobile geographically⁶, though this speaks to the elasticity of labor supply to *regions* and not to *individual employers* (which is what matters for monopsony power).

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

⁶See 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 (net of the cost of the elastic inputs \mathbf{K}), 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:

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

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:

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

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 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:

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

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).

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); 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.

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 :

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

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} :

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

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) and Ottaviano and Peri (2012), we allow for distinct native and migrant labor inputs (within education-experience cells) which are imperfect substitutes:

$$L_{ext} = Z(N_{ext}, M_{ext}) \quad (14)$$

We will ultimately impose a CES structure on Z 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:

$$\log W_{N_{ext}} = \log \left\{ A_{ext} [Z(N_{ext}, M_{ext})]^{\sigma_X - 1} \frac{\partial Z(N_{ext}, M_{ext})}{\partial N_{ext}} \right\} - \phi_N \left(\frac{M_{ext}}{N_{ext}} \right) \quad (15)$$

$$\log W_{M_{ext}} = \log \left\{ A_{ext} [Z(N_{ext}, M_{ext})]^{\sigma_X - 1} \frac{\partial Z(N_{ext}, M_{ext})}{\partial M_{ext}} \right\} - \phi_M \left(\frac{M_{ext}}{N_{ext}} \right) \quad (16)$$

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

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

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. Our empirical implementation imposes more structure on the technology and mark-downs and this section describes our identification strategy under these restrictions. For consistency with Card (2009), Manacorda, Manning and Wadsworth (2012) and Ottaviano and Peri (2012), we assume Z has CES form:

$$Z(N, M) = (N^{\sigma_Z} + \alpha_Z M^{\sigma_Z})^{\frac{1}{\sigma_Z}} \quad (18)$$

where α_Z is a migrant-specific productivity shifter, 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_N and ϕ_M can be written as log-linear functions of $\frac{M}{N}$:

$$\phi_N\left(\frac{M}{N}\right) = \phi_{0N} + \phi_{1N} \log \frac{M}{N} \quad (19)$$

$$\phi_M\left(\frac{M}{N}\right) = \phi_{0N} + \Delta\phi_0 + (\phi_{1N} + \Delta\phi_1) \log \frac{M}{N} \quad (20)$$

where we permit the two mark-downs to have different 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 $\log \frac{M}{N}$.⁷

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

$$\log W_N = \log A - \phi_{0N} - (1 - \sigma_X) \log N - (\sigma_Z - \sigma_X) \log \left[1 + \alpha_Z \left(\frac{M}{N} \right)^{\sigma_Z} \right]^{\frac{1}{\sigma_Z}} - \phi_{1N} \log \frac{M}{N} \quad (21)$$

$$\log W_M = \log A + \log \alpha_Z - \phi_{0N} - \Delta\phi_0 - (1 - \sigma_X) \log N \quad (22)$$

⁷If 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.

$$-(\sigma_Z - \sigma_X) \log \left[1 + \alpha_Z \left(\frac{M}{N} \right)^{\sigma_Z} \right]^{\frac{1}{\sigma_Z}} - (1 - \sigma_Z + \phi_{1N} + \Delta\phi_1) \log \left(\frac{M}{N} \right)$$

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

Clearly, it is impossible to separately identify a constant in the productivity shifter A from one in the mark-downs, ϕ_{0N} . Intuitively, the observed level of wages can be rationalized by one (A, ϕ_{0N}) combination, but also by a larger A and ϕ_{0N} .⁸ One may be able to 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: $\phi_N \left(\frac{M}{N} \right) = \phi_M \left(\frac{M}{N} \right)$. In terms of (19) and (20), $\Delta\phi_0 = \Delta\phi_1 = 0$.
2. **H2 (Independent mark-downs)**: Natives' mark-downs are independent of migrant share, i.e. $\phi'_N \left(\frac{M}{N} \right) = 0$. 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. $\phi'_M \left(\frac{M}{N} \right) = 0$. 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.

⁸There 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.

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:

$$\log \frac{W_M}{W_N} = \log \alpha_Z - \Delta\phi_0 - (1 - \sigma_Z + \Delta\phi_1) \log \frac{M}{N} \quad (23)$$

which we estimate by regressing $\log \frac{W_M}{W_N}$ on $\log \frac{M}{N}$. Equation (23) shows the identification problem: the intercept cannot disentangle α_Z from $\Delta\phi_0$; and the slope coefficient cannot disentangle σ_Z from $\Delta\phi_1$. But conditional on $H1$ (i.e. $\Delta\phi_0 = \Delta\phi_1 = 0$), we can identify the technology parameters α_Z 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:

$$\log W_N + (1 - \sigma_Z) \log N = \log A - \phi_{0N} - (\sigma_Z - \sigma_X) \log (N^{\sigma_Z} + \alpha_Z M^{\sigma_Z})^{\frac{1}{\sigma_Z}} - \phi_{1N} \log \frac{M}{N} \quad (24)$$

Using our (α_Z, σ_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)⁹ and (ii) the cell “Armington” aggregator $(N^{\sigma_Z} + \alpha_Z M^{\sigma_Z})^{\frac{1}{\sigma_Z}}$. We can then estimate (24) by regressing $[\log W_N + (1 - \sigma_Z) \log N]$ on $\log (N^{\sigma_Z} + \alpha_Z M^{\sigma_Z})^{\frac{1}{\sigma_Z}}$ and $\log \frac{M}{N}$; and the coefficient on $\log \frac{M}{N}$ 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 pair of (α_Z, σ_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

⁹This 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.

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 use US census data to study how immigration affects native and migrant wages across education-experience cells. 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 2017 (Ruggles et al., 2017).¹⁰ 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.¹¹ 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 experience¹², 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 workers (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.

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.

¹⁰The 1960 census does not report migrants' year of arrival, but we require this information to construct our instruments. In particular, we need to know the employment stocks of migrants living in the US for no more than ten years. We impute these stocks using education cohort sizes by country of origin in 1950, combined with origin-specific data on employment rates. See Appendix G.1 for further details.

¹¹Borjas (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.

¹²To 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.

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 college 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.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

¹³Specifically: 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.

experience groups. We denote our instrument as \tilde{N}_{ext} , for each of 32 education-experience cells (e, x) and 7 observation years t (between 1960 and 2017).

(ii) Old migrants. We construct our instrument for “old” migrants \tilde{M}_{ext}^{old} (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}_{ext}^{new} . Combining this with the old migrant instrument, we can now predict the *total* migrant stock as $\tilde{M}_{ext} = \tilde{M}_{ext}^{old} + \tilde{M}_{ext}^{new}$.

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.8, 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.

¹⁴Llull (2018a) 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 2017. 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), without accounting for changes in cell-level demand. This suggests demand shocks are relatively unimportant in the determination of migrant share, which can help explain why our OLS and IV estimates look similar below.

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 (α_Z, σ_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 relative migrant productivity α_Z in (23) as:

$$\log \alpha_{Zext} = \log \bar{\alpha}_Z + u_{ext} \quad (25)$$

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

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

where β_0 identifies $\log \bar{\alpha}_Z - \Delta\phi_0$, 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

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 -0.14, and β_1 is -0.033. These numbers are comparable to Ottaviano and Peri (2012).¹⁷ Under the hypothesis of equal mark-downs $H1$ (i.e. $\Delta\phi_0 = \Delta\phi_1 = 0$), β_0 identifies within-cell productivity differentials $\log \bar{\alpha}_Z$, and β_1 identifies $-(1 - \sigma_Z)$, implying a large elasticity of substitution of $\frac{1}{1-\sigma_Z} = 30$ 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 ($\Delta\phi_0 > 0$), 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,

¹⁵Borjas, 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.

¹⁶As 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.5.

¹⁷For 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 2017) 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 $\beta_1 = -0.033$); 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:

$$\alpha_{Zext} = \alpha_{Zex} + \alpha_{Zt} + u_{ext} \quad (27)$$

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 same specification in first differences: i.e. regressing $\Delta \log \frac{W_{Mext}}{W_{Next}}$ on $\Delta \log \frac{M_{ext}}{N_{ext}}$ and year effects (the education-experience effects are eliminated); but this makes little difference.

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.10 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 and 7, we instrument $\log \frac{M_{ext}}{N_{ext}}$ with $\log \frac{\tilde{M}_{ext}}{\tilde{N}_{ext}}$, where $\tilde{M}_{ext} = \tilde{M}_{ext}^{new} + \tilde{M}_{ext}^{old}$ 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 -0.032 in column 5); though looking at the standard errors, the differences are statistically insignificant. This suggests that relative migrant/native demand shocks account for comparatively little of the variation in relative skill-specific supply, $\log \frac{M_{ext}}{N_{ext}}$, conditional on the various fixed effects. To summarize, our mean β_0 varies from -0.09 to -0.16, and β_1 from zero to -0.033.

6.2 Testing the null of equal and independent mark-downs

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

¹⁸In column 7, the instrument is differenced - like the endogenous variable.

turn to the equation for native wages (24). We parameterize the cell-level productivity shifter A_{ext} in (17) as:

$$\log A_{ext} = d_{ex} + d_{et} + d_{xt} + v_{ext} \quad (28)$$

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:

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

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 (α_Z, σ_Z) . We use our β_1 estimate in column 5 of Table 2, which implies $\sigma_Z = 1 - 0.032$; and we back out the $\alpha_{Z_{ext}}$ in each labor market cell as the residual, i.e. $\log \alpha_{Z_{ext}} = \log \frac{W_{M_{ext}}}{W_{N_{ext}}} - \beta_1 \log \frac{M_{ext}}{N_{ext}}$. 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.9 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 $\log (N_{ext}^{\sigma_Z} + \alpha_{Z_{ext}} M_{ext}^{\sigma_Z})^{\frac{1}{\sigma_Z}}$ 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, 2018a, Monras, 2020), the human capital choices of existing US residents (Hunt, 2017; Llull, 2018b), 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 $\log (N_{ext}^{\sigma_Z} + \alpha_{Zext} M_{ext}^{\sigma_Z})^{\frac{1}{\sigma_Z}}$ using $\log (\tilde{N}_{ext}^{\sigma_Z} + \alpha_{Zext} \tilde{M}_{ext}^{\sigma_Z})^{\frac{1}{\sigma_Z}}$.

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 50.¹⁹

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 (and statistically insignificant in IV). If σ_Z is close to 1 (as Table 2 suggests, at least under $H1$), these γ_1 estimates would 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 context.²⁰ For illustration, identifying cell composition with the migrant share, our IV estimate of γ_2 is -0.63 (column 7 of Panel A). That is, conditional on $H1$, a 1 pp expansion of the migrant share allows firms to mark down native wages by 0.63% more. The first differenced estimates are similar: the equivalent specification yields a γ_2 of -0.43 (in column 9).

¹⁹These can be assessed against standard Stock and Yogo (2005) weak instrument critical values.

²⁰In contrast, Lull's (2018a) 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.

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 $H2$), 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. $\alpha_Z = \sigma_Z = 1$. In this environment, we would attribute any deviation of β_0 and β_1 from zero (in the relative wage equation) to the differential competition effects, $\Delta\phi_0$ 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_Z 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 to -0.57 from -0.63; and in first differences (column 9), it drops from -0.43 to -0.36.

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.²¹ In Panel

²¹Unlike in Panel A of Tables 3 and 4, we impose equal α_Z values in every labor market cell.

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 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.

7 Robustness and empirical extensions

In this section, we first consider the robustness of our estimates of the migrant share effect, γ_2 , in the native wage equation (29) to: (i) the effect of outliers, (ii) wage definition and weighting, (iii) instrument specification, (iv) accounting for dynamics, (v) broad education groups, (vi) broad experience groups, and (vii) occupational downgrading. We then consider heterogeneity in γ_2 by (viii) education and experience and (ix) new and old migrants. And finally, we consider (x) the robustness of our assumption of CES technology and (xi) labor supply responses to migration-driven wage variation. We discuss each point briefly here, and we offer greater detail and regression tables in the marked appendices. For simplicity, we impose $\alpha_Z = \sigma_Z = 1$ throughout, so the dependent variable in the native wage equation (29) collapses to log native wages and the cell aggregator to log total employment, $\log(N_{ext} + M_{ext})$.

(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).²² 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.

(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.

²²For 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.

(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, our IV estimates are robust to replacing the two instruments with the predicted log native and migrant stocks, $\log \tilde{N}_{ext}$ and $\log \tilde{M}_{ext}$: see Appendix Table A5.

(iv) Dynamics (Appendix H.4). 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).

(v) Broad education groups (Appendix H.5). Our results are also robust to a specification with two education groups (college and high school “equivalents”), instead of four.²³ 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. The γ_2 estimates (on migrant share) are larger than before, exceeding -1 under fixed effects, and ranging from -0.5 to -1.2 in first differences (Appendix Table A9). Interestingly, γ_1 (the elasticity to total cell employment) is now consistently negative and mostly exceeds -0.1: this matches the findings of Card and Lemieux (2001), who use a similar two-group education classification.²⁴ For $\sigma_Z \approx 1$, this implies an elasticity of substitution between experience groups (within education nests) of less than 10.

(vi) Broad experience groups (Appendix H.5). There may also be concerns 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 A9 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.

²³“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.5.

²⁴In 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.

(vii) Occupational downgrading (Appendix H.6). 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.6, 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. Reassuringly, this makes little difference to our estimates of the migrant share effect, γ_2 .

(ix) Heterogeneity by education and experience (Appendix H.7). Do the migrant share effects differ across labor market cells? To address this question, we alternately interact the migrant share in (29) with a college dummy (taking 1 for cells with any college education) and a high-experience dummy (for 20+ years). In OLS, our γ_2 estimate is entirely driven by non-college workers. Intuitively, one might expect that lower income migrants suffer disproportionately from a lack of outside options, allowing employers to extract relatively more rents from their native co-workers. However, we do not find differential effects by education in IV. With respect to experience, we find no evidence of heterogeneous effects.

(ix) Heterogeneous effects of new and old migrants (Appendix H.8). Are mark-downs more responsive to newer migrants? On the one hand, newer migrants may supply labor less elastically to firms, allowing them to extract larger rents from labor. However, they may also be less assimilated into native labor markets and offer less direct competition (see the discussion in Section 4.1). To address this, we control separately for shares of new migrants $\frac{M_{ext}^{new}}{N_{ext}+M_{ext}}$ (in the US for up to new years) and old migrants $\frac{M_{ext}^{old}}{N_{ext}+M_{ext}}$ (more than ten years) 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 $\frac{\tilde{M}_{ext}^{old}}{\tilde{N}_{ext}+\tilde{M}_{ext}}$: these perform remarkably well in fixed effects (Appendix Table A15), but offer little power in first differences. The IV estimates (column 2 of Appendix Table A16) do suggest that new migrants have a somewhat larger impact (-0.82 compared to -0.53), though we see the reverse in OLS (column 1).

(x) Assumption of CES technology (Appendix H.9). One may be concerned that our assumption of a CES technology drives our results, but the evidence in Appendix H.9 suggests CES offers a reasonable description of the data.

(xi) Labor supply responses (Appendix H.10). Do the mark-down effects elicit changes in employment rates? Dustmann, Schoenberg and Stuhler (2016) stress the im-

portance of labor supply responses to migration; and using similar skill-cell variation to our own, Borjas (2003) and Monras (2020) estimate significant effects on native employment rates as well as wages. To study the cell-level labor supply elasticity²⁵, we estimate:

$$\log ER_{Next} = \delta_0 + \delta_1 \log W_{Next} + d_{ex} + d_{et} + d_{xt} + e_{ext} \quad (30)$$

where $\log ER_{Next}$ is the log of mean annual native employment hours. The regressor of interest is the (composition-adjusted) log native wage, and we control for the full set of interacted fixed effects. Borjas (2017) uses a similar specification to estimate employment elasticities; we build on his work by (i) adjusting employment rates for changes in demographic composition (as we do for wages - which greatly reduces the standard errors) and by (ii) applying the instruments from our native wage equation (i.e. predicted total employment and predicted migrant share). In our fixed effect specification, we estimate δ_1 as 0.66 in OLS and 1.01 in IV (Appendix Table A17). The first stage of the IV estimate is entirely driven by the predicted migrant share (as opposed to predicted total employment, consistent with our findings in Table 4), which we attribute to the mark-down channel: this suggests that larger mark-downs, driven by immigration, reduce native employment rates.

We also repeat the exercise for migrants, replacing the employment rate and wage variables in (30) with migrant equivalents. Our δ_1 estimates are smaller than for natives, taking 0.3 in our preferred fixed effect specification. This suggests that migrants supply labor relatively inelastically to the market, consistent with Borjas (2017). Of course, this is not the same as migrants supplying labor inelastically to individual *firms* (i.e. $R_M < R_N$ or $\epsilon_M < \epsilon_N$). But the two stories are certainly consistent, and this offers additional support for our interpretation of the mark-down effects: firms are able to set larger mark-downs by exploiting an inelastic supply of migrant labor.

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 also quantify these effects, based on our estimates above.

²⁵ δ_1 in equation (30) is most naturally interpreted as a cell-level labor supply elasticity. But in certain non-competitive models, it may also be conflated with demand-side effects. In particular, Chassamboulli and Palivos (2013), Chassamboulli and Peri (2015), Amior (2017) and Albert (forthcoming) note that migrants' low wage demands may stimulate job creation (for a given marginal product of labor). However, we estimate a large *positive* δ_1 , which suggests this job creation effect is relatively weak in this context.

Specifically, we predict the impact of an immigration shock equal to 1% of total employment in 2017²⁶, holding migrants’ skill mix fixed. We simulate the effects 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 0.84.²⁷

8.1 Perfect competition

We present our results in Table 5. 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_Z) 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.

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

²⁶Our 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).

²⁷Blau 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 28. 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.²⁸ 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 Monopsony

Column 2 now introduces monopsony. We begin with the simple case where mark-downs are equal for natives and migrants (i.e. $\Delta\phi_{0N} = \Delta\phi_{1N} = 0$) 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_Z 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-

²⁸Card (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.²⁹ 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.³⁰

In column 3, we now allow mark-downs to vary with migrant share, but we continue to assume they are the same for natives and migrants (i.e. $\Delta\phi_{0N} = \Delta\phi_{1N} = 0$). For this column, we specify the mark-downs as linear functions of $\log \frac{M}{N}$: we calibrate ϕ_{1N} (the coefficient on $\log \frac{M}{N}$) to 0.119 (based on column 6 of Table 4's Panel A), and we set ϕ_{0N} to ensure a 10% share of monopsony rents at baseline. We now see universally negative effects on native wages, averaging -0.6%. The mark-down effects are identical for all cells (to see this, notice each cell's wage effect differs by the same amount from column 2): this is because the migrant skill mix is unchanged, so the shift in $\log \frac{M}{N}$ (which determines mark-downs in column 3) does not vary across cells. 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 0.70% of net output. The total native surplus (0.22%) 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 $\alpha_Z = \sigma_Z = 1$ (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 ϕ_{1N} , according to the specification of Panel B in Table 4 (as opposed to Panel A). The net output response is now slightly larger, since natives and migrants are perfect substitutes within cells (so diminishing returns to immigration are weaker). But overall, the results change little.

Finally, columns 5-6 replicate the exercise of columns 3-4, but specifying the mark-down response in terms of migrant share $\frac{M}{M+N}$ (we calibrate the native mark-down effect ϕ_{1N} to 0.628 and 0.570 respectively, based on column 7 of Table 4). The size of the mark-down effect is now larger in cells with larger migrant shares at baseline (so dropouts suffer especially). The effects are otherwise qualitatively similar to columns 3-4, though smaller on average: the mean native wage effect is about -0.4, rather than -0.6.

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

²⁹One 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.

³⁰Though these migrants may still be earning more than in their country of origin.

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).

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 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. 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.

It is worth stressing the policy implications are nuanced: one cannot conclude that immigration is generally harmful for native workers. If policy interventions can make the labor market more competitive (by limiting the power of firms to set mark-downs), immigration would only have the surplus-raising feature for native labor. See e.g. Edo and Rapoport (2019) for evidence on minimum wages. On the other hand, interventions ostensibly designed to protect native wages by deterring immigration (such as restricting migrants’ access to welfare benefits) 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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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:

$$\Pi(\mathbf{L}, \mathbf{p}_K) = \max_{\mathbf{K}} \{F(\mathbf{L}, \mathbf{K}) - \mathbf{p}_K' \mathbf{K}\} \quad (\text{A1})$$

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:

$$\mathbf{F}_K(\mathbf{L}, \mathbf{K}) = \mathbf{p}_K \quad (\text{A2})$$

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:

$$\Pi(\mathbf{L}, \mathbf{p}_K) = F(\mathbf{L}, \mathbf{K}(\mathbf{L}, \mathbf{p}_K)) - \mathbf{p}_K' \mathbf{K}(\mathbf{L}, \mathbf{p}_K) \quad (\text{A3})$$

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:

$$\Pi_L(\mathbf{L}, \mathbf{p}_K) = F_L(\mathbf{L}, \mathbf{K}(\mathbf{L}, \mathbf{p}_K)) + [\mathbf{F}_K - \mathbf{p}_K]' \frac{\partial \mathbf{K}(\mathbf{L}, \mathbf{p}_K)}{\partial \mathbf{L}} = F_L(\mathbf{L}, \mathbf{K}(\mathbf{L}, \mathbf{p}_K)) \quad (\text{A4})$$

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:

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

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

$$\tilde{\mathbf{M}} = \zeta \mathbf{M} \quad (\text{A6})$$

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:

$$\mathbf{p} = \tilde{c}(\mathbf{w}, \mathbf{p}) \quad (\text{A7})$$

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.³¹ From standard theory, \tilde{c} will be homogenous of degree 1 in its arguments,

³¹As 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.

increasing and concave. One can solve (A7) to give a “reduced form” cost function:

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

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:

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

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 $\tilde{e}(\mathbf{p})u$, 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:

$$e(\mathbf{w}) = \tilde{e}(c(\mathbf{w})) \quad (\text{A10})$$

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:

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

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

$$e_w(\mathbf{w}) = \tilde{e}_p(c(\mathbf{w})) c_w(\mathbf{w}) = \mathbf{X}(c(\mathbf{w})) \mathbf{A}(\mathbf{w}) \quad (\text{A12})$$

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:

$$\mathbf{L} = N\eta + M\mu \quad (\text{A13})$$

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.³² As total income must equal total expenditure for natives and migrants alike, we must have:

$$\eta\mathbf{w} = e(\mathbf{w})u^n \quad (\text{A14})$$

and

$$\mu\mathbf{w} = e(\mathbf{w})u^m \quad (\text{A15})$$

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

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

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:

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

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.

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:

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

³²Because 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

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):

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

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

$$Mdu^m = -Ndu^n \quad (\text{A20})$$

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.³³ This would require an expression for the change in wages. Differentiating (A17) leads to:

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

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

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

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

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

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).

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 dis-

³³Note that this is migrant utility in the host country: it says nothing about whether there are gains from migration as a whole.

criminate (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 $\tilde{F}(L_j, \dots, L_J)$, 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:

$$Z(N, M) = \tilde{F}((\eta_1 N + \mu_1 M), \dots, (\eta_J N + \mu_J M)) \quad (\text{A24})$$

The partial derivative of Z with respect to N is:

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

which is the mean marginal product of natives. Similarly, the partial derivative with

respect to M is:

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

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:

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

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:

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

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 $\frac{\partial \bar{F}}{\partial L_j}$; 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:

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

where ϕ_M is the migrant aggregate mark-down:

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

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 $\phi_N\left(\frac{M}{N}\right)$ 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 $\epsilon_M = \epsilon_N$.

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 $\frac{M}{N} \rightarrow 0$ or $\frac{M}{N} \rightarrow \infty$. 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:

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

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:

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

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:

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

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:

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

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:

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

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

$$\log W_N = \log A - (1 - \sigma_X) \log N + \log \left[\frac{z\left(\frac{M}{N}\right) - \frac{M}{N} z'\left(\frac{M}{N}\right)}{z\left(\frac{M}{N}\right)^{1-\sigma_X}} \right] - \phi_N\left(\frac{M}{N}\right) \quad (\text{A39})$$

$$\log W_M = \log A - (1 - \sigma_X) \log N + \log \left[\frac{z'\left(\frac{M}{N}\right)}{z\left(\frac{M}{N}\right)^{1-\sigma_X}} \right] - \phi_M\left(\frac{M}{N}\right) \quad (\text{A40})$$

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.³⁴

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:

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

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.

³⁴Identification may be feasible if we assume the difference between ϕ_N and ϕ_M converges to zero as $\frac{M}{N} \rightarrow 0$ or $\frac{M}{N} \rightarrow \infty$, 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.

F Computing effects on wages, surplus and distribution

F.1 Overview of wage effects

In this appendix, we describe how we compute the impact of an expansion of the migrant stock, holding their skill mix fixed, on average wages and the native surplus - as presented in Table 5. We begin by deriving the wage effects. 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:

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

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

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

$$\begin{aligned} \log W_{Nex} = & \log(\alpha_e \alpha_{ex}) + (1 - \sigma_E) \log \tilde{Y} + (\sigma_E - \sigma_X) \log L_e \\ & + (\sigma_X - \sigma_Z) \log L_{ex} + (\sigma_Z - 1) \log N_{ex} - \phi_{Nex} \end{aligned} \quad (\text{A44})$$

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

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 to 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 Components of wage equations

How does the immigration shock affect the various components of (A44) and (A45)? Notice first that, holding the native stock fixed, a small 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:

$$\frac{d \log M_{ex}}{\left(\frac{dM}{M+N}\right)} = \frac{N + M}{M} \quad (\text{A46})$$

In turn, the education-experience aggregator L_{ex} will increase by:

$$\frac{d \log L_{ex}}{\left(\frac{dM}{M+N}\right)} = \frac{d \log L_{ex}}{d \log M_{ex}} \cdot \frac{d \log M_{ex}}{\left(\frac{dM}{M+N}\right)} = \frac{\alpha_{Zex} M_{ex}^{\sigma_Z}}{N_{ex}^{\sigma_Z} + \alpha_{Zex} M_{ex}^{\sigma_Z}} \cdot \frac{d \log M_{ex}}{\left(\frac{dM}{M+N}\right)} = \frac{\tilde{F}_{Mex} M_{ex}}{\tilde{F}_{Mex} M_{ex} + \tilde{F}_{Nex} N_{ex}} \cdot \frac{d \log M_{ex}}{\left(\frac{dM}{M+N}\right)} \quad (\text{A47})$$

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

$$\tilde{F}_{Nex} = \exp(\phi_{Nex}) W_{Nex} \quad (\text{A48})$$

$$\tilde{F}_{Mex} = \exp(\phi_{Mex}) W_{Mex} \quad (\text{A49})$$

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). The education aggregator L_e increases by:

$$\frac{d \log L_e}{\left(\frac{dM}{M+N}\right)} = \frac{d \log L_e}{d \log L_{ex}} \cdot \frac{d \log L_{ex}}{\left(\frac{dM}{M+N}\right)} = \frac{\alpha_{ex} L_{ex}}{\sum_{x'} \alpha_{ex'} L_{ex'}} \cdot \frac{d \log L_{ex}}{\left(\frac{dM}{M+N}\right)} = \frac{F_{ex}^M M_{ex} + F_{ex}^N N_{ex}}{\sum_{x'} (F_{ex'}^M M_{ex'} + F_{ex'}^N N_{ex'})} \cdot \frac{d \log L_{ex}}{\left(\frac{dM}{M+N}\right)} \quad (\text{A50})$$

where the second equality follows from (13), and where $\frac{F_{ex}^M M_{ex} + F_{ex}^N N_{ex}}{\sum_{x'} (F_{ex'}^M M_{ex'} + F_{ex'}^N N_{ex'})}$ will equal the wage bill share of experience group x (within education group e) under perfect competition. And finally, net output \tilde{Y} increases by:

$$\frac{d \log \tilde{Y}}{\left(\frac{dM}{M+N}\right)} = \frac{d \log \tilde{Y}}{d \log L_e} \cdot \frac{d \log L_e}{\left(\frac{dM}{M+N}\right)} = \frac{\alpha_e L_e}{\sum_{e'} \alpha_{e'} L_{e'}} \cdot \frac{d \log L_e}{\left(\frac{dM}{M+N}\right)} = \frac{\sum_{x'} (F_{ex'}^M M_{ex'} + F_{ex'}^N N_{ex'})}{\sum_{e', x'} (F_{e'x'}^M M_{e'x'} + F_{e'x'}^N N_{e'x'})} \cdot \frac{d \log L_e}{\left(\frac{dM}{M+N}\right)} \quad (\text{A51})$$

where the second equality follows from (12), and where $\frac{\sum_{x'} (F_{ex'}^M M_{ex'} + F_{ex'}^N N_{ex'})}{\sum_{e', x'} (F_{e'x'}^M M_{e'x'} + F_{e'x'}^N N_{e'x'})}$ will equal the wage bill share of education group e under perfect competition.

F.3 Mark-down effects

Finally, consider the mark-down effects, which fall on workers in the same cell (i.e. $e' = e$ and $x' = x$). Suppose first we specify the native and migrant mark-downs, ϕ_{Nex} and ϕ_{Mex} , as linear functions of $\log \frac{M_{ex}}{N_{ex}}$, with coefficients of ϕ_{1N} and $\phi_{1N} + \Delta\phi_1$ respectively,

as we do in (19) and (20). Then, we can write:

$$\frac{d\phi_{Nex}}{\left(\frac{dM}{M+N}\right)} = \phi_{1N} \frac{d \log M_{ex}}{\left(\frac{dM}{M+N}\right)} \quad (\text{A52})$$

$$\frac{d\phi_{Mex}}{\left(\frac{dM}{M+N}\right)} = (\phi_{1N} + \Delta\phi_1) \frac{d \log M_{ex}}{\left(\frac{dM}{M+N}\right)} \quad (\text{A53})$$

However, if we define ϕ_{1N} as the linear effect of the cell-specific migrant share $\frac{M_{ex}}{M_{ex}+N_{ex}}$, we can write:

$$\frac{d\phi_{Nex}}{\left(\frac{dM}{M+N}\right)} = \phi_{1N} \frac{d\left(\frac{M_{ex}}{M_{ex}+N_{ex}}\right)}{d \log M_{ex}} \cdot \frac{d \log M_{ex}}{\left(\frac{dM}{M+N}\right)} = \phi_{1N} \frac{N_{ex}M_{ex}}{(N_{ex} + M_{ex})^2} \cdot \frac{d \log M_{ex}}{\left(\frac{dM}{M+N}\right)} \quad (\text{A54})$$

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

F.4 Distributional effects and immigration surplus

The equations above allow us to compute the average native and migrant wage effects (by education group and on aggregate), as well as the impact on the (long-run) net output \tilde{Y} . We now turn to Panel C of Table 5. 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) :

$$d(W_{Mex}M_{ex}) = W_{Mex}M_{ex} \left(1 + \sum_{e',x'} \frac{d \log W_{Mex}}{d \log M_{e'x'}} \right) d \log M \quad (\text{A56})$$

where $\sum_{e',x'} \frac{d \log W_{Mex}}{d \log M_{e'x'}}$ aggregates the impact of immigration in the various labor market cells (e', x') on migrant wages in (e, x) . Similarly, the change in native wage income in cell (e, x) can be written as:

$$d(W_{Nex}N_{ex}) = W_{Nex}N_{ex} \left(\sum_{e',x'} \frac{d \log W_{Nex}}{d \log M_{e'x'}} \right) d \log M \quad (\text{A57})$$

To compute the total change in the migrant and native wage bills, we sum (A56) and (A57) over labor market cells (e, x) . And we express these changes relative to net output \tilde{Y} , where \tilde{Y} can be written as:

$$\tilde{Y} = \sum_{e,x} (F_{ex}^M M_{ex} + F_{ex}^N N_{ex}) \quad (\text{A58})$$

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:

$$\frac{dR}{\tilde{Y}} = d \log \tilde{Y} - \sum_{e,x} \frac{d(W_{Nex}N_{ex})}{\tilde{Y}} - \sum_{e,x} \frac{d(W_{Mex}M_{ex})}{\tilde{Y}} \quad (\text{A59})$$

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

$$\frac{S}{\tilde{Y}} = \frac{dR}{\tilde{Y}} + \sum_{e,x} \frac{d(W_{Nex}N_{ex})}{\tilde{Y}} \quad (\text{A60})$$

G Further details on data

G.1 Disaggregation of migrant stocks in 1960 census

The 1960 census does not report migrants' year of arrival, but we require this information for the construction of the instruments, as well as for the empirical specifications which disaggregate between new and old migrants (i.e. in Table A16). In particular, we need to know the employment stocks of migrants living in the US for no more than ten years, by country of origin and education-experience cell.

For each country of origin and labor market cell, our strategy is to predict these stocks using the size of the same cohort ten years later. For example, to predict the 1960 stock of new Mexican migrants (with up to ten years in the US) among high school graduates with 25-30 years of labor market experience, we use information on the 1970 stock of high school graduate Mexicans with 11-20 years in the US and 35-40 years of experience.

To predict 1960 employment stocks using (same-cohort) population ten years later, we exploit the relationship between these same variables in future decades (when they are both observed). Specifically, we regress the log employment stock of new migrants, by (i) 164 countries of origin, (ii) 32 education-experience cells and (iii) four census years (1970, 1980, 1990 and 2000), on the log population stock of the same cohort ten years later. To allow for cell-specific deviations, we also control for interacted education-experience-region fixed effects, where we account for 12 regions (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).

We then use the regression estimates (and fixed effects) to predict the employment stocks of new migrants in 1960, conditional on the within-cohort population stocks in

1970. Our approach here will account for cell differences in employment rates, as well as any systematic contraction of migrant cohorts over time (due to emigration). In particular, the coefficient on the future log population (i.e. ten years later) is 0.87. This suggests about 10% of immigrants leave the country over each decade, which is consistent with estimates from Ahmed and Robinson (1994).

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}_{ext}^{new} . 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:

$$\log M_{oext}^{new} = \lambda_0^{Mnew} + \lambda_1^{Mnew} \log HistoricalCohortSize_{oext} + \lambda_2^{Mnew} Mobility_{ex} + Region_o + \varepsilon_{oext}^{Mnew} \quad (A61)$$

where the dependent variable, M_{oext}^{new} , 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.³⁵ 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 (A61) 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 effects³⁶, $Region_o$, which account for the fact that demographic shifts in certain regions matter more for emigration to the US. As it turns out, origin cohort size delivers substantial

³⁵The 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/>.

³⁶Specifically: 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.

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 (A61), 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 :

$$\tilde{M}_{ext}^{new} = \sum_o \exp \left(\hat{\lambda}_0^{Mnew} + \hat{\lambda}_2^{Mnew} Mobility_{ex} + Region_o \right) \cdot HistoricalCohortSize_{oext}^{\hat{\lambda}_1^{Mnew}} \quad (A62)$$

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 (A61), 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 (A61). 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 (A61). 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:

$$Mobility_{ex} = \log \left[\frac{1}{2} (ShareDiffState5yr_{ex} + ShareDiffState5yr_{ex-1}) \right] \quad (A63)$$

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.

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 1960-2017 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 $\tilde{M}_{ext} = \tilde{M}_{ext}^{old} + \tilde{M}_{ext}^{new}$).

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 1960-2017 in old migrants' share of employment hours, i.e. $\frac{M_{ext}^{old}}{N_{ext}+M_{ext}}$. In Panel B, we predict this change with our instruments: i.e. we report changes in $\frac{\tilde{M}_{ext}^{old}}{\tilde{N}_{ext}+\tilde{M}_{ext}^{old}}$. Similarly, Panel C reports changes in the new migrants share, $\frac{M_{ext}^{new}}{N_{ext}+M_{ext}}$; and Panel D predicts these using changes in $\frac{\tilde{M}_{ext}^{new}}{\tilde{N}_{ext}+\tilde{M}_{ext}^{new}}$.

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

In this appendix, we assess the robustness of our estimates of the migrant share effect, γ_2 , in the native wage equation (29), test for heterogeneity in these effects, and estimate labor supply responses to migrant-driven wage variation. For simplicity, we impose $\alpha_Z = \sigma_Z = 1$ throughout, so the dependent variable in the native wage equation (29) collapses to log native wages and the cell aggregator to log total employment, $\log(N_{ext} + M_{ext})$.

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.

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.

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 our two instruments with the predicted log native and migrant employment, i.e. $\log \tilde{N}_{ext}$ and $\log \tilde{M}_{ext}$. Columns 1-4 are otherwise identical to columns 3-6 in Table 3 (Panel B), and columns 5-6 are otherwise identical to columns 7 and 9 in Table 4 (Panel B).

The instruments take the correct sign in the first stage: the migrant share is decreasing in $\log \tilde{N}_{ext}$ but increasing in $\log \tilde{M}_{ext}$. The F-statistics are small in the fixed effect specification (about 5), but they are reasonably large in first differences (above 15). Comparing the second stage estimates to Table 4, the standard errors are unsurprisingly larger. But the coefficients are also larger: the fixed effect estimate increases from -0.57 to -0.87, and the first differenced estimate from -0.36 to -0.53.

H.4 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 2017 (where the lagged outcome corresponds to 2010). For IV, this requires two additional instruments; and we use the lags of our existing instruments.

We present our first stage estimates in Appendix Table A6, and our OLS and IV estimates in Appendix Table A7. 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 A7. 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 A6), 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 A7 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.5 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.³⁷

We report first stage estimates in Table A8, and OLS and IV estimates in columns 1-4 of Table A9. Notice that γ_1 (the elasticity to total cell employment) is now consistently negative and mostly exceeds -0.1. For $\sigma_Z = 1$, this implies an elasticity of substitution between experience groups (within education nests) of less than 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.³⁸ The γ_2 estimate (on migrant share) now exceeds -1 under fixed effects (columns 1-2), for both OLS and IV. In first differences (columns 3-4), it reaches -0.5 in OLS and -1.2 in IV, though standard errors are large in the latter case.

³⁷For example, consider the OLS coefficient on $\frac{M}{N+M}$ in column 1 of Table A9. 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 $[-1.324, -0.783]$. 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 $[-1.298, -0.771]$.

³⁸In 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.

In columns 5-8 of Table A9, 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 A9 shows the estimates (and standard errors) are little affected after aggregating to larger 10-year groups.

H.6 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, denoted ex . Let $\Pi_{O \times EX}^M$ 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 $\Pi_{O \times EX}^M$ sum to 1). We base these shares on averages across all sample years. Similarly, let $\Pi_{EX \times O}^N$ 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 $\Pi_{EX \times O}^N$ sum to 1). Using these matrices, we can probabilistically allocate migrant education-experience cells to native education-experience cells, according to their occupational distribution:

$$\mathbf{M}_{EX \times T}^{occ} = \Pi_{EX \times O}^N \Pi_{O \times EX}^M \mathbf{M}_{EX \times T} \quad (\text{A64})$$

where $\mathbf{M}_{EX \times T}$ is the matrix of *actual* migrant employment stocks by education-experience cell and time, and $\mathbf{M}_{EX \times T}^{occ}$ 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:

$$\tilde{\mathbf{M}}_{EX \times T}^{occ} = \mathbf{\Pi}_{EX \times O}^N \mathbf{\Pi}_{O \times EX}^M \tilde{\mathbf{M}}_{EX \times T} \quad (\text{A65})$$

where $\tilde{\mathbf{M}}_{EX \times T}^{occ}$ 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_{ext}^{occ} (and replacing the instruments accordingly). For simplicity, we impose $\alpha_Z = \sigma_Z = 1$, so the dependent variable collapses to log native wages and the cell aggregator to log total employment, $\log(N_{ext} + M_{ext}^{occ})$. Appendix Table A10 suggests the instruments work well for the occupation-imputed stocks.

We present OLS and IV estimates in Appendix Table A11. In our basic specification (columns 1 and 3), the effect of migrant share is negative (with coefficients of -0.3 and -1.4), though the standard errors are large: the coefficients are not significantly different from zero. It appears the large standard errors stem from a collinearity problem. Once we drop the cell aggregator (whose coefficient is also insignificant), the effect of the migrant share is remarkably close to what we see in Table 4 in the main text: -0.50 in OLS (column 2) and -0.66 in IV (column 4), with standard errors of 0.2. When we estimate these equations in first differences (columns 5-8), the patterns are qualitatively similar. This suggests our estimates are robust to concerns about occupational downgrading.

H.7 Heterogeneous effects by education and experience

Another pertinent question is whether the mark-down effects differ across labor market cells. To study this heterogeneity, we alternately interact the migrant share in (29) with a college dummy (taking 1 for cells with any college education) and a high-experience dummy (for 20+ years). These interactions require additional instruments: we use the interactions between the predicted migrant share and the college/experience dummies.

We report our first stage estimates in Appendix Tables A12 and A13, and the OLS and IV estimates in Appendix Table A14. In OLS, the migrant share responses (which identify the mark-down effects) are entirely driven by non-college workers, both in the fixed effect and first differenced specifications. Intuitively, one might expect that lower income migrants suffer disproportionately from a lack of outside options, allowing employers to extract relatively more rents from their native co-workers. However, we do not find differential effects by education in IV. With respect to experience, we find no evidence of heterogeneous effects in OLS or IV.

H.8 Heterogeneous effects of new and old migrants

Are the mark-downs more responsive to newer migrants? Theoretically, it is not clear what to expect. On the one hand, new migrants may supply labor less elastically to firms, allowing them to extract larger rents from labor. But they may also be less assimilated into native labor markets and offer less direct competition (see Appendix D.4).

Our approach is to control separately for the shares of new migrants $\frac{M_{ext}^{new}}{N_{ext}+M_{ext}}$ (in the US for up to new years) and old migrants $\frac{M_{ext}^{old}}{N_{ext}+M_{ext}}$ (more than ten years) in the native wage equation (29). We construct distinct instruments for each, i.e. $\frac{\tilde{M}_{ext}^{new}}{N_{ext}+M_{ext}}$ and $\frac{\tilde{M}_{ext}^{old}}{N_{ext}+M_{ext}}$. Table A15 reports first stage estimates: our instruments perform remarkably well in fixed effects, but offer little power in first differences (F-statistics are all below 5).

Appendix Table A16 presents our OLS and IV estimates. In general, the effects of new and old migrants are similar. Column 2 (IV fixed effects) does suggest new migrants have a somewhat larger impact (-0.82 compared to -0.53), though we see the reverse in column 1 (OLS). In first differences, the standard errors are generally too large to make any definitive claims.

H.9 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. This requires an assumption on the functional form of Z . In line with the existing literature (Card, 2009; Manacorda, Manning and Wadsworth, 2012; Ottaviano and Peri, 2012), we assume Z has CES form. In this section, we consider the empirical robustness of this assumption.

If we are willing to impose constant returns to scale, the log relative wage (of migrants to natives) must depend only on the relative supply of migrants, $\frac{M}{N}$: see equation (A41).

The assumption of CES imposes that the relationship between the log relative wage and log relative supply is *linear*: see equation (23). Therefore, conditional on constant returns, it is sufficient to study the linearity of the relationship between the log relative wage and log relative supply.

In Appendix Figure A2, we offer scatter-plots which illustrate our estimates of β_1 (the coefficient on $\log \frac{M}{N}$) in the relative wage equation (26). Specifically, we will consider columns 4-8 of Table 2: these are OLS and IV estimates, for both fixed effect specifications (with interacted education-experience effects and year effects) and first differenced specifications (with year effects only). We follow the logic of the Frisch-Waugh theorem, taking identical steps to those in part (i) of Section 7: we plot the relationship between the residualized x and y-variable (purging the fixed effects); and in the case of IV, we predict our x-variable (the log relative supply) using the first stage regression.

By construction, the slope coefficients are identical to the β_1 estimates in Panel B of Table 2. Clearly, there is plenty of variation around the fit lines. But by inspection, where there is a relationship, there is no convincing reason here to reject the standard assumption of linearity.

H.10 Labor supply responses

To study the cell-level elasticity of labor supply, we estimate:

$$\log ER_{Next} = \delta_0 + \delta_1 \log W_{Next} + d_{ex} + d_{et} + d_{xt} + e_{ext} \quad (\text{A66})$$

where $\log ER_{Next}$ is the log of mean annual native employment hours. Just as in our wage sample (and like Borjas, 2003), we exclude enrolled students when computing employment rates. The regressor of interest is the (composition-adjusted) log native wage (which we expect to take a positive coefficient), and we control for the full set of interacted fixed effects. We also study first differenced specifications, where the d_{ex} effects are eliminated. Borjas (2017) uses a similar specification to estimate employment elasticities; we build on his work by adjusting employment rates for changes in demographic composition (as we do for wages³⁹) and by instrumenting wages using migration shocks.

³⁹Our 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.

We present estimates of the elasticity δ_1 in Panel A of Appendix Table A17. For raw employment rates, our OLS estimate is 0.5 using fixed effects (column 1) and 0.9 in first differences (column 5). After adjusting employment rates for changes in demographic composition, these become 0.7 (column 2) and 0.8 (column 6) respectively.

Of course, the OLS estimates may be conflated with omitted cell-specific supply shocks, driven e.g. by changes in preferences. Depending on how these covary with wages (conditional on the various fixed effects), the bias could go in either direction. In columns 3 and 7, we now introduce the instruments from our native wage equation: (i) predicted log total employment (in the labor market cell) and (ii) predicted migrant share. It is worth recalling that our instruments are constructed using population (and not employment) data, so they are not conflated with variation in employment choices. The first stage in Panel C can be interpreted as a reduced form wage equation, regressing wages directly on the instruments. Consistent with our findings in Table 4, only the predicted migrant share has power; and we also offer an “IV2” specification which excludes the total employment instrument.

Turning to the second stage, IV yields somewhat larger native employment elasticities, reaching 1 for fixed effects (column 4) and 1.2 for first differences (column 8). Notice these estimates are identified entirely from the predicted migrant share, which our model associates with the mark-down channel. This suggests that larger mark-downs, driven by immigration, have lowered native employment rates.

In Panel B, we repeat the exercise for migrants, replacing the employment rate and wage variables with migrant equivalents. Our δ_1 estimates are universally smaller than those of natives (except in column 8, where the standard errors balloon⁴⁰). This suggests that migrants supply labor relatively inelastically to the market, which reflects the evidence from Borjas (2017). Of course, this is not the same as migrants supplying labor inelastically to individual *firms* (i.e. $R_M < R_N$ or $\epsilon_M < \epsilon_N$). But the two stories are certainly consistent, and this offers additional support for our interpretation of the mark-down effects: firms are able to set larger mark-downs by exploiting an inelastic supply of migrant labor.

⁴⁰As Panel D shows, the instrument has no power for migrant wages in first differences.

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
<i>Panel A: Migrant share of employment hours, 1960</i>								
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
<i>Panel B: Change in migrant share of employment hours, 1960-2017</i>								
HS dropouts	0.142	0.304	0.447	0.513	0.579	0.582	0.526	0.402
HS graduates	0.082	0.125	0.174	0.188	0.210	0.173	0.105	0.029
Some college	0.057	0.071	0.076	0.085	0.100	0.075	0.046	0.015
College graduates	0.084	0.120	0.142	0.156	0.130	0.113	0.063	0.034
<i>Panel C: Predicted change in migrant share, 1960-2017</i>								
HS dropouts	0.173	0.325	0.437	0.459	0.518	0.522	0.438	0.330
HS graduates	0.107	0.149	0.180	0.187	0.223	0.167	0.092	0.004
Some college	0.034	0.051	0.082	0.096	0.095	0.085	0.050	0.021
College graduates	0.006	0.043	0.096	0.155	0.132	0.118	0.078	0.022
<i>Panel D: Change in log native wages, 1960-2017</i>								
HS dropouts	-0.055	-0.146	-0.187	-0.099	-0.039	-0.029	-0.030	0.036
HS graduates	-0.231	-0.215	-0.207	-0.129	-0.081	-0.019	-0.012	-0.012
Some college	-0.218	-0.168	-0.107	-0.049	0.013	0.062	0.097	0.113
College graduates	0.048	0.112	0.178	0.237	0.261	0.302	0.292	0.283
<i>Panel E: Mean log migrant-native wage differential</i>								
HS dropouts	-0.002	-0.106	-0.124	-0.140	-0.142	-0.144	-0.123	-0.089
HS graduates	-0.049	-0.106	-0.131	-0.139	-0.134	-0.143	-0.133	-0.117
Some college	-0.033	-0.082	-0.093	-0.093	-0.108	-0.115	-0.089	-0.087
College graduates	0.018	-0.031	-0.065	-0.079	-0.109	-0.129	-0.133	-0.131

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 1960-2017. Panel C predicts changes in the migrant share using our instruments: i.e. we report changes in $\frac{\hat{M}}{N+M}$. Panel D reports changes over 1960-2017 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 1960-2017, 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.

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Table 2: Model for log relative migrant-native wages

	Basic estimates			Fixed effects: Edu*Exp, Year		First diff + Year effects	
	Raw wages	Composition-adjusted		Composition-adjusted		Composition-adjusted	
	OLS	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>Panel A: OLS and IV estimates</i>							
$\log \frac{M}{N}$	-0.033*** (0.004)	0.001 (0.004)	0.004 (0.006)	-0.019** (0.007)	-0.032*** (0.010)	-0.017* (0.009)	-0.022** (0.010)
Constant (or mean intercept)	-0.138*** (0.012)	-0.098*** (0.012)	-0.090*** (0.017)	-0.135*** (0.014)	-0.161*** (0.020)	-	-
<i>Panel B: First stage estimates</i>							
$\log \frac{\tilde{M}}{N}$	-	-	1.092*** (0.051)	-	1.128*** (0.070)	-	1.038*** (0.049)
Observations	224	224	224	224	224	192	192

Panel A reports estimates of equation (26), across 32 education-experience cells and 7 time observations (over 1960-2017). 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. Finally, columns 6-7 are estimated in first differences, controlling 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)
<i>Panel A: Imposing equal mark-downs (H1), $\Delta\phi_0 = \Delta\phi_1 = 0$</i>						
$\log Z(\tilde{N}, \tilde{M})$	1.041*** (0.097)	0.073 (0.112)	1.103*** (0.081)	0.028 (0.019)	0.846*** (0.091)	0.043** (0.016)
$\log \frac{\tilde{M}}{\tilde{N}}$	0.007 (0.065)	0.987*** (0.120)				
$\frac{\tilde{M}}{\tilde{N}+\tilde{M}}$			0.585** (0.272)	1.124*** (0.076)	0.954*** (0.294)	0.983*** (0.113)
<i>Panel B: Imposing $\alpha_Z = \sigma_Z = 1$</i>						
$\log(\tilde{N} + \tilde{M})$	1.050*** (0.093)	0.056 (0.111)	1.110*** (0.078)	0.025 (0.018)	0.862*** (0.089)	0.043*** (0.015)
$\log \frac{\tilde{M}}{\tilde{N}}$	0.011 (0.063)	0.975*** (0.116)				
$\frac{\tilde{M}}{\tilde{N}+\tilde{M}}$			0.623** (0.264)	1.117*** (0.075)	1.023*** (0.300)	0.979*** (0.114)
SW F-stat: Panel A	94.94	55.01	209.60	213.46	95.65	76.36
SW F-stat: Panel B	96.50	55.22	230.20	218.65	103.37	76.11
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 1960-2017). There are two endogenous variables: the cell aggregator $\log Z(N, M) = \log(N^{\sigma_Z} + \alpha_Z M^{\sigma_Z})^{\frac{1}{\sigma_Z}}$ and the cell composition. We consider two specifications for the cell aggregator: in Panel A, we identify α_Z and σ_Z using the estimates from column 5 of Table 2, under the hypothesis of equal mark-downs (H1: $\Delta\phi_0 = \Delta\phi_1 = 0$); and in Panel B, we impose that $\alpha_Z = \sigma_Z = 1$, 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 $\frac{M}{N+M}$. For each endogenous variable, the corresponding instrument is constructed using the identical functional form over the predicted native and migrant employment, i.e. \tilde{N} and \tilde{M} . 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)
<i>Panel A: Imposing equal mark-downs (H1), $\Delta\phi_0 = \Delta\phi_1 = 0$</i>									
$\log Z(N, M)$	0.060*** (0.015)	0.072*** (0.015)	0.021 (0.023)	0.052*** (0.019)	0.052 (0.031)	-0.008 (0.029)	0.028 (0.018)	0.048** (0.018)	0.010 (0.021)
$\log \frac{M}{N}$	-0.047** (0.019)		-0.098*** (0.016)		-0.001 (0.040)	-0.119*** (0.030)			
$\frac{M}{N+M}$		-0.312*** (0.080)		-0.521*** (0.067)	-0.516** (0.191)		-0.628*** (0.093)	-0.380*** (0.074)	-0.434*** (0.091)
<i>Panel B: Imposing $\alpha_Z = \sigma_Z = 1$</i>									
$\log(N + M)$	0.032** (0.015)	0.041*** (0.014)	-0.006 (0.023)	0.022 (0.019)	0.022 (0.032)	-0.034 (0.029)	-0.001 (0.018)	0.022 (0.018)	-0.011 (0.020)
$\log \frac{M}{N}$	-0.038** (0.018)		-0.088*** (0.015)		-0.002 (0.041)	-0.109*** (0.029)			
$\frac{M}{N+M}$		-0.258*** (0.080)		-0.466*** (0.067)	-0.459** (0.195)		-0.570*** (0.092)	-0.323*** (0.071)	-0.359*** (0.088)
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 1960-2017). 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 $\log Z(N, M) = \log(N^{\sigma_Z} + \alpha_Z M^{\sigma_Z})^{\frac{1}{\sigma_Z}}$ and cell composition. In Panel A, we identify α_Z and σ_Z using the estimates from column 5 of Table 2, under the hypothesis of equal mark-downs (H1: $\Delta\phi_0 = \Delta\phi_1 = 0$); and in Panel B, we impose that $\alpha_Z = \sigma_Z = 1$, 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: Simulation of immigration shock equal to 1% of total employment

	(1)	(2)	(3)	(4)	(5)	(6)
Impose equal mark-downs ($H1$)?	Yes	Yes	Yes	No	Yes	No
Impose $\alpha_Z = \sigma_Z = 1$?	No	No	No	Yes	No	Yes
Mean native mark-down	0	0.1	0.1	0.1	0.1	0.1
Specification of mark-down response	None	None	$\log \frac{M}{N}$	$\log \frac{M}{N}$	$\frac{M}{M+N}$	$\frac{M}{M+N}$
Native mark-down response ϕ_{1N}	0	0	0.119	0.109	0.628	0.570
<i>Panel A: Native wages (% changes)</i>						
HS dropouts	-0.465	-0.465	-1.137	-1.199	-1.272	-1.316
HS graduates	0.037	0.037	-0.635	-0.627	-0.471	-0.473
Some college	0.115	0.115	-0.557	-0.521	-0.248	-0.236
College graduates	0.024	0.024	-0.648	-0.607	-0.466	-0.437
Average	0.040	0.040	-0.632	-0.605	-0.424	-0.411
<i>Panel B: Migrant wages (% changes)</i>						
HS dropouts	-0.688	-0.688	-1.360	-1.439	-1.530	-1.587
HS graduates	-0.151	-0.151	-0.823	-0.82	-0.691	-0.694
Some college	-0.067	-0.067	-0.739	-0.705	-0.439	-0.427
College graduates	-0.161	-0.161	-0.832	-0.793	-0.663	-0.633
Average	-0.236	-0.236	-0.908	-0.900	-0.784	-0.782
<i>Panel C: Net long run output and immigration surplus</i>						
% change in net output	0.934	0.934	0.934	0.979	0.934	0.979
<i>Decomposition:</i>						
(i) Δ Migrant wage income (% net output)	0.901	0.815	0.715	0.711	0.736	0.731
(ii) Δ Native wage income (% net output)	0.033	0.030	-0.477	-0.451	-0.328	-0.312
(iii) Δ Monopsony rents (% net output)	0	0.089	0.697	0.719	0.526	0.560
Total native surplus (% net output) = (ii) + (iii)	0.033	0.119	0.219	0.268	0.198	0.248

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 2017, 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 natives and migrants alike, and the remaining columns permit mark-downs to respond to migrant composition (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 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
<i>Panel A: Change in old migrant share of employment hours, 1960-2017</i>								
HS dropouts	0.038	0.114	0.294	0.404	0.482	0.512	0.466	0.360
HS graduates	0.048	0.075	0.124	0.146	0.173	0.147	0.092	0.023
Some college	0.041	0.055	0.063	0.073	0.087	0.069	0.043	0.015
College graduates	0.035	0.046	0.075	0.115	0.108	0.100	0.056	0.032
<i>Panel B: Predicted change in old migrant share, 1960-2017</i>								
HS dropouts	0.064	0.120	0.201	0.291	0.387	0.431	0.360	0.269
HS graduates	0.043	0.053	0.095	0.127	0.172	0.138	0.077	-0.002
Some college	0.026	0.034	0.060	0.072	0.083	0.080	0.051	0.025
College graduates	0.039	0.077	0.092	0.153	0.141	0.125	0.088	0.035
<i>Panel C: Change in new migrant share of employment hours, 1960-2017</i>								
HS dropouts	0.104	0.191	0.153	0.109	0.097	0.071	0.059	0.042
HS graduates	0.034	0.05	0.05	0.041	0.037	0.026	0.013	0.006
Some college	0.016	0.016	0.014	0.013	0.013	0.007	0.004	0.000
College graduates	0.049	0.075	0.067	0.041	0.022	0.012	0.007	0.002
<i>Panel D: Predicted change in new migrant share, 1960-2017</i>								
HS dropouts	0.109	0.205	0.236	0.168	0.131	0.092	0.077	0.060
HS graduates	0.064	0.096	0.085	0.060	0.050	0.029	0.015	0.006
Some college	0.008	0.017	0.022	0.024	0.013	0.005	-0.001	-0.004
College graduates	-0.033	-0.034	0.004	0.001	-0.009	-0.006	-0.010	-0.013

"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 1960-2017) in old migrants' share of employment hours, i.e. $\frac{M_{ext}^{old}}{N_{ext}+M_{ext}}$, across the four education and eight experience groups.

Panel B predicts these changes using our instruments: i.e. we report changes in $\frac{\tilde{M}_{ext}^{old}}{\tilde{N}_{ext}+M_{ext}}$. Panels C and D repeat this exercise for new migrants, reporting changes in $\frac{M_{ext}^{new}}{N_{ext}+M_{ext}}$ and $\frac{\tilde{M}_{ext}^{new}}{\tilde{N}_{ext}+M_{ext}}$ 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)
<i>Panel A: Fixed effects (N = 224)</i>									
$\log Z(N, M)$	-0.004 (0.019)	-0.001 (0.018)	-0.002 (0.018)	0.496*** (0.019)	0.509*** (0.022)	0.522*** (0.027)	0.996*** (0.019)	1.053*** (0.068)	0.960*** (0.106)
$\frac{M}{N+M}$	-0.583*** (0.120)	-0.570*** (0.092)	-0.570*** (0.086)	-0.583*** (0.120)	-1.579*** (0.091)	-1.981*** (0.085)	-0.583*** (0.120)	-3.097*** (0.239)	-4.032*** (0.265)
<i>Panel B: First differences (N = 192)</i>									
$\log Z(N, M)$	-0.016 (0.022)	-0.011 (0.020)	-0.012 (0.020)	0.484*** (0.022)	0.500*** (0.024)	0.518*** (0.028)	0.984*** (0.022)	1.072*** (0.061)	1.000*** (0.072)
$\frac{M}{N+M}$	-0.399*** (0.107)	-0.359*** (0.088)	-0.353*** (0.087)	-0.399*** (0.107)	-1.393*** (0.102)	-1.813*** (0.116)	-0.399*** (0.107)	-3.010*** (0.292)	-3.981*** (0.356)
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)
<i>Panel A: Unweighted estimates</i>								
$\log(N + M)$	-0.020 (0.015)	0.043** (0.019)	-0.015 (0.016)	0.019 (0.026)	-0.038* (0.022)	0.032 (0.020)	-0.025 (0.022)	0.035 (0.022)
$\frac{M}{N+M}$	-0.510*** (0.072)	-0.518*** (0.128)	-0.473*** (0.085)	-0.558*** (0.125)	-0.355*** (0.103)	-0.275** (0.130)	-0.302*** (0.095)	-0.277** (0.106)
<i>Panel B: Weighted by cell employment</i>								
$\log(N + M)$	-0.021 (0.017)	0.051** (0.024)	-0.020 (0.017)	0.026 (0.030)	-0.063** (0.027)	0.018 (0.024)	-0.055* (0.028)	0.023 (0.026)
$\frac{M}{N+M}$	-0.536*** (0.079)	-0.466*** (0.147)	-0.494*** (0.090)	-0.511*** (0.141)	-0.456*** (0.127)	-0.280* (0.162)	-0.383*** (0.123)	-0.273* (0.137)
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
	$\log(N + M)$ (1)	$\frac{M}{N+M}$ (2)	$\log(N + M)$ (3)	$\frac{M}{N+M}$ (4)	$\log W_N$ (5)	$\log W_N$ (6)
$\log \tilde{N}$	0.795*** (0.095)	-0.143*** (0.029)	0.599*** (0.081)	-0.090*** (0.015)		
$\log \tilde{M}$	0.072 (0.108)	0.085** (0.031)	0.060 (0.101)	0.090*** (0.018)		
$\log(N + M)$					-0.054 (0.061)	-0.035 (0.034)
$\frac{M}{N+M}$					-0.874** (0.346)	-0.532** (0.221)
SW F-stat	5.06	5.27	19.72	15.14	-	-
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 an alternative specification of the instruments. In the main text, our two instruments are $\log(\tilde{N} + \tilde{M})$ and $\frac{\tilde{M}}{\tilde{N} + \tilde{M}}$; but here, we replace these with the predicted log native and migrant employment, $\log \tilde{N}$ and $\log \tilde{M}$. 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: Robustness of native wage effects to dynamics: First stage

	$\log(N + M)$		$\log(\tilde{N} + \tilde{M})$: Lagged	$\frac{M}{N+M}$		$\frac{\tilde{M}}{\tilde{N}+\tilde{M}}$: Lagged
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Panel A: First stage for fixed effect estimates ($N = 192$)</i>						
$\log(\tilde{N} + \tilde{M})$	1.098*** (0.105)	0.864*** (0.103)	0.272*** (0.092)	0.031 (0.022)	0.010 (0.014)	0.017 (0.013)
$\log(\tilde{N} + \tilde{M})$: Lagged		0.146* (0.074)	0.855*** (0.096)		-0.020 (0.018)	0.017* (0.009)
$\frac{\tilde{M}}{\tilde{N}+\tilde{M}}$	0.808** (0.307)	-0.692 (0.526)	-2.047*** (0.586)	1.183*** (0.077)	0.941*** (0.136)	0.062 (0.075)
$\frac{\tilde{M}}{\tilde{N}+\tilde{M}}$: Lagged		2.218*** (0.585)	1.143* (0.620)		0.250** (0.116)	0.824*** (0.078)
<i>Panel B: First stage for fixed differenced estimates ($N = 160$)</i>						
$\log(\tilde{N} + \tilde{M})$	0.900*** (0.101)	0.763*** (0.095)	0.429*** (0.101)	0.053*** (0.018)	0.030* (0.015)	0.003 (0.012)
$\log(\tilde{N} + \tilde{M})$: Lagged		0.074 (0.080)	0.877*** (0.101)		0.033 (0.020)	0.014 (0.009)
$\frac{\tilde{M}}{\tilde{N}+\tilde{M}}$	1.331*** (0.266)	0.712** (0.269)	-0.607 (0.476)	1.047*** (0.121)	0.935*** (0.140)	-0.010 (0.066)
$\frac{\tilde{M}}{\tilde{N}+\tilde{M}}$: Lagged		2.043*** (0.546)	0.396 (0.419)		0.453*** (0.145)	0.862*** (0.078)
SW F-stat: Panel A	132.66	52.50	49.05	211.84	20.41	30.03
SW F-stat: Panel B	83.79	34.47	116.35	76.58	39.95	28.13

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 A7. 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 $\alpha_Z = \sigma_Z = 1$, 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 A7: Robustness of native wage effects to dynamics: OLS and IV

	Fixed effects				First differences			
	OLS (1)	OLS (2)	IV (3)	IV (4)	OLS (5)	OLS (6)	IV (7)	IV (8)
$\log(N + M)$	0.033 (0.021)	0.062** (0.028)	0.000 (0.017)	-0.007 (0.029)	0.020 (0.020)	0.039* (0.022)	-0.013 (0.019)	-0.024 (0.027)
$\log(\tilde{N} + \tilde{M})$: Lagged		-0.007 (0.022)		0.017 (0.021)		0.000 (0.000)		0.040** (0.018)
$\frac{M}{N+M}$	-0.440*** (0.064)	-0.271*** (0.090)	-0.544*** (0.064)	-0.479*** (0.125)	-0.328*** (0.072)	-0.273*** (0.094)	-0.365*** (0.069)	-0.289*** (0.084)
$\frac{M}{N+M}$: Lagged		-0.387** (0.149)		-0.030 (0.147)		-0.263* (0.133)		0.031 (0.165)
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 2017 (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-numbered columns, we report estimates of the basic specification (without lags) using the shorter sample. We impose that $\alpha_Z = \sigma_Z = 1$, 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 $\log(N + M)$. 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 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: Broad education and experience groups: First stage

	Two education groups				Four experience groups			
	Fixed effects		First differences		Fixed effects		First differences	
	$\log(N+M)$	$\frac{M}{N+M}$	$\log(N+M)$	$\frac{M}{N+M}$	$\log(N+M)$	$\frac{M}{N+M}$	$\log(N+M)$	$\frac{M}{N+M}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\log(\tilde{N} + \tilde{M})$	0.924*** (0.081)	-0.009 (0.008)	0.765** (0.272)	0.015 (0.009)	1.146*** (0.108)	0.032 (0.030)	0.918*** (0.113)	0.053** (0.024)
$\frac{\tilde{M}}{\tilde{N}+\tilde{M}}$	3.152** (1.076)	0.615*** (0.121)	1.977 (1.593)	0.675*** (0.138)	0.446 (0.319)	1.016*** (0.103)	1.109** (0.429)	0.739*** (0.159)
SW F-stat	122.44	48.00	9.06	22.68	87.31	97.05	78.63	25.30
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 A9. 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.5 for further details on these groupings. We impose that $\alpha_Z = \sigma_Z = 1$, 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 $\log(N+M)$. 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 A9: 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)
$\log(N+M)$	-0.126*** (0.042)	-0.170*** (0.057)	-0.063* (0.033)	-0.116 (0.085)	0.004 (0.020)	-0.003 (0.023)	0.008 (0.018)	0.004 (0.019)
$\frac{M}{N+M}$	-1.053*** (0.127)	-1.528*** (0.321)	-0.528*** (0.125)	-1.199* (0.575)	-0.454*** (0.069)	-0.515*** (0.116)	-0.418*** (0.091)	-0.407*** (0.116)
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.5 for further details on these groupings. We impose that $\alpha_Z = \sigma_Z = 1$, 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 $\log(N+M)$. 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 A8. 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 A10: Occupation-imputed migrant stocks: First stage

	Fixed effects			First differences		
	$\log(N + M^{occ})$	$\frac{M^{occ}}{N + M^{occ}}$	$\frac{M^{occ}}{N + M^{occ}}$	$\log(N + M^{occ})$	$\frac{M^{occ}}{N + M^{occ}}$	$\frac{M^{occ}}{N + M^{occ}}$
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(\tilde{N} + \tilde{M}^{occ})$	0.567*** (0.168)	-0.009 (0.025)		0.314** (0.153)	0.039** (0.018)	
$\frac{\tilde{M}^{occ}}{\tilde{N} + \tilde{M}^{occ}}$	-2.193*** (0.663)	0.638*** (0.125)	0.668*** (0.074)	-2.505*** (0.530)	0.821*** (0.130)	0.649*** (0.067)
SW F-stat	25.66	22.27	81.46	10.02	12.72	95.30
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} . These estimates correspond to the IV specifications in columns 3-4 and 7-8 of Table A11. We impose that $\alpha_Z = \sigma_Z = 1$, 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 1-3 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 A11: 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)
$\log(N + M^{occ})$	0.036 (0.035)		-0.127 (0.102)		0.013 (0.032)		-0.117 (0.101)	
$\frac{M^{occ}}{N + M^{occ}}$	-0.292 (0.191)	-0.502** (0.192)	-1.414* (0.740)	-0.664*** (0.215)	-0.270* (0.156)	-0.343*** (0.104)	-1.073* (0.574)	-0.369*** (0.104)
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} . We impose that $\alpha_Z = \sigma_Z = 1$, 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 1-4 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 A10. 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: Heterogeneous effects by education: First stage

	Fixed effects			First differences		
	$\log(N + M)$ (1)	$\frac{M}{N+M}$ (2)	$\frac{M}{N+M} * \text{Coll}$ (3)	$\log(N + M)$ (4)	$\frac{M}{N+M}$ (5)	$\frac{M}{N+M} * \text{Coll}$ (6)
$\log(\tilde{N} + \tilde{M})$	1.126*** (0.081)	0.011 (0.019)	-0.008 (0.009)	0.833*** (0.098)	0.025 (0.015)	-0.003 (0.005)
$\frac{\tilde{M}}{\tilde{N} + \tilde{M}}$	0.671** (0.265)	1.074*** (0.071)	-0.070* (0.036)	1.053*** (0.297)	0.997*** (0.113)	-0.072*** (0.025)
$\frac{\tilde{M}}{\tilde{N} + \tilde{M}} * \text{Coll}$	0.474 (0.502)	-0.423** (0.191)	0.640*** (0.096)	-0.677 (0.861)	-0.400** (0.159)	0.630*** (0.067)
SW F-stat	107.03	89.14	30.26	73.16	69.64	44.37
Observations	224	224	224	192	192	192

This table presents first stage estimates for the native wage equation (29), but this time interacting the migrant share with a college dummy (taking 1 for the "some college" and college graduate cells). These estimates correspond to the IV specifications in columns 2 and 6 of Table A14. We require one more instrument, so we interact our migrant share predictor with the college dummy. We impose that $\alpha_Z = \sigma_Z = 1$, 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 1-3 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 A13: Heterogeneous effects by experience: First stage

	Fixed effects			First differences		
	$\log(N+M)$	$\frac{M}{N+M}$	$\frac{M}{N+M} * (\text{Exp} \geq 20)$	$\log(N+M)$	$\frac{M}{N+M}$	$\frac{M}{N+M} * (\text{Exp} \geq 20)$
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(\tilde{N} + \tilde{M})$	0.961*** (0.088)	0.052** (0.019)	0.007 (0.008)	0.770*** (0.093)	0.055*** (0.017)	0.009 (0.006)
$\frac{\tilde{M}}{\tilde{N}+\tilde{M}}$	1.029** (0.443)	1.044*** (0.074)	0.014 (0.024)	1.882*** (0.520)	0.860*** (0.120)	0.005 (0.032)
$\frac{\tilde{M}}{\tilde{N}+\tilde{M}} * (\text{Exp} \geq 20)$	-0.924** (0.337)	0.166** (0.064)	1.210*** (0.018)	-2.001*** (0.475)	0.277*** (0.099)	1.215*** (0.023)
SW F-stat	114.40	217.11	88.34	39.45	45.02	40.30
Observations	224	224	224	192	192	192

This table presents first stage estimates for the native wage equation (29), but this time interacting the migrant share with a dummy for labor market cells with 20+ years of experience. These estimates correspond to the IV specifications in columns 4 and 8 of Table A14. We require one more instrument, so we interact our migrant share predictor with the experience dummy. We impose that $\alpha_Z = \sigma_Z = 1$, 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 1-3 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 A14: Heterogeneous effects by education and experience: OLS and IV

	Fixed effects				First differences			
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\log(N+M)$	0.032* (0.018)	-0.003 (0.017)	0.034 (0.021)	0.01 (0.017)	0.029 (0.019)	-0.028 (0.023)	0.021 (0.022)	-0.019 (0.028)
$\frac{M}{N+M}$	-0.429*** (0.063)	-0.577*** (0.101)	-0.516*** (0.101)	-0.607*** (0.117)	-0.318*** (0.070)	-0.364*** (0.087)	-0.319*** (0.106)	-0.300* (0.150)
$\frac{M}{N+M} * \text{Coll}$	0.507* (0.274)	-0.073 (0.362)			0.314* (0.181)	-0.502 (0.346)		
$\frac{M}{N+M} * (\text{Exp} \geq 20)$			0.071 (0.070)	0.063 (0.066)			-0.009 (0.095)	-0.095 (0.138)
Observations	224	224	224	224	192	192	192	192

This table presents OLS and IV estimates of the native wage equation (29), but now accounting for differential effects of migrant share among the college-educated (i.e. some college or college graduate) and older workers (20+ years of experience). We impose that $\alpha_Z = \sigma_Z = 1$, 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 1-4 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 Tables A12 and A13. 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: Impact of new and old migrant shares: First stage

	Fixed effects			First differences		
	$\log(N+M)$ (1)	$\frac{M^{new}}{N+M}$ (2)	$\frac{M^{old}}{N+M}$ (3)	$\log(N+M)$ (4)	$\frac{M^{new}}{N+M}$ (5)	$\frac{M^{old}}{N+M}$ (6)
$\log(\tilde{N} + \tilde{M})$	1.004*** (0.078)	0.042** (0.016)	0.004 (0.011)	1.014*** (0.085)	0.051*** (0.014)	-0.009 (0.008)
$\frac{\tilde{M}^{new}}{\tilde{N} + \tilde{M}}$	2.229*** (0.497)	0.708*** (0.214)	0.090 (0.104)	3.266*** (0.894)	0.544** (0.225)	0.077 (0.124)
$\frac{\tilde{M}^{old}}{\tilde{N} + \tilde{M}}$	-0.304 (0.293)	-0.115 (0.082)	1.415*** (0.074)	1.681*** (0.573)	0.112 (0.110)	1.097*** (0.095)
SW F-stat	108.62	15.40	386.59	2.99	1.26	4.08
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 A16. We impose that $\alpha_Z = \sigma_Z = 1$, 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 A16: Impact of new and old migrants: OLS and IV

	Fixed effects		First differences	
	OLS (1)	IV (2)	OLS (3)	IV (4)
$\log(N+M)$	0.014 (0.021)	0.018 (0.023)	0.023 (0.027)	-0.017 (0.056)
$\frac{M^{new}}{N+M}$	-0.377*** (0.131)	-0.820** (0.374)	-0.287 (0.173)	-0.225 (0.745)
$\frac{M^{old}}{N+M}$	-0.487*** (0.063)	-0.532*** (0.070)	-0.308** (0.138)	-0.362 (0.306)
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 $\alpha_Z = \sigma_Z = 1$, 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 A15. 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: Elasticity of employment rates

	Fixed effects				First differences			
	Log raw emp rate	Composition-adjusted			Log raw emp rate	Composition-adjusted		
	OLS (1)	OLS (2)	IV1 (3)	IV2 (4)	OLS (5)	OLS (6)	IV1 (7)	IV2 (8)
<i>Panel A: Native elasticity</i>								
Log native wage	0.528* (0.271)	0.663*** (0.167)	1.007*** (0.361)	0.984*** (0.345)	0.898*** (0.327)	0.778*** (0.206)	1.546*** (0.409)	1.156** (0.436)
<i>Panel B: Migrant elasticity</i>								
Log migrant wage	0.029 (0.134)	0.261* (0.138)	0.345 (0.458)	0.283 (0.448)	0.277** (0.134)	0.200** (0.091)	1.012 (0.809)	1.493 (1.833)
<i>Panel C: First stage for native wages</i>								
$\log(\tilde{N} + \tilde{M})$			-0.015 (0.018)				-0.024 (0.018)	
$\frac{\tilde{M}}{\tilde{N} + \tilde{M}}$			-0.637*** (0.103)	-0.599*** (0.072)			-0.363*** (0.095)	-0.290*** (0.085)
<i>Panel D: First stage for migrant wages</i>								
$\log(\tilde{N} + \tilde{M})$			-0.020 (0.025)				0.004 (0.021)	
$\frac{\tilde{M}}{\tilde{N} + \tilde{M}}$			-0.420*** (0.117)	-0.371*** (0.108)			-0.083 (0.158)	-0.096 (0.136)
Observations	224	224	224	224	192	192	192	192

Panel A reports OLS and IV estimates of native employment rate elasticities, based on the empirical specification in (A66). The dependent variable is the log mean annual hours of natives in each labor market cell (excluding enrolled students), and the regressor of interest is the composition-adjusted native wage. Panel B repeats the exercise for migrants, replacing the employment and wage variables with migrant equivalents. In columns 2-4 and 6-8, we adjust employment rates for changes in demographic composition, following identical steps to those described in Section 5.2 (but this time, estimating linear regressions for annual employment hours, including zeroes for individuals who do not work). In the IV1 specification, we instrument the wage variable with predicted log total employment (in the labor market cell) and the predicted migrant share; and in the IV2 specification, we use the predicted migrant share alone. First stage estimates are reported in Panels C and D. 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. 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

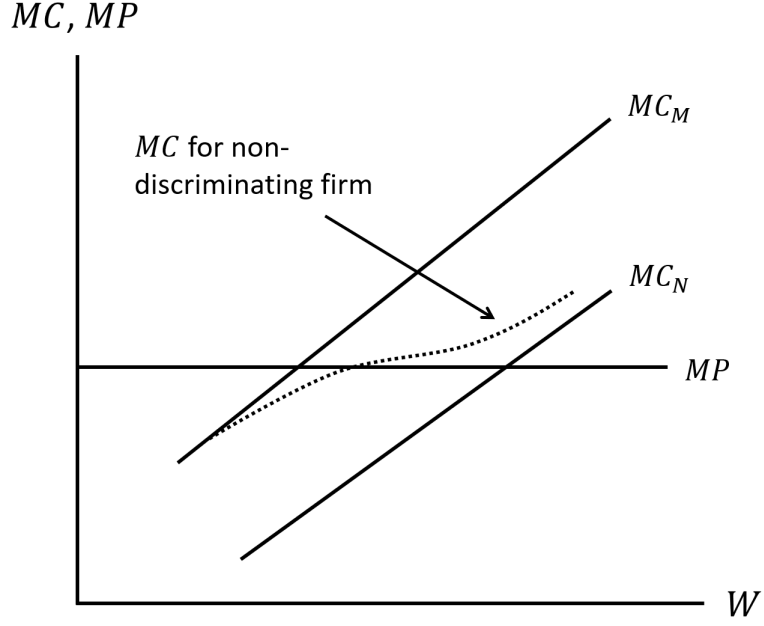


Figure 1: Optimal wages for discriminating and non-discriminating firms

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 $\frac{\partial \bar{F}}{\partial L_j}$. 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.

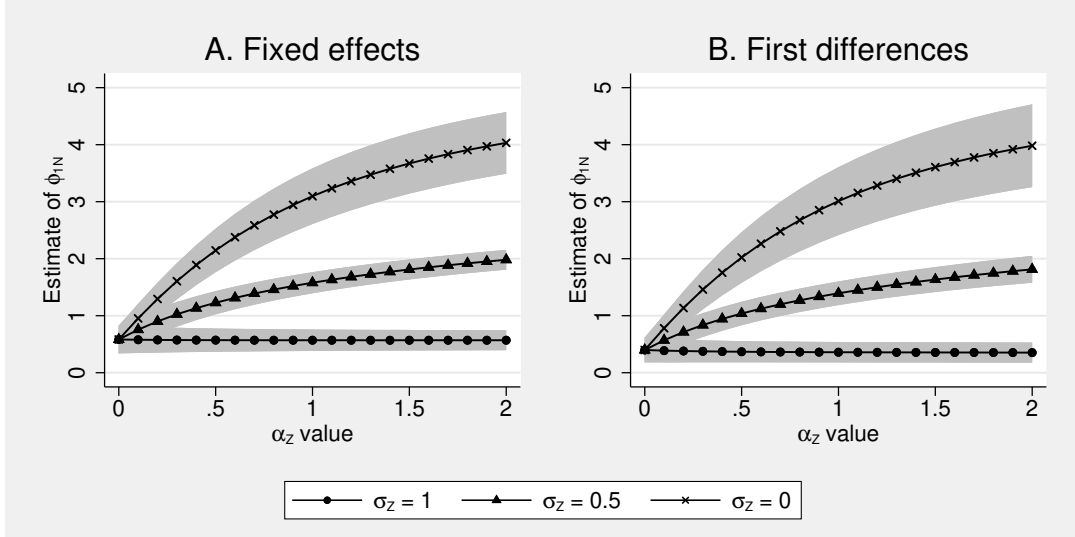


Figure 2: Native mark-down response ϕ_{1N} for different (α_Z, σ_Z)

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.

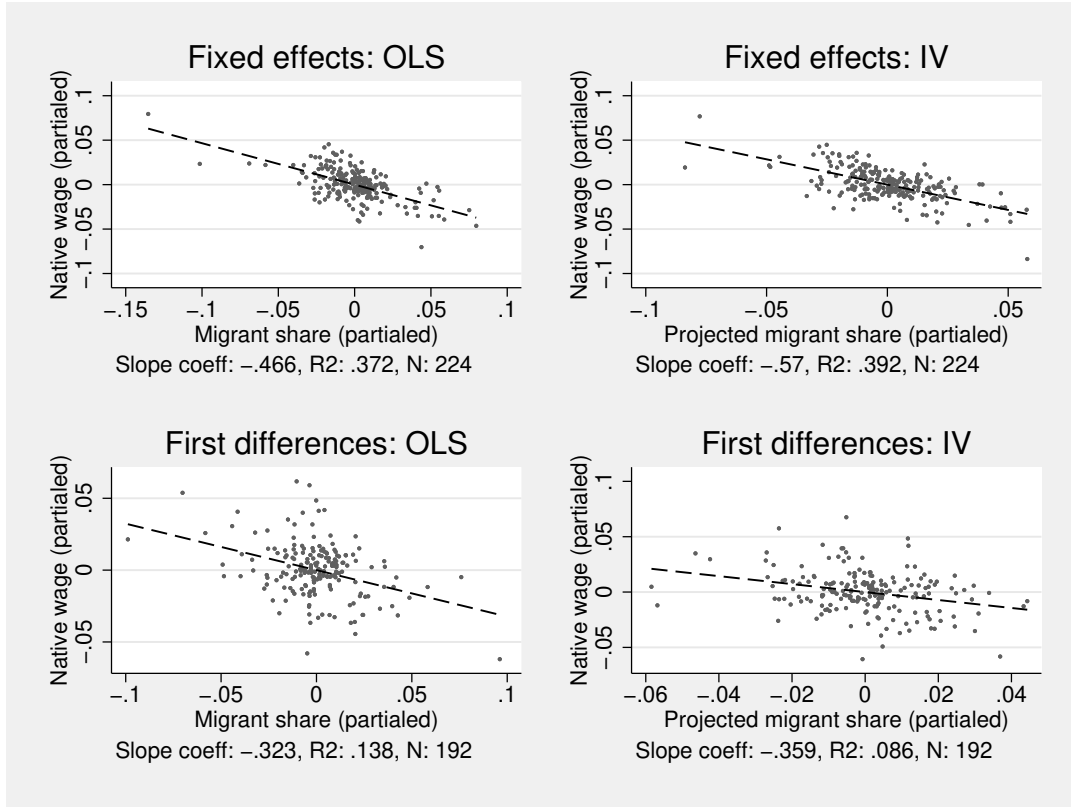


Figure 3: Visualization of native wage responses to migrant share

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.

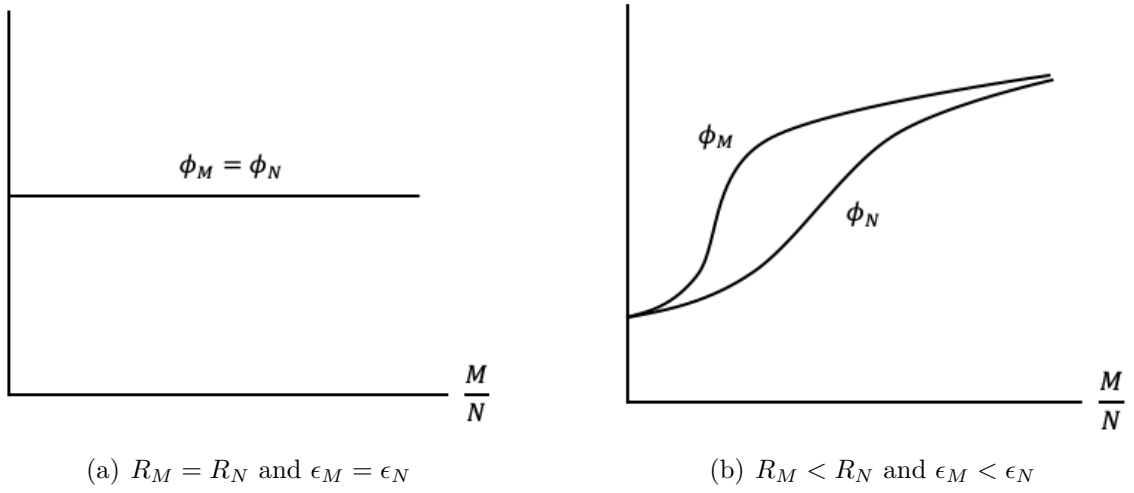


Figure A1: Aggregate mark-down functions

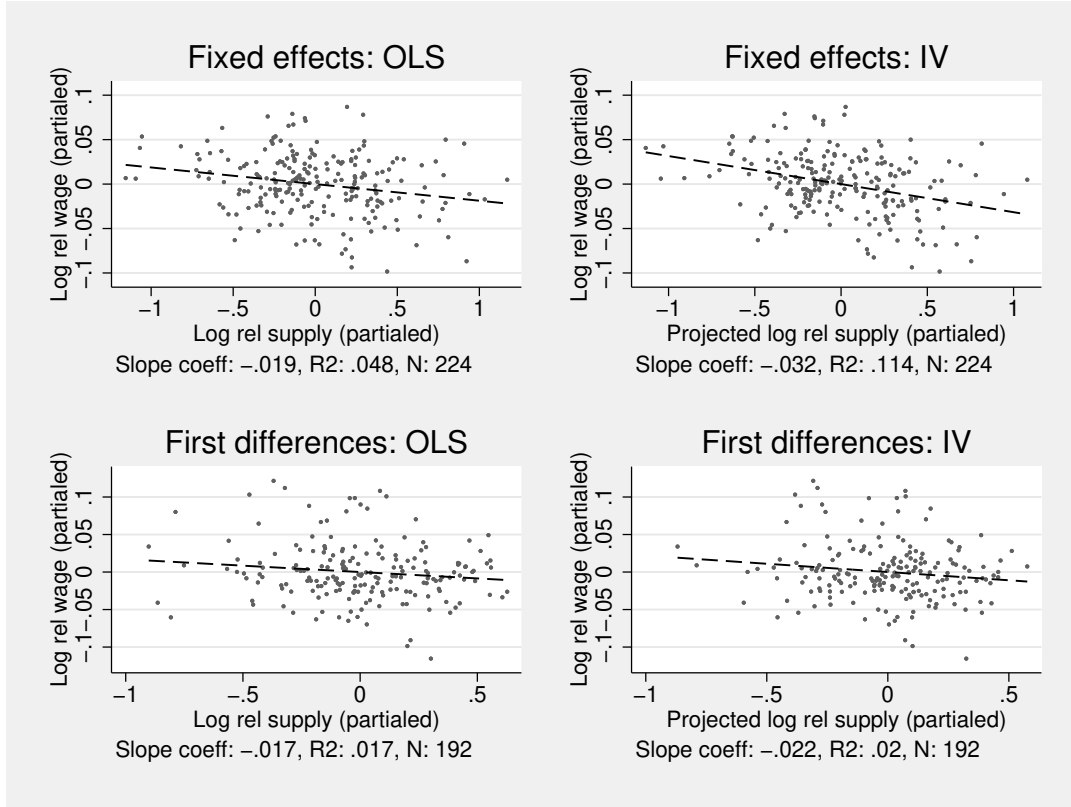


Figure A2: Visualization of relative wage equation estimates

This figure graphically illustrates the OLS and IV effects of the (composition-adjusted) log relative migrant-native wage, $\log \frac{w_M}{w_N}$, on log relative supply, $\log \frac{M}{N}$, based on columns 4-8 of Table 2. For the OLS plot, we partial out the effect of the various fixed effects from both the log relative wage (on the y-axis) and the log relative supply (on the x-axis). For IV, we first replace the log relative supply with its linear projection on the instrument and fixed effects; and we then follow the same procedure as for OLS. In the fixed effect specifications, we control for interacted education-experience and year fixed effects; and in first differences, we control for year effects only