MONOPSONY AND THE WAGE EFFECTS OF MIGRATION

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Abstract

In a competitive labor market, immigration affects native wages only through changes in *marginal products*. In a generalization of the well-known "immigration surplus" result, we show that a larger supply of migrants (keeping their skill mix constant) must always increase the marginal product of the average native worker in the long run (if capital is supplied elastically), for any convex technology with constant returns. However, in a monopsonistic labor market, immigration may also allow firms to impose larger *mark-downs* on wages. We show the traditional competitive model is overidentified, and we reject its restrictions using US census data commonly studied in the literature. Our estimates point to an adverse mark-down effect for native labor, which quantitatively dominates changes in their marginal products. Firms' capture of rents from migrants significantly expands the *total* surplus going to natives (i.e. to firms and workers combined), but it also redistributes income *among* natives (from workers to firms). JEL Codes: J31, J42, J61. Word count: 13,890.

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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 types of labor and capital; but we demonstrate it holds for any number of labor types, any number of (intermediate or final) goods, and any form of technology, as long as it is convex and 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]

Our second contribution is an estimable model of the impact of immigration in the absence of perfect competition. In this environment, the wage of skill type j natives will depend on both their marginal product *and* any mark-down ϕ_j as a result of monopsony

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

power:

$$\log W_j = \log MP_j - \phi_j \tag{1}$$

Just as there are good theoretical reasons to believe that natives' marginal products are sensitive to immigration, our contention is that the same is true of the mark-downs, if firms' monopsony power depends on the labor share of migrants. In particular, if migrants supply labor to firms less elastically than natives (or migrants' reservation wages are lower), immigration will lead to higher mark-downs on natives and migrants alike. We develop a theoretical, yet estimable, model to assess this possibility. 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.

There are a number of reasons why migrants may supply labor to firms less elastically (or have lower reservation wages). First, migrants may be less efficient in job search, due to lack of information, language barriers, exclusion from social networks or undocumented status (Hotchkiss and Quispe-Agnoli, 2013; Albert, forthcoming) or visa-related restrictions on labor mobility (see e.g. Depew, Norlander and Sørensen, 2017, on the H1B, or Naidu, Nyarko and Wang, 2016). Second, migrants may discount their time in the host country more heavily, perhaps because they intend to only work there for a limited period (see Dustmann and Weiss, 2007), or there may be binding visa time limits or deportation risk. Third, migrants may face more restricted access to out-of-work

[2] Using 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.

benefits. Finally, 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). These intuitions are consistent with a range of empirical evidence: Hotchkiss and Quispe-Agnoli (2009), Hirsch and Jahn (2015) and Borjas (2017) confirm that migrants do indeed supply labor less elastically; and 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. Also, using a structural model, Nanos and Schluter (2014) find that migrants demand lower wages (for given productivity). And Dustmann, Ku and Surovtseva (2019) show that migrants' reservation wages (and occupation quality) are sensitive to exchange rate fluctuations. Beyond this, the expenditures of *individual* employers on foreign recruitment (whether through political lobbying, 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) suggest they care about access to migrant labor; and this is difficult to explain if wages are equal to marginal products.

But rather than relying on this literature, our third contribution is to directly test the claim that monopsony power depends on the migrant share - using standard wage and employment data from the US census, as analyzed by Borjas (2003) and Ottaviano and Peri (2012) among others. We use a standard structural model with a nested CES technology (as in Ottaviano and Peri, 2012, or Manacorda, Manning and Wadsworth, 2012), but we relax the assumption of perfect competition. Wages of each labor type depend on both the cell-specific marginal products and the cell-specific mark-downs, where cells are defined by education and experience. The marginal products are determined by the 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). Our empirical strategy is related to Beaudry, Green and Sand (2012), who study the role of industrial composition in wage-setting under imperfect competition.[3]

We test (and reject) the null hypothesis that 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 that of 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 0.5-0.6% more; and the effect is similar for migrants. We show that the model is not fully point-identified but is set-identified and an analysis of alternative calibrations suggests this impact on native mark-downs 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 do indeed 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.

Our findings also shed new light on other debates in the empirical literature. A key source of contention is the appropriate functional form for migration shocks. While Borjas (2003 and 2014) uses the migrant share in the labor market cell, Peri and Sparber (2011) and Card and Peri (2016) argue this generates an artificial bias because of the endogeneity of the native labor supply (see e.g. Hunt, 2017; Llull, 2018*b*) which appears in the share's denominator, preferring instead a measure based on migrants' contribution to the size of the cell. In our model, there is a role both for the *size* of the cell (which determines the impact on marginal products) and the *mix* of the cell (i.e. the migrant share), which accounts for the extent of labor market competition within the cell. We attempt to address the empirical concerns by introducing instruments for native and migrant labor supply, based on education cohort sizes at the previous observation both at home (for US residents) and abroad (for new immigrants). See also Llull (2018*a*) and Monras (forthcoming) for earlier attempts to instrument for cell-specific immigration.

Given the apparent fragility of the competitive markets assumption, one may choose

[3]They show that wage bargains (for given productivity) depend on local industrial composition, since this affects workers' outside options. In our paper, it is the composition of the labor force which matters.

to abandon structural approaches to estimating wage effects altogether - in favor of more empirical reduced-form strategies. Dustmann, Schoenberg and Stuhler (2016) recommend this strategy, 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: 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. In practice, the reduced-form approach is typically restricted to studying the impact of particular migration events, which bring particular skill mixes. Though natural experiments may offer remarkably clean identification (see e.g. Dustmann, Schoenberg and Stuhler, 2017; Edo, forthcoming; Monras, forthcoming), it may be difficult to extrapolate to other scenarios. Instead, 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" (i.e. the total income gains of natives), which is known 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. Interestingly, the impact of immigration on the mark-downs is larger if migrants compete more closely with natives; whereas the reverse is true for the marginal products (Borjas, 1995). Our mark-down results 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 (Amior, 2017).

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. In Section 4, we describe our data, which are based on the classic studies of Borjas (2003) and Ottaviano and Peri (2012); and we then turn to identification and our empirical strategy in Section 5. 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 results: Impact on natives' 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.[4] Underpinning our results are the crucial assumptions of constant returns to scale (CRS) and convex technology (which requires 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 these firms' rents - and we return to this point in Section 8 below.

Consider the following production function:

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

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

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

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

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

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

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

2.1 Homogeneous natives and migrants

Suppose there are two fixed labor inputs, natives and migrants: $\mathbf{L} = (N, M)$; so long run output (net of the costs of elastic inputs) is $\widetilde{F}(N, M)$. Each group is homogeneous, though they may differ from each other. The two-input case was originally analyzed[5] by Borjas (1995), but we summarize it here as it provides a useful foundation for more general results:

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

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

Proof. If there are two factor inputs with CRS and convex technology (i.e. diminishing returns to individual factors), the inputs must be Q-complements: i.e. $\widetilde{F}_{NM}(N, M) \geq 0$, where subscripts denote partial derivatives, and with equality only if N and M are perfect substitutes. Intuitively, convexity ensures diminishing marginal 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 MP of natives is increasing in migrant supply M, unless the two inputs are perfect substitutes. □

2.2 Heterogeneous skills

Proposition 1 is well-known: see e.g. Borjas (2014, p. 65). But perhaps it is specific to the extreme case of two inputs. To investigate this, suppose there are J types of (fixed) labor inputs in the economy, 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 respectively. 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 type-j 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:

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

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

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

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

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

i.e. output can be expressed as a function Z of the total number of natives N and migrants M, where the skill mix of these groups is subsumed in Z. The function $Z(N, M)$ must have CRS if $\tilde{F}(L_1, .., L_J)$ does. And the partial derivative of $Z(N, M)$ with respect to N can be written as:

$$Z_N(N, M) = \sum_j \eta_j \tilde{F}_j(L_1, .., L_J) \tag{5}$$

which is the average native MP (or, under perfect competition, the average native wage). Similarly, the partial derivative of $Z(N, M)$ with respect to M is equal to the average migrant MP. In this way, we have reduced a production function with arbitrarily many types of labor to one with only two composite inputs, N and M. Furthermore, Z satisfies the usual properties of production functions, with marginal products of the composite inputs equal to the average MP. And with two labor types, CRS and convexity, we already know (from Proposition 2) that an increase in the supply of one group (e.g. migrants) must increase the average MP of the other, as long as 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 will have no effect on natives' MPs, because they are effectively perfect substitutes (at the aggregate level). □

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

It is not entirely clear how well-known Proposition 3 is in the current literature. Dustmann, Frattini and Preston (2012) use a CES production function satisfying the requirements above and conclude: "For *small* levels of immigration, we should therefore 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 a CES production function 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 the size of the surplus will depend on the amount of immigration and the extent of skill differences between natives and migrants.

2.3 Changing the skill mix of immigration

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

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 an economy with multiple (intermediate or final) goods, in which all sectors satisfy CRS and convex technology, with perfect competition in all product and labor markets, and with all consumers having 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 for the multiple good case.

2.5 Robustness of conclusions

To summarize, any model, theoretical or empirical, which imposes CRS, convexity and a perfectly elastic supply of capital (or non-labor) inputs, must *always* predict that more immigration (holding migrants' skill mix constant) weakly increases native labor's average MP in a closed economy, irrespective of the data used for estimation.

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 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* native-owned factors in the $\mathbf{L}$ vector, whether labor or capital; and native labor may lose out on average. But to the extent that capital (and other non-labor) inputs become elastic in the "long run", the entire surplus will ultimately pass to native labor. Certainly, there are various objections to this long run scenario: persistent immigration may depress wages if capital cannot accumulate fast enough (Borjas, 2019), though immigration may also generate increasing returns if there are human capital externalities. Nevertheless, Ottaviano and Peri (2012) argue that long run macroeconomic trends are consistent with CRS and elastic capital.

In a competitive labor market, 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 does admit the possibility of *negative* wage effects (even if MPs increase), if immigration increases the monopsony power of firms.

3 Modeling imperfect competition

3.1 Existing literature

There is a small existing literature which models the impact of migration under imperfect competition. The earliest 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 reservation wages: 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. We offer a simple framework which accounts for both.

3.2 Imperfect competition and mark-downs

We account for imperfect competition by modeling wage mark-downs. Based on (1) in the introduction, we summarize the wage of type j workers as:

$$\log W_j = \log \tilde{F}_j - \phi_j \tag{7}$$

where $\tilde{F}_j$ is the marginal product (for long run output), and $\phi_j \geq 0$ is the mark-down, equal to zero in a perfectly competitive market. In what follows, we interpret the mark-downs as arising from a simple monopsony model (as used by Card et al., 2018), where the market power of wage-setting firms depends on the elasticity of labor supply they individually face. But a wage equation like (7) may alternatively be derived from a bargaining model (see e.g. Barnichon and Zylberberg, 2019, for an exposition where matching is not entirely random), where wages depend on marginal products, reservation wages and workers' bargaining power.

We define labor markets j sufficiently narrowly, such that all constituent natives and migrants in that labor market are perfect substitutes. For each labor type j denote the market wage by W_j. The allocation of natives and migrants across these markets may differ (according to the η and μ vectors defined above), whether because of divergent productive specializations (e.g. Peri and Sparber, 2009, emphasize comparative advantage in communication or manual tasks) or labor market discrimination. We do not permit discrimination *within* markets; but this will not be restrictive, if markets are defined sufficiently narrowly. The market wage is determined by the standard monopsony formula, $W_j = \frac{\epsilon_j}{1+\epsilon_j}\tilde{F}_j$, where ϵ_j is the elasticity of labor supply to individual firms (rather than to the market as a whole). Consequently, the mark-down ϕ_j in (7) can be expressed as:

$$\phi_j = \log\left(1 + \epsilon_j^{-1}\right) \tag{8}$$

ϵ_j can be written as a weighted average of the elasticities of native and migrant labor supply to firms (denoted ϵ_N and ϵ_M respectively), with the weight depending on the migrant share in market j:

$$\epsilon_j = \epsilon_N + \frac{\mu_j M}{\mu_j M + \eta_j N}\left(\epsilon_M - \epsilon_N\right) \tag{9}$$

and where μ_j and η_j are the shares of migrants M and natives N allocated to market j. This shows how the extent of monopsony power can depend on the migrant share.

3.3 Aggregation

Our analysis above applies to markets j which are sufficiently narrow such that all constituent natives and migrants are perfect substitutes. In practice, we assume we cannot observe these "true" markets: rather, we simply observe an aggregate of them. However, Proposition 3 allows us to model this aggregate: we combine the output of the individual markets j using a convex CRS function $Z(N, M)$, which subsumes the submarket allocations η and μ, and which depends solely on the total native and migrant stocks. Our approach here builds on an existing literature on such aggregations in the production function and growth literature (Houthakker, 1955; Levhari, 1968; Jones, 2005; Growiec, 2008) and the ideas of Dustmann, Schoenberg and Stuhler (2016). As we show in Appendix D, the average native and migrant wage can be written as:

$$\log W_N = \log Z_N - \phi_N \left(\frac{M}{N} \right) \tag{10}$$

$$\log W_M = \log Z_M - \phi_M \left(\frac{M}{N} \right) \tag{11}$$

where Z_N and Z_M are the average native and migrant MPs, and ϕ_N and ϕ_M are the aggregated native and migrant mark-downs. Note that ϕ_N and ϕ_M will differ if natives and migrants are allocated differently across unobserved submarkets, in which case each are distinct functions of the migrant share.

Our interpretation of Z as an *aggregation* of many markets is important to our specification. Suppose instead that the N and M arguments of $Z(N, M)$ represent two distinct skill inputs. Firms would then set distinct wages for each input, so natives would be sheltered from any direct competition from migrants (beyond any effect migrants may have on their marginal products). This would rule out any effect of immigration on mark-downs, even if firms had market power. Direct competition would only arise in the extreme case where natives and migrants are perfect substitutes and therefore compete in the same market. In contrast, our aggregation approach allows imperfect competition to coexist with direct competition at the level of observed labor markets.

3.4 Impact of immigration on aggregate mark-downs

We wish to know how immigration affects the aggregate mark-downs, ϕ_N and ϕ_M. These effects are largely determined by the differential between the native and migrant elasticities, ϵ_N and ϵ_M. To illustrate this point, we now work intuitively through some cases of interest. We refer readers to Appendix D for a more formal exposition.

Consider first the case where natives and migrants supply labor to firms with equal elasticities, i.e. $\epsilon_M = \epsilon_N$. Based on (9), the overall elasticities ϵ_j are then independent of migrant share and invariant with submarket j. And so, natives will face the same 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 migrant share in Figure Ia. In the empirical analysis, we will treat this case (of equal and independent mark-downs) as our null hypothesis. This environment is implicitly assumed by the seminal studies in the literature: mark-downs are fixed constants, and immigration only affects wages through marginal products. Note that perfect competition is a special case of $\epsilon_M = \epsilon_N$, where both ϵ_M and ϵ_N are infinite, and both ϕ_N and ϕ_M equal zero, irrespective of migrant share.

[Figure I here]

In Figure Ib, we consider the case where migrants supply labor less elastically to firms ($\epsilon_M < \epsilon_N$), as the evidence detailed in the introduction might suggest. Migrants must, on average, be in submarkets j with larger migrant shares and larger mark-downs; and therefore, $\phi_M \geq \phi_N$. However, ϕ_M and ϕ_N must converge to equality as $\frac{M}{N} \to 0$ or $\frac{M}{N} \to \infty$. Intuitively, as the labor force becomes exclusively native or migrant, the elasticity facing firms converges to the native or migrant one, in which case all workers will face the same mark-down. Also, 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. And given the equality of ϕ_M and ϕ_N in the limits, the differential between ϕ_M and ϕ_N must be non-monotonic in $\frac{M}{N}$.[6] The final case, $\epsilon_M > \epsilon_N$, is of course the reverse of $\epsilon_M < \epsilon_N$, given the symmetry of the model.

The response of the mark-downs ϕ_N and ϕ_M to migrant share will depend on the extent of labor market segregation, i.e. the deviation between the native and migrant skill mixes, η and μ. Greater segregation will moderate the impact of immigration on

[6]In Appendix D, we summarize the differential between ϕ_M and ϕ_N as the covariance between submarket migrant allocations and submarket mark-downs.

mark-downs, as the *submarket* migrant shares become less responsive to the *aggregate-level* migrant supply M (if their skill mix μ is held fixed). This offers an interesting counterpoint to the impact of immigration on the average native MP, which is *increasing* in the extent of segregation (see Proposition 4).

To summarize, for the average native, the effect of immigration on mark-downs may in principle offset its (positive) effect on marginal products. We have offered one story for the relationship between the mark-downs and migrant share (in terms of differential elasticities), but there may be others - and we do not rule these out.

We now turn to the estimation of the mark-down effects. These estimates will have validity even if the source of the mark-downs differs from that proposed here. We first discuss the data we use for estimation, and we then set out our empirical methodology.

4 Data

4.1 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 in education-experience cells. But our interpretation of these estimates is different, being based on our monopsony model.

We construct our data in a similar way to these earlier studies, but we extend the time horizon: we use IPUMS (Ruggles et al., 2017) census extracts of 1960, 1970, 1980, 1990 and 2000, and American Community Survey (ACS) samples of 2010 and 2017.[7] 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.[8] But we also consider

[7] The 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 for further details.

[8] Borjas (2014) further divides college graduates into undergraduate and postgraduate degree-holders.

specifications with two groups: college and high-school equivalents. Following Borjas (2003; 2014) and Ottaviano and Peri (2012), we divide each education group into eight categories of potential labor market experience, based on 5-year intervals between 1 and 40 years - though we also estimate specifications with four 10-year categories. To predict experience, we assume high school dropouts begin work at 17, high school graduates at 19, those with "some college" at 21, and college graduates at 23.

We identify employment stocks with hours worked by demographic cell, and wages with log weekly earnings of full-time workers (at least 35 weekly hours and 40 weeks per year), weighted by weeks worked - though we study robustness to using hourly wages. Following the recommendation of Borjas (2003, 2014), we exclude enrolled students from the wage sample.

4.2 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 some specifications.

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

We choose not to account for this distinction, as there are very few postgraduates early in our sample.

grants, but replacing the race indicators with dummies covering 12 region of origin[9] in our regressions.

4.3 Instruments

An important concern is that both native and migrant employment stocks, by education-experience cell, may be endogenous to wages. Unobserved cell-specific demand shocks may affect the labor supply or human capital choices of both 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, forthcoming). We use instruments to predict employment stocks (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).

Our instrument for native employment is based on cohort sizes and education choices ten years earlier. For individuals aged over 33, we predict current employment using the ten-year lagged native employment stock (within education groups), separately by single-year age. This is not feasible for 18-33s: given our assumptions on graduation dates, some of them will not have reached their final education status. For this group, we begin with the ten-year lagged total cohort size (again, separately by single-year age); and we allocate these individuals to education groups using the education shares (also lagged ten years) of the cohort which is ten years older. Having predicted population stocks by single-year age and education, we then aggregate to 5-year experience groups. And we then linearly project the log native employment stock (across cells and years) on the log predicted population. The predicted employment stock, $\tilde{N}_{ext}$, then serves as our instrument. We construct our instrument for "old" migrants, $\tilde{M}^{old}_{ext}$, in an identical way.

Analogously to our approach for existing US residents, we predict "new" migrant inflows using lagged cohort sizes in origin countries. This is motivated by Hanson, Liu and McIntosh (2017), who relate the rise and fall of US low skilled immigration to changing

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

fertility patterns in Latin America. We are also building on Llull (2018*a*) and Monras (forthcoming), who 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 lagged population stocks.

We predict cell-specific inflows using estimates from the following regression:

$$\log M_{oext}^{new} = \lambda_0 + \lambda_1 \log \left(OriginPop_{oext-10}\right) + \lambda_2 Mobility_{ex} + OriginRegion_o + \varepsilon_{oext} \quad (12)$$

where our dependent variable, M_{oext}^{new}, is the US employment stock of new migrants (with up to ten years in the US) at each observation year t (between 1960 and 2017), for each of 164 origin countries o and 32 education-experience cells (e, x). We take this information from our ACS and census samples. $OriginPop_{oext-10}$ is the population 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.[10] We assign cohorts aged 18-33 to education groups in the same way as for US natives, based on the education choices of the previous cohort at origin. For a given cohort size, one would of course expect more emigration among more mobile demographic groups - especially the young. To account for this, we also include a cell-specific measure of mobility, $Mobility_{ex}$, equal to the cross-state migration rate[11] within the US in 1960. And finally, we control for a set of 12 region of origin effects (see footnote 9), which account for the fact that demographic shifts in certain regions matter more for migratory flows to the US.

Using our predicted values for $\log M_{oext}^{new}$, we then impute total inflows by education-

[10]The Barro-Lee data offer population counts by country, education and 5-year age category for individuals aged 15 or over. We identify Barro and Lee's "complete tertiary" education category with college graduates, "incomplete tertiary" with some college, "secondary complete" with high school graduates, and all remaining categories with high school dropouts. We impute single-year age counts by dividing the 5-year stocks equally across their single-year components. To predict lagged 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/*.

[11]This is the share of natives in each demographic cell who lived in a different state 5 years previously.

experience cell (e, x) for the ten years before each observation year t, by taking exponents and summing over origin countries o. We denote this predicted employment stock of new migrants as $\tilde{M}^{new}_{ext}$. Effectively, this is a weighted average of lagged cohort sizes in origin countries, where the weights depend on origin-specific migration propensities and cell-specific mobility. And we can now predict the total migrant stock as $\tilde{M}_{ext} = \tilde{M}^{old}_{ext} + \tilde{M}^{new}_{ext}$.

4.4 Descriptive statistics

Table I sets out a range of descriptive statistics, across our 32 education-experience cells. All wage data in the table is adjusted for changes in demographic composition, and we have normalized the wage changes in Panel C to have mean zero across all groups. The average migrant employment share was just 5% in 1960 (Panel A), but reached 24% by 2017. This expansion was disproportionately driven by high school dropouts (Panel B). Over the same period, native wages have declined most (in relative terms) among the young and low educated (Panel C).

[Table I here]

Panel D 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).

5 Empirical model

We now turn to our empirical model. We begin by discussing identification of the markdown effects, and we then set out our estimation strategy. To make our model empirically tractable, we will impose particular functional forms. Our approach consists of two steps. First, we estimate a relative migrant-native wage equation; and we then use the parameters from this equation (plus some auxiliary assumptions) to estimate a native wage equation. This approach offers a simple way to test the assumption of zero markdown effects, which previous structural models in the literature have implicitly imposed.

5.1 Production technology and wages

Our empirical strategy is to exploit variation across education-experience cells, following a long-standing empirical literature beginning with Borjas (2003). We model these cells as the lowest (observable) level of a nested CES structure. In the long run, output $\tilde{Y}_t$ at time t (net of the elastic inputs' costs) depends on the composite labor inputs, L_{et}, of education groups e:

$$\tilde{Y}_t = \left(\sum_e \alpha_{et} L_{et}^{\sigma_E}\right)^{\frac{1}{\sigma_E}} \tag{13}$$

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

$$L_{et} = \left(\sum_x \alpha_{ext} L_{ext}^{\sigma_X}\right)^{\frac{1}{\sigma_X}} \tag{14}$$

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:

$$L_{ext} = Z\left(N_{ext}, M_{ext}\right) \tag{15}$$

We will ultimately impose a CES structure on Z also; but for now, we assume only constant returns and convexity. As explained above, Z can be interpreted as an aggregation of many unobserved labor types or submarkets: this approach permits imperfect substitutability to coexist with direct competition between natives N and migrants M. While equation (4) performs this transformation at the national level, we now perform it within education-experience cells.

We can then write equations for average native and migrant wages in education-experience cells, based on (10) and (11):

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

$$\log W_{Mext} = A_{ext} \left[Z\left(N_{ext}, M_{ext}\right)\right]^{\sigma_X - 1} Z_M\left(N_{ext}, M_{ext}\right) - \phi_M\left(\frac{M_{ext}}{N_{ext}}\right) \quad (17)$$

The first term in each equation is the marginal product, and the second is the cell-level mark-down. We allow both the native and migrant mark-downs to depend (in possibly different ways) on the cell-level migrant composition, $\frac{M_{ext}}{N_{ext}}$. Finally, A_{ext} is a cell-level productivity shifter:

$$A_{ext} = \alpha_{et}\alpha_{ext}\left(\frac{\tilde{Y}_t}{L_{et}}\right)^{1-\sigma_E} L_{et}^{1-\sigma_X} \quad (18)$$

which summarizes the impact of all other labor market cells, as well as the general level of productivity.

5.2 Identification of mark-down effects

In principle, we would like to estimate the cell-level wage equations (16) and (17). 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 migrant share. This represents the case of equal elasticities ($\epsilon_N = \epsilon_M$) described in Figure Ia, of which perfect competition is a special case (where the mark-downs are equal to zero).

We begin by considering identification in the abstract, without imposing particular functional forms on Z, ϕ_N and ϕ_M. Assuming the cell aggregator Z has constant returns, and suppressing the *ext* (education-experience-time) subscripts, it can be written as:

$$Z(N, M) = Nz\left(\frac{M}{N}\right) \tag{19}$$

for some single-argument function z. Using (19), the wage equations (16) and (17) can then be expressed as:

$$\begin{aligned}
\log W_N &= \log A - (1-\sigma_X)\log N + \log\left[\frac{z\left(\frac{M}{N}\right) - \frac{M}{N}z'\left(\frac{M}{N}\right)}{z\left(\frac{M}{N}\right)^{1-\sigma_X}}\right] - \phi_N\left(\frac{M}{N}\right) && (20)\\
\log W_M &= \log A - (1-\sigma_X)\log N + \log\left[\frac{z'\left(\frac{M}{N}\right)}{z\left(\frac{M}{N}\right)^{1-\sigma_X}}\right] - \phi_M\left(\frac{M}{N}\right) && (21)
\end{aligned}$$

where σ_X represents the substitutability between experience groups, and A is the cell-level productivity shifter defined by (18).

Clearly, it is impossible to separately identify a constant in A from one in the mark-downs, ϕ_N and ϕ_M. Intuitively, the observed level of wages can be rationalized by one set of general productivity and mark-downs, but also by a higher level of productivity and larger mark-downs.[12] 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 relationship between the mark-downs and the migrant share, if this relationship is different for natives and migrants. 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 (20) and (21), 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

[12]There may also be a price mark-up if there is imperfect competition in the product market. Any such mark-up is unlikely to depend on the migrant share in the workforce, so we subsume this in the constant.

(z, ϕ_N, ϕ_M), as we only have two equations.[13]

But 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, i.e. $\phi_N\left(\frac{M}{N}\right) = \phi_M\left(\frac{M}{N}\right)$.

2. $H2$ **(Independent mark-downs)**: Natives' mark-downs are independent of migrant share, i.e. $\phi_N'\left(\frac{M}{N}\right) = 0$.

Of course, $H1$ and $H2$ jointly imply that migrants' mark-downs are also independent of migrant share, i.e. $\phi_M'\left(\frac{M}{N}\right) = 0$. In the model of Section 3, both $H1$ and $H2$ follow from the $\epsilon_N = \epsilon_M$ case, where natives and migrants supply labor to firms with equal elasticities: see Figure Ia. But while we use the $\epsilon_N = \epsilon_M$ case to motivate $H1$ and $H2$, our tests of these claims will have validity irrespective of the underlying theory of imperfect competition. Furthermore, for any theory, it will always be true that perfect competition is a special case of the joint hypothesis of $H1$ and $H2$, with both mark-downs equal to zero.

It turns out we can test this joint hypothesis: $H1$ implies restrictions which make $H2$ testable. Conditional on equal mark-downs ($H1$), the difference between (20) and (21) collapses to:

$$\log\frac{W_M}{W_N} = \log\left[\frac{z'\left(\frac{M}{N}\right)}{z\left(\frac{M}{N}\right) - \frac{M}{N}z'\left(\frac{M}{N}\right)}\right] \tag{22}$$

Using (22), variation in $\frac{M}{N}$ can then identify $z\left(\frac{M}{N}\right)$ up to a constant. And with knowledge of z, we can identify the native mark-down $\phi_N\left(\frac{M}{N}\right)$ up to a constant, using (20). 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

[13]Identification may be feasible as $\frac{M}{N} \to 0$ or $\frac{M}{N} \to \infty$, if one accepts our micro-foundation for the mark-downs. As we argue in Section 3.4, the difference between ϕ_N and ϕ_M must converge to 0 at the limits. So, taking differences between (20) and (21), 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.

(conditional on native employment N, which identifies the substitutability σ_X between experience groups). 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.

5.3 Empirical specification

Above, we have considered identification in the abstract; and we now turn to estimation and testing in practice. To this end, we impose more structure on the technology and mark-down functions. Assume Z has CES form:

$$Z(N, M) = (N^{\sigma_Z} + \alpha_Z M^{\sigma_Z})^{\frac{1}{\sigma_Z}} \tag{23}$$

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). From this, it follows that:

$$z\left(\frac{M}{N}\right) = \left[1 + \alpha_Z \left(\frac{M}{N}\right)^{\sigma_Z}\right]^{\frac{1}{\sigma_Z}} \tag{24}$$

And suppose we approximate the mark-downs ϕ_N and ϕ_M by log-linear functions of $\frac{M}{N}$:

$$\phi_N\left(\frac{M}{N}\right) = \phi_{0N} + \phi_{1N} \log \frac{M}{N} \tag{25}$$

$$\phi_M\left(\frac{M}{N}\right) = \phi_{0N} + \Delta\phi_0 + (\phi_{1N} + \Delta\phi_1) \log \frac{M}{N} \tag{26}$$

where we permit the two mark-downs to have different intercepts and different sensitivity to $\frac{M}{N}$. Note that equal mark-downs ($H1$) would imply $\Delta\phi_0 = \Delta\phi_1 = 0$, and independence of the native mark-down ($H2$) would imply $\phi_{1N} = 0$. Though we express the mark-downs as functions of $\log \frac{M}{N}$, there are some 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 E. But as we now show, we can better illustrate the identification problem by formulating (25) and (26) in terms of $\log \frac{M}{N}$.

Applying (24)-(26) to (20) and (21) respectively, and taking differences, yields the following expression for log relative wages:

$$\log \frac{W_M}{W_N} = \log \alpha_Z - \Delta\phi_0 - (1 - \sigma_Z + \Delta\phi_1) \log \frac{M}{N} \tag{27}$$

Equation (27) illustrates the identification problem: the intercept of the relative wage equation only allows us to estimate $(\log \alpha_Z - \Delta\phi_0)$, and the slope coefficient $-(1 - \sigma_Z + \Delta\phi_1)$.[14] Manacorda, Manning and Wadsworth (2012) and Ottaviano and Peri (2012) implicitly solve this problem by assuming equal mark-downs ($H1$), i.e. $\Delta\phi_0 = \Delta\phi_1 = 0$. Though we cannot test $H1$ in isolation, as we have explained above, we are able to test the joint hypothesis of $H1$ and $H2$.

In practice, our strategy is the following. Under the assumption of equal mark-downs ($H1$), we identify α_Z and σ_Z using the relative wage equation (27). Using (20), (24) and (25), the native wage can then be written as:

$$\log W_N + (1 - \sigma_Z) \log N = \log A - \phi_{0N} - (\sigma_Z - \sigma_X) \log \left(N^{\sigma_Z} + \alpha_Z M^{\sigma_Z}\right)^{\frac{1}{\sigma_Z}} - \phi_{1N} \log \frac{M}{N} \tag{28}$$

The left-hand side of (28) is a weighted average of log native wages and employment. This has precedent in the literature on skill-biased technical change: see e.g. Berman, Bound and Griliches (1994). If, for example, the production nest Z is Cobb-Douglas (so $\sigma_Z = 0$), the left-hand side is the log wage bill of natives.

Using our estimates of (α_Z, σ_Z), we can then regress $[\log W_N + (1 - \sigma_Z) \log N]$ on $\log \left(N^{\sigma_Z} + \alpha_Z M^{\sigma_Z}\right)^{\frac{1}{\sigma_Z}}$ and $\log \frac{M}{N}$; and the estimated coefficient on $\log \frac{M}{N}$ will identify ϕ_{1N}. Intuitively, the effect of immigration on the marginal products must enter through the cell "Armington" aggregator; so conditional on this, the cell composition $\log \frac{M}{N}$ will pick

[14] If we write (25) and (26) 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.

up the mark-down effect. The hypothesis of independent native mark-downs ($H2$) then yields a testable overidentifying restriction: that $\phi_{1N} = 0$. We have framed this test using the native wage equation (28), 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 (27) and the native levels equation (28).

6 Estimates of wage effects

We now turn to our empirical estimates. We begin by estimating the relative wage equation (27). 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 (28). 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 (27) as:

$$\alpha_{Zext} = \bar{\alpha}_Z + u_{ext} \tag{29}$$

for education e, experience x and time t, where $\bar{\alpha}_Z$ is the mean across education-experience cells, and the deviations u_{ext} have mean zero. (29) yields the following specification:

$$\log \frac{W_{Mext}}{W_{Next}} = \beta_0 + \beta_1 \log \frac{M_{ext}}{N_{ext}} + u_{ext} \tag{30}$$

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 (30) in Table II. In line with Ottaviano and Peri (2012), we cluster our standard errors by the 32 education-experience groups. 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.[15]

[Table II here]

In column 1, we present OLS estimates for "raw" wages (i.e. not adjusted for changes in demographic composition): β_0 takes a value of -0.14, and β_1 is -0.033. These numbers are comparable to Ottaviano and Peri (2012).[16] 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 an 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 estimates are somewhat sensitive to specification. Adjusting wages for composition in column 2 reduces the coefficients substantially, and especially β_1: this reflects Ruist's (2013) findings on migrant cohort effects. One may also be concerned that the relative migrant supply, $\frac{M_{ext}}{N_{ext}}$, is endogenous to within-cell relative demand shocks in the error, u_{ext}. In column 3, we attempt to address this problem by instrumenting $\log \frac{M_{ext}}{N_{ext}}$ 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. The first stage has considerable power: see Panel B. But, our β_1 estimate in Panel A remains at zero. Following Ottaviano and Peri, we next respecify α_{Zext} to include interacted education-experience and year fixed effects:

$$\alpha_{Zext} = \alpha_{Zex} + \alpha_{Zt} + u_{ext} \tag{31}$$

[15]As Cameron and Miller (2015) emphasize, these adjustments do not entirely eliminate the bias. But even when we reduce the number of clusters to 16, bootstrapped estimates suggest the bias is small in this data: see Section 7.2.

[16]For full-time wages of men and women combined, with no fixed effects, Ottaviano and Peri estimate a β_1 of -0.044: see column 4 of their Table 2. The small difference is partly due to our extended year sample (we include 2010 and 2017) and restricted wage sample (like Borjas, 2003, we exclude students).

which now enter our empirical specification. In columns 4-5, instead of a constant, we report the mean intercept across all cells (averaging the fixed effects). β_1 now turns negative again (reaching -0.039 in IV), and the mean β_0 expands. Columns 6-7 estimate the same specifications 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). The instrument is also differenced, and it continues to offer substantial power (see column 7 of Panel B). The IV estimate of β_1 remains negative, though a little smaller than under fixed effects. To summarize, our mean β_0 varies from -0.07 to -0.18, and β_1 from zero to -0.039.[17]

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 turn to the equation for native wages (28). We parameterize the cell-level productivity shifter A_{ext} in (18) as:

$$A_{ext} = d_{ex} + d_{et} + d_{xt} + v_{ext} \tag{32}$$

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 (18), notice the d_{et} pick up productivity shocks α_{et} and labor supply effects at the education nest level; 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 (28) can then be estimated using:

$$\begin{aligned}[\log W_{Next} + (1-\sigma_Z)\log N_{ext}] &= \gamma_0 + \gamma_1 \left[\log\left(N_{ext}^{\sigma_Z} + \alpha_{Zext} M_{ext}^{\sigma_Z}\right)^{\frac{1}{\sigma_Z}}\right] \\ &\quad + \gamma_2 \log \frac{M_{ext}}{N_{ext}} + d_{ex} + d_{et} + d_{xt} + v_{ext}\end{aligned} \tag{33}$$

[17] Borjas, Grogger and Hanson (2012) find the β_1 coefficient is also 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.

Based on (28), 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 ϕ_{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 (33), where all variables of interest are differenced and the d_{ex} fixed effects eliminated.

As we have explained above, under equal mark-downs ($H1$), equation (30) identifies the technology parameters (α_Z, σ_Z). We use our β_1 estimate in column 5 of Table II, which implies $\sigma_Z = 1 - 0.039$; and we back out the α_{Zext} in each labor market cell as the residual, i.e. $\alpha_{Zext} = \log \frac{W_{Mext}}{W_{Next}} - \beta_1 \log \frac{M_{ext}}{N_{ext}}$ (based on the mean intercept in column 5, the average $\log \alpha_{Zext}$ is -0.177). These allow us to construct the two bracketed terms (the augmented wage variable and cell aggregator) in (33) 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 two right hand side variables in (33) rely on different sources of variation: native employment N_{ext} increases the aggregator $\log \left(N_{ext}^{\sigma_Z} + \alpha_{Zext} M_{ext}^{\sigma_Z}\right)^{\frac{1}{\sigma_Z}}$ but diminishes the migrant composition $\log \frac{M_{ext}}{N_{ext}}$; whereas migrant employment M_{ext} increases both. However, there are a number of concerns about their exogeneity. First, omitted demand shocks at the interaction of education, experience and time (in v_{ext} in (32)) may generate unwanted selection: both through the arrival of new immigrants (see Llull, 2018*a*, Monras, forthcoming) and the human capital choices of existing US residents (Hunt, 2017; Llull, 2018*b*). 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. In particular, the cell aggregator $\log \left(N_{ext}^{\sigma_Z} + \alpha_{Zext} M_{ext}^{\sigma_Z}\right)^{\frac{1}{\sigma_Z}}$ is a generated regressor and will therefore contain some noise. To address these challenges, we construct instruments for the two right hand side variables by combining our predicted native and migrant stocks, $\tilde{N}_{ext}$ and $\tilde{M}_{ext}$: we instrument $\log \frac{M_{ext}}{N_{ext}}$ using $\log \frac{\tilde{M}_{ext}}{\tilde{N}_{ext}}$, and $\log\left(N_{ext}^{\sigma_Z} + \alpha_{Zext} M_{ext}^{\sigma_Z}\right)^{\frac{1}{\sigma_Z}}$ using $\log\left(\tilde{N}_{ext}^{\sigma_Z} + \alpha_{Zext}\tilde{M}_{ext}^{\sigma_Z}\right)^{\frac{1}{\sigma_Z}}$.

[Tables III and IV here]

In Panel A of Table III, we present our first stage estimates for equation (33), imposing the hypothesis of equal mark-downs ($H1$). Each instrument drives its corresponding endogenous variable with considerable power: the Sanderson and Windmeijer (2016) F-statistics, which account for multiple endogenous variables, range from 17 to 89.

Panel A of Table IV presents the second stage results (we return to Panel B below). Our estimates of γ_1 are mostly positive (which would imply $\sigma_X > \sigma_Z$) but close to zero. If σ_Z is close to 1 (as Table II 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. The statistical significance of γ_2 leads us to reject the null hypothesis 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.[18] For illustration, identifying cell composition with the migrant share, our IV estimate of γ_2 is -0.62 (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 0.62% more. The first differenced estimates are similar: the equivalent specification yields a γ_2 of -0.57 (in column 9).

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

To summarize, the fact that γ_2 is significantly different from zero allows us to reject the null hypothesis of equal and independent mark-downs (i.e. the joint hypothesis of $H1$ and $H2$). In our model in Section 3, this joint hypothesis corresponds to the case of equal native and migrant elasticities ($\epsilon_N = \epsilon_M$). Crucially, perfect competition (i.e. zero mark-downs) is a special case of this joint hypothesis, irrespective of the underlying model.

6.3 Set identification of key parameters

Above, we have offered a simple two-step procedure which tests (and rejects) the joint hypothesis of equal and independent mark-downs. If we are willing to accept $H1$ (equal mark-downs), our γ_2 estimates imply that a 1 pp increase in the migrant share expands the native mark-down by 0.62%. However, we are unable to test $H1$ in isolation. If it is not satisfied in reality, the true mark-down effect ϕ_{1N} may be entirely different from what our γ_2 estimate suggests: 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 (33) 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 ϕ_{1N} 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 (33), 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 III and

IV. 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), the coefficient on γ_1 now drops to zero (from 0.04 in Panel A), and the coefficient γ_2 on the migrant share (which identifies ϕ_{1N}) drops to -0.55 from -0.62.

[Figure II here]

In Figure II, 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.[19] In panel A, we focus on the IV fixed effect specification (comparable with column 7 of Table IV), with native wages adjusted for composition, and with the mark-down effect written in terms of the migrant share $\frac{M_{ext}}{N_{ext}+M_{ext}}$.

Compared with other (α_Z, σ_Z) values, our ϕ_{1N} estimates in Table IV (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 relatively more complementary in technology. This would imply that immigration is relatively 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.

In Panel B of Figure II, we repeat the exercise for the IV first differenced specification (comparable to column 9 of Table IV). The effects are much the same, though the (shaded) 95% confidence intervals are wider. We offer more complete regression tables for a selection of (α_Z, σ_Z) values in Appendix Table A1.

[19] Note that, unlike in Panel A of Table II, our approach here is to impose equal α_Z values in every labor market cell.

6.4 Comparison with existing empirical literature

To summarize, our estimates reject the null hypothesis of equal and independent mark-downs, of which perfect competition is a special case. We are unable to point identify the mark-down response to the migrant share, ϕ_{1N}. But comparing a broad range of calibrations, our estimates suggest a 1 pp increase in migrant share increases the native mark-down by at least 0.5% (with larger effects for certain specifications of technology).

Of course, we are not the first to estimate a native wage equation across education-experience cells. But equation (33) is distinctive in controlling simultaneously for cell size (i.e. the Armington aggregator) *and* cell composition (migrant share). Intuitively, the aggregator controls for the impact of immigration on marginal products, allowing the migrant share to identify the mark-down effect.

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 the earlier work of 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 zero or slightly positive. 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. 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 (33) 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 the native stock in the education-experience cell appears in the denominator of the migrant share $\frac{M_{ext}}{N_{ext}+M_{ext}}$. Unobserved cell-specific demand shocks (which raise wages and draw in natives) may then generate a spurious negative relationship between wages and the migrant share. However, our IV strategy should in principle address this concern.

In short, our estimates are driven by similar variation to previous studies (abstracting from our instruments and residualized wages); but our contribution is to give these effects a different interpretation.

7 Robustness and empirical extensions

7.1 Outliers, wage definition, weighting, instruments, and occupational downgrading

We now consider the robustness of our native wage equation (33). First, one may be concerned that the migrant share effects, γ_2, are driven by outliers. To address this, Figure III 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 IV. 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, $\log(N_{ext} + M_{ext})$.

[Figure III here]

For the OLS plot, we partial out the effect 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). For IV, we first replace both (i) log total employment and (ii) migrant share with their linear projections on the instruments and fixed effects; and we then follow the same procedure as for OLS. By construction, the slope coefficients are identical to the γ_2 estimates in Panel B of Table IV. And by inspection of the plots, it is clear these effects are not driven by outliers. On the contrary, the correlation between the partialed variables is remarkably strong, at least in the fixed effect specifications.

In Appendix Table A2, 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.

One may also be concerned that our predictor for the migrant stock, $\tilde{M}_{ext}$, is largely noise; and that the first stage 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. But in Appendix Table A3, we show our IV estimates are robust to replacing the migrant share instrument $\frac{\tilde{M}_{ext}}{\tilde{N}_{ext}+\tilde{M}_{ext}}$ with its numerator $\tilde{M}_{ext}$.

Finally, 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. 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 any measurement error to attenuate our (negative) estimates of the impact of migrant share, Dustmann, Schoenberg and Stuhler (2016) show that particular patterns of downgrading may also artificially inflate the effects. In Appendix H.4, in the spirit of Card (2001), we probabilistically allocate migrants (of given education and experience) to native cells according to their occupational distribution. This makes little difference to our estimates of the effect of migrant share.

7.2 Broad education and experience groups

We next study an alternative specification with two (instead of four) education groups. 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. For this exercise, 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.[20]

We report OLS and IV estimates in columns 1-4 of Table V; and we leave the first stage estimates to Appendix Table A6. For simplicity, we continue to impose $\alpha_Z = \sigma_Z = 1$. Notice that γ_1 (the elasticity to total cell employment) is now consistently negative and lies around -0.1. For $\sigma_Z = 1$, this implies an elasticity of substitution between experience groups (within education nests) of 10. These estimates are similar to those of Card and Lemieux (2001), who use an equivalent two-group education classification.[21] The γ_2 estimates (on migrant share) now increase to -1 in the OLS and IV fixed effect specifications. The first differenced estimates remain closer to -0.5; but the standard errors in IV now balloon, which reflects the weakness of the instruments in this particular specification (as Appendix Table A6 shows, the F-statistics are below 4).

[Table V here]

In columns 5-8 of Table V, 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 appears to make little difference to our baseline estimates in Table IV.

To summarize, conditional on cell size, the effect of migrant share on native wages appears to be reasonably robust to alternative skill group definitions.

[20]For example, consider the OLS coefficient on $\frac{M_{ext}}{N_{ext}+M_{ext}}$ in column 1 of Table V. 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 $[-1.310, -0.775]$.

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

7.3 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 (33) 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.

[Table VI here]

We report our first stage estimates in Appendix Tables A7 and A8, and the OLS and IV estimates in Table VI. 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. Still, we do not find differential effects by education in IV, though the first stage F-statistics are small (never above 5). With respect to experience, we find no evidence of heterogeneous effects in OLS or IV.

7.4 Heterogeneous effects of new and old migrants

We next explore whether mark-downs are 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, so there may be less direct competition (see the discussion in Section 3.4).

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 (33). We construct distinct instruments for each, i.e. $\frac{\tilde{M}_{ext}^{new}}{\tilde{N}_{ext}+\tilde{M}_{ext}}$ and $\frac{\tilde{M}_{ext}^{old}}{\tilde{N}_{ext}+\tilde{M}_{ext}}$. Appendix Table A9 reports the first stage: our instruments perform remarkably well in fixed effects, but $\frac{\tilde{M}_{ext}^{new}}{\tilde{N}_{ext}+\tilde{M}_{ext}}$ has no explanatory power in first differences.

[Table VII here]

Table VII presents our OLS and IV estimates. In the fixed effect specification (columns 3-4), there is no significant difference in the impact of new and old migrants. In first differences though, the standard errors are generally too large to identify their effect.

7.5 Impact on employment rates

We focus in this paper on wage effects, and we have taken employment as given throughout. But, Dustmann, Schoenberg and Stuhler (2016) stress the importance of labor supply responses to migration; and indeed, using similar skill-cell variation to our own, Borjas (2003) and Monras (forthcoming) estimate significant effects on native employment rates as well as wages. This question is especially pertinent in the context of monopsony: Chassamboulli and Palivos (2013) and Chassamboulli and Peri (2015) argue that migrants' low wage demands may stimulate job creation; and Amior (2017) and Albert (forthcoming) note that, under certain parameterizations, such a job creation effect may dominate any adverse wage effects in the determination of native welfare. However, if the job creation response is weak, native employment may also contract - in response to the lower wages.

To estimate the elasticity of employment to wages, we use the following specification:

$$\log ER_{Next} = \delta_0 + \delta_1 \log W_{Next} + d_{ex} + d_{et} + d_{xt} + e_{ext} \tag{34}$$

where $\log ER_{Next}$ is the log of mean annual native employment hours. Like Borjas (2003), we exclude enrolled students from our employment rate sample. The regressor of interest is the (composition-adjusted) log native wage, 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 wages[22]) and by instrumenting wages using migration shocks.

[22] Our motivation for adjusting employment rates is the same as for wages: changes in either outcome

[Table VIII here]

We present estimates of the native employment elasticity δ_1 in Panel A of Table VIII. 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 for 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 demand shocks. 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 stressing that our instruments are constructed using population (and not employment) data, so they are not conflated with variation in employment rates. 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 IV, 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 much larger native employment elasticities, reaching 1.2 for fixed effects (column 4) and 1.3 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. The IV estimates are difficult to interpret because of weak instruments (see the first stage in Panel D), but we do see similar patterns in OLS. 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. $\epsilon_M < \epsilon_N$). But the two stories are certainly consistent, and

may be conflated with observable demographic shifts (within education-experience cells). We follow identical steps to those described in Section 4.2; but this time, we estimate linear regressions for annual employment hours (including zeroes for individuals who do not work) rather than log wages.

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: Level and distribution

8.1 Overview

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 - and the distributional effects somewhat larger. In this section, we discuss how the introduction of monopsony affects the immigration surplus, both the level and distribution.

We consider the general implications and also quantify the effects, based on our estimates above. Specifically, we predict the impact of an immigration shock equal to 1% of total employment in 2017, holding migrants' skill mix (and the native employment stock) fixed. We simulate the effects in a "long run" scenario (where non-labor 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. For comparability, we have chosen to calibrate the upper nests using Ottaviano and Peri's (2012) estimates (based on their "Model A"): specifically, we set σ^E (i.e. the elasticity of substitution between education aggregates) to 0.7, and σ^X (between experience aggregates) to 0.84.

8.2 Perfect competition case

We present our results in Table IX. 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 elasticity of substitution 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 (30). Using these parameter estimates, we predict the change in native and migrants wages (Panels A and B) and the change in output and immigration surplus (Panel C), following the hypothesized immigration shock. Appendix F provides details on how these effects are computed: they account for the effect of immigration in each cell on every other cell.

[Table IX here]

Under perfect competition (column 1), the average native wage rises in response to the immigration shock - as Proposition 3 requires. The average effect is small (0.04%), but this hides large distributional effects. In particular, we predict the wage of native high-school dropouts declines by 0.5%, though this is offset by wage increases in other education groups. This is a consequence of the concentration of migrants in the dropout category, so a larger number of migrants (holding their skill mix constant) increases the relative supply of dropouts in the economy.[23]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" (that is, output net of the costs of the elastic non-labor 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

[23]Card (2009) and Ottaviano and Peri (2012) emphasize that these distributional effects disappear 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.

to individual factors. 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). Finally, total native wage income expands because their wages grow on average.

8.3 Monopsony case

Column 2 now introduces monopsony. To clarify the role played by monopsony, we first assume the mark-down is the same for natives and migrants alike (i.e. $\Delta\phi_{0N} = \Delta\phi_{1N} = 0$) and does not depend on the share of migrants in the cell (so $\phi_{1N} = 0$). The introduction of monopsony power means there are monopsony rents in the economy, and the level of these at baseline is an important parameter. As our earlier discussion has made clear, the *level* of the mark-down is not identified by our model (which studies only wages and employment); and there is no commonly accepted estimate in the literature. For illustrative purposes, we assume the share of monopsony rents at baseline is 10%: in terms of our model, we have $\phi_{0N} = 0.1$. Since mark-downs are equal for natives and migrants in this specification, the lower nest 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 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, as firms take a cut from the new migrants' marginal product. Following the convention that capital is owned by natives (see e.g. Borjas, 1995), we assume all firms are native-owned.[24] The total native surplus then expands to 0.12% of net long run output, most of which manifests as monopsony rents. The change in rents

[24] In reality, one would expect part of these profits to go to migrants - especially if migrants often work for migrant-owned firms. However, since we lack information on this, we have chosen not to explore this further.

will be larger or smaller according to their baseline level. In this scenario, the impact of immigration on wages under monopsony is the same as under perfect competition. But employers now also benefit from immigration, which increases their incentive to encourage immigration.

In column 3, we now allow mark-downs to vary with cell composition, 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 0.116 (based on column 6 of Table IV's Panel A), and we set ϕ_{0N} to ensure a 10% share of monopsony rents in the 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 the difference in wage effects between columns 2 and 3 is the same for all groups): this is because we assume 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 large growth of monopsony rents, which we calibrate to 0.68% of net output. The total native surplus (0.22%) is larger than before, as firms are capturing a larger share of rents from migrant labor.

In column 4, we allow for mark-downs to vary between natives and migrants: 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 IV (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 the migrant share $\frac{M}{M+N}$ (we now calibrate the native mark-down effect ϕ_{1N} to 0.620 and 0.546 respectively, based on Panels A and B of column 7, Table IV). In this case, the magnitude of the mark-down effect differs across cells: it is larger in cells with a larger migrant share at baseline. The effects are otherwise qualitatively similar to columns 3-4, though somewhat smaller on average: the mean native wage effect is about -0.4, rather than -0.6. On the other hand, high school dropouts suffer more in this specification, as this group has a larger migrant share (so it faces a larger mark-down effect).

Overall, our results suggest the existence of monopsony power has potentially important implications for the impact of immigration. The presence of monopsony may significantly expand the immigration surplus: native-owned firms take a cut from new migrants' marginal products, and they can also exploit immigration to impose larger mark-downs on the existing migrant workforce. To the extent that mark-downs depend on migrant share, this will of course also be to the disadvantage of native workers.

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 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 independent of the migrant share, of which perfect competition (and zero mark-downs) is a special case; and we reject this hypothesis using standard US data on employment and wages. Under an alternative framework with monopsonistic firms, our estimates suggest that immigration may in fact depress mean native wages overall - even in a "long-run" setting with perfectly elastic capital. The fact that firms capture rents from migrants may significantly expand the total surplus going to natives, but it also has important distributional implications.

It is worth stressing that the policy implications are nuanced: one cannot conclude that migration 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, as we have noted in the introduction, interventions ostensibly designed to protect native wages by stemming the flow of migrants (such as restricting access of migrants 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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Tables and figures

Table I: Descriptive statistics

	Experience groups							
	1-5	6-10	11-15	16-20	21-25	26-30	31-35	36-40
Panel A: Migrant share of employment hours, 1960								
HS dropouts	0.035	0.037	0.040	0.045	0.045	0.053	0.083	0.127
HS graduates	0.016	0.017	0.024	0.031	0.030	0.046	0.074	0.115
Some college	0.027	0.033	0.041	0.045	0.042	0.058	0.073	0.094
College graduates	0.031	0.038	0.045	0.048	0.058	0.064	0.092	0.111
Panel B: Change in migrant share of employment hours, 1960-2017								
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
Panel C: Change in log native wages, 1960-2017								
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
Panel D: Mean log migrant-native wage differential								
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 in 1960, across the four education and eight experience groups; and Panel B reports changes in this share over 1960-2017. Panel C reports changes over 1960-2017 in composition-adjusted log native (weekly) wages, normalized to mean zero across all groups. Panel D 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 4.2.

Table II: 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)
Panel A: OLS and IV estimates							
log $\frac{M}{N}$	-0.033***	0.001	0.013	-0.019**	-0.039***	-0.017*	-0.028**
	(0.004)	(0.004)	(0.010)	(0.007)	(0.012)	(0.009)	(0.012)
Constant (or mean intercept)	-0.138***	-0.098***	-0.071**	-0.135***	-0.177***	0.017***	0.020***
	(0.012)	(0.012)	(0.027)	(0.014)	(0.024)	(0.003)	(0.003)
Panel B: First stage estimates							
log $\frac{\tilde{M}}{N}$	-	-	1.186***	-	1.400***	-	0.890***
	-	-	(0.122)	-	(0.134)	-	(0.115)
Observations	224	224	224	224	224	192	192

Panel A reports estimates of equation (30), across 32 education-experience cells and 7 year 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 these columns reports the mean intercept (accounting for the fixed effects) across all cells. 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 III: First stage for native wage model

	Fixed effects				First differences	
	$\log Z(N,M)$	$\log \frac{M}{N}$	$\log Z(N,M)$	$\frac{M}{N+M}$	$\log Z(N,M)$	$\frac{M}{N+M}$
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Imposing equal mark-downs (H1), $\Delta\phi_0 = \Delta\phi_1 = 0$						
$\log Z\left(\tilde{N},\tilde{M}\right)$	1.595***	-0.768***	1.609***	-0.029	1.032***	-0.019
	(0.199)	(0.201)	(0.191)	(0.028)	(0.174)	(0.022)
$\log \frac{\tilde{M}}{\tilde{N}}$	0.142	0.802***				
	(0.129)	(0.118)				
$\frac{\tilde{M}}{\tilde{N}+\tilde{M}}$			1.018	1.249***	0.328	0.789***
			(0.651)	(0.195)	(0.766)	(0.176)
Panel B: Imposing $\alpha_Z = \sigma_Z = 1$						
$\log\left(\tilde{N}+\tilde{M}\right)$	1.578***	-0.798***	1.617***	-0.036	1.046***	-0.025
	(0.193)	(0.204)	(0.188)	(0.029)	(0.168)	(0.020)
$\log \frac{\tilde{M}}{\tilde{N}}$	0.123	0.798***				
	(0.126)	(0.118)				
$\frac{\tilde{M}}{\tilde{N}+\tilde{M}}$			1.088	1.233***	0.349	0.779***
			(0.653)	(0.193)	(0.764)	(0.174)
SW F-stat: Panel A	35.74	89.17	75.21	47.61	49.31	16.93
SW F-stat: Panel B	33.57	84.40	72.33	48.03	53.05	17.47
Observations	224	224	224	224	192	192

This table presents first stage estimates for the native wage equation (33), across 32 education-experience cells and 7 year observations (over 1960-2017). There are two endogenous variables: the cell aggregator $\log Z(N,M) = \log\left(N^{\sigma_Z} + \alpha_Z M^{\sigma_Z}\right)^{\frac{1}{\sigma_Z}}$ and the cell composition. We consider two specifications for the cell aggregator: in Panel A, we identify α_Z and σ_Z using the estimates from column 5 of Table II, 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 II. 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 IV: Model for native wages

	Fixed effects							First differences	
	Raw wages		Comp-adjusted					Comp-adjusted	
	OLS	OLS	OLS	OLS	OLS	IV	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Imposing equal mark-downs (H1), $\Delta\phi_0 = \Delta\phi_1 = 0$									
$\log Z(N, M)$	0.066***	0.079***	0.027	0.060***	0.059*	0.007	0.039**	0.056***	-0.001
	(0.015)	(0.015)	(0.023)	(0.019)	(0.031)	(0.031)	(0.018)	(0.018)	(0.034)
$\log \frac{M}{N}$	-0.050**		-0.101***		-0.001	-0.116***			
	(0.019)		(0.016)		(0.040)	(0.030)			
$\frac{M}{N+M}$		-0.326***		-0.536***	-0.533***		-0.620***	-0.394***	-0.569***
		(0.080)		(0.067)	(0.192)		(0.090)	(0.074)	(0.160)
Panel B: Imposing $\alpha_Z = \sigma_Z = 1$									
$\log(N + M)$	0.032**	0.041***	-0.006	0.022	0.022	-0.026	0.004	0.022	-0.025
	(0.015)	(0.014)	(0.023)	(0.019)	(0.032)	(0.031)	(0.019)	(0.018)	(0.032)
$\log \frac{M}{N}$	-0.038**		-0.088***		-0.002	-0.105***			
	(0.018)		(0.015)		(0.041)	(0.029)			
$\frac{M}{N+M}$		-0.258***		-0.466***	-0.459**		-0.546***	-0.323***	-0.473***
		(0.080)		(0.067)	(0.195)		(0.090)	(0.071)	(0.149)
Observations	224	224	224	224	224	224	224	192	192

Panels A and B present OLS and IV estimates of the native wage equation (33), across 32 education-experience cells and 7 year 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 II, 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 III. Robust standard errors, clustered by 32 education-experience cells, are in parentheses. We apply the same small-sample corrections as detailed in Table II. 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 V: Native wage effects in broad education and experience groups

	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***	-0.114*	-0.063*	-0.081	0.004	0.000	0.008	-0.001
	(0.042)	(0.056)	(0.033)	(0.134)	(0.020)	(0.022)	(0.018)	(0.022)
$\frac{M}{N+M}$	-1.053***	-1.016***	-0.528***	-0.769	-0.454***	-0.503***	-0.418***	-0.454***
	(0.127)	(0.275)	(0.125)	(0.873)	(0.069)	(0.110)	(0.091)	(0.142)
Observations	112	112	96	96	112	112	96	96

This table presents OLS and IV estimates of the native wage equation (33), but this time across broader labor market cells. In columns 1-4, we study 2 broad education groups (college and high-school equivalents) and 8 experience groups; and in columns 5-8, we study the original 4 education groups, but 4 broad experience groups (1-10, 11-20, 21-30 and 31-40 years of experience). See Section 7.2 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 A6. Robust standard errors, clustered by 16 education-experience cells, are in parentheses. We apply the same small-sample corrections as detailed in Table II. 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 VI: Heterogeneous effects by education and experience

	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*	0.006	0.034	0.011	0.029	-0.138	0.021	-0.029
	(0.018)	(0.019)	(0.021)	(0.020)	(0.019)	(0.188)	(0.022)	(0.038)
$\frac{M}{N+M}$	-0.429***	-0.534***	-0.516***	-0.575***	-0.318***	-0.835	-0.319***	-0.441***
	(0.063)	(0.118)	(0.101)	(0.111)	(0.070)	(0.708)	(0.106)	(0.144)
$\frac{M}{N+M}$ * Coll	0.507*	0.082			0.314*	-2.548		
	(0.274)	(0.513)			(0.181)	(3.480)		
$\frac{M}{N+M}$ * (Exp ≥ 20)			0.071	0.045			-0.009	-0.046
			(0.070)	(0.067)			(0.095)	(0.100)
Observations	224	224	224	224	192	192	192	192

This table presents OLS and IV estimates of the native wage equation (33), 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 A7 and A8. Robust standard errors, clustered by 32 education-experience cells, are in parentheses. We apply the same small-sample corrections as detailed in Table II. 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 VII: Impact of new and old migrants on native wages

	Fixed effects		First differences	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
$\log(N+M)$	0.014	0.011	0.023	-0.248
	(0.021)	(0.022)	(0.027)	(1.319)
$\frac{M^{new}}{N+M}$	-0.377***	-0.663**	-0.287	4.825
	(0.131)	(0.319)	(0.173)	(30.169)
$\frac{M^{old}}{N+M}$	-0.487***	-0.532***	-0.308**	-1.577
	(0.063)	(0.076)	(0.138)	(6.473)
Observations	224	224	192	192

This table presents OLS and IV estimates of the native wage equation (33), 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 A9. Robust standard errors, clustered by 32 education-experience cells, are in parentheses. We apply the same small-sample corrections as detailed in Table II. 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 VIII: Elasticity of employment rates

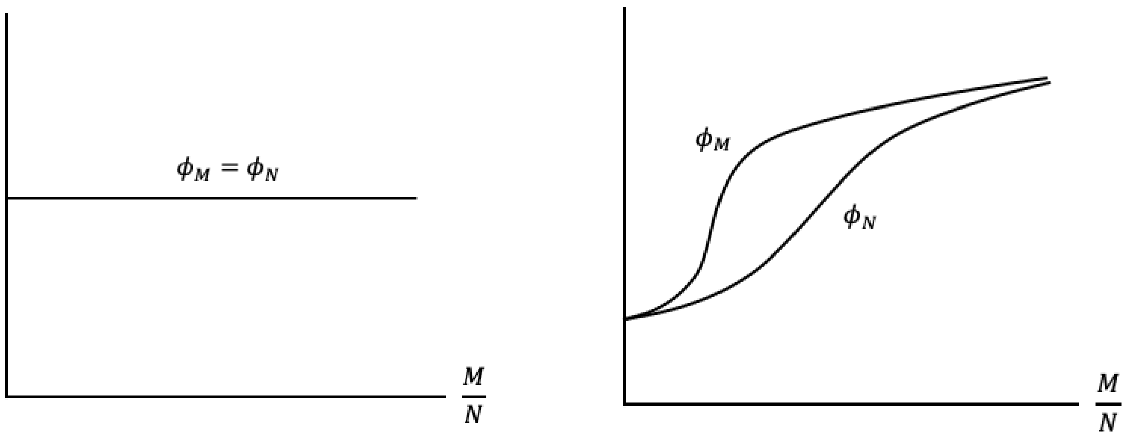
	Fixed effects				First differences			
	Log raw emp rate	Composition-adjusted			Log raw emp rate	Composition-adjusted		
	OLS	OLS	IV1	IV2	OLS	OLS	IV1	IV2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Native elasticity								
Log native wage	0.528*	0.663***	1.226***	1.204***	0.898***	0.778***	1.660***	1.270***
	(0.271)	(0.167)	(0.386)	(0.352)	(0.327)	(0.206)	(0.312)	(0.309)
Panel B: Migrant elasticity								
Log migrant wage	0.029	0.261*	0.555	0.603	0.277**	0.200**	0.580	-6.645
	(0.134)	(0.138)	(0.526)	(0.540)	(0.134)	(0.091)	(0.720)	(122.055)
Panel C: First stage for native wages								
$\log\left(\tilde{N}+\tilde{M}\right)$			0.026				-0.014	
			(0.028)				(0.027)	
$\frac{\tilde{M}}{\tilde{N}+\tilde{M}}$			-0.669***	-0.726***			-0.378***	-0.352***
			(0.148)	(0.142)			(0.083)	(0.067)
Panel D: First stage for migrant wages								
$\log\left(\tilde{N}+\tilde{M}\right)$			0.011				0.017	
			(0.040)				(0.029)	
$\frac{\tilde{M}}{\tilde{N}+\tilde{M}}$			-0.374*	-0.397*			0.044	0.013
			(0.193)	(0.202)			(0.236)	(0.222)
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 (34). 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 4.2 (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 II. 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 IX: 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	0.116	0.105	0.620	0.546
Panel A: Native wages (% changes)						
HS dropouts	-0.462	-0.462	-1.117	-1.176	-1.259	-1.285
HS graduates	0.038	0.038	-0.617	-0.604	-0.464	-0.453
Some college	0.116	0.116	-0.539	-0.499	-0.243	-0.222
College graduates	0.025	0.025	-0.630	-0.585	-0.459	-0.418
Average	0.041	0.041	-0.614	-0.582	-0.417	-0.393
Panel B: Migrant wages (% changes)						
HS dropouts	-0.691	-0.691	-1.346	-1.422	-1.522	-1.561
HS graduates	-0.156	-0.156	-0.811	-0.803	-0.689	-0.679
Some college	-0.072	-0.072	-0.727	-0.688	-0.439	-0.418
College graduates	-0.165	-0.165	-0.820	-0.776	-0.661	-0.620
Average	-0.241	-0.241	-0.896	-0.883	-0.781	-0.767
Panel C: Net long run output and immigration surplus						
% change in net output	0.934	0.934	0.934	0.979	0.934	0.979
Decomposition:						
(i) Δ Migrant wage income (% net output)	0.900	0.815	0.717	0.713	0.737	0.733
(ii) Δ Native wage income (% net output)	0.034	0.031	-0.464	-0.434	-0.323	-0.298
(iii) Δ Monopsony rents (% net output)	0	0.089	0.682	0.699	0.520	0.544
Total native surplus (% net output) = (ii) + (iii)	0.034	0.120	0.218	0.265	0.198	0.246

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 to 0.7 and σ_X 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 IV). 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).



(a) $\epsilon_M = \epsilon_N$ (b) $\epsilon_M < \epsilon_N$

Figure I: Mark-down functions for $\epsilon_M = \epsilon_N$ and $\epsilon_M < \epsilon_N$

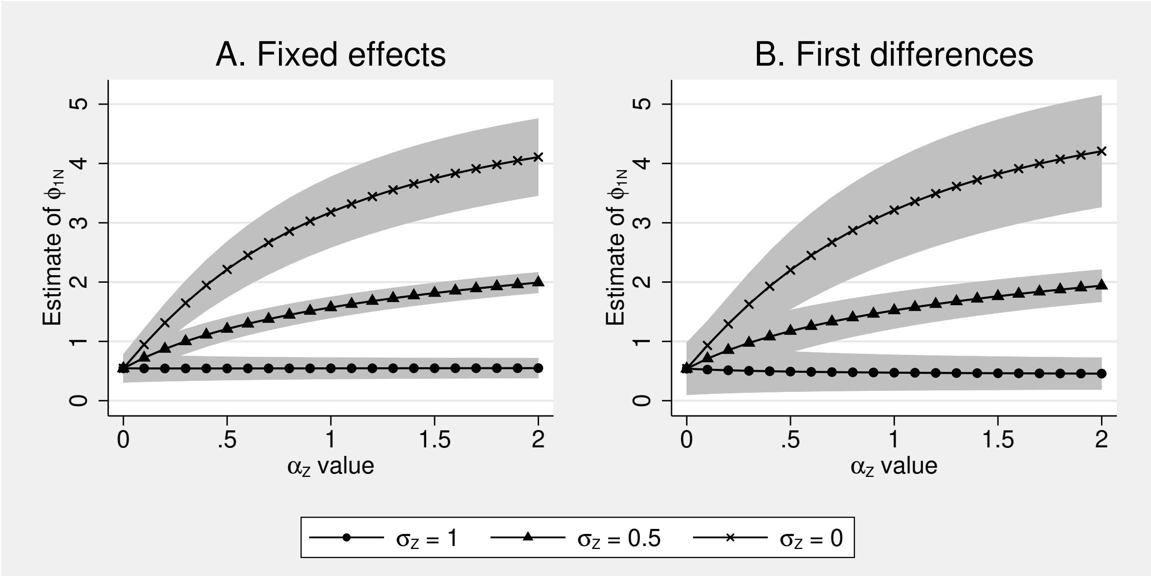


Figure II: Native mark-down response ϕ_{1N} for different (α_Z, σ_Z)

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 (33). The estimates for $\alpha_Z = \sigma_Z = 1$ are identical to columns 7 and 9 of Panel B of Table IV. Other plotted values replicate the exercise of these columns, but for different (α_Z, σ_Z) values. See the notes accompanying Table IV for further details. The shaded areas are 95% confidence intervals on our γ_2 estimates. We offer more formal regression tables for a selection of (α_Z, σ_Z) values in Appendix Table A1.

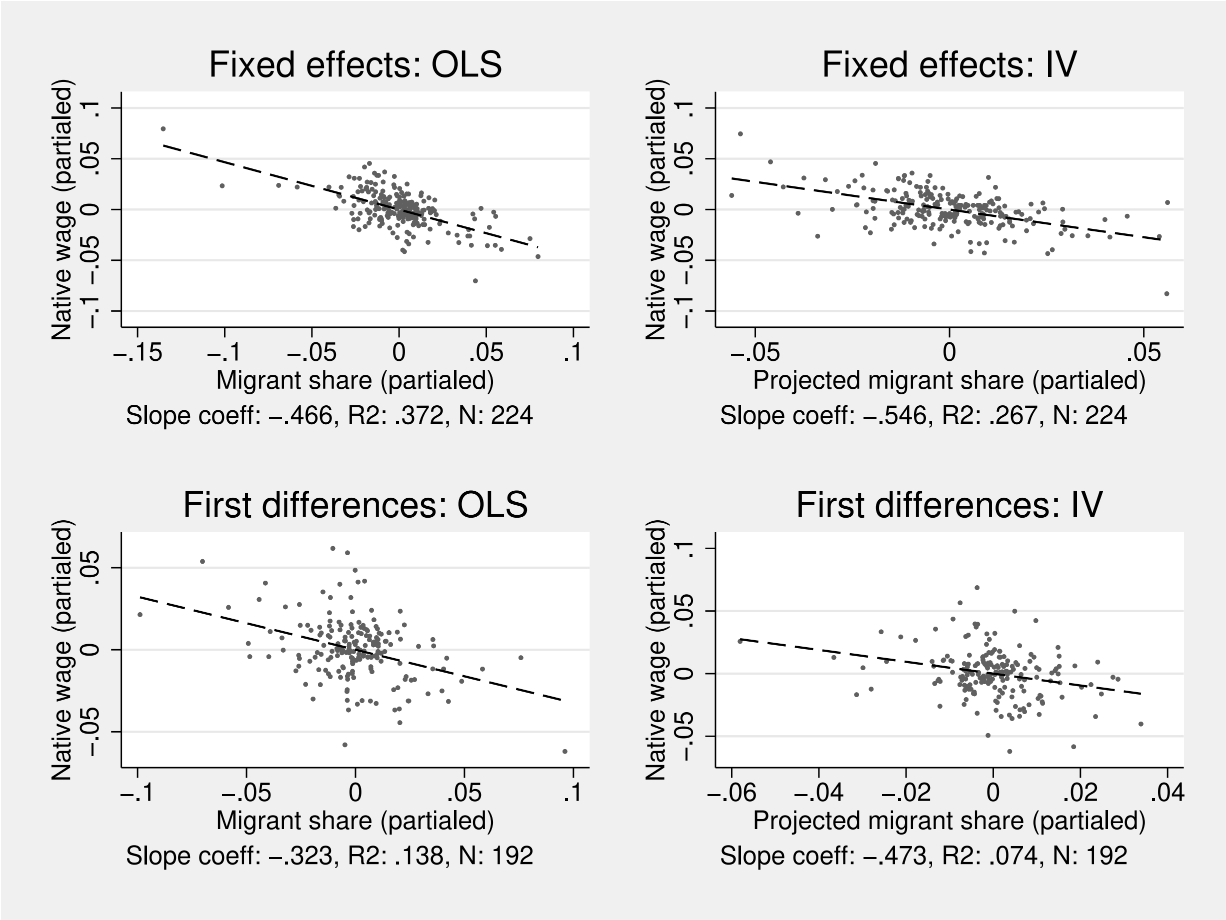


Figure III: Visualization of native wage responses to migrant share

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 IV. 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.

Appendices: For Online Publication

A Long-run production function

Suppose the production function can be written as $F(\mathbf{L}, \mathbf{K})$, where $\mathbf{L}$ is a vector of inputs that are treated as fixed (perhaps because they are in inelastic supply or simply for analytical convenience) and $\mathbf{K}$ a vector of other inputs (possibly including capital) 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 non-labor inputs:

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

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

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

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

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

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

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

$$\Pi_{\mathbf{L}}\left(\mathbf{L},\mathbf{p_K}\right) = F_L\left(\mathbf{L},\mathbf{K}\left(\mathbf{L},\mathbf{p_K}\right)\right) + \left[\mathbf{F_K}-\mathbf{p_K}\right]' \frac{\partial \mathbf{K}\left(\mathbf{L},\mathbf{p_K}\right)}{\partial \mathbf{L}} = F_{\mathbf{L}}\left(\mathbf{L},\mathbf{K}\left(\mathbf{L},\mathbf{p_K}\right)\right) \quad \text{(A4)}$$

where the second equality follows from (A2).

Therefore, assuming non-labor inputs are elastically supplied, we can write the long-run production function as $\tilde{F}\left(\mathbf{L}\right) = \Pi\left(\mathbf{L},\mathbf{p_K}\right)$ 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 two 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:

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

where $\mathbf{p}$ is the $K \times 1$ vector of prices, and the cost function $\tilde{c}$ will depend on the $J \times 1$ vector of wages $\mathbf{w}$ and (if there are intermediate or capital good inputs) the vector of goods prices.[25] From standard theory, $\tilde{c}$ will be homogenous of degree 1 in its arguments, increasing and concave. One can solve (A7) to give a "reduced form" cost function:

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

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

Let $a_{kj}\left(\mathbf{w}\right)$ 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:

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

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

C.2 Consumption

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

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

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

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

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

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

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

C.3 Introducing natives and migrants

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

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

Since natives and migrants differ in skill mix, they may have different levels of utility in equilibrium. Let u^n denote the average utility of natives, and u^m the average utility of migrants.[26] As total income must equal total expenditure for natives and migrants alike, we must have:

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

and

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

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

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

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

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

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

Equations (A14), (A15) and (A17) appear to consist of $J+2$ equations in $J+2$ unknowns $(\mathbf{w}, u_n, u_m)$. But as usual, 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.

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

C.4 Assessing the impact of immigration

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

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

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

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

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

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

which implies that average native and migrant utility must move in opposite directions, if there is any change at all. But this does not tell us who gains and who loses.[27] This would require an expression for the change in wages. Differentiating (A17) leads to:

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

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

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

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

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

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

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

D Aggregation of monopsony model

D.1 Aggregation of production

The purpose of this appendix is to describe how our simple monopsony model for a single unobservable submarket j, outlined in Section 3.2, can be aggregated to the national level (or to any observable labor market cell). At the aggregate level, suppose there are M migrants, a fraction μ_j of which are exogenously allocated to submarket j; and there are N natives, who are allocated according to fraction η_j. The economy consists of many such submarkets j, whose long run output (net of the costs of elastic inputs) is aggregated according to the function $\tilde{F}\left(L_j, .., L_J\right)$, which we assume to be homogeneous of degree 1. As we have described in Section 3.2, natives and migrants are perfect substitutes within these submarkets.

Following equation (4) and Proposition 3, we can define an aggregate production function in terms of N and M as:

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

The partial derivative of Z with respect to N is:

$$Z_N(N, M) = \sum_j \eta_j \tilde{F}_j \tag{A25}$$

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

$$Z_M(N, M) = \sum_j \mu_j \tilde{F}_j \tag{A26}$$

which is the mean marginal product of migrants. In this way, we have reduced $\tilde{F}$ to an aggregated production function over two composite inputs (N and M), whose marginal products are equal to those of the average native and migrant. The feasibility of this aggregation follows from 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 Average wages

Using (8), the average wage in submarket j is:

$$\log W_j = \log \tilde{F}_j - \log\left(1 + \epsilon_j^{-1}\right) \tag{A27}$$

where $\tilde{F}_j$ is the marginal product of submarket j labor; and the second term is the markdown, which depends on the elasticity ϵ_j of labor supply to firms in the submarket. In turn, ϵ_j is a weighted average of native and migrant elasticities (ϵ_N and ϵ_M); and using (9), it can be written as a function of the migrant and native submarket allocations:

$$\epsilon\left(\frac{\mu_j M}{\eta_j N}\right) = \epsilon_N + \frac{\mu_j M}{\mu_j M + \eta_j N}\left(\epsilon_M - \epsilon_N\right) \tag{A28}$$

If natives supply labor more elastically ($\epsilon_N > \epsilon_M$), ϵ_j will be decreasing in the migrant share.

Let W_N be the mean native wage. This will be a weighted average of the wages (A27) across the various submarkets, with weights equal to η_j:

$$\log W_N = \log Z_N (N, M) - \phi_N \left(\frac{M}{N}\right) \tag{A29}$$

where we have applied the aggregation in (A25), and where ϕ_N is the native aggregate mark-down:

$$\phi_N \left(\frac{M}{N}\right) = \log \frac{\sum_j \eta_j \tilde{F}_j \left[1 + \epsilon \left(\frac{\mu_j M}{\eta_j N}\right)^{-1}\right]}{\sum_j \eta_j \tilde{F}_j} \tag{A30}$$

which is a function of the migrant share. Similarly, the mean migrant wage can be written as:

$$\log W_M = \log Z_M (N, M) - \phi_M \left(\frac{M}{N}\right) \tag{A31}$$

where ϕ_M is the migrant aggregate mark-down:

$$\phi_M \left(\frac{M}{N}\right) = \log \frac{\sum_j \mu_j \tilde{F}_j \left[1 + \epsilon \left(\frac{\mu_j M}{\eta_j N}\right)^{-1}\right]}{\sum_j \mu_j \tilde{F}_j} \tag{A32}$$

D.3 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 submarkets j are completely segregated (i.e. each is entirely composed of either natives or migrants, so $\mu_j \eta_j = 0$ for all j), whether due to skills or discrimination. This implies that $\phi_j = \log \left(1 + \epsilon_N^{-1}\right)$ in all native markets (where $\eta_j > 0$), so the aggregate native mark-down $\phi_N \left(\frac{N}{M}\right)$ depends only on the native supply elasticity. Similarly, complete segregation implies that $\phi_j = \log \left(1 + \epsilon_M^{-1}\right)$ in all migrant submarkets (where $\mu_j > 0$), so the migrant mark-down $\phi_M \left(\frac{M}{N}\right)$ will only depend on the migrant elasticity.

However, if there is any overlap of natives and migrants across submarkets j, the aggregate mark-downs will depend on the migrant share (except under the null hypothesis of interest, where $\epsilon_N = \epsilon_M$). To study this dependence, consider first the extreme ends of the support. As $\frac{M}{N} \to 0$, both the aggregate native and migrant mark-downs (i.e. ϕ_N and ϕ_M) will converge to $\log\left(1+\epsilon_N^{-1}\right)$, i.e. a function only of the native supply elasticity. Similarly, as $\frac{M}{N} \to \infty$, both ϕ_N and ϕ_M will converge to $\log\left(1+\epsilon_M^{-1}\right)$, a function only of the migrant elasticity.

More generally, for intermediate values of $\frac{M}{N}$, the differential between the aggregate migrant and native mark-downs (ϕ_M and ϕ_N) will depend on the submarket elasticity function $\epsilon\left(\frac{\mu_j M}{\eta_j N}\right)$ and the differential between ϵ_M and ϵ_N. Define $\tilde{\eta}_j = \frac{\eta_j \tilde{F}_j}{\sum_j \eta_j \tilde{F}_j}$ and $\tilde{\mu}_j = \frac{\mu_j \tilde{F}_j}{\sum_j \mu_j \tilde{F}_j}$. From (A30) and (A32), we then have that:

$$\begin{aligned}
\exp(\phi_M) - \exp(\phi_N) &= \sum_j \tilde{\mu}_j \left[1 + \epsilon\left(\frac{\mu_j M}{\eta_j N}\right)^{-1}\right] - \sum_j \tilde{\eta}_j \left[1 + \epsilon\left(\frac{\mu_j M}{\eta_j N}\right)^{-1}\right] \qquad \text{(A33)}\\
&= \sum_j \tilde{\eta}_j \left(\frac{\tilde{\mu}_j}{\tilde{\eta}_j}\right) \left[1 + \epsilon\left(\frac{\mu_j M}{\eta_j N}\right)^{-1}\right] - \sum_j \tilde{\eta}_j \left[1 + \epsilon\left(\frac{\mu_j M}{\eta_j N}\right)^{-1}\right]\\
&= E_\eta\left[\frac{\tilde{\mu}_j}{\tilde{\eta}_j}\left\{1 + \epsilon\left(\frac{\mu_j M}{\eta_j N}\right)^{-1}\right\}\right] - E_\eta\left[\frac{\tilde{\mu}_j}{\tilde{\eta}_j}\right] E_\eta\left[1 + \epsilon\left(\frac{\mu_j M}{\eta_j N}\right)^{-1}\right]\\
&= Cov_\eta\left[\frac{\tilde{\mu}_j}{\tilde{\eta}_j}, \epsilon\left(\frac{\mu_j M}{\eta_j N}\right)^{-1}\right]
\end{aligned}$$

where the expectation E_η is taken with respect to the distribution $\tilde{\eta}_j$, and we are using the fact that $E_\eta\left[\frac{\tilde{\mu}_j}{\tilde{\eta}_j}\right] = 1$. If $\epsilon_N > \epsilon_M$ (i.e. if natives supply labor to firms more elastically than migrants), the overall submarket elasticity $\epsilon\left(\frac{\mu_j M}{\eta_j N}\right)$ will be a decreasing function of the ratio $\frac{\tilde{\mu}_j}{\tilde{\eta}_j}$; so the covariance in the final line of (A33) will be positive, and the aggregate mark-down will be larger for migrants. Intuitively, migrants will be disproportionately located in migrant-intensive submarkets (which are less competitive). But as mentioned above, the differential between ϕ_M and ϕ_N must converge to zero as the overall native-migrant ratio $\frac{M}{N}$ goes to either zero or ∞. And consequently, the differential will not be monotonic in $\frac{M}{N}$.

E Functional form of mark-down effects

In this appendix, we study the relationship between the mark-down ϕ_j in submarket j and the migrant cell composition. We argue that a linear relationship between ϕ_j and the migrant share $\frac{M_j}{N_j+M_j}$ offers a better approximation than one between ϕ_j and the relative log migrant supply $\log \frac{M_j}{N_j}$.

In our model, the mark-down depends on the migrant share if the elasticity of labor supply to firms is different for natives and migrants, i.e. if $\epsilon_N \neq \epsilon_M$. From (9), the elasticity of labor supply facing firms in a given submarket j is equal to:

$$\epsilon_j = \epsilon_N + \frac{M_j}{N_j + M_j}\Delta\epsilon \tag{A34}$$

where $\frac{M_j}{N_j+M_j}$ is the migrant share in the submarket, ϵ_N is the native elasticity, and $\Delta\epsilon \equiv \epsilon_M - \epsilon_N$ is the difference between the migrant and native elasticities. Note that the overall elasticity ϵ_j is linear in $\frac{M_j}{N_j+M_j}$, with slope equal to the difference in elasticities.

In the wage equations (20) and (21), it is the mark-down ϕ_j which is relevant, rather than the labor supply elasticity ϵ_j. The mark-down in submarket j is:

$$\phi_j = \log \frac{1+\epsilon_j}{\epsilon_j} \tag{A35}$$

The derivative of the mark-down with respect to the migrant share is:

$$\frac{d\phi_j}{d\left(\frac{M_j}{N_j+M_j}\right)} = -\frac{1}{\epsilon_j\left(1+\epsilon_j\right)}\Delta\epsilon \tag{A36}$$

Notice that the migrant share $\frac{M_j}{N_j+M_j}$ has no effect on the mark-down ϕ_j 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. And importantly, 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:

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

This derivative 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 markdown 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 $\frac{M_j}{N_j+M_j}$.

F Computation of 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 IX. We begin with the wage equations (16) and (17). Imposing CES technology on the lowest-level education-experience nest Z (in line with (23)), we have:

$$\begin{aligned} W_{Nex} &= \exp\left(-\phi_{Nex}\right)\alpha_e\left(\frac{L_e}{\tilde{Y}}\right)^{\sigma_E-1}\alpha_{ex}\left(\frac{L_{ex}}{L_e}\right)^{\sigma_X-1}\left(\frac{N_{ex}}{L_{ex}}\right)^{\sigma_Z-1} && \text{(A38)} \\ W_{Mex} &= \exp\left(-\phi_{Mex}\right)\alpha_e\left(\frac{L_e}{\tilde{Y}}\right)^{\sigma_E-1}\alpha_{ex}\left(\frac{L_{ex}}{L_e}\right)^{\sigma_X-1}\alpha_Z\left(\frac{M_{ex}}{L_{ex}}\right)^{\sigma_Z-1} && \text{(A39)} \end{aligned}$$

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

$$\log W_{Nex} = \log\left(\alpha_e\alpha_{ex}\right) + \left(1-\sigma_E\right)\log\tilde{Y} + \left(\sigma_E-\sigma_X\right)\log L_e \quad \text{(A40)}$$

$$+ (\sigma_X - \sigma_Z) \log L_{ex} + (\sigma_Z - 1) \log N_{ex} - \phi_{Nex}$$

$$\log W_{Mex} = \log (\alpha_e \alpha_{ex} \alpha_Z) + (1 - \sigma_E) \log \tilde{Y} + (\sigma_E - \sigma_X) \log L_e \tag{A41}$$

$$+ (\sigma_X - \sigma_Z) \log L_{ex} + (\sigma_Z - 1) \log M_{ex} - \phi_{Mex}$$

Consider an immigration shock equal to 1% of total employment, holding the skill mix of migrants fixed, and holding the native stock N fixed. Using (A40) and (A41), 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 (A41). 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 (A40) and (A41)? 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:

$$\frac{d \log M_{ex}}{\left(\frac{dM}{M+N}\right)} = \frac{N + M}{M} \tag{A42}$$

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

$$\frac{d \log L_{ex}}{\left(\frac{dM}{M+N}\right)} = \frac{d \log L_{ex}}{d \log M_{ex}} \cdot \frac{d \log M_{ex}}{\left(\frac{dM}{M+N}\right)} = \frac{\alpha_{Zex} M_{ex}^{\sigma_Z}}{N_{ex}^{\sigma_Z} + \alpha_{Zex} M_{ex}^{\sigma_Z}} \cdot \frac{d \log M_{ex}}{\left(\frac{dM}{M+N}\right)} = \frac{\tilde{F}_{Mex} M_{ex}}{\tilde{F}_{Mex} M_{ex} + \tilde{F}_{Nex} N_{ex}} \cdot \frac{d \log M_{ex}}{\left(\frac{dM}{M+N}\right)} \tag{A43}$$

where the second equality follows from (23), and where:

$$\tilde{F}_{Nex} = \exp(\phi_{Nex}) W_{Nex} \tag{A44}$$

$$\tilde{F}_{Mex} = \exp(\phi_{Mex}) W_{Mex} \tag{A45}$$

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:

$$\frac{d \log L_e}{\left(\frac{dM}{M+N}\right)} = \frac{d \log L_e}{d \log L_{ex}} \cdot \frac{d \log L_{ex}}{\left(\frac{dM}{M+N}\right)} = \frac{\alpha_{ex} L_{ex}}{\sum_{x'} \alpha_{ex'} L_{ex'}} \cdot \frac{d \log L_{ex}}{\left(\frac{dM}{M+N}\right)} = \frac{F_{ex}^M M_{ex} + F_{ex}^N N_{ex}}{\sum_{x'} \left(F_{ex'}^M M_{ex'} + F_{ex'}^N N_{ex'}\right)} \cdot \frac{d \log L_{ex}}{\left(\frac{dM}{M+N}\right)} \tag{A46}$$

where the second equality follows from (14), and where $\frac{F_{ex}^M M_{ex} + F_{ex}^N N_{ex}}{\sum_{x'} \left(F_{ex'}^M M_{ex'} + F_{ex'}^N N_{ex'}\right)}$ 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:

$$\frac{d \log \tilde{Y}}{\left(\frac{dM}{M+N}\right)} = \frac{d \log \tilde{Y}}{d \log L_e} \cdot \frac{d \log L_e}{\left(\frac{dM}{M+N}\right)} = \frac{\alpha_e L_e}{\sum_{e'} \alpha_{e'} L_{e'}} \cdot \frac{d \log L_e}{\left(\frac{dM}{M+N}\right)} = \frac{\sum_{x'} \left(F_{ex'}^M M_{ex'} + F_{ex'}^N N_{ex'}\right)}{\sum_{e',x'} \left(F_{e'x'}^M M_{e'x'} + F_{e'x'}^N N_{e'x'}\right)} \cdot \frac{d \log L_e}{\left(\frac{dM}{M+N}\right)} \tag{A47}$$

where the second equality follows from (13), and where $\frac{\sum_{x'} \left(F_{ex'}^M M_{ex'} + F_{ex'}^N N_{ex'}\right)}{\sum_{e',x'} \left(F_{e'x'}^M M_{e'x'} + F_{e'x'}^N N_{e'x'}\right)}$ 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 (25) and (26). Then, we can write:

$$\frac{d\phi_{Nex}}{\left(\frac{dM}{M+N}\right)} = \phi_{1N} \frac{d \log M_{ex}}{\left(\frac{dM}{M+N}\right)} \tag{A48}$$

$$\frac{d\phi_{Mex}}{\left(\frac{dM}{M+N}\right)} \quad = \quad (\phi_{1N} + \Delta\phi_1)\,\frac{d\log M_{ex}}{\left(\frac{dM}{M+N}\right)} \tag{A49}$$

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:

$$\frac{d\phi_{Nex}}{\left(\frac{dM}{M+N}\right)} \quad = \quad \phi_{1N}\frac{d\left(\frac{M_{ex}}{M_{ex}+N_{ex}}\right)}{d\log M_{ex}} \cdot \frac{d\log M_{ex}}{\left(\frac{dM}{M+N}\right)} = \phi_{1N}\frac{N_{ex}M_{ex}}{\left(N_{ex}+M_{ex}\right)^2} \cdot \frac{d\log M_{ex}}{\left(\frac{dM}{M+N}\right)} \tag{A50}$$

$$\frac{d\phi_{Mex}}{\left(\frac{dM}{M+N}\right)} \quad = \quad (\phi_{1N} + \Delta\phi_1)\,\frac{d\log M_{ex}}{\left(\frac{dM}{M+N}\right)} = (\phi_{1N} + \Delta\phi_1)\,\frac{N_{ex}M_{ex}}{\left(N_{ex}+M_{ex}\right)^2} \cdot \frac{d\log M_{ex}}{\left(\frac{dM}{M+N}\right)} \tag{A51}$$

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

$$d\left(W_{Mex}M_{ex}\right) = W_{Mex}M_{ex}\left(1 + \sum_{e',x'}\frac{d\log W_{Mex}}{d\log M_{e'x'}}\right)d\log M \tag{A52}$$

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:

$$d\left(W_{Nex}N_{ex}\right) = W_{Nex}N_{ex}\left(\sum_{e',x'}\frac{d\log W_{Nex}}{d\log M_{e'x'}}\right)d\log M \tag{A53}$$

To compute the total change in the migrant and native wage bills, we sum (A52) and (A53) over labor market cells (e, x). And we express these changes relative to net output

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

$$\tilde{Y} = \sum_{e,x} \left(F^M_{ex} M_{ex} + F^N_{ex} N_{ex} \right) \tag{A54}$$

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

$$\frac{dR}{\tilde{Y}} = d \log \tilde{Y} - \sum_{e,x} \frac{d \left(W_{Nex} N_{ex} \right)}{\tilde{Y}} - \sum_{e,x} \frac{d \left(W_{Mex} M_{ex} \right)}{\tilde{Y}} \tag{A55}$$

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

$$\frac{S}{\tilde{Y}} = \frac{dR}{\tilde{Y}} + \sum_{e,x} \frac{d \left(W_{Nex} N_{ex} \right)}{\tilde{Y}} \tag{A56}$$

G 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 VII). 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 impute these stocks using the size of the same cohort ten years later. For example, to impute 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 the 1970 stock of high school graduate Mexicans with 11-20 years in the US and 35-40 years of experience.

We then use the 1970 population stocks to predict the 1960 employment stocks. To this end, we exploit the relationship between these variables in future years, 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 0.88. This suggests about 10% of immigrants leave the country over each decade, which is consistent with estimates from Ahmed and Robinson (1994).

H Supplementary empirical estimates

H.1 Regression tables corresponding to Figure II

In Appendix Table A1, we offer complete regression tables (i.e. estimates of the native wage equation (33)) corresponding to a selection of (α_Z, σ_Z) values in Figure II. Notice that column 2 (with $\alpha_Z = \sigma_Z = 1$) is identical to columns 7 and 9 in Panel B of Table IV.

[Appendix Table A1]

H.2 Robustness to wage definition and weighting

In Appendix Table A2, we confirm that our IV estimates of the native wage equation (33) are robust to the choice of wage variable and weighting.

[Appendix Table A2]

In each specification, the right hand side is identical to columns 7 and 9 of Panel B of Table IV, 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 4.2. The estimates in Panel A are unweighted (as in Table IV); while in Panel B, we weight observations by total cell employment. It turns out the estimates are very similar across all specifications.

H.3 Alternative specification for instrument

One may also 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 A3, we show the IV estimates are robust to replacing the migrant share instrument $\frac{\tilde{M}_{ext}}{\tilde{N}_{ext}+\tilde{M}_{ext}}$ with its numerator $\tilde{M}_{ext}$. In practice, we scale $\tilde{M}_{ext}$ by 10^{-9} to make the coefficients visible in the table. For the purposes of this exercise, we impose throughout that $\alpha_Z = \sigma_Z = 1$, so the dependent variable collapses to log native wages and the cell aggregator to log total employment, $\log(N_{ext} + M_{ext})$. Columns 1-4 are otherwise identical to columns 3-6 in Table III (Panel B), and columns 5-6 are comparable to columns 7 and 9 in Table IV (Panel B).

[Appendix Table A3]

The instruments take the correct sign in the first stage: in particular, the migrant share is decreasing in $\log\left(\tilde{N}_{ext} + \tilde{M}_{ext}\right)$ but increasing in $\tilde{M}_{ext}$; and the associated F-statistics are reasonably large, especially in first differences. Comparing the second stage estimates to Table IV, the standard errors are unsurprisingly larger. But the coefficients are similar in magnitude: the fixed effect estimate is somewhat smaller (decreasing from -0.55 to -0.41), but the first differenced estimate is larger (increasing from -0.47 to -0.68).

H.4 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). Suppose there are O occupations, denoted o, and EX education-experience cells, denoted ex. Let $\mathbf{\Pi}^{M}_{O\times EX}$ be a matrix, with O rows and EX columns, which allocates migrant education-experience cells to occupations, where the (o, ex) element is the share of education-experience ex migrant labor which is employed in occupation o (so the columns of $\mathbf{\Pi}^{M}_{O\times EX}$ sum to 1). We base these shares on averages across all sample years. Similarly, let $\mathbf{\Pi}^{N}_{EX\times O}$ be an $EX \times O$ matrix which allocates occupations to native education-experience cells, where the (ex, o) element is the share of occupation o native labor which has education-experience ex (so the columns of $\mathbf{\Pi}^{N}_{EX\times O}$ sum to 1). Using these matrices, we can probabilistically allocate migrant education-experience cells to native education-experience cells, according to their occupational distribution:

$$\mathbf{M}^{occ}_{EX\times T} = \mathbf{\Pi}^{N}_{EX\times O}\mathbf{\Pi}^{M}_{O\times EX}\mathbf{M}_{EX\times T} \tag{A57}$$

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

$$\tilde{\mathbf{M}}^{occ}_{EX\times T} = \mathbf{\Pi}^{N}_{EX\times O}\mathbf{\Pi}^{M}_{O\times EX}\tilde{\mathbf{M}}_{EX\times T} \tag{A58}$$

where $\tilde{\mathbf{M}}^{occ}_{EX\times T}$ is the imputed stock of immigrants by education and experience, as described in Section 4.3.

Using this data, we now re-estimate the native wage equation (33), but replacing education-experience migrant stocks M_{ext} with occupation-imputed stocks M^{occ}_{ext} (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, $\log\left(N_{ext} + M^{occ}_{ext}\right)$. Appendix Table A4 suggests the instruments work reasonably well for the occupation-imputed stocks.

[Appendix Tables A4 and A5]

We present our OLS and IV estimates in Appendix Table A5. In our basic specification (columns 1 and 3), the effect of migrant share is negative (with a coefficient of about -0.3), 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 IV in the main text: -0.5 in OLS (column 2) and -0.6 in IV (column 4), with standard errors of about 0.2. When we estimate these equations in first differences (columns 5-8), the patterns are qualitatively similar.

H.5 Supplementary first stage estimates

In Appendix Table A6, we report first stage estimates corresponding to the IV specifications in Table V in the main text (i.e. broad education and experience groups). In Appendix Tables A7 and A8, we do the same for the IV specifications in Table VI (heterogeneity by education and experience). And Appendix Table A9 reports first stage estimates corresponding to Table VII (new and old migrants).

[Appendix Tables A6-A9 here]

Appendix Tables

Table A1: IV estimates of native wage equation for selection of (α_Z, σ_Z) values

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Fixed effects ($N = 224$)									
$\log Z(N, M)$	0.002	0.004	0.003	0.502***	0.510***	0.519***	1.002***	1.039***	0.971***
	(0.020)	(0.019)	(0.019)	(0.020)	(0.024)	(0.030)	(0.020)	(0.076)	(0.103)
$\frac{M}{N+M}$	-0.546***	-0.546***	-0.549***	-0.546***	-1.573***	-1.992***	-0.546***	-3.180***	-4.108***
	(0.118)	(0.090)	(0.083)	(0.118)	(0.089)	(0.086)	(0.118)	(0.294)	(0.320)
Panel B: First differences ($N = 192$)									
$\log Z(N, M)$	-0.031	-0.025	-0.027	0.469***	0.481***	0.496***	0.969***	1.067***	1.009***
	(0.037)	(0.032)	(0.034)	(0.037)	(0.040)	(0.046)	(0.037)	(0.097)	(0.124)
$\frac{M}{N+M}$	-0.540**	-0.473***	-0.457***	-0.540**	-1.523***	-1.939***	-0.540**	-3.213***	-4.208***
	(0.217)	(0.149)	(0.133)	(0.217)	(0.152)	(0.135)	(0.217)	(0.418)	(0.463)
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 (33)) corresponding to a selection of (α_Z, σ_Z) values in Figure II. These replicate the exercises of columns 7 and 9 of Table IV (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 A2: Robustness of native IV estimates to wage variable and weighting

	Fixed effects				First differences			
	FT weekly wages		Hourly wages		FT weekly wages		Hourly wages	
	Men	Women	Men	Women	Men	Women	Men	Women
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Unweighted estimates								
$\log(N+M)$	-0.008	0.031	0.003	0.014	-0.045	-0.003	-0.027	0.005
	(0.017)	(0.022)	(0.019)	(0.027)	(0.031)	(0.043)	(0.028)	(0.036)
$\frac{M}{N+M}$	-0.469***	-0.554***	-0.399***	-0.563***	-0.448***	-0.514*	-0.359***	-0.464**
	(0.073)	(0.146)	(0.081)	(0.121)	(0.125)	(0.287)	(0.116)	(0.205)
Panel B: Weighted by cell employment								
$\log(N+M)$	-0.017	0.046*	-0.011	0.028	-0.075**	-0.009	-0.063*	-0.001
	(0.019)	(0.026)	(0.019)	(0.032)	(0.034)	(0.039)	(0.034)	(0.037)
$\frac{M}{N+M}$	-0.526***	-0.471***	-0.456***	-0.470***	-0.568***	-0.470*	-0.461***	-0.425*
	(0.075)	(0.163)	(0.084)	(0.139)	(0.137)	(0.272)	(0.137)	(0.216)
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 (33) to the wage definition and choice of weighting. Throughout, the right hand side is identical to columns 7 and 9 of Panel B of Table IV, and we also use the same instruments. Odd columns estimate the impact on the wages of native men, and even columns on 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 demographic composition, in line with the method described in Section 4.2. The estimates in Panel A are unweighted (as in Table IV); 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 II. 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 A3: Model for native wages: Alternative instrument specification

	First stage				Second stage	
	Fixed effects (FE)		First differences (FD)		FE	FD
	$\log(N+M)$	$\frac{M}{N+M}$	$\log(N+M)$	$\frac{M}{N+M}$	$\log W_N$	$\log W_N$
	(1)	(2)	(3)	(4)	(5)	(6)
$\log\left(\tilde{N}+\tilde{M}\right)$	1.462***	-0.137***	1.022***	-0.082***		
	(0.141)	(0.030)	(0.130)	(0.015)		
$\tilde{M} \times 10^{-9}$	-0.058	0.134***	-0.152	0.139***		
	(0.095)	(0.040)	(0.123)	(0.022)		
$\log(N+M)$					0.022	-0.042
					(0.033)	(0.041)
$\frac{M}{N+M}$					-0.406*	-0.683***
					(0.220)	(0.230)
SW F-stat	18.47	9.39	37.70	31.19	-	-
Observations	224	224	192	192	224	192

This table replicates the first and second stage estimates of the native wage equation (33) in Tables III and IV, but using an alternative instrument for migrant share. In the main text, our two instruments are $\log\left(\tilde{N}+\tilde{M}\right)$ and $\frac{\tilde{M}}{\tilde{N}+\tilde{M}}$; but here, we replace $\frac{\tilde{M}}{\tilde{N}+\tilde{M}}$ with $\tilde{M} \times 10^{-9}$, the predicted migrant employment *level* (which we have scaled to make the coefficients visible). Columns 1-4 are otherwise identical to columns 3-6 in Table III, and columns 5-6 are otherwise identical to columns 7 and 9 in Panel B of Table IV. See the notes under Tables III and IV for additional details. *** p<0.01, ** p<0.05, * p<0.1.

Table A4: First stage for occupation-imputed migrant stocks

	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)
$\log\left(\tilde{N} + \tilde{M}^{occ}\right)$	0.479**	0.035		0.306	0.043*	
	(0.221)	(0.028)		(0.199)	(0.022)	
$\frac{\tilde{M}^{occ}}{\tilde{N}+\tilde{M}^{occ}}$	-4.214***	1.008***	0.914***	-4.190***	1.036***	0.856***
	(0.879)	(0.134)	(0.068)	(0.705)	(0.134)	(0.072)
SW F-stat	19.82	23.16	178.30	9.11	11.67	140.88
Observations	224	224	224	192	192	192

This table presents first stage estimates for the native wage equation (33), 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 A5. 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 II. 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 A5: Native wage responses to occupation-imputed migrant stocks

	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		0.049		0.013		-0.128	
	(0.035)		(0.099)		(0.032)		(0.142)	
$\frac{M^{occ}}{N+M^{occ}}$	-0.292	-0.502**	-0.325	-0.618***	-0.270*	-0.343***	-1.202	-0.384***
	(0.191)	(0.192)	(0.750)	(0.211)	(0.156)	(0.104)	(0.875)	(0.104)
Observations	224	224	224	224	192	192	192	192

This table presents OLS and IV estimates of the native wage equation (33), but this time replacing education-experience migrant stocks, M_{ext}, with occupation-imputed stocks, M^{occ}_{ext}. Similarly, we replace our migrant stock instruments, $\tilde{M}_{ext}$, with occupation-imputed equivalents, $\tilde{M}^{occ}_{ext}$. 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 A4. Robust standard errors, clustered by 32 education-experience cells, are in parentheses. We apply the same small-sample corrections as detailed in Table II. 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 A6: First stage for broad education and experience groups

	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)
$\log(N+M)$	1.041***	-0.064***	0.767**	-0.055***	1.756***	-0.026	1.091***	-0.004
	(0.187)	(0.018)	(0.304)	(0.015)	(0.256)	(0.045)	(0.168)	(0.036)
$\frac{M}{N+M}$	1.283	0.297***	-0.195	0.223**	1.044	1.129***	0.346	0.563**
	(0.949)	(0.100)	(1.099)	(0.090)	(0.788)	(0.270)	(0.723)	(0.221)
SW F-stat	7.91	17.37	2.02	3.38	50.07	26.97	34.45	6.64
Observations	112	112	96	96	112	112	96	96

This table presents first stage estimates for the native wage equation (33), but this time across broader labor market cells. These estimates correspond to the IV specifications in Table V. In columns 1-4, we study 2 broad education groups (college and high school equivalents) and 8 experience groups; and in columns 5-8, we study the original 4 education groups, but 4 broad experience groups (1-10, 11-20, 21-30 and 31-40 years of experience). See Section 7.2 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 II. 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 A7: First stage for college interactions

	Fixed effects			First differences		
	$\log(N+M)$	$\frac{M}{N+M}$	$\frac{M}{N+M}$ * Coll	$\log(N+M)$	$\frac{M}{N+M}$	$\frac{M}{N+M}$ * Coll
	(1)	(2)	(3)	(4)	(5)	(6)
$\log\left(\tilde{N}+\tilde{M}\right)$	1.632***	-0.027	-0.040**	1.068***	-0.018	-0.046***
	(0.166)	(0.024)	(0.016)	(0.133)	(0.019)	(0.009)
$\frac{\tilde{M}}{\tilde{N}+\tilde{M}}$	1.385**	1.415***	-0.282***	1.665***	1.195***	-0.323***
	(0.595)	(0.103)	(0.059)	(0.505)	(0.121)	(0.047)
$\frac{\tilde{M}}{\tilde{N}+\tilde{M}}$ * Coll	-1.890**	-1.162***	0.517***	-3.282**	-1.038***	0.492***
	(0.850)	(0.223)	(0.110)	(1.295)	(0.205)	(0.083)
SW F-stat	4.81	5.34	3.69	1.17	1.49	1.00
Observations	224	224	224	192	192	192

This table presents first stage estimates for the native wage equation (33), but this time interacting the migrant share with a collge dummy (taking 1 for the "some collge" and college graduate cells). These estimates correspond to the IV specifications in columns 1-2 and 5-6 of Table VI. 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 II. 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: First stage for experience interactions

	Fixed effects			First differences		
	$\log(N+M)$	$\frac{M}{N+M}$	$\frac{M}{N+M}$ * (Exp $\geq$ 20)	$\log(N+M)$	$\frac{M}{N+M}$	$\frac{M}{N+M}$ * (Exp $\geq$ 20)
	(1)	(2)	(3)	(4)	(5)	(6)
$\log\left(\tilde{N}+\tilde{M}\right)$	1.331***	0.007	0.017	0.899***	0.008	0.013
	(0.190)	(0.026)	(0.019)	(0.179)	(0.025)	(0.011)
$\frac{\tilde{M}}{\tilde{N}+\tilde{M}}$	1.451**	1.177***	0.222***	0.802	0.680***	0.192***
	(0.656)	(0.191)	(0.068)	(0.850)	(0.177)	(0.065)
$\frac{\tilde{M}}{\tilde{N}+\tilde{M}}$ * (Exp $\geq$ 20)	-1.632***	0.250**	1.775***	-2.244***	0.495**	1.676***
	(0.581)	(0.113)	(0.043)	(0.715)	(0.192)	(0.069)
SW F-stat	64.59	86.34	96.49	27.75	14.60	19.35
Observations	224	224	224	192	192	192

This table presents first stage estimates for the native wage equation (33), 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 3-4 and 7-8 of Table VI. 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 II. The relevant 95% critical value for the T distribution (with $G-1=31$ degrees of freedom, where G is the number of clusters) is 2.04. *** p<0.01, ** p<0.05, * p<0.1.

Table A9: First stage for new and old migrant shares

	Fixed effects			First differences		
	$\log(N+M)$	$\frac{M^{new}}{N+M}$	$\frac{M^{old}}{N+M}$	$\log(N+M)$	$\frac{M^{new}}{N+M}$	$\frac{M^{old}}{N+M}$
	(1)	(2)	(3)	(4)	(5)	(6)
$\log\left(\tilde{N}+\tilde{M}\right)$	1.522***	0.052*	-0.046*	0.434***	0.035*	-0.033***
	(0.197)	(0.029)	(0.023)	(0.081)	(0.019)	(0.011)
$\frac{\tilde{M}^{new}}{\tilde{N}+\tilde{M}}$	2.581**	0.730**	-0.162	0.084	0.088	0.053
	(1.247)	(0.321)	(0.142)	(0.954)	(0.169)	(0.081)
$\frac{\tilde{M}^{old}}{\tilde{N}+\tilde{M}}$	-0.727	-0.468	2.509***	-0.330	0.197	1.693***
	(1.235)	(0.329)	(0.225)	(1.189)	(0.240)	(0.185)
SW F-stat	115.34	14.58	113.88	0.04	0.03	0.04
Observations	224	224	224	192	192	192

This table presents first stage estimates for the native wage equation (33), 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 VII. 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 $\log(N+M)$. 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 II. 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.