Immigrants and the US Wage Distribution*

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Abstract

A large body of literature estimates the relative wage impacts of immigration on low- and high-skill natives, but it is unclear how these effects map onto changes of the wage distribution. I document the movement of foreign-born workers in the US wage distribution, showing that, since 1980, they have become increasingly overrepresented in the bottom. Downgrading of education and experience obtained abroad partially drives this pattern. I then undertake two empirical approaches to deepen our understanding of the way foreign-born workers shape the wage structure. First, I estimate a standard theoretical model featuring constant elasticity of substitution technology and skill types stratified across wage deciles. Second, I estimate reduced-form quantile treatment effects by constructing a ceteris paribus counterfactual wage distribution with lower immigration levels. Both analyses uncover a similar monotone pattern: a one percentage point increase in the share of foreign-born leads to a 0.2–0.3 (0.2–0.4) percent wage decrease (increase) in the bottom (top) decile and asserts no significant pressure in the middle. When analyzing the drivers of this pattern, I find suggestive evidence for a novel mechanism through which local labor markets absorb foreign-born workers: occupational differentiation of immigrants relative to natives.

Keywords: immigration, local labor markets, wage structure, counterfactual distribution, quantile treatment effects.

JEL Codes: C21, J15, J21, J31, R23.

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1 Introduction

Since the early 1980s, the stock of immigrants to the US has been rapidly increasing and potentially disrupting labor markets across the country. Over the same period, the US wage distribution has experienced significant and uneven changes. Traditional economic models predict that foreign-born can affect relative wages so long, they alter the relative supplies of different skill types, thus directly changing the earnings structure (Borjas, 2013; Card, 2005). The overlapping nature of both phenomena further implies a possible linkage between them.

A large body of literature estimates this relative wage impact of immigration on low- and high-skill native workers. While this analysis is motivated by theoretical considerations, economic theory itself does not give definitive classification of exactly which workers comprise each skill group. For instance, is a worker with a single year of college experience low- or high-skill? This choice turns out to have important implications on the estimated effects of immigration.[1] Moreover, even if one knew the exact definition of each skill type, correct classification may be undermined by potential undervaluing of foreign-born workers' human capital attributes and credentials obtained abroad. Indeed, Batalova et al. (2018) estimates that one in four college-educated immigrants work in low-skill occupations (see also Dustmann et al., 2013). Measurement error in schooling and labor market experience presents another challenge to the correct allocation into skill types (Ashenfelter and Krueger, 1994). Even if we ignore these methodological hurdles, it is not clear how the predicted relative wage effects project onto changes in the earnings distribution.

The main goal of this study is precisely quantifying this mapping. I advance the literature by studying how the relative immigration wage impacts predicted by the textbook model translate into the wage structure. My analysis is guided by the intuition that higher skill imbalance between foreign and native workers asserts stronger wage pressure while a balanced immigrant flow expands the economy, leaving relative wages unaffected. An underlying theme throughout the paper is the stratification of skill types based on a unidimensional productivity measure – their location

[1] See Section 3.1 below for more details. Researchers have developed strategies for separating workers into skill groups, such as estimating the elasticity of substitution between different types of workers. Borjas et al. (2008) shows that in the immigration context, this approach is sensitive to the exact regression specification.

in the wage distribution (Dustmann et al., 2013). As explained later, this choice overcomes the methodological issues mentioned above.

In the first part of the paper, I extensively document the location and evolution of immigrants in the US earnings distribution since 1980. I begin with tracking their nationwide progression by quintile, which gives a first-order hint as to which native skill groups ought to experience the largest imbalance. I then test for skill downgrading among immigrants by comparing their position in the wage distribution with a prediction based on their skills having the same returns as natives. Next, I zoom in on their geographic and birthplace distributions and calculate skill concentration indexes for immigrants and natives in the cities with the largest stock of foreign-born. These indexes represent direct measures of relative shares distortion, further indicating the extent of possible relative wage effects.

In the second part of the paper, I attempt to make progress toward identifying the way immigrants reshape the wage distribution. To set ideas, I build a simple theoretical model of labor supply and demand featuring native and foreign-born workers within multiple skill groups and constant elasticity of substitution (CES) production technology. The model highlights the intuition that relative wage effects are a function of immigration-induced skill imbalance. Skill groups are defined by workers' position in the real wage distribution. This circumvents issues regarding the exact mapping of education and experience to skill types, possible skill downgrading among immigrants, or measurement error in schooling or effective experience. Moreover, using more disaggregate skill groups enables investigation of possibly heterogeneous effects within, for instance, broadly defined low and high skill types. I proceed with two distinct empirical strategies.

First, I estimate the main prediction of the theoretical CES model, relating local wages among natives and immigration pressure in the same skill group. To operationalize the uncertainty and flexibility of skill types, I use ordered probit regressions to predict every worker's decile of the *national* wage distribution (i.e., their skill type) as a function of their pre-determined characteristics. This procedure assigns probabilistic values for every worker to all skill groups (as in Card, 2001). It is designed to isolate variation of skill-specific labor stock plausibly unrelated to unobserved local labor demand factors. Labor supply for each spatial area is the sum of the skill-specific probabilities across all workers employed in the labor market. Intuitively, because this calculation is based on national and not local wage structures, it is uncorrelated with city-level shocks attracting immigrants. This quantity could also be viewed as the local stock of workers expected to be in each skill group in an economy without labor demand or supply distortions. Skill-specific wages are the corresponding regression-adjusted midpoint quantiles among native workers. For instance, if the bottom decile comprises the lowest skill type, its wage in each labor market is the respective 5th percentile of the local wage distribution.

Second, I estimate reduced-form quantile treatment effects (QTEs) of foreign-born workers using recent methodological advances by Chernozhukov et al. (2013) from the decomposition literature. Namely, I construct a ceteris paribus 2015 counterfactual wage distribution with lower immigration pressure. To account for potential endogenous selection of immigrants into labor markets, I incorporate a control function approach into the underlying distributional regressions. The control function is based on the shift-share networks instrument based on 1940 immigrant settlements. Comparing the actual and counterfactual earnings distributions at various quantiles of interest yields estimates of the impact of immigration. Additionally, I use this methodology to analyze other counterfactual immigration scenarios, such as keeping immigration levels or country-of-origin distribution fixed, as observed in 1980.

Descriptively, I find that since 2000, the wave of foreign-born workers to the US has become increasingly overrepresented in the bottom of the natives' wage distribution. While the foreign skill distribution was somewhat evenly spread in the 1980s, the US began receiving disproportionally more low-skill workers. Partially driving this pattern is skill downgrading in the labor market – immigrants' human capital is undervalued relative to natives'. In other words, there are more immigrants in the bottom of the distribution than what their education and experience would suggest. Furthermore, over time, the foreign-born workforce has become more locally concentrated by skill and dissimilar to natives, thus placing more pressure on the overrepresented low-skill group. These descriptive findings set an expectation of more severe skill imbalance in the bottom and the top of the wage distribution.

The causal results uncover heterogeneous impacts of immigrants on the wage distribution. Namely, foreign-born workers exert weak pressure in the very bottom and increase wages in the top, leaving the vast majority of the distribution largely unaffected. The results from the two considerably distinct empirical exercises are surprisingly in line with each other. A one percentage point increase in the share of foreign-born labor is associated with a 0.2-0.3 (0.2-0.4) percentage point decrease (increase) in the bottom (top) decile of the wage structure. Although most of the estimated magnitudes are small, they can certainly be masked when one focuses on two broadly defined skill groups. The pattern I observe is consistent with a recent summary of the literature by the National Academy of Sciences (NAS, 2017) but sheds a new perspective on the "winners" and "losers" of immigration. All in all, the small magnitudes suggest foreign-born workers did not play a key role in the observed wage structure changes.

To shed light on the potential drivers of this monotone pattern, I focus on the occupational distribution of immigrants and natives within skill groups. The motivation is that labor markets are, at least partially, segmented along occupations, as suggested by the wide range of occupations within each decile. If foreign-born workers are more differentiated relative to natives, they assert stronger downward wage pressure on fewer occupational groups, leaving a relatively larger segment less affected. To formalize this intuition, I calculate dissimilarity indexes between natives and immigrants for each decile of the wage distribution. I then compare this index to the estimated wage impacts of immigration net of the effects predicted by the CES model. The two patterns are strikingly overlapping: they are high in the bottom, lower in the middle, and high in the top. This result suggests a novel mechanism through which local labor markets can absorb foreign-born with small wage consequences: occupational differentiation among immigrants.

The data sources are the Integrated Public Use Microdata Samples (IPUMS) of the 1940, 1980, 1990, and 2000 US Censuses and the American Community Surveys (ACS) for 2008 and 2015. The outcome variable is real weekly wages among natives and spatial areas are Commuting Zones. Identification is based on (*i*) using variation in predicted labor supply stock by skill group based on the national rather than local wage distribution, (*ii*) controlling for city-specific time-varying productivity shocks as proxied by a Bartik index, and (*iii*) the immigrant networks instrument (Card, 2001) with 1940 as a base year. The first strategy is designed to purge local demand factors simultaneously attracting workers and raising earnings, while the second one additionally controls for them directly. The instrument relies on the assumption that a series of major geopolitical events throughout the post-1940 period (such as the end of World War II, the Bracero agricultural program, the Cuban Revolution, the Vietnam war, and the passage of the extensive Immigration and Nationality Act of 1965) have shuffled the local country-of-origin mix, breaking the autocorrelation between earlier immigrant settlements and current economic conditions. Throughout the paper, I conduct a series of robustness checks, such as focusing on native men and urban labor markets, using five or ten skill groups, using metropolitan areas, and focusing on hourly instead of weekly wages. None of these choices plays a crucial role in the results.

This paper is related to a large literature estimating the labor market effects of immigrants on native workers. Economic theory is consistent with a wide range of scenarios depending on the specific model and its built-in adjustment mechanisms. For instance, closed-economy models unambiguously predict negative (positive) wage effects for similarly (differently) skilled natives as a result of an immigration inflow. On the contrary, in open-economy Heckscher–Ohlin (HO) models, changes in input factors are offset by adjustments in the output mix; hence, immigration has no impact on relative wages.[2] Empirical studies have overall found small to null average effects, although a rich variety of estimates exists (e.g., Borjas, 2015; Peri and Yasenov, 2019; Ottaviano and Peri, 2012; Hunt, 1992; Monras, 2015).[3] Several papers analyze the effect of immigration on different points of the natives' wage distribution with mixed findings.[4] Most prominently, Dust-

[2]Many factors affect the theoretical prediction on the wage impact of foreign-born workers. These include the rate of capital adjustment, the degree of open economy trade, output mix adjustment, the degree of substitution in production between immigrants and natives, and labor demand effects. Distinguishing between short- and long-term effects is also crucial in any theoretical model. See Borjas (2013); Dustmann et al. (2008); Gaston and Nelson (2000) for thorough discussions on the relevant theoretical predictions.

[3]For recent reviews of the broader empirical literature, see Dustmann et al. (2017); Lewis and Peri (2015); NAS (2017); Peri (2016).

[4]Related to this strand of studies, but still focusing on "ow" (high school equivalent) and "high" (college equivalent) skill groups, Card (2009) relates relative immigrant shares across these groups in the US to the relative residual variance among natives wages. He finds no significant role of foreign-born workers on the rise of within-group

mann et al. (2013) build a model in which skill groups are defined as workers' positions in the wage distribution. Using data from the UK, they find that foreign-born workers depress wages below the 20th percentile but lead to wage increases in the top of the distribution. They also document significant skill-downgrading of foreign-born workers, which further motivates my approach. Next, Olney (2012) performs a similar empirical analysis across US states and incorporates offshoring into the analytical framework, showing no discernible effects of foreign-born workers. All these studies rely on the network-based shift-share instrument to isolate variation in immigration exposure unrelated to local factors. Lastly, Choe and Van Kerm (2014) analyze Luxembourg data utilizing the recentered influence function (RIF) regressions pioneered by Firpo et al. (2009). Without accounting for the endogenous selection of immigrants to localities, their analysis also uncovers no significant impact on various percentiles of the distribution.

My paper, although related, significantly differs from the aforementioned studies in several important ways. First, I study the wage structure in the US.[5] Labor markets in the US and Europe differ substantially in important aspects, such as labor and capital mobility, wage and employment rigidity, collective bargaining coverage, active labor market policies, etc. Research has shown that differences in labor market institutions impact the competition between native and foreign labor (Angrist and Kugler, 2003; Foged et al., 2019). It is therefore not clear how the findings from Europe would translate to the US. Second, I build a counterfactual wage structure and estimate reduced-form quantile treatment effects relative to a scenario with lower immigration levels, which is an entirely novel approach in the literature. Moreover, my empirical specification, motivated by the theoretical model, uses variation of immigrants across skill groups within each local labor market. This specification captures exposure to foreign labor more effectively than the overall share of immigrants, a crude measure used in most previous studies. The skill composition of foreign workers varies widely across cities (e.g., predominantly low skill in Los Angeles, CA, and

inequality.

[5]To the best of my knowledge, Olney (2012) is the only study which also uses US data. His paper is focused on estimating the joint effects of offshoring and immigration, building on a novel theoretical model and focusing on the 2000-2006 period. I extend his analysis, covering a longer time span and using variation in exposure to foreign-born labor across local labor markets rather than state-industry cells.

high skill in Austin, TX); hence, their mere share in the labor market is an inadequate measure of competition with native workers (see Card, 2001, 2005). Lastly, I build on Dustmann et al. (2013)'s idea and combine it with the probabilistic assignment to skill groups (as in Card, 2001) and prediction of workers' locations in the wage distribution (as in Greenwood et al., 1997). The justification and benefits this choice entails are laid out in Section 3.1.

2 Theoretical Model

Each local labor market in every time period produces a single good (Y) using capital (K) and labor aggregate (L), modeled in a Cobb-Douglas production function:

$$Y = AL^{1-\alpha}K^{\alpha}.$$

Here, A denotes an exogenous total factor productivity parameter and $\alpha \in (0,1)$ is the income share of capital. To reduce the notational burden, I leave implicit indexing local labor markets and time periods. To further simplify the exposition, all parameters are assumed to be time-invariant.

The labor input L is a Constant Elasticity of Substitution (CES) aggregate of $j = 1 \ldots J$ skill types:

$$L = \left(\sum_j \theta_j L_j^{\beta} \right)^{\frac{1}{\beta}},$$

where θ_j is a relative productivity parameter and $\frac{1}{1-\beta}$ denotes the elasticity of substitution between the skill groups. It measures the percentage change in the ratio of any two types of workers m and n, $\left(\frac{L_m}{L_n}\right)$, in response to a given percentage change in relative wages, $\left(\frac{w_m}{w_n}\right)$. Therefore, the higher the elasticity, the more easily substitutable are the different labor types. The groups are perfect substitutes when $\beta = 1$; hence, the elasticity is infinite. Skill types are stratified across deciles or quintiles of the wage distribution (see Section 3.1). This CES framework is the main workhorse in the labor demand literature studying the causes of inequality (e.g., Card and Lemieux, 2001; Goldin and Katz, 2009), the effects of technological changes (e.g., Acemoglu and

Autor, 2011) and the impacts of immigration (e.g., Borjas, 2003; Card, 2009; Dustmann et al., 2013; Ottaviano and Peri, 2012), among other topics.

For simplicity, capital is assumed fixed. In a competitive market, firms choose labor and capital quantities, taking input prices as given while the output serves as a numeraire and price is normalized to one. Profit maximization implies all input prices equal their respective marginal products. Upon totally differentiating the first order condition and taking logs, I obtain a simple linear expression relating skill-specific (log) wages and exposure to immigrants for each labor market (Dustmann et al., 2013):

$$\Delta log w_j = \Delta\psi - (1-\beta)\Delta log L_j + \Delta log\theta_j,$$

where $\psi = log(A(1-\alpha)\frac{K}{L}^{\alpha}L^{1-\beta})$ is a city-specific demand shifter common to all skill groups and $log\theta_j$ is a city- and group-specific productivity component. This expression makes clear that the relative wages of any two skill groups are a function of the relative share of foreign-born and the ratio of their productivity parameters, while all citywide factors cancel out.

Each labor type L_j is made up of native (L_j^{NAT}) and immigrant (L_j^{IMM}) workers who are perfect substitutes $(L_j = L_j^{NAT} + L_j^{IMM})$. The change in the (log) labor supply for each skill group following an exogenous influx of immigrants is then equal to $\Delta log L_j^{NAT} + \frac{\Delta L_j^{IMM}}{L_j}$. I assume that immigrants supply their labor inelastically while natives' labor supply is elastic with an exogenous elasticity parameter η[6], such that $\Delta log L_j^{NAT} = \mu + \eta\Delta log w_j + \delta_j$, where μ is an intercept common to all skill types and δ_j is a city- and group-specific supply shifter.

Equating labor supply and labor demand yields a simple linear expression relating skill-specific (log) wages and exposure to immigrants:

$$\Delta log w_j = \Delta\tilde{\psi} - \frac{(1-\beta)}{1-\eta(\beta-1)}\frac{\Delta L_j^{IMM}}{L_j} + \Delta\tilde{\phi}_j, \tag{1}$$

where $\Delta\tilde{\psi} = \frac{\Delta\psi-(1-\beta)\mu}{1-\eta(\beta-1)}$ is common to all skill groups' city-level parameter and $\Delta\tilde{\phi}_j = \frac{\Delta log\theta_j-(1-\beta)\delta_j}{1-\eta(\beta-1)}$

[6] More precisely, η measures the percentage change in the supply of native labor in response to a percentage change in their earnings.

is a city- and group-specific productivity term. Changes in skill-specific wages are a function of the pressure induced by skill-specific foreign labor, as measured by the change in their stock as percent of the relevant pre-existing labor force. This is the key relationship of interest in the empirical section below.

3 Empirical Strategy and Data

3.1 Skill Groups and Concentration Measures

3.1.1 Definitions and Measures

A starting point and a distinct feature throughout the empirical analyses is the choice of defining skills by workers' location in the wage distribution (as in Dustmann et al., 2013). This is contrary to the leading existing approach where workers' education and experience levels determine the labor type (e.g., Borjas, 2003; Ottaviano and Peri, 2012; Manacorda et al., 2012)), but it offers several important advantages.

First, being agnostic about how more primitive human capital attributes map onto skill groups circumvents a debate on the correct definition of a low-skill labor type. This has important implications for the estimated effects of immigration in the US (see Borjas et al., 2008; Ottaviano and Peri, 2012). Since the 1990s, there has been a disproportionately large number of foreign-born high school dropouts, arriving mostly from Mexico and Central America. Intuitively, treating high school dropouts and graduates as a single production input considerably diffuses the competition forces between native and foreign-born workers across a much larger segment of the labor market. Alternatively, assuming these education groups are distinct and non-substitutable inputs results in estimating more concentrated competition and stronger downward wage pressure among native dropouts.

A second advantage of my approach is avoiding the assumption that immigrants' credentials are valued in the same way as they are for natives. To the extent to which English language proficiency or academic institutions' quality and curriculum play important roles in the labor market, immigrants may not retain the full potential of their education and experience earned abroad. Employers may penalize credentials obtained in foreign languages or education systems with which they are less familiar or that are of worse quality (e.g., Card and Krueger, 1992). For instance, it is unclear whether a college graduate from Bulgaria can "compete" for job opportunities with an otherwise similar US high school graduate, Associate's degree holder, or college student. This renders classifying foreign-born workers into skill groups potentially problematic. Dustmann et al. (2013) show evidence for skill downgrading in the UK whereby foreign-born workers are over-represented in the bottom of the distribution relative to what their skills suggest. Following their work, in the subsection below, I describe the method I use to analyze skill downgrading in the US.

Third, this choice also avoids possible misclassification due to measurement error in schooling/experience, both of which have shown to be significant in certain cases (see Ashenfelter and Krueger, 1994; Dustmann et al., 2013).[7] Lastly, the assumption that individuals' rank in the earnings structure depends on their skill level has a long history in labor economics. For instance, it can be motivated by traditional human capital wage-determination models, in which earnings equal the price of a skill multiplied by its quantity (e.g., Heckman and Sedlacek, 1985; Fortin and Lemieux, 1998).

Rather than using observed location in the wage structure, I estimate *national-level* probability of being in each skill group using pre-determined workers' characteristics and ordered probit regressions. Skill groups could be distinct deciles or quintiles of the national wage distribution. This assignment cleans away part of the variation of labor types across spatial areas due to endogenous demand-pull factors. It also deals with the endogeneity of local wages with respect to immigration flows. The sum of skill-specific probabilities across all workers within a locality is the expected skill-specific stock of labor in the absence of local labor demand distortions. This mechanism can alternatively be viewed as assigning a probabilistic value of belonging to each

[7] The approach I undertake is similarly prone to misclassification due to measurement error in wages (e.g. Bound and Krueger, 1991). However, this will be problematic only for individuals at the cutoff points between two distinct skill groups (i.e., around decile/quintile cutoffs).

skill type, generalizing the standard procedure of attaching a single skill label to each worker. It thus recognizes the flexibility of earnings potential stemming from temporary occupational choice, life cycle dynamics, etc.

I run ordered probit regressions separately for native and immigrant workers and for each time period in the sample. I adjust all wages with a local price index to account for differential costs of living across areas (more on this in Section 3.5). The outcome is a discrete variable corresponding to the decile/quintile of the wage distribution. I flexibly control for demographic wage determinants such as education level dummies, experience, experience squared, race dummies, gender, marriage, and veteran status indicators, as well as all two- and three-way interactions. Additionally, in the regressions for foreign-born workers, I include country-of-origin dummies, years since arrival to the US, their interaction, and interactions with years of education. These variables are proxies for immigrant assimilation and strongly predict wages. Each probit model ultimately yields predicted probabilities of belonging to each skill group for every worker.

3.1.2 Skill Downgrading

This section discusses a method to analyze skill downgrading among immigrants in the US, following Dustmann et al. (2013). I begin by constructing a predicted wage structure for natives based on their demographic characteristics. Next, I assign the estimated returns to these characteristics to foreign-born workers – that is, I construct predicted immigrants' earnings assuming their demographic and human capital characteristics are valued as they are for natives. This procedure yields the predicted stock of foreign-born at each point in the wage distribution. I also calculate the observed immigrants' stock in the actual wage structure and take the ratio of the latter to the former.

This ratio is designed to indicate whether immigrants' credentials are over/undervalued in US labor markets. A value greater (smaller) than one at a particular point in the distribution implies immigrants are overrepresented in that segment relative to a scenario in which their human capital attributes are valued as they are for natives. Hence, a skill downgrading story is consistent with this ratio being greater (smaller) than one in the bottom (top) of the distribution. In practice, I perform this procedure for five percentile bin intervals and estimate regressions separately for men and women, as well as each time period in the sample.

3.1.3 Imbalance Indexes

Motivated by the insight that immigrant workers may alter natives' wages so long that they distort relative labor shares, I measure their skill concentration in two ways. The first index captures immigrants' skill concentration relative to an even baseline scenario (Herfindahl concentration index), while the second one measures skill clustering relative to the native workforce (Duncan dissimilarity index). First, given a population of workers with a characteristic k (e.g., country of origin or a city of residence) and a categorization of $j = 1 \ldots J$ skill types, the concentration index among group k is defined as:

$$\textit{Concentration Index}_k = \sum_{j=1}^{J} b_{jk}^2,$$

where b_{jk} is the share of type j. By construction, the index takes on values between 0 and 1, with a higher value indicating stronger concentration intensity and hence relative labor shares imbalance. For instance, in the extreme case in which a particular immigrant group k (e.g., Bulgarian foreign-born) is comprised only of low-skill workers ($b_{1k} = 1$ and hence *Concentration Index*$_k = 1$), their presence will place strong downward wage pressure on low-skill natives, since their labor is now relatively more abundant.

The concentration index measures the degree to which a particular group is concentrated relative to a completely even distribution. However, when interested in relative labor shares distortions among native workers at the local labor market level, this may be an informative but not an ideal measure. For instance, native workers in Washington, DC, are disproportionally high-skill, in which case a high-skill immigration wave may keep relative labor shares (and hence wages) undisturbed. To account for this, I use a measure of dissimilarity between immigrant and native groups.

Second, the dissimilarity index measures the skill type evenness with which the two nativity groups are distributed within each labor market. For each group (e.g., city) k, it is defined as:

$$\textit{Dissimilarity Index}_k = \frac{1}{2} \times \sum_{j=1}^{J} |b_{jk}^{IMM} - b_{jk}^{NAT}|,$$

where b_{jk}^{x} indicates the respective share of labor type j among the population $x \in \{IMM, NAT\}$ with characteristic k. By construction, the index takes on values between 0 and 0.5, with higher ones representing a higher degree of dissimilarity between the two nativity groups. It is interpreted as the percentage of foreign-born which need to be reallocated in order to maintain a completely uniform distribution of skill groups. Note that, in a constant returns to scale world, it is precisely this scenario that ensures no wage effects of immigration. This is indeed the index of interest when measuring native relative shares distortion induced by foreign-born flows.

3.2 Theoretical Method

Next, I outline the empirical specification based on equation (1) derived from the theoretical CES model. Let r denote local labor market (or city) and t time period, while j still indexes skill groups. The equation I estimate is:

$$\Delta log w_{rt}^{j} = \gamma_0^j + \gamma_1^j \Delta p_{jrt} + \gamma_2^j \Delta \mathbf{X}_{rt}^{j} + \delta_t^j + \kappa_r^j + \Delta \epsilon_{rt}^{j}, \tag{2}$$

where

$$\Delta p_{jrt} = \frac{L_{jrt+1}^{IMM} - L_{jrt}^{IMM}}{L_{jrt}}.$$

The quantity Δp_{jrt} measures the local change in the stock of immigrants between two time periods as a proportion of the initial labor force.[8] The superscript j denotes that I estimate this equation separately for each skill group (decile), thus obtaining the effect of immigration on the entire wage

[8]This specification avoids spurious endogeneity concerns of less careful choices, such as differences in the share of foreign-born (see Card and Peri, 2016).

distribution. The outcome variable is the change in log real weekly wages among native workers. First-differencing over time periods eliminates all citywide skill-specific and time-invariant factors affecting labor markets (e.g., $\Delta\tilde{\psi}$). Next, $\Delta\mathbf{X}_{rt}$ are time-varying control variables (e.g., Bartik growth index [9] demographics) and $\Delta\epsilon_{rt}$ is an idiosyncratic mean-zero error term. The term δ_t captures decade-specific fixed effects, allowing for differential trends in earnings by skill. Similarly, κ_r controls for city-level trends, which may differ by decile.

The coefficient of interest, γ_1, is a function of the elasticity of substitution between the labor types ($\frac{1}{1-\beta}$) and the labor supply elasticity of natives (η).[10] It is interpreted as the percent change in natives' wages for a one percentage point increase in local immigration stock. All regressions are weighted by the labor force size and the standard errors are clustered at the local labor market level, accounting for residual autocorrelation in wages within cities across time. I estimate equation (2) with OLS and 2SLS using the networks-based instrument outlined in Section 3.4.

As explained in Section 3.1 above, I use predicted rather than observed skill type j. In particular, skill-specific labor supply in the local labor market, L_{jrt}, is the sum of all skill-specific probabilities across both native and immigrant workers in city r and time period t. Alternatively, this quantity can be interpreted as the number of workers in (r, t) who are expected to be of type j in the absence of market distortions. For instance, imagine a single city comprises only two workers and there are two skill groups. Furthermore, considering their characteristics and the national wage distribution, these individuals have predicted probabilities of belonging to the bottom and top skill groups equal to 0.8 and 0.2, respectively. In this scenario, I would calculate that this city has 1.6 low-skill workers and 0.4 high-skill ones.

Skill-specific wages ($logw_{jr}$) are the corresponding midpoint quantiles of the local native (log) earnings distribution. For instance, if skill types are defined as deciles (quintiles) of the earnings structure, the wage for the lowest skill group in city r is the 5th (10th) quantile in the local dis-

[9] Specifically, it is constructed as follows: $Bartik_{rt} = \sum_q share_{qr}^{1980} \times \Delta^{1980} EMPL_{qt}$ where q denotes industry, $share_{qr}^{1980}$ is the 1980 industry share in locality r, and $\Delta^{1980} EMPL_{qt}$ represents the nationwide growth of industry q between 1980 and t.

[10] Separately estimating this parameter for each skill group can be thought of as allowing one or both elasticity parameters to vary by decile.

tribution, the wage for the second-lowest is the 15th (30th) quantile, etc. I use Mincerian wages by purging differences in natives' observable characteristics to account for differential sorting of workers into local labor markets. Namely, I regress natives' wages on the human capital variables included in the probit regressions and city fixed effects, and I calculate the corresponding quantiles of the predicted residuals for each labor market and skill type. This regression adjustment reduces the sampling variation and, most importantly, is designed to account for bias arising from correlations between immigration exposure and observable attributes of natives. I repeat this procedure for every time period in the sample.

3.3 Counterfactual Distribution Method

In addition to estimating the relationship derived from the CES model, I use a reduced-form method to measure the impact of immigration on the wage distribution. The thought experiment is comparing the observed wage structure with a ceteris paribus one that would have prevailed with lower immigration levels. To construct this counterfactual distribution, I use recent econometric advances by Chernozhukov et al. (2013) from the decomposition literature. A brief illustration of the empirical method is in order.

Let $F_{logw}(\cdot)$ and $F_{logw|p}(\cdot)$ denote the marginal and conditional cumulative log wage distribution functions (CDFs). For the time being, with the goal of simplifying the exposition, I ignore individual characteristics and assume wages depend only on immigration exposure p. Let p stand for current immigration levels, while $\tilde{p}$ denotes a percentage point lower pressure, so that the estimates have a semi-elasticity interpretation similar to equation (2). I can decompose the counterfactual marginal wage distribution of interest, $F^C_{logw|\tilde{p}}(\cdot)$, into a mixture of the observed wage structure and the foreign-born marginal distributions as follows:

$$F^C_{logw|\tilde{p}}(\cdot) \equiv \int F_{logw|p}(\cdot) dF_{\tilde{p}}(\cdot).$$

Chernozhukov et al. (2013) propose tracing out $F_{logw|p}(\cdot)$ with a continuum of binary regressions in which the outcome is an indicator for $logw$ taking on a lower value.[11] The authors establish bootstrap validity results and practical procedures for correctly estimating confidence intervals for this counterfactual distribution. The second term, $F_{\tilde{p}}(\cdot)$, is a marginal distribution which could be estimated with standard density estimation methods (e.g., Silverman, 1998). An implicit assumption here is that changes in the marginal distribution $F_p(\cdot)$ do not alter the conditional density $F_{logw|p}(\cdot)$. In other words, changing immigration levels, p, does not shift structural economic parameters that change the relationship between p and $logw$. Given that I consider small changes in p, this assumption is unlikely to be violated.

The object of interest in this framework is the QTE, defined as the horizontal difference between the observed and the counterfactual CDFs at any given quantile τ. Given estimates of the two distributions, these are easily calculated as:

$$Q\hat{T}E(\tau) = \hat{F}^{-1}_{logw|p}(\tau) - \hat{F}^{-1,C}_{logw|\tilde{p}}(\tau).$$

The QTEs are interpreted as the percent change in the τ-th quantile of the wage structure for a ceteris paribus increase in immigration exposure by one percentage point. Note here that τ proxies for skill as it refers to position in the distribution. For example, if skill types are stratified across deciles (quintiles), $QTE(5)$ ($QTE(10)$) corresponds to the wage impact on the "average" worker in the bottom skill group.

To approximate the natives' wage distribution $F_{logw|p}(\cdot)$, I use a series of distribution regressions controlling for Mincerian-type and city-level characteristics:

$$logw_{irj} = \beta_0 + \beta_1 p_{rj} + \beta_2 \mathbf{X}_i + \beta_3 \mathbf{W}_{rj} + \sigma_r + \mu_j + \epsilon_{irj}, \tag{3}$$

where i denotes worker, r labor market, and j skill group. The term p_{rj}, meant to capture immigra-

[11] A related and commonly-used method to construct this counterfactual uses reweighing and is proposed by DiNardo et al. (1996). Chernozhukov et al. (2013) explain that the two approaches are equivalent when the model is fully saturated. For an alternative, simulation-based approach, see Machado and Mata (2005). Fortin et al. (2011) provide a thorough review of the decomposition literature, documenting the advantages and disadvantages of each approach.

tion exposure, is the share of foreign-born labor in city r and skill type j. The vector $\mathbf{X}_i$ contains individual level covariates and their interactions, also included in the ordered probit regressions, while $\mathbf{W}_{rj}$ includes the Bartik index for employment growth, controlling for local demand-pull shocks. Lastly, σ_r and μ_j represent city and skill fixed effects, capturing aggregate factors affecting local labor markets and skill types.

As discussed in Section 3.4 below, p^t_{rj} is likely to be correlated with labor demand shocks simultaneously attracting foreign-born and raising wages (Borjas et al., 1996). In order to interpret the estimated $QTE(\tau)$'s as causal, I need to address this endogeneity problem. I use control functions, which are a general method for dealing with endogenous variables in non-linear settings. A control function is a variable which, when added in a regression equation, renders an endogenous variable suitably exogenous, allowing consistent estimation of policy effects. This function is generally unknown and usually estimated in a first step (see Cameron and Trivedi, 2005; Wooldridge, 2015).

To proceed, I model immigration exposure as follows:

$$p_{irj} = \alpha_0 + \alpha_1 \hat{p}_{rj} + \alpha_2 \mathbf{X}_i + \alpha_3 \mathbf{W}_{rj} + \sigma_r + \mu_j + u_{irj},$$

where $\hat{p}_{rj}$ is the shift-share instrumental variable described below and all other terms are defined as above. In this framework, the control function is the estimated residual $\hat{u}_{irj}$. The formal identification assumption is a quantile independence between the structural error term (ϵ_{irj}) and the immigration share (p_{rj}) conditional on the control function ($\hat{u}_{irj}$) and all exogenous covariates and fixed effects. Note that this condition, although common, is stronger than the usual mean independence in traditional linear models, as it must hold at each point of the distribution.

To summarize the estimation, using cross-sectional data in a single time period, I first regress the immigration share p_{jr} on the shift-share instrument $\hat{p}_{jr}$ and all exogenous variables $\mathbf{X}_i$, $\mathbf{W}_{rj}$ and fixed effects and obtain the predicted residuals $\hat{u}_{irj}$. These serve as the control function and are added to equation (3). I then proceed to estimate the counterfactual wage distribution using distribution regressions. The conditional earnings distribution given the included controls, $F_{logw|p}(\cdot)$, is estimated using 100 linear regressions and inverted to get the quantile function. Standard errors are obtained from 20 bootstrap replications. As a robustness check, I use a logistic model. All regressions are weighted by Census personal weight. To account for correlation in earnings within cities, I use a cluster bootstrap method with 20 replications of the entire estimation. Lastly, I obtain the $QTE(\tau)$'s of interest by juxtaposing the actual and counterfactual earnings structures.

Differences between the Two Approaches. The two methodological approaches rest on slightly different identification assumptions and estimate similar but distinct quantities. First, the theoretical model requires that the shift-share instrument separately satisfies the exclusion restriction for immigrants in each decile of the wage distribution – namely, that the predicted stock of immigrants is uncorrelated with local labor demand shocks for each skill group. On the contrary, the counterfactual distribution model assumes quantile independence between the structural error term (i.e., labor demand) and immigration share conditional on the control function – that is, the conditional quantile function of the structural error does not depend on immigration exposure at any point of the distribution.[12] It further requires that changes in the marginal density of immigration exposure do not result in changes in the conditional density of log wages given immigration levels. Second, the former approach yields an estimate of the average effect of immigration in each decile, while the latter one directly compares two full wage distributions at each point. Third, the theoretical approach is derived from a formal labor supply and demand model and, thus, the estimated coefficients have a clear interpretation in terms of structural elasticity parameters. The latter approach instead yields purely reduced-form data-driven estimates. The two approaches will yield different results if, for instance, the shift-share exogeneity varies non-trivially along the wage distribution or if position in the earnings structure is an unstable proxy for skill. In the first case, the identification assumption may be differentially satisfied, while in the second one, the two methods

[12] Lee (2007) formally states the identification assumption for the control function approach in a quantile regression framework. Note that, in the first step, I use a distribution mean regression to estimate the conditional wage distribution, which I later invert to obtain the quantile function. An alternative approach is to directly estimate the conditional quantile function using a linear quantile regression model, which is the framework studied by Lee (2007). I choose the former mainly due to its computational advantage, and my results are robust to this alternative choice.

would estimate different objects.

3.4 The Shift-Share Networks Instrument

It is well-known that immigrants are not randomly dispersed across cities but self-select into certain localities. They are particularly likely to locate into places with booming labor demand, where wages and employment are on upward trajectories (Borjas et al., 1996). Hence, identifying the causal effect of immigrants requires using isolating plausible exogenous variation in their stock. The national-level probit regressions are designed to mitigate such endogeneity concerns. Their skill group predicted probabilities are "clean" of local demand factors because they (*i*) are estimated using pre-determined worker characteristics and (*ii*) predict location in the national, not local, wage structure. Additionally, the Bartik index further controls for local time-varying productivity shocks, which may serve as pull factors in attracting foreign-born workers to booming markets. To go one step further, I use an instrumental variable strategy based on the well-known network instrument (Card, 2001).

Possibly due to the importance of immigrant networks – for instance, in channeling information or in the variety of ethnic goods and services – newly-arriving foreign-born are more likely to settle in areas with a larger community of co-nationals (Bartel, 1989). Examples include large early settlements of Irish in Boston, Mexicans in Los Angeles, and Italians in Philadelphia. This provides an opportunity for constructing an instrumental variable, which can predict the current immigrant labor force but is plausibly unrelated to other factors attracting foreign-born (e.g., local labor demand forces). Specifically, we can allocate the total immigrant stock proportional to the respective foreign-born shares in an earlier period, by country of origin. The argument for the exclusion restriction rests on the idea that the distribution of immigrants in an earlier time period is exogenous to current local labor demand conditions.

Precisely, for migrants from each country of origin c, let ρ_{cr}^{1940} denote their share located in city r in year 1940, π_{jc} denote their national share in skill group j, and ω_{tc} denote their the national stock at time t. Note that a series of large-scale international or immigration-related events – such as the end of World War II, the end of the Bracero agricultural program, the Cuban Revolution, the Vietnam and Korean wars, and the passage of the Immigration and Nationality Act of 1965 – took place post-1940. The idea is that they reshuffled the country-of-origin mix among foreign-born workers to break the autocorrelation between unobserved demand shocks that attracted immigrants in the past. Assuming each term is unrelated to *local* demand factors, I construct the instrumental variable $\Delta\tilde{p}_{jrt}$ as follows:

$$\Delta\hat{p}_{jrt} = \frac{\hat{L}^{IMM}_{jrt+1} - \hat{L}^{IMM}_{jrt}}{\hat{L}^{IMM}_{jrt} + L^{NAT}_{jrt}},$$

where

$$\hat{L}^{IMM}_{jrt} = \sum_{c} \rho^{1940}_{cr} \times \pi_{jc} \times \omega_{tc}.$$

This is commonly referred to as shift-share, supply-push, Bartik-style, network-based, or enclave instrument. Examples of studies using an instrument based on this argument are Card (2001, 2009); Cortes (2008); Dustmann et al. (2013); Foged and Peri (2016), among numerous others.

3.5 Data

The data sources are the Integrated Public Use Microdata samples from the US Census 1940, 1980, 1990, and 2000, and the American Community Surveys (ACS) 2008 and 2015 (Ruggles et al., 2015). The decennial datasets are representative 1-in-20 national random samples and the ACSs are 1-in-100 samples. As a main geographical unit approximating local labor markets, I use the definition of Commuting Zones (CZ). They are independent regions defined as grouping of counties with strong commuting ties within. The Census datasets consistently identify 722 distinct CZs in the US mainland. I verify the robustness of the results using Metropolitan Statistical Areas (MSAs) instead, in which case I restrict the sample to 119 consistently defined MSAs in this time period.[13]

The main sample consists of workers age 18–64 in the labor force, not in group quarters or

[13] All MSA results exclude year 2015 because IPUMS' *metarea* variable is unavailable for this time period.

self-employed, and with positive reported earnings. I loosely refer to this group as “labor force” throughout the paper. All results are estimated from a sample of native workers only. Similarly, to control for compositional changes, all skill group (quintile/decile) assignments are based on the native wage distribution. Following the literature, I define immigrants as individuals who are foreign-born, naturalized citizens, or non-US citizens. To avoid issues with differential female labor force participation in early time periods, I run specifications with male workers only.

The outcome variable is log real weekly wages for native-born workers. It is constructed by dividing each respondent’s annual total pre-tax wage and salary income by the usual works worked and adjusting for local cost of living using a local price index following Moretti (2013). Specifically, I estimate state-year level “monthly gross rental costs” (contract rent amount plus additional costs for utilities and fuels) for two- and three-bedroom rental units with the 2008 median standardized to one. This adjustment is meant to correct for the fact that, for instance, a $20 hourly wage does not carry the same purchasing power in San Francisco, CA, as in Memphis, TN. It asserts that, in estimating nationally based wage bins, earnings across localities are comparable. As a robustness check, I also use hourly real wages calculated by dividing weekly wages by the reported usual hours worked per week.

When estimating the theoretical model, in the main specification, I use 10 skill groups, each one corresponding to a separate decile of the wage distribution. The final dataset is a CZ-skill group panel with observations for years 1980, 1990, 2000, 2008, and 2015, resulting in a sample size of 36,100. As a robustness check, I use five skill types stratified across quintiles of the same distribution. When estimating quantile treatment effects with the reduced-form approach, I use cross-sectional worker-level data for a separate time period. I use year 1940 as a base time period in constructing the shift-share instrument.

4 Results

4.1 Descriptive Findings

The Position of Immigrants in the Wage Distribution. Figure 1 tracks the evolution of immigrants in the natives' wage distribution from 1980 until 2015 by quintile and decade. The vertical bars represent the stock of foreign-born workers (in millions), and the dashed line displays their share in the labor force (right vertical axis). The leftmost bar in each time period refers to the lowest quintile (i.e., the bottom 20 percentiles), the second bar denotes the second quintile (i.e., 21th-40th percentiles), etc. By construction, the stock of native workers in each quintile is equal, so the bars can also be interpreted as ratios of immigrants to natives by skill group.

The stock and proportion of immigrants have both increased steadily and substantially and, more importantly, their skill mix has become more unevenly distributed over time. In 1980, there were about one million foreign-born workers in each quintile, resulting in a total stock of about 4.9 million, equivalent to 6.5% of the labor force. Around the year 2000, the US started receiving disproportionally more low-skill foreign labor. In 2015, the US hosted 6.2 million immigrants in the lowest quintile alone. This number for the highest skill group was 2.8 million and the overall share of foreign-born in the labor force surpassed 17.5%. The increasing skill imbalance among foreign-born is highlighted by the rising concentration index over time: it was equal to 0.21 in 1980, increased to 0.24 in 2000 and 2008, and dropped back to 0.23 in 2015. As predicted by the CES model, this concentration pattern may certainly place downward pressure on the wages of low-skill natives, while high-skill workers are predicted to experience relative gains.

Figure A1 presents the position of immigrants in the wage structure by cohort of arrival to the US. In each time period, I restrict the sample to immigrants who arrived between 10 and 20 years prior to the survey. For example, immigrants who came to the US between 1960 and 1970 (1970 and 1980) are observed in the 1980 (1990) Census. I make no restrictions based on age so that compositional effects are possible. Such effects may arise if, for instance, the US received proportionally more young (or low-skill) immigrants over time. In terms of immigration policy shifts, the year 1965 marks the passage of the Immigration and Nationality Act, which abolished the quota-based admission criteria dating back to the 1920s. The new system dictates that higher priority is given to relatives of US citizens and permanent residents, as well as foreign-born with specialized skills. Figure A1 shows that, without controlling for compositional changes, the cohort performance in the labor market closely follows the aggregate pattern.

Skill Downgrading. Next, I compare this observed stock of immigrants by skill group to the predicted number of foreign-born based on their human capital characteristics. I provide two pieces of evidence that immigrants' skills are downgraded across US labor markets, motivating the choice of stratifying skills across positions in the wage distribution. First, Figure 2 shows the stock of immigrants by education group over time. The education groups range from secondary or lower (lightest shade of gray) to Master's degree or higher (darkest shade of gray), with darker color corresponding to higher educational attainment. Note that these bins do not correspond to equal native labor force size and hence do not have a ratio interpretation as in Figure 1.

We do not observe a strong overrepresentation in the bottom of the education distribution as we do in the wage structure. For instance, in 2015 there were nearly as many college experienced foreign-born (9.5 million) as high school graduates or workers with lower education (10.2 million). Assuming a strong correlation between education and earnings, this pattern suggests a potential undervaluing of immigrants' education credentials. Nevertheless, education is not the only factor determining one's rank in the wage structure. I therefore test for skill downgrading more directly using a regression framework following the methodology explained in Section 3.1.

Second, Figure 3 presents the ratio of observed to predicted number of immigrants at each point of the wage distribution and time period. The predictions are based on a scenario in which immigrants' characteristics are valued in the same way as they are for natives. These include education and experience possibly obtained abroad in foreign languages and education systems. Put concisely, I estimate the wage returns to individual characteristics for natives in a regression framework and assign these returns to immigrants. This yields a predicted wage structure among foreign-born and hence stock of immigrants in each point of the distribution. Lastly, I take the ratio of the actual stock of immigrants to the predicted one. A value greater (smaller) than one indicates foreign-born are over(under)-represented in that segment of the distribution. Similarly, a flat line with a value of one is consistent with an even number of predicted and observed stock of foreign-born throughout the wage structure, and hence no systematic skill down/upgrading.

The figure shows that, regardless of time period, foreign-born are overrepresented in the bottom and in some years underrepresented in the top. Put differently, among otherwise identical native and foreign-born workers, the former are more likely to rank higher in the wage distribution. There are about twice as many immigrants in the segment around the 20th wage percentile as predicted by their skills. This magnitude is in line with the extent of downgrading in the UK documented by Dustmann et al. (2013). There emerges no particular pattern over time.

Figure A2 shows how the strength of this skill downgrading varies by length of stay in the US. Each panel shows a separate group of immigrants ordered by tenure in the country, from shortest to longest. If employers value labor market experience in the US, we might expect the extent of downgrading to diminish with a longer stay here. This is indeed what Figure A2 shows. While in Panel A we see that among newly-arrived foreign-born, there are 2.5 times more workers around the 20th percentile than predicted by their skills, this ratio drops down to about 1.3–1.5 for immigrants with 20 or more years of experience in the US, shown in Panel C. Nevertheless, this pattern is still present and does not seem to disappear even among foreign-born with extensive length of stay in the US.

Taken together, Figures 1–3 imply there are more immigrants in the bottom of the wage distribution compared to what their skills suggest – i.e., their skills are downgraded in US labor markets. This renders classifying immigrants into skill types based on their education and experience inadequate and motivates the choice of using location in the wage distribution as a more direct skill proxy.

Heterogeneity by Birthplace. Next, I focus on which immigrant groups have contributed the most to the large and imbalanced growth over the last decades. Panel A of Figure 4 presents the 2015 skill group distribution by area of origin for the five largest origin groups: Mexico, Rest of

Americas, India, Eastern Europe, and China. These sending areas account for nearly three out of four (73.9%) foreign-born in the labor force. All values within an immigrant group across skills sum up to one. Note that, by definition, the skill shares among the native workforce are all equal to 0.2 (20%), so deviations from this value are interpreted as a sign of imbalance. Foreign-born from Mexico and the rest of Latin America are predominantly low-skill, heavily represented in the bottom of the wage structure. Only 3.9% of them ranked in the top quintile, while 41.8% were below the 20th percentile. On the other hand, immigrants from India are more likely to be high skill: 40% of them fall into the top wage quintile. Lastly, the Chinese and the Eastern Europeans are the most balanced groups by skill type, minimally disrupting skill type shares among natives at the aggregate level.

To give a sense of how this pattern has evolved over time, Panel B shows the 1980–2015 growth rate for each origin group and skill type. The growth rates of Mexican and Latin American foreign-born have not been as concentrated as their current distribution. For instance, the Mexican-born labor force in the bottom (top) quintile grew by a factor of 6 (4.1). This implies the Mexican community in 1980 was also unevenly distributed by skill type, although to a slightly smaller degree. On the other hand, immigrants from India have grown most in the top (growth rate equal to 14.8) and the bottom (13.8) of the skill distribution. The flows from Eastern Europe have been surprisingly evenly distributed, suggesting the immigrant group was balanced in 1980 as well.

All in all, this figure demonstrates the significant variation of skill types by country of origin. Immigrants from Mexico and Latin America are, on average, low-skill, while foreign-born from China and India are more likely to fall into the top of the wage distribution. Appendix Table A1 shows more detailed related statistics and extends this analysis to other areas of origin.

Geographic Heterogeneity. National trends are limited in giving insights relating to relative skill share imbalance because workers compete for jobs locally. To gain a better perspective of the competition between natives and foreign-born, I zoom in on specific CZs. Panel A of Figure 5 shows the largest immigrant skill group in 1980 by CZ. Darker shades of red correspond to higher skill level. There is a significant variation of immigrant skill types across spatial areas. The majority of the West was home to mostly low-skill foreign-born, originating mostly from Latin America and Mexico and in part from Europe. At the same time, the Midwest and parts of the North had the largest groups of high-skill immigrants, mostly Europeans.

To illustrate the dynamics of the spatial allocation by skill, Panel B of Figure 5 shows the same values for 2015. Foreign-born skill groups have grown more dispersed over time, with an increase in state variation of the most representative skill group. The two lowest skill types are the most representative in the majority of cities. This is the case for most of the West and the entire state of California and is driven by foreign-born from Mexico and Latin America. On the other hand, high-skill immigrants – mostly arriving from India, China, and Europe – are most common in Seattle, WA, parts of Texas, the Midwest, and the Northeast. Overall, the figure illustrates the considerable variation in immigrant skill groups across localities, facilitating the estimation of their impact on the wage structure.

To zoom in on local skill share distortions one degree further, Figure 6 presents skill group concentration (black squares) and dissimilarity (blue diamonds) indexes in the top immigrant-receiving cities for years 1980 (Panel A) and 2015 (Panel B). Higher values correspond to stronger concentration and more uneven skill distribution between immigrants and natives. Three features of this figure are noteworthy. First, foreign-born workers have become more concentrated by skill over time within local labor markets. This pattern is driven by low skill only (e.g., in Los Angeles, CA, and Miami, FL), as well as by low- and high-skill immigrants (e.g., in New York, NY, and Seattle, WA). Second, immigrants are now more concentrated by skill than natives in each CZ (concentration indexes for natives are not shown here). In 1980, this was not true for a third of these cities: Chicago, IL; Houston, TX; Washington, DC; and Seattle, WA. Lastly, and perhaps most importantly, the native and immigrant workforce has become, on average, more dissimilar over time, as illustrated by the increasing dissimilarity index within cities. While in 1980 only a single city (Los Angeles, CA) had a dissimilarity index higher than 0.25, in 2015 half of the cities in this figure had such values (New York, NY; Chicago, IL; Houston, TX; Washington, DC; Dallas, TX). In a constant return to scale world, a balanced skill mix implies a production expansion in which relative input prices are unaffected.

Ordered Probits and Predicting Skill Types. As explained in Section 3.1, I predict workers' location in the national earnings structure with ordered probit regressions. A primary benefit of this procedure is to purge local demand factors simultaneously attracting workers and raising input prices. I generate predicted probabilities for each individual belonging to every skill group, which I use to calculate city-level skill-specific labor supply. Before proceeding to estimating the theoretical model, it is useful to verify the extent to which these regressions correctly predict workers' positions in the earnings structure.

Panel A of Table A3 shows some observed demographic characteristics in 2015 by quintile. The figures look very similar for all time periods. As we move to upper parts of the wage distribution, the workforce is comprised of fewer women, fewer ethnic minorities (except for Asians), more highly educated, fewer high school dropouts, fewer young people, and more married workers. Interestingly, 16% of all workers in the bottom quintile in 2015 were college graduates. This signals the inability to capture productivity using education level alone and highlights the need to stratify skill types along other dimensions. This panel asserts well-documented facts that whites, men, and more educated and experienced workers earn higher wages in the labor market.

Panel B shows the same characteristics as predicted by the ordered probit regressions – that is, I assign every individual the quintile with the highest predicted probability and summarize demographics by skill group. Note that this is a stricter classification than the one I use to calculate labor supply, where I use the variation in probabilities across all skill groups for each worker. For example, a certain individual may have a predicted probability of 0.7 of belonging to the bottom quintile and 0.3 of belonging to the second lowest quintile. In this table, they would be classified in the bottom one, but when calculating the number of workers by skill group in the analyses below, they will contribute to the second lowest quintile (with 0.3 times their Census sampling weight) as well as to the bottom one. While the model does not replicate the observed demographics exactly, it captures the general trends quite well. As we move higher in the earnings structure, it predicts the presence of fewer women, more whites, higher educated, and more married individuals. This strong correlation asserts that the ordered probit regressions have a reasonable power in predicting location in the earnings distribution.

Summary of Descriptive Findings. To summarize the descriptive evidence, (*i*) since the 1980s, the US has received a large wave of foreign-born, which over time has become disproportionally more low-skill, more locally concentrated by skill, and more dissimilar to the native workforce; (*ii*) their skills and credentials are downgraded in US labor markets, motivating the choice of using rank in the wage structure as a more direct measure of skill; and (*iii*) there is significant variation of skill types by country of origin and city of residence. Overall, these findings set an expectation of potential effects in the two tails of the wage distribution, with little impact in the middle. Specifically, in the light of the increased college attainment of the native labor force over the same time period, these patterns suggest foreign-born workers have rendered low(high)-skill labor relatively more (less) abundant, potentially placing downward (upward) wage pressure on its price. I now move on to using this geographic variation of immigrants across the US to analyze their impact on natives' wage distribution.

4.2 The Effects of Immigrants on the Wage Distribution

4.2.1 Theoretical Model Estimates

Main Result. Figure 7 shows the main result from estimating the theoretical CES model. Each circle represents the estimated $\hat{\gamma}_1$ coefficient from equation (2) via 2SLS for a separate skill group, while the shaded regions denote 95% confidence intervals. Skill groups in this main specification are defined as deciles of the distribution, so that the first square denotes the average effect of immigration on the bottom decile, the second one on the second decile, etc. The outcome variable is Mincerian log real weekly wages adjusted with a local price index and measured for native workers only. All regressions control for Bartik employment growth and are weighted by labor market population, and all standard errors are clustered at the CZ level.

Immigration has a (weakly) monotone impact across the wage structure. The effects are negative but small in the very bottom, positive in the very top, and economically insignificant for the large majority of the labor force in the middle of the distribution. All estimates are semi-elasticities and can be interpreted as follows: a one percentage point increase in foreign-born workers leads to a decrease (an increase) in natives' wages by 0.27 (0.72) percentage points in the very bottom (top) of the distribution. The average effect on the entire distribution, on the other hand, is very close to zero, masking this heterogeneity. Note that these estimates control for endogenous self-selection of immigrants into localities by (*i*) estimating the local labor stock using nationally based skill-specific probabilities, (*ii*) controlling for Bartik index measuring local productivity shocks and city fixed effects, and (*iii*) using the shift share instrument. In a series of robustness checks below, I verify the sensitivity of these results to various specification changes.

Robustness Checks. Next, Figure 8 shows six different robustness checks. All graphs and regressions follow the conventions of the previous figure. Table A4 presents all estimated coefficients along with standard errors. Panel A displays the results when using hourly wages as an outcome variable. These are constructed by dividing the respondents' weekly wages by the reported usual number of hours worked per week. The estimates remain very similar to the main results. The negative effects in both the bottom and the top are smaller in magnitude: -0.15 and 0.63 respectively. In Panel B, I use a specification with five (instead of ten) skill groups, and each circle is interpreted as the average effect of immigration on the respective quintile of the weekly wage distribution. The coefficient in the bottom is more negative (-0.48), but the other magnitudes and the overall monotone pattern remain unchanged. In Panel C, I use metropolitan areas (MSAs) instead of CZs to define labor markets, as commonly done in urban economics. The estimate for the impact on the lowest skill group is larger in magnitude (-0.37), while the other coefficients remain similar.

In Panel D, I estimate the effects on a sample of men to account for potentially differential female labor force participation, which may correlate with immigrant location choices and labor demand shocks. The estimates are slightly noisier due to the smaller sample from which wages are estimated, but the (weakly) monotone pattern is virtually unchanged. Next, in Panel E, I estimate (2) with OLS, not relying on the networks instrument. The effect in the bottom is less negative (-0.04), while the coefficient in the top has decreased to 0.33. These differences may reflect bias arising from immigrants endogenously choosing their location, which may not be completely controlled for in this panel. Lastly, in Panel F, I restrict the sample to CZs with above-median rural-urban continuum code in 2003, as defined by the US Department of Agriculture. This choice is designed to focus on spatial areas in which immigrants are more prevalent, since many rural CZs do not have a significant immigrant presence. It does not affect the results considerably and the monotone pattern is clear in this panel as well.

Overall, the results show a weakly monotone relationship between the wage impact of immigrants and skill level. Immigrant and native workers exhibit some degree of labor market competition in the low-skill segment, resulting in a small negative effect. On the other hand, native and foreign-born workers are production complements in the top of the wage distribution, where the estimated impact of immigration is positive. This finding holds across a series of robustness checks and estimation methods.

4.2.2 Counterfactual Distribution Estimates

Main Result. Figure 9 mirrors Figure 7 and shows the results from the counterfactual distribution method described in Section 3.3. Each dot presents the estimated QTE of immigrants on the respective point of the natives' wage distribution. The outcome variable is Mincerian log real weekly wages adjusted with a local price index and measured for native workers only. The coefficients have a semi-elasticity interpretation, similar to the estimates in the previous subsection. The results in Figure 9 are based on 2015 ACS data and use a specification with 10 skill groups. All coefficients are very precisely estimated, and hence confidence intervals are omitted from the figure. In addition, all regressions are weighted by Census sampling weight and control for Mincerian characteristics (as in the ordered probit models), Bartik index for local demand shocks, control function, and city and skill fixed effects.

Again, we find that the impact of immigration is monotone across the distribution, with negative values in the bottom, economically insignificant effects in the large middle part, and positive values in the top. A one percentage point increase in the share of immigrants leads to a 0.25 percent decrease in wages in the very bottom and a 0.24 percent increase in the top. The majority of the workforce in the middle of the distribution experiences no economically significant wage effects due to immigration. The effects are smaller in magnitude compared to the ones in Figure 7, but they follow the same pattern. I now move on to investigating the robustness of this result.

Robustness Checks. Next, Figure 10 presents several robustness checks following the different specification choices presented in Figure 8. In Panel A, I use hourly instead of weekly wages as an outcome. The estimates in the bottom of the distribution are virtually unchanged, while the coefficients in the top are slightly higher – the semi-elasticity is equal to 0.47 in the top decile. Next, in Panel B, I use a specification with five instead of ten skill groups. Note that, unlike the results presented in Figure 8, the methodology here uncovers effects on the entire distribution, not only on the midpoints of the skill groups. The only difference relative to the results in Figure 9 is that exposure to immigration is measured across five instead of ten labor types. The negative (positive) effects in the bottom (top) are magnified, but the general pattern holds. In Panel C, I use MSAs instead of CZs to denote local labor markets, with little change to the estimated coefficients. This choice avoids using variation from rural areas with limited immigration exposure.

Next, in Panel D, I focus on a sample of native men to account for possible differential female labor force participation across cities. In Panel E, I present the results from the main specification for all time periods in my sample. Interestingly, in 1980, when immigration was at the lowest and most balanced level (as depicted in Figure 1), its wage consequences were virtually null throughout the distribution. Starting in 1990, with more imbalanced immigrant flows, we begin to see the familiar monotone pattern previously observed. Lastly, in Panel F, I focus on a sample of CZs with above-median rural-urban continuum code in 2003, as designated by the US Department of Agriculture. None of these choices significantly changes the estimated coefficients. All estimates and standard errors are presented in Table A5 as well. Each row shows the quantile treatment effect at a separate point of the wage distribution. The columns represent different specifications and robustness checks from Figures 9 and 10. Cluster bootstrapped standard errors accounting for within-CZ residual correlation in wages are estimated based on Chernozhukov et al. (2013) and shown in parenthesis.

Overall, similarly to the CES model results, the counterfactual analysis uncovers small, monotone treatment effects of foreign-born workers on natives' earnings. Note that the two approaches estimate a similar but slightly different quantity. When discussing the lowest skill group, the results from the theoretical approach measure the average impact of immigration on the entire bottom decile. On the other hand, the counterfactual distribution method explicitly compares two distributions at any point of interest: an actual one and a counterfactual one with lower immigration levels. Nevertheless, the two approaches yield similar results. Immigrants place downward pressure on the very low-skill natives: a one percentage point increase in the share of foreign-born leads to a 0.2 to 0.3 percent decrease in natives' wages in the bottom decile and a similar or even larger magnitude increase in the top one. The overall average effect, as well as the impact on the middle of the distribution, are close to null. This pattern is consistent across a series of robustness checks and subsamples.

4.3 Mechanisms

One can gain an insight into the mechanisms driving this pattern by zooming in on the occupational concentration of immigrants and natives within skill groups. Even within skill types and CZs, labor markets may be (at least partially) segmented along occupational categories. This is motivated by the wide variety of occupations represented among workers in any given decile. For instance, in 2015, the bottom decile comprises cashiers, farm workers, construction laborers, hairdressers, and teachers, among many others. In fact, the distribution is so spread out that the top category (cashiers) accounts for only 6.8% of the total workforce in that decile. Building on this idea, I calculate the occupational dissimilarity index between native and foreign-born workers for each skill group. Intuitively, within each decile, higher occupational differentiation of immigrants will likely exert stronger wage pressure among natives in fewer occupations, and hence lead to less negative *average* wage effects.

My approach is to compare this dissimilarity index to the predicted (by the CES model) and estimated (by the counterfactual distribution method) wage effects of immigration. The CES model can be used to simulate changes in natives' wages following a percentage point increase in immigration, a commonly-used practice in the literature (e.g., Borjas, 2003; Ottaviano and Peri, 2012). Given a set of parameter values, I can generate semi-elasticities corresponding to the total effect of immigrants, which can be compared to the estimated quantile treatment effects.[14]

Panel A of Figure 11 plots the simulated wage impacts of immigration as predicted by the CES model. Each dot presents the semi-elasticity in the respective decile of the wage distribution. Each line corresponds to the prediction when using a different elasticity of substitution parameter. Note that this is the elasticity between skill groups, not between immigrants and natives within skill groups (who are assumed to be perfect substitutes). Larger values denote more substitutable skill groups, and hence smaller implied wage effects following a labor supply shift. As a reference value, the elasticity of substitution between high school graduates and college-educated workers is often found to be around 1.4 (e.g., Katz and Murphy, 1992). To some extent, this prediction is a function of the mirror image of the bins shown in Figure 1. The predicted wage effects of immigration are negative in the bottom, increase monotonically from the 20th to the 70th percentiles, and then drop while remaining positive. This pattern is robust to using different values for the elasticity of substitution parameters.

Next, Panel B of the same figure plots the difference between the estimated wage effects of immigration and this prediction. The former are obtained using the results from the counterfactual distribution method presented in Figure 9. Values greater (smaller) than zero correspond to the estimated impact being higher than predicted. Regardless of the choice for the elasticity of substitution parameter, this difference is positive in the bottom and in the top than it is in the middle. In other words, this is where the effect of immigration is higher (i.e., more positive) than what the CES model predicts.

To shed some light on the potential drivers of this pattern, in Panel C I plot the occupational dis-

[14] I set the labor share (s_L) to 2/3 and estimate the income share of skill group from the 2015 ACS data. To show the sensitivity to different choices, I experiment with several values for the elasticity of substitution parameter.

similarity index between immigrants and natives at each skill group (decile) for various occupation aggregations: 29 distinct occupational categories (black solid line), 80 categories (blue dashed), and 383 categories (green dotted). Regardless of the choice of aggregation level, the dissimilarity index is highest among the bottom and top skill group and lowest in the middle. In other words, foreign-born labor induces larger occupational imbalances among the lowest-skill native workers and much weaker imbalances among medium-skill natives.[15] The figures in Panels B and C follow the same pattern: the quantities they present increase between the first and second deciles, decrease until about the 6th decile, and increase toward the end of the distribution. A small exception is a dip from the second-highest to the highest deciles observed in Panel C, which is only present in one of the results in Panel B.

For example, among workers in the bottom decile, where differentiation is high, immigrants are heavily represented in farming, agriculture, and housekeeping, while natives specialize in teaching and administrative occupations. Given this pattern, an influx of low-skill immigrants will likely assert stronger wage pressure on native farmers and housekeepers, while leaving the other low-skill occupations – a relatively large segment of the low-skill labor market – less affected. Similarly, in the top decile, where differentiation is also high, immigrants are disproportionally more represented among postsecondary teachers and scientists, while natives are more likely to be lawyers and managerial supervisors.

The striking similarity of the U-shapes of the difference in estimated and predicted wage effects and the occupational dissimilarity index suggests a novel mechanism through which local labor markets absorb foreign-born workers. Specifically, occupational differentiation of immigrants helps explain the commonly reported overall small effects of foreign-born workers (e.g., Lewis and Peri, 2015; Dustmann et al., 2017). This adds to the list of previously documented adjustment mechanisms: complementarity in the production process (Ottaviano and Peri, 2012), occupational upgrading of natives (Foged and Peri, 2016), task specialization (Peri and Sparber, 2009), and capital-labor complementarity and changes in the output mix (Lewis, 2011; Clemens et

[15] Figure A3 in the Appendix shows that this result holds for every time period in the sample. Each panel plots this occupational dissimilarity index for a separate year and the U-shaped pattern holds throughout.

al., 2018).

4.4 Counterfactual Scenarios

The empirical methodology outlined in Section 3.3 allows for more general counterfactual analysis, as it presents a flexible toolbox for building a wage distribution under a wide variety of immigration scenarios. I conduct two such exercises. In the first one, I build a counterfactual 2015 earnings distribution with immigration levels as observed in 1980. In the language of equation (3), this means comparing the $logw_{irj}^{2015}$ wage distribution that arises from p_{rj}^{2015} with the one associated with p_{rj}^{1980}, keeping $\mathbf{X}_i$ and $\mathbf{W}_{rj}$ fixed. I then compare this new distribution with the actual 2015 wage structure to answer what would have happened to current wages had immigration been kept at the 1980 levels ceteris paribus.

The second exercise instead uses the immigration stock as observed in 2015, but keeps the skill distribution of foreign-born as it was in 1980. More specifically, I first calculate the total number of immigrants in 2015 in each CZ and skill group. Next, I allocate their countries of origin following the respective origin distribution in 1980. Lastly, to each CZ and country-of-origin group, I assign the respective median skill level as observed in 1980 and then calculate the associated immigration exposure p_{rj}^{c}. I then compare the $logw_{irj}^{2015}$ wage distribution to the one that arises under the counterfactual immigration exposure p_{rj}^{c}. This exercise answers what would have happened to 2015 wages had immigration levels remained as observed while keeping the skill composition as it was in 1980.

How has the US immigration policy changed over the 1980–2015 time period? Perhaps the most significant reform to the admission process was the series of measures passed as a response to the September 11 attacks. These included heightened visa control; extensive screening and background checks; and collecting, storing, and sharing data between various government agencies. Foreign-born of Arab, Muslim, and South Asian descent were subject to additional scrutiny. The Immigration Reform and Control Act of 1986 (IRCA), although not directly aimed at changing admission criteria, also considerably impacted many immigrant groups residing in the US. It was meant to control the rates of illegal immigration by making it more difficult for unauthorized foreign-born to find employment. The two counterfactual exercises described above undo the immigration changes introduced by these policies in a slightly different way: the first one keeps the immigration levels fixed, while the second one holds the immigrant characteristics constant.

Figure 12 presents the results. The blue line with circles shows the QTEs from the first exercise, which keeps immigration levels at the 1980 levels. The yellow line with triangles displays the effects from the second exercise: keeping immigrants' skill distribution as it was in 1980. All estimates reflect a comparison between the observed 2015 wage structure and the respective counterfactual one. Vertical bars represent 95% confidence intervals, which are constructed similarly to the estimates above.

Both exercises show that in these counterfactual worlds, wages in the bottom of the distribution would be slightly higher and the ones in the top would be significantly lower. At the same time, the majority of the wage earners in the middle would experience no significant changes. Under the first scenario, the bottom decile would experience a boost of about 3.3%, while the losses in the top would be more significant: 8.6%. This pattern is unsurprising given that, as presented in Figure 1, over the 1980–2015 period, the flow of immigrants was concentrated in the bottom of the wage distribution. Given the presented results on the impact of immigration, all else equal, shutting down this inflow would make low(high)-skilled natives relatively better (worse) off. The magnitudes for the second scenario are smaller: gains of 0.9% in the bottom and losses of 2.9% in the top. This difference in magnitudes is explained by the fact that the first scenario presents much more drastic change to the exposure of immigration by altering its size rather than just shuffling its skill composition. Overall, in both counterfactual scenarios, the most significant changes in the wage distribution would take place in the top.

5 Discussion

This study has two main goals. The first is to document the position and movement of immigrants in the US wage distribution over time. I begin by presenting the concentration of foreign-born across quintiles and find that they are increasingly more represented in the bottom. Downgrading of education and experience obtained abroad play a role in this overrepresentation. In other words, when comparing otherwise identical foreign and native workers, the latter is more likely to earn higher wages. I also document significant heterogeneity in their positions in the wage distribution by country of origin and across localities. Moreover, in most major cities, the immigrant population has become more concentrated by skill over time. Guided by a labor supply and demand model, these patterns taken together suggest that foreign-born workers may place an increasingly intensifying downward wage pressure on the bottom of the wage distribution.

The second goal is to study the effect of immigrants on wage distribution. I use two distinct empirical approaches – estimating a theoretical CES model and constructing a reduced-form counterfactual wage distribution. Both methods uncover similar (weakly) monotone effects. Across most specifications, I estimate small negative semi-elasticities below the 10th percentile, larger positive ones above the 80th, and economically insignificant impacts for the majority of the wage earners in the middle. A one percentage point increase in the share of immigrants is associated with a 0.2–0.3 percent wage decrease in the bottom decile and a 0.2–0.4 percent wage increase in the top. These magnitudes imply the rise of immigration over the past few decades is unlikely to have played a major role in changing the earnings structure. Nevertheless, they are masked by an aggregate analysis of the impact on the average worker and shine novel light on the "winners" and "losers" of immigration in the US.

How do these magnitudes compare with the literature on the wage impacts of immigration? A recent meta-analysis by Foged et al. (2019) summarizing 1,548 semi-elasticities from 48 academic studies can help place my estimates in perspective. The authors find that the 25th and 75th percentiles of the distribution correspond to -0.4 and 0.3 respectively, a range containing most of the coefficients reported here. Hence, my results are well within the range of the previously reported estimates. It is also useful to contrast these estimates with the ones from Dustmann et al. (2013), who study the effects of immigrants on the wage distribution in the UK. While both studies document negative effects in the bottom and positive ones in the top, the two sets of results differ in several ways. Specifically, Dustmann et al. (2013) find a non-monotone pattern partially resembling an inverted U-shape whereby the magnitude of the estimated semi-elasticity peaks around the 60th percentile and decreases as we move toward the top. The authors explain this result with lower immigrant density in the UK in the middle skill segment. Moreover, their estimated semi-elasticities are larger in magnitude – as negative as -0.75 in the bottom and as positive and large as 0.66 in the middle. Foged et al. (2019) find that labor market institutions (which differ between the US and the UK) play a role in affecting the wage impacts of foreign-born workers. It is likely that differences in institutions and norms plays out in the immigration-induced changes of the wage structure. Lastly, my results suggest that immigration asserts no pressure in the middle, while the estimates in Dustmann et al. (2013) imply statistically significant effects nearly throughout. Hence, I view this paper as complementing theirs while highlighting the difference in wage impact of immigration between the two economies.

This study is not without limitations. First and most importantly, motivated by the simple theoretical model, I relate natives' earnings and foreign-born induced pressure within the same skill group, which may omit cross-skill complementarity and spillover effects (see Ottaviano and Peri, 2012). This is sometimes referred to as direct partial wage impacts. For instance, high-skill immigrants may affect low- or middle-skill natives, but my analysis focuses on the interaction between high-skill natives and immigrants. Therefore, my estimates should be taken as lower bounds of the total wage impact of foreign-born workers. Capturing such cross-skill effects requires more complex modeling and does not lend itself to the statistical methodologies I employ here. Second, an inherent limitation of studying wage distribution is that one has to be employed and earn a wage in order to appear in the sample. Hence, any effects on unemployment or participation are not accounted for in my estimates. Lastly, research has shown that survey nonresponse, which is present in the Census and ACS data, is highest in the top and bottom of the earnings distribution, specifically where my analysis uncovers statistically significant effects (e.g., Bollinger et al., forthcoming).

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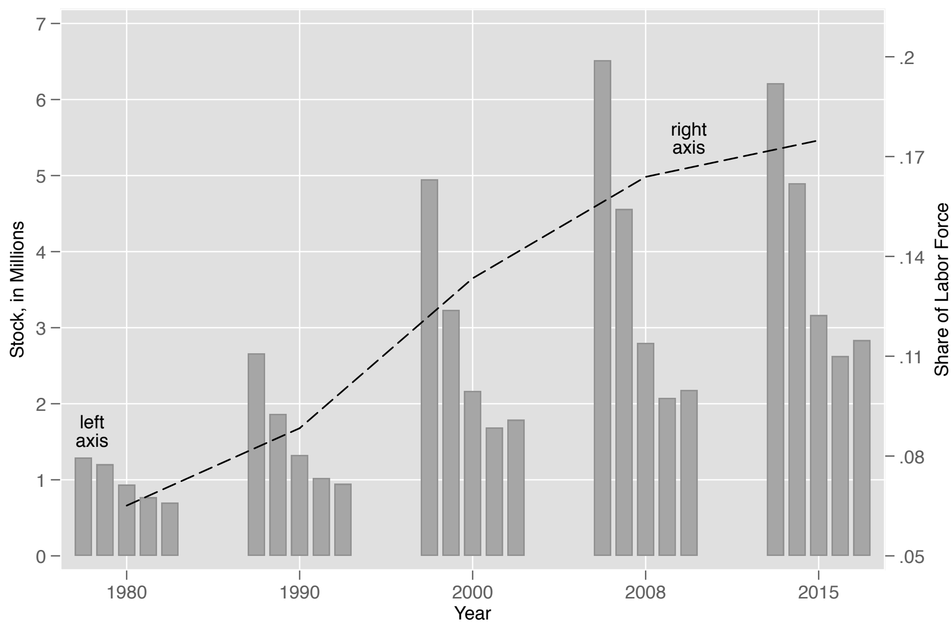
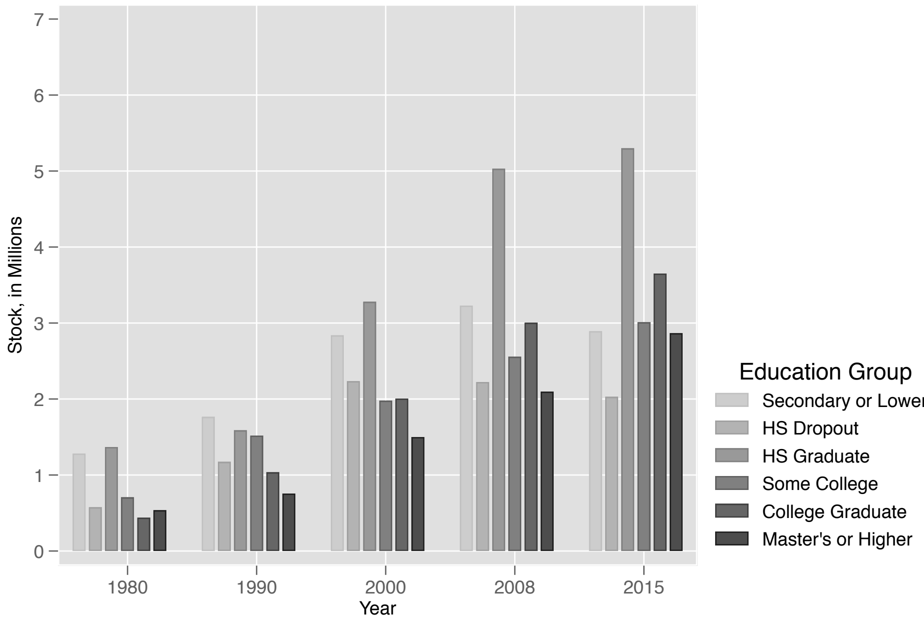
6 Figures

Figure 1: Position of Immigrants in the Natives' Wage Distribution by Quintile, 1980–2015



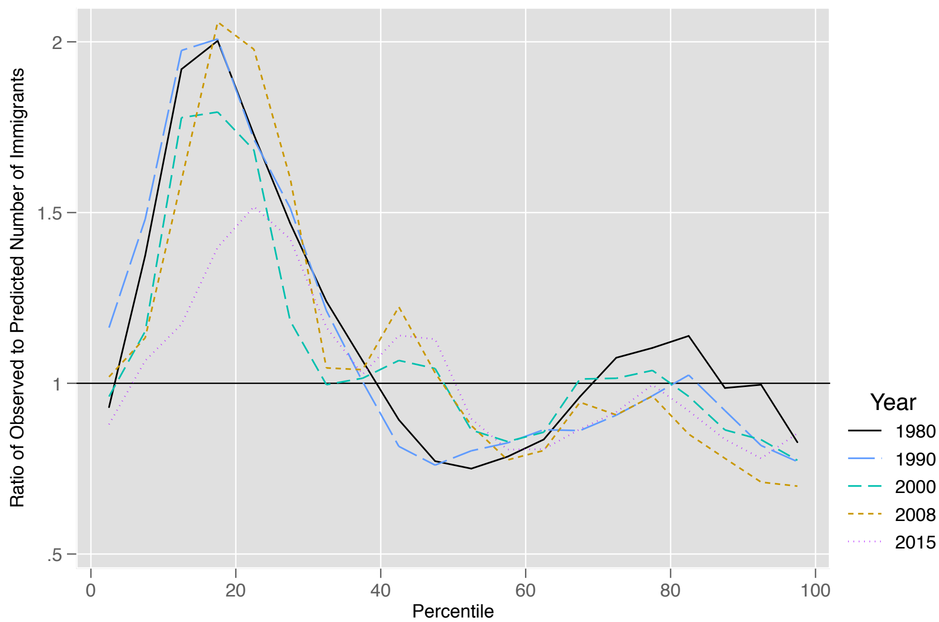
Notes: Each bin shows the observed stock of foreign-born workers (in millions) in a separate quintile of the natives' weekly wage distribution and year. The black dashed line displays the share of immigrants in the labor force, shown in the right vertical axis. The sample consists of all individuals age 18–64 with potential experience between 1 and 40 years, in the labor force, not self-employed, not in group quarter, not in school, and with positive reported earnings.

Figure 2: Number of Immigrants by Education Group, 1980–2015



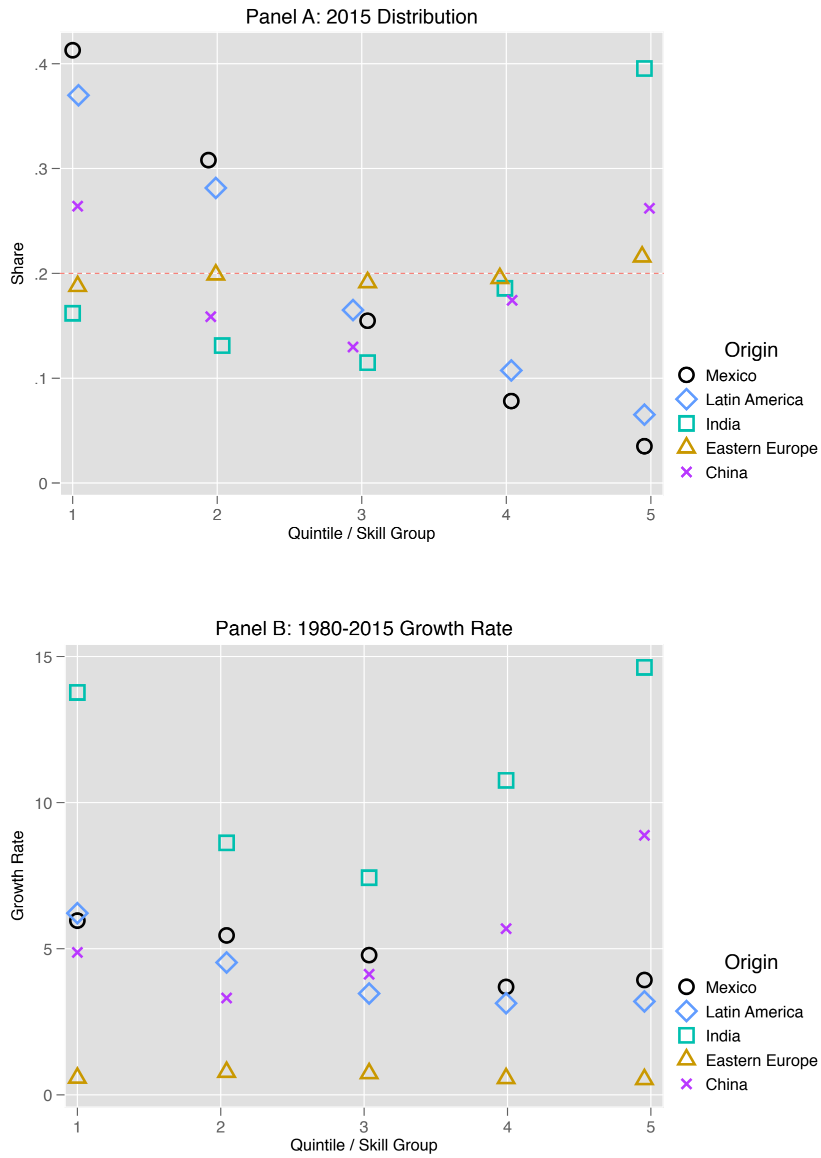
Notes: Each bin shows the observed stock of foreign-born workers (in millions) in a separate education category and year. The sample is the same as in Figure 1.

Figure 3: Overrepresentation of Immigrants in the Natives' Wage Distribution, 1980–2015



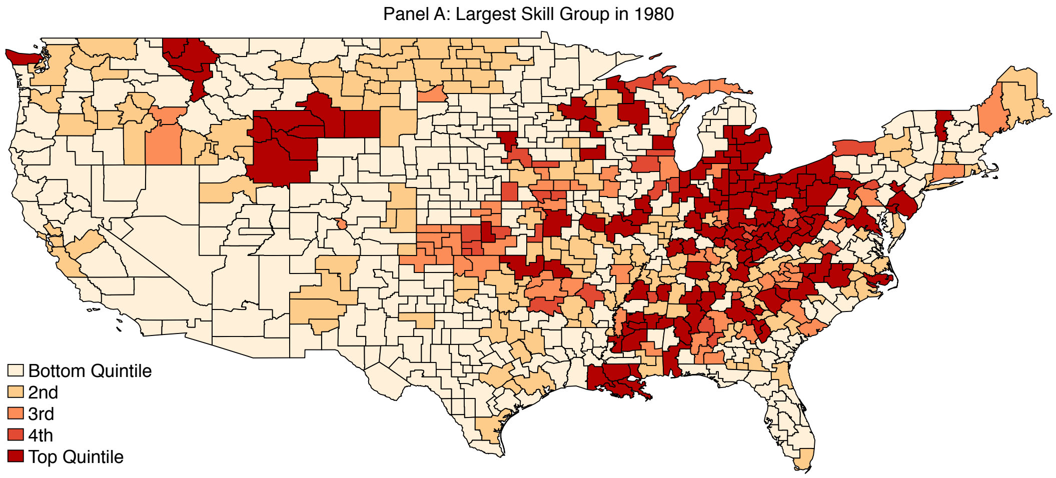
Notes: Each line shows the ratio of observed to predicted stock of foreign-born workers in the natives' wage distribution for a separate year. Predictions are based on immigrants' characteristics being valued at the same rate as for natives. Ratios greater than one correspond to immigrants being overrepresented in that segment of the wage distribution. The sample is the same as in Figure 1.

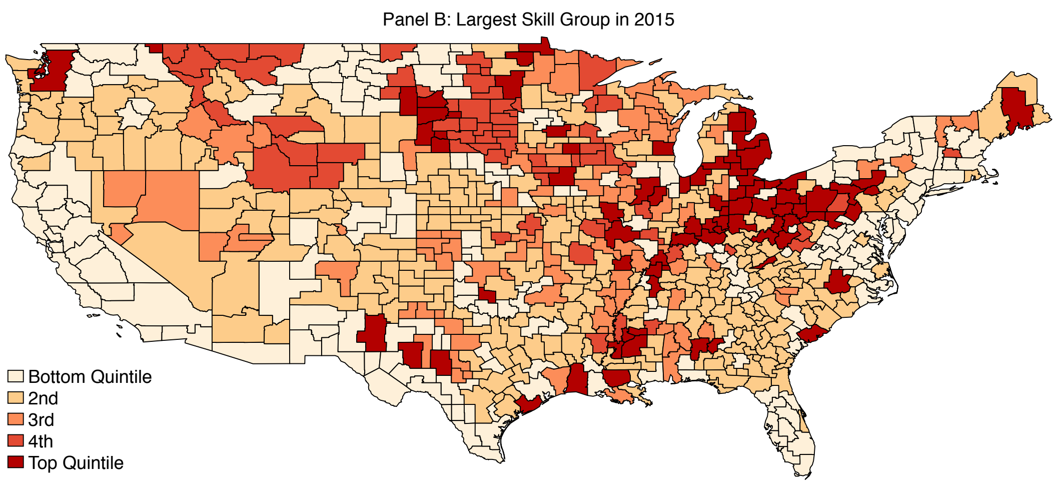
Figure 4: Skill Group Distribution of Immigrants by Area of Origin, 1980–2015



Notes: Panel A shows the 2015 immigrant skill distribution for the five largest areas of origin. All shares within an immigrant group sum up to one. Panel B presents the 1980–2015 growth rate for each skill and origin group. The sample is the same as in Figure 1.

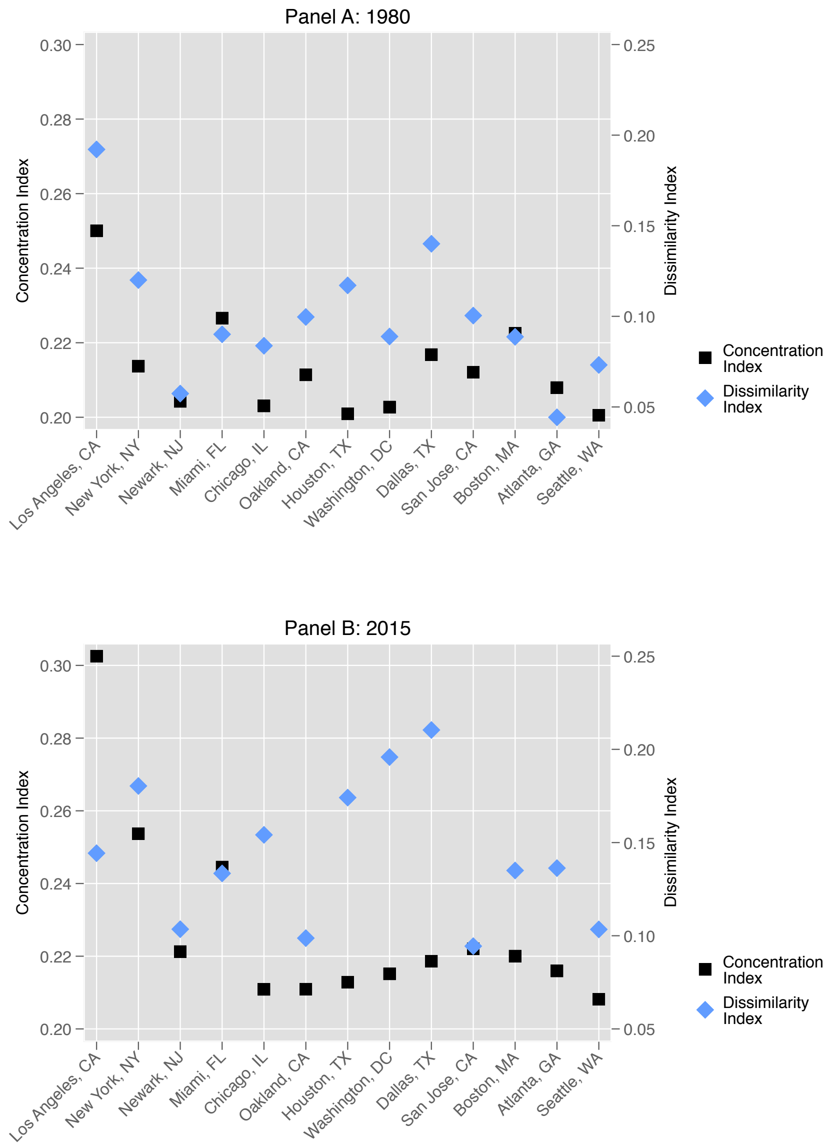
Figure 5: Geographic Distribution of Immigrants by Skill Group, 1980–2015





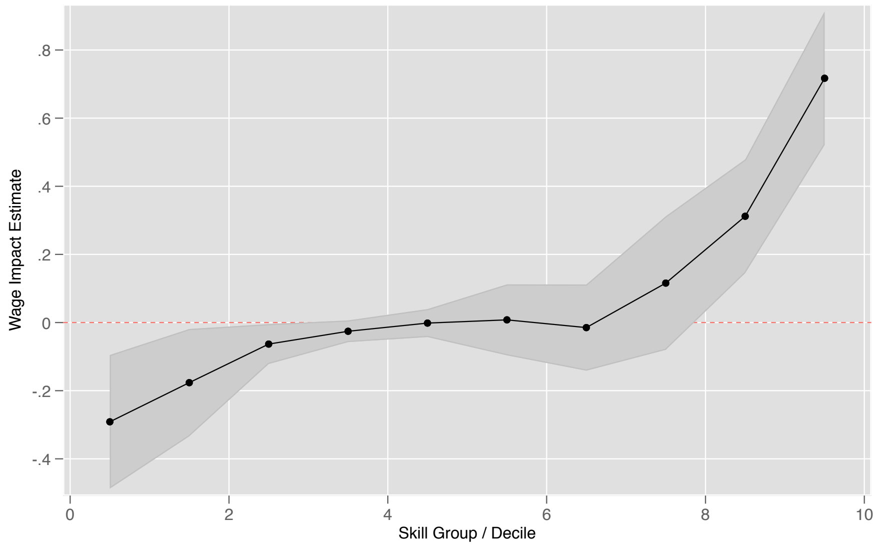
Notes: Panel A shows the largest immigrant skill group in 1980 for each Commuting Zone. Panel B does the same for year 2015. Darker shades of red correspond to higher quintile/skill group. The sample is the same as in Figure 1.

Figure 6: Concentration Indexes by Nativity and Skill Group in the Top Immigrant-Receiving Cities, 1980–2015



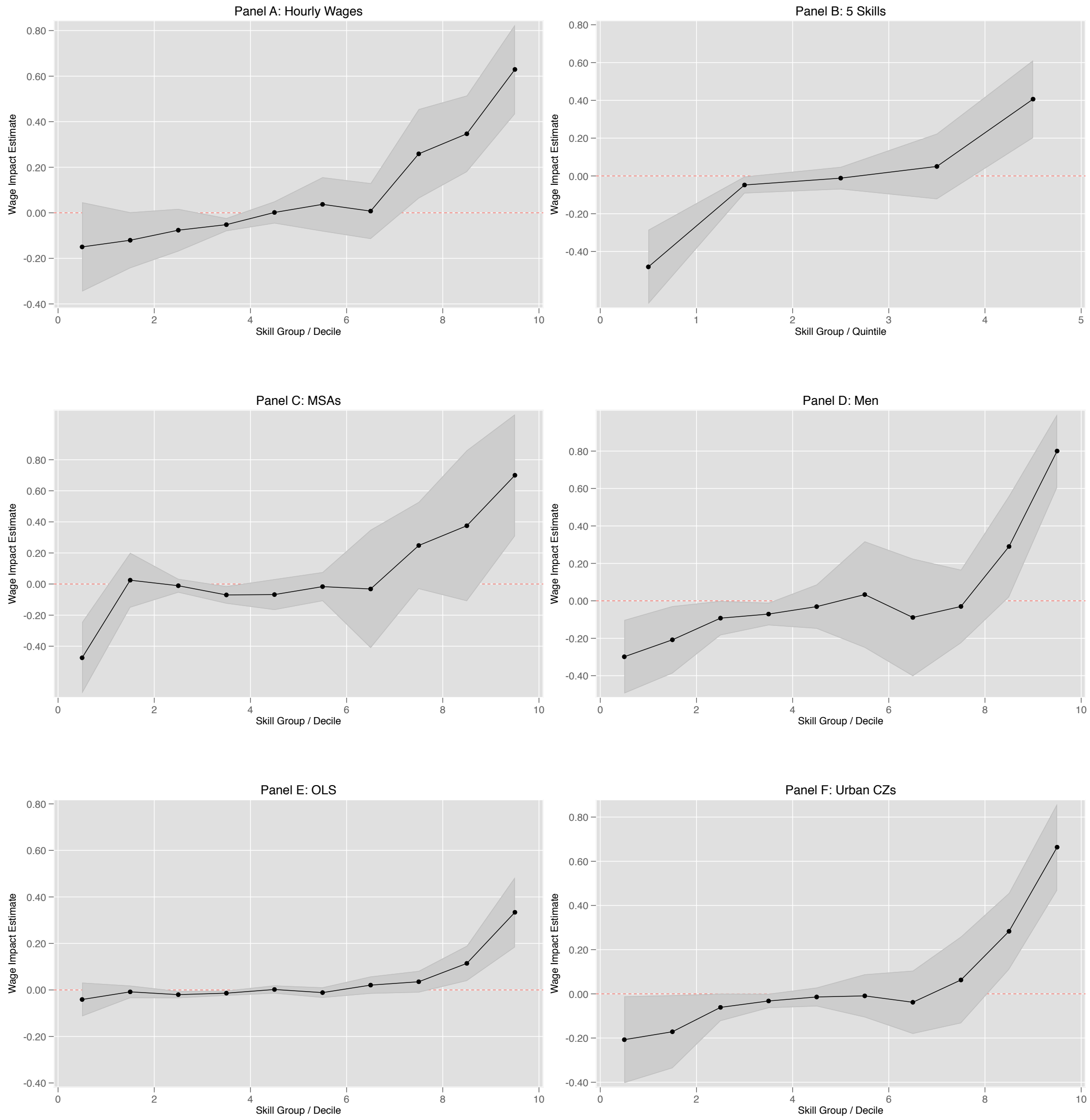
Notes: Concentration (left axis) indexes for immigrants and natives and dissimilarity (right axis) indexes for 1980 in Panel A and 2015 in Panel B in the largest immigrant-receiving Commuting Zones. Higher concentration (dissimilarity) index values correspond to stronger skill group concentration (dissimilarity with natives). The sample is the same as in Figure 1.

Figure 7: The Impact of Immigrants on Natives' Wage Distribution: Theoretical Model Approach



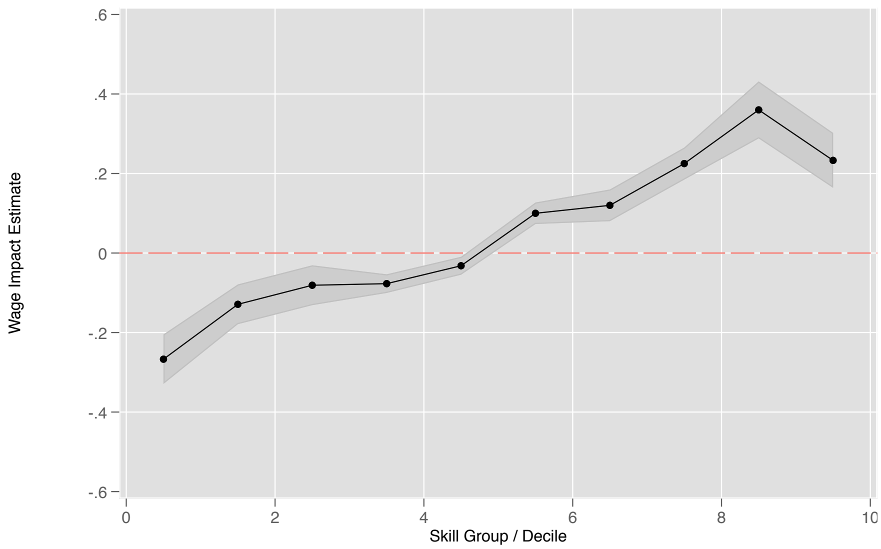
Notes: Each point is an estimated coefficient γ_1 from equation (2) via 2SLS on a specific skill group (decile), denoted on the horizontal axis. The dashed horizontal line shows the regression coefficient from a pooled regression of all skill groups. The shaded region denotes 95% confidence intervals, with standard errors clustered at the CZ level. All regressions control for Bartik index for local labor demand shocks. The outcome variable is log real weekly wages adjusted with a local price index. The sample is the same as in Figure 1.

Figure 8: The Impact of Immigrants on Natives' Wage Distribution: Robustness Checks



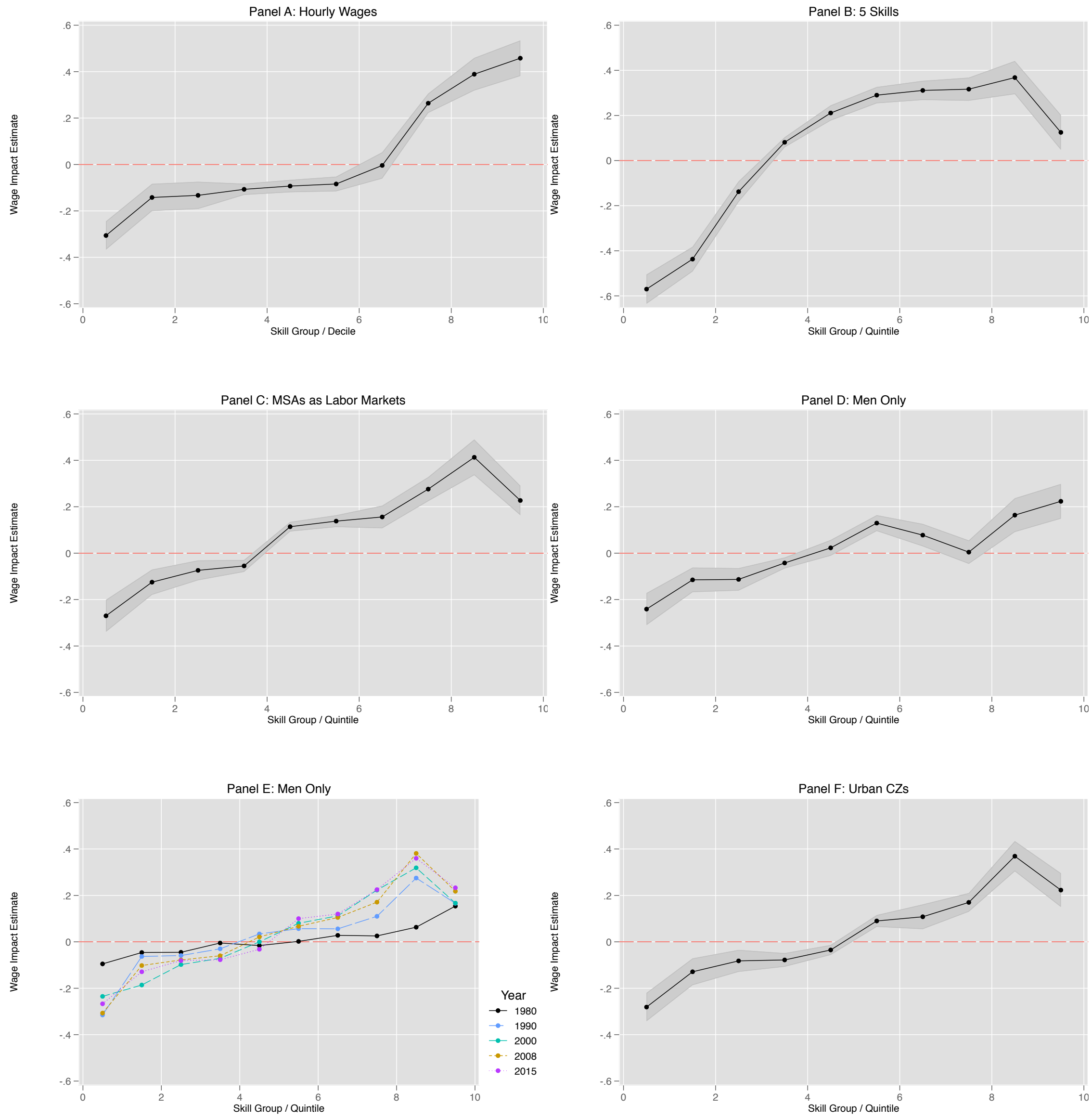
Notes: Each point is an estimated coefficient γ_1 from equation (2) via 2SLS on a specific skill group (decile), denoted on the horizontal axis, and each panel represents a distinct robustness check, denoted in the header. The dashed horizontal line shows the regression coefficients from a pooled regression of all skill groups. The shaded region denotes 95% confidence intervals, with standard errors clustered at the CZ level. All regressions control for Bartik index for local labor demand shocks. The outcome variable is log real weekly (hourly in Panel A) wages adjusted with a local price index. The sample consists of all individuals (male only in Panel D; urban areas only in Panel F) age 18–64 with potential experience between 1 and 40 years, in the labor force, not self-employed, not in group quarter, not in school, and with positive reported earnings.

Figure 9: Quantile Treatment Effects of the Impact of Immigrants on the Wage Distribution



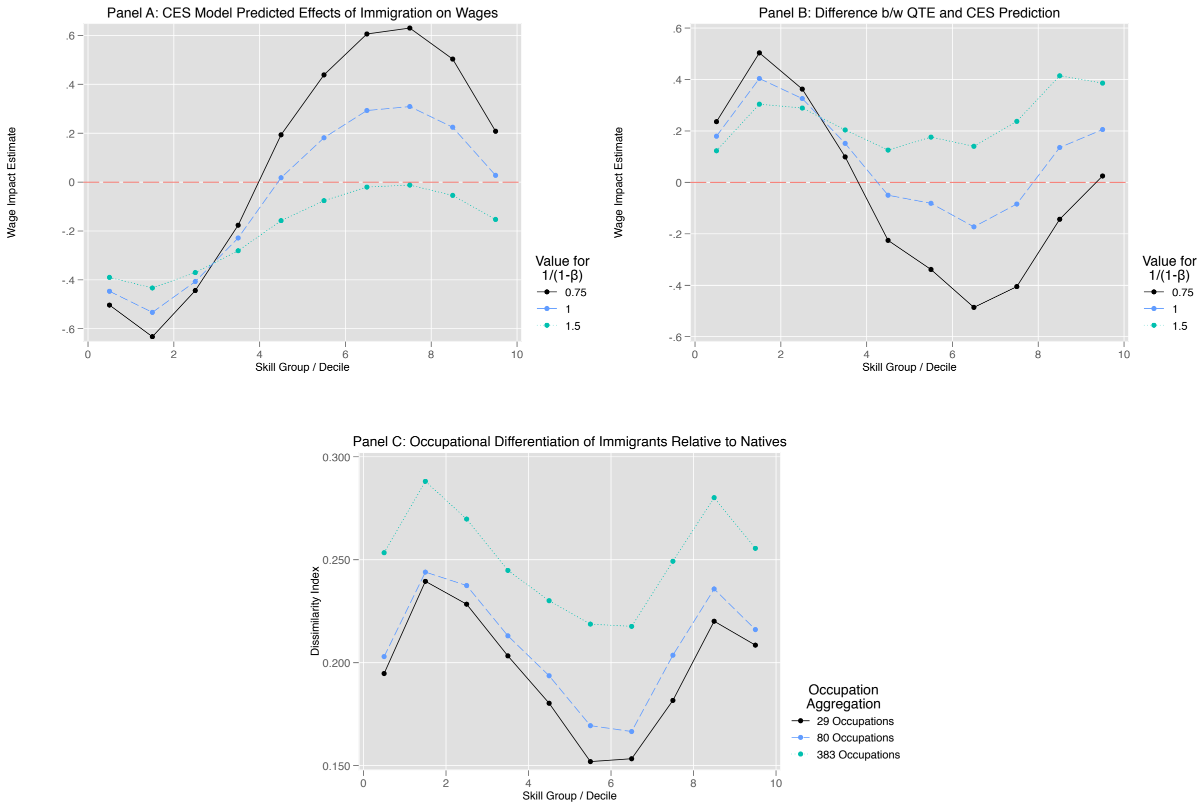
Notes: Each dot is an estimated QTE at a specific point in the wage distribution, denoted on the horizontal axis. These are constructed by comparing the 2015 wage distribution with a counterfactual one with lower immigration levels. See Section 3.3 for more details on the methodology. All coefficients are precisely estimated and standard errors are omitted (see Table A5). All regressions control for Bartik index for local labor demand shocks and include a control function based on the networks instrument. The first stage is estimated with 100 distributional regressions using a linear probability model. The outcome variable is log real weekly wages adjusted with a local price index. The sample is the same as in Figure 1.

Figure 10: Quantile Treatment Effects of the Impact of Immigrants on the Wage Distribution: Robustness Checks



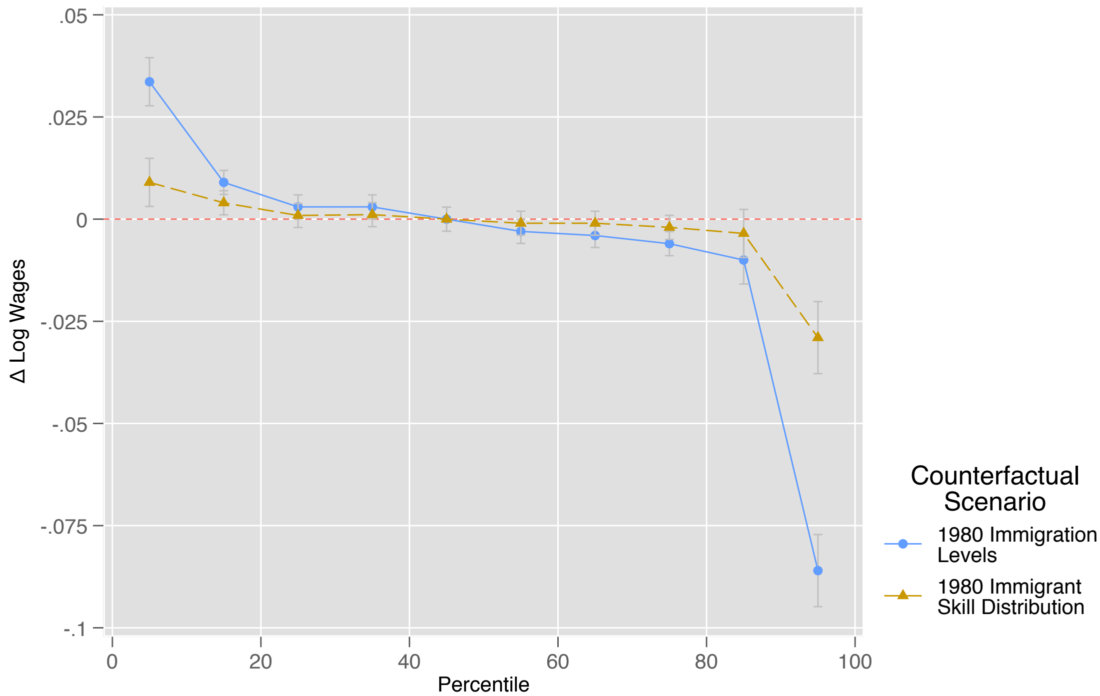
Notes: Each point is an estimated QTE at a specific point of the wage distribution, denoted on the horizontal axis, and each panel represents a distinct robustness check, denoted in the header. These are constructed by comparing the 2015 wage distribution with a counterfactual one with lower immigration levels. See Section 3.3 for more details on the methodology. All coefficients are precisely estimated and standard errors are omitted (see Table A5). All regressions control for Bartik index for local labor demand shocks and include a control function based on the networks instrument. The first stage is estimated with 100 distributional regressions using a linear probability model. The outcome variable is log real weekly (hourly in Panel A) wages adjusted with a local price index. The sample consists of all individuals (male only in Panel D; urban areas only in Panel F) age 18–64 with potential experience between 1 and 40 years, in the labor force, not self-employed, not in group quarter, not in school, and with positive reported earnings.

Figure 11: Predicted Wage Impacts and Occupational Differentiation of Immigrants, 1980–2015



Notes: Panel A shows the predicted wage effects of immigration by the CES model outlined in Section 2 for various values of the elasticity of substitution parameter. Panel B plots the difference between the estimated wage impacts of immigration using the decomposition method for year 2015, presented in Figure 9 and the CES prediction. Panel C displays the occupational dissimilarity index between immigrants and natives for year 2015 and various occupation aggregations. The sample is the same as in Figure 1.

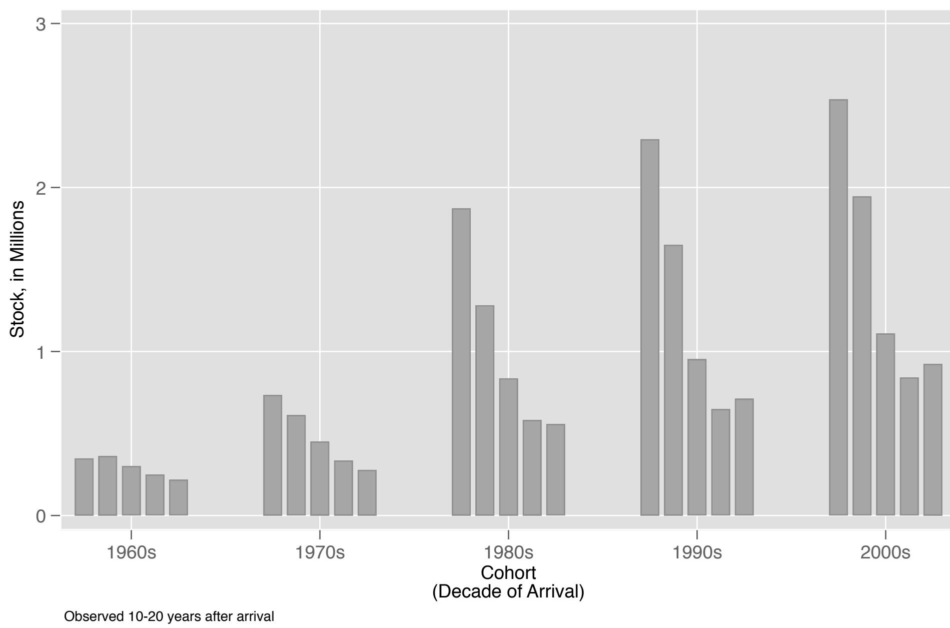
Figure 12: Counterfactual Scenarios: 2015 Wage Distribution with 1980 Immigration Levels and Skill Composition



Notes: The blue line with circles shows the difference between the observed 2015 wage structure and a counterfactual one with 1980 immigration levels. The yellow line with triangles presents the same values for 1980 skill distribution but 2015 immigration levels. Vertical lines correspond to 95% confidence intervals. See Section 3.3 for more details. The sample is the same as in Figure 1.

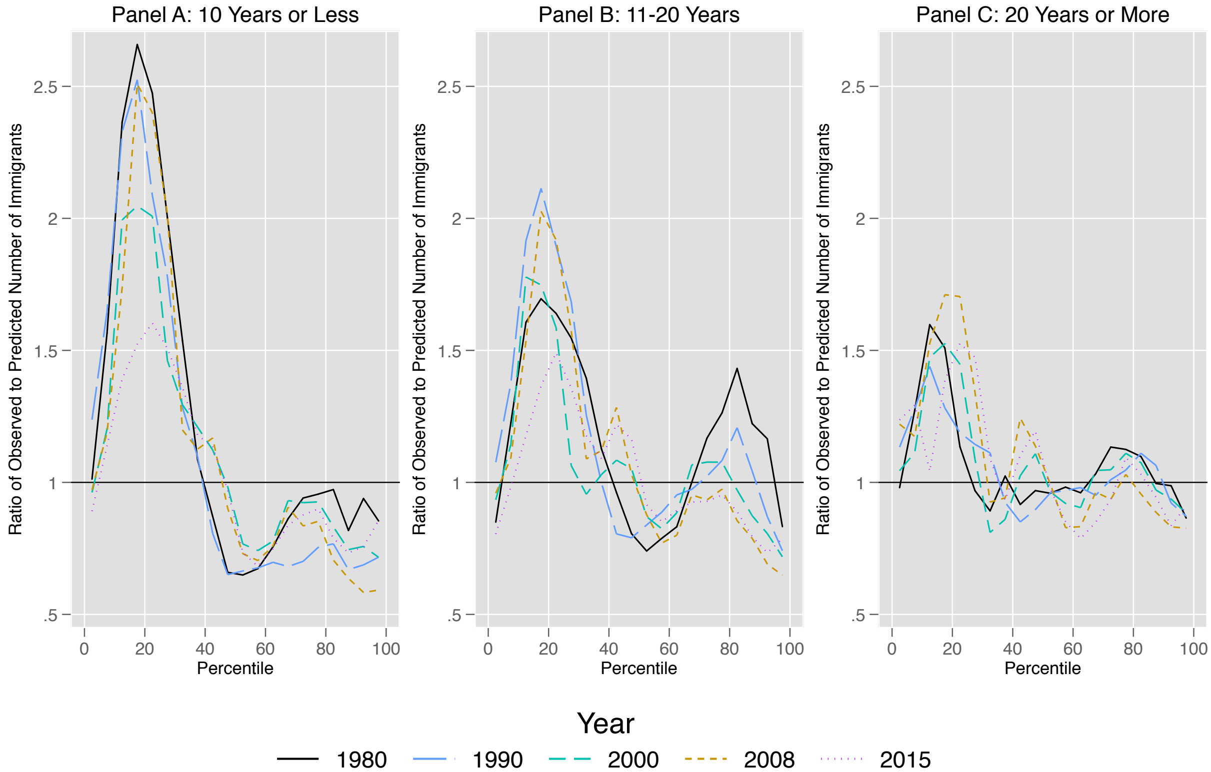
7 Appendix: Figures and Tables

Figure A1: Position of Immigrants in the Natives' Wage Distribution by Quintile and Cohort of Arrival, 1960–2000



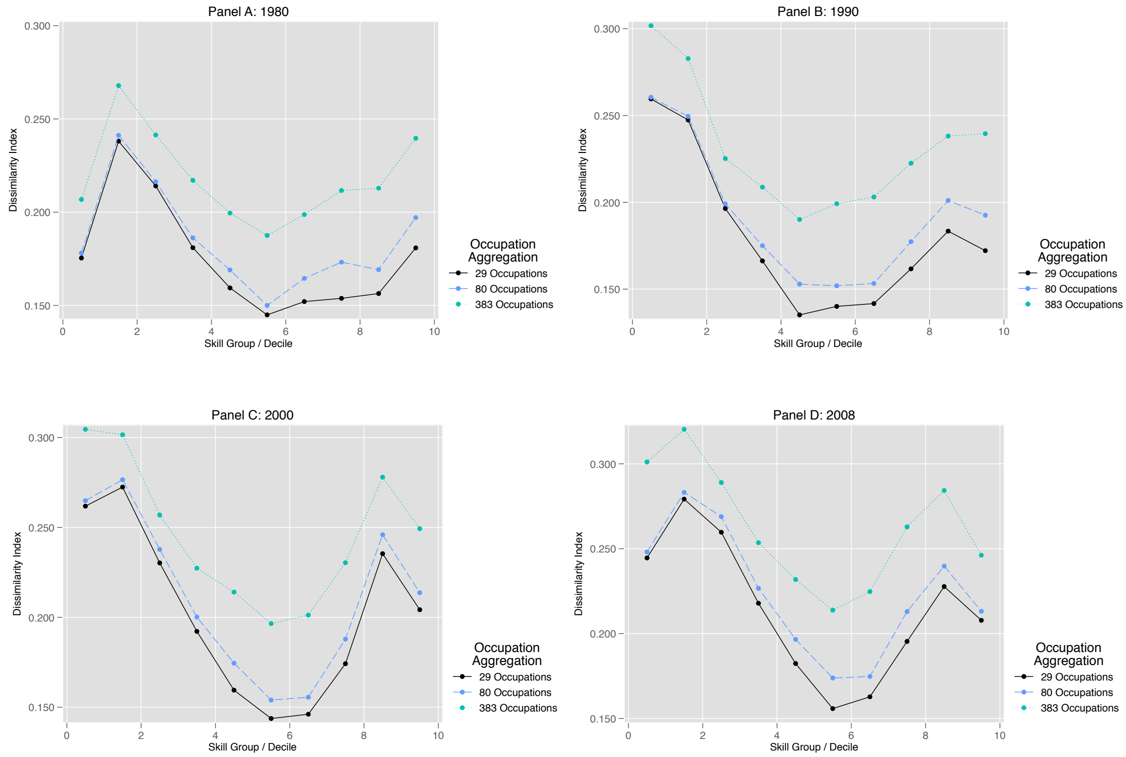
Notes: Each bin shows the observed stock of foreign-born workers (in millions) in a separate quintile of the natives' weekly wage distribution by cohort of arrival, denoted on the horizontal axis. Each cohort is observed 10–20 years after arrival to the US. For instance, the cohort of foreign-born who arrived between 1960 and 1970 is observed in the 1980 Census. The sample is the same as in Figure 1.

Figure A2: Overrepresentation of Immigrants in the Natives' Wage Distribution by Length of Stay in the US, 1980–2015



Notes: Each line shows the ratio of observed to predicted stock of foreign-born workers in the natives' wage distribution for a separate year. Each panel is restricted to immigrants with a different length of stay in the US, denoted in the header. Predictions are based on immigrants' characteristics being valued at the same rate as for natives. Ratios greater than one correspond to immigrants being overrepresented in that segment of the wage distribution. The sample is the same as in Figure 1.

Figure A3: Occupational Dissimilarity between Immigrants and Natives, 1980–2008



Notes: This figure extends Panel C in Figure 11 for all other time periods in my sample, denoted in the panel headers — that is, each line presents the occupational dissimilarity index between natives and immigrants by skill group and for various occupation aggregations. The sample is the same as in Figure 1.

Table A1: Shares and Growth Rates among Immigrants by Birthplace and Skill, 1980–2015

Panel A: Shares, 2015

	Skill Group / Quintile						
	1st	2nd	3rd	4th	5th	Count (in mil.)	Concentration Index
US	0.20	0.20	0.20	0.20	0.20	93.2	0.20
Mexico	0.42	0.31	0.16	0.08	0.04	6.0	0.30
Rest of Americas	0.37	0.29	0.17	0.11	0.07	5.0	0.26
India	0.16	0.13	0.12	0.19	0.40	1.6	0.25
Eastern Europe	0.19	0.20	0.19	0.20	0.22	1.1	0.20
China	0.26	0.16	0.13	0.18	0.27	1.1	0.22
Africa	0.25	0.25	0.17	0.17	0.16	0.9	0.21
Rest of Asia	0.25	0.22	0.17	0.15	0.20	0.9	0.21
Philippines	0.23	0.22	0.20	0.20	0.15	0.9	0.20
Western Europe	0.14	0.14	0.16	0.20	0.35	0.8	0.23
Vietnam	0.28	0.24	0.16	0.17	0.15	0.6	0.21
Korea	0.21	0.18	0.17	0.19	0.25	0.4	0.20

Panel B: Growth Rates, 1980–2015

	Skill Group / Quintile					
	1st	2nd	3rd	4th	5th	Growth Rate
US	0.32	0.32	0.32	0.32	0.33	0.3
Mexico	5.96	5.53	4.75	3.89	4.09	5.3
Rest of Americas	6.22	4.60	3.44	3.33	3.35	4.5
India	13.77	8.70	7.40	10.96	14.78	11.6
Eastern Europe	0.58	0.85	0.71	0.76	0.69	0.7
China	4.88	3.39	4.10	5.88	9.04	5.3
Africa	19.50	15.33	11.89	12.47	9.17	13.5
Rest of Asia	5.55	4.85	4.23	3.99	5.66	4.9
Philippines	4.56	2.37	2.60	3.35	4.39	3.2
Western Europe	-0.45	-0.44	-0.28	-0.09	0.55	-0.2
Vietnam	10.03	6.91	5.96	11.60	27.80	9.3
Korea	2.24	1.85	2.91	4.54	6.80	3.2

Notes: Each column in Panel A lists the observed labor force shares among foreign-born in each quintile of the natives' wage distribution by birthplace, denoted in each row. The last column shows the concentration index for the respective group. The columns in Panel B display the changes in the stock of workers as a share of the 1980 population. The sample is the same as in Figure 1.

Table A2: Labor Force Shares by Nativity, Skill Group, and Commuting Zone, 2015

	Panel A: % Natives						*Panel B*: % Immigrants						*Panel C*: Nat - Imm	
	Skill Group / Quintile						Skill Group / Quintile							
	1st	2nd	3rd	4th	5th	Concentration Index	1st	2nd	3rd	4th	5th	Concentration Index	Δ Concentration Index	Dissimilarity Index
Los Angeles, CA	0.32	0.23	0.17	0.16	0.12	0.23	0.47	0.23	0.13	0.11	0.07	0.30	-0.08	0.14
New York, NY	0.23	0.21	0.19	0.20	0.18	0.20	0.39	0.23	0.15	0.14	0.09	0.25	-0.05	0.18
Newark, NJ	0.24	0.18	0.20	0.17	0.21	0.20	0.33	0.19	0.16	0.14	0.17	0.22	-0.02	0.10
Miami, FL	0.24	0.25	0.22	0.16	0.14	0.21	0.33	0.29	0.17	0.12	0.09	0.24	-0.03	0.13
Chicago, IL	0.19	0.16	0.20	0.19	0.26	0.20	0.26	0.25	0.18	0.14	0.17	0.21	-0.01	0.15
Oakland, CA	0.21	0.18	0.18	0.21	0.22	0.20	0.29	0.20	0.15	0.17	0.19	0.21	-0.01	0.10
Houston, TX	0.17	0.17	0.18	0.21	0.27	0.21	0.26	0.25	0.16	0.14	0.19	0.21	-0.01	0.17
Washington, DC	0.17	0.16	0.17	0.22	0.28	0.21	0.29	0.23	0.15	0.15	0.18	0.22	-0.00	0.20
Dallas, TX	0.16	0.17	0.20	0.21	0.26	0.21	0.25	0.29	0.16	0.12	0.18	0.22	-0.01	0.21
San Jose, CA	0.24	0.18	0.17	0.19	0.22	0.20	0.30	0.19	0.12	0.15	0.25	0.22	-0.02	0.09
Boston, MA-NH	0.21	0.21	0.20	0.21	0.18	0.20	0.30	0.24	0.15	0.16	0.15	0.22	-0.02	0.14
Atlanta, GA	0.15	0.20	0.18	0.20	0.26	0.21	0.19	0.30	0.14	0.16	0.21	0.22	-0.01	0.14
Seattle, WA	0.18	0.18	0.21	0.19	0.23	0.20	0.22	0.24	0.15	0.15	0.24	0.21	-0.01	0.10

Notes: Each column lists the observed labor force shares in 2015 and each skill group/quintile of the natives' wage distribution for the Commuting Zones with largest stock of immigrants. Panel A shows these for natives and Panel B for immigrants. The last columns in Panels A and B show the concentration index of the respective nativity group. Panel C displays the differences in the concentration index and the dissimilarity index between the two nativity groups. The sample is the same as in Figure 1.

Table A3: Observed and Predicted Demographic Characteristics by Skill Group, 2015

Panel A: Observed

	Skill Group / Quintile				
	1st	2nd	3rd	4th	5th
Female	0.59	0.52	0.49	0.43	0.32
White	0.51	0.57	0.67	0.74	0.80
Black	0.15	0.15	0.13	0.10	0.07
Hispanic	0.29	0.23	0.15	0.10	0.06
Asian	0.06	0.05	0.05	0.06	0.08
Age	37.21	38.95	40.96	42.89	45.58
Age < 35	0.50	0.45	0.37	0.29	0.18
Years Schooling	12.39	12.92	13.76	14.62	15.78
High School Dropouts	0.18	0.12	0.07	0.04	0.02
College Graduate	0.16	0.20	0.32	0.46	0.66
Foreign-Born	0.25	0.21	0.15	0.12	0.13
Married	0.40	0.45	0.54	0.63	0.73

Panel B: Predicted

	Skill Group / Quintile				
	1st	2nd	3rd	4th	5th
Female	0.62	0.57	0.44	0.49	0.23
White	0.43	0.57	0.79	0.82	0.82
Black	0.18	0.15	0.11	0.09	0.05
Hispanic	0.34	0.20	0.08	0.06	0.04
Asian	0.04	0.09	0.02	0.03	0.09
Age	34.44	42.02	42.12	44.45	46.20
Age < 35	0.54	0.45	0.40	0.27	0.17
Years Schooling	11.44	13.19	13.52	14.74	16.55
High School Dropout	0.22	0.06	0.03	0.02	0.00
College Graduate	0.02	0.21	0.23	0.59	0.78
Foreign-Born	0.27	0.29	0.01	0.04	0.15
Married	0.30	0.53	0.48	0.67	0.82

Notes: Panel A shows demographic characteristics by skill group/quintile of the observed natives' wage distribution. Panel B does the same for the predicted earnings structure by the ordered probit regressions. Each worker's predicted skill group refers to the one with highest predicted probability. All figures are for the year 2015. The sample is the same as in Figure 1.

Table A4: The Impact of Immigrants on the Natives' Wage Distribution

	Outcome Variable: Log Real Weekly Wage						
Decile / Skill Group	(1) Baseline	(2) Hourly Wages	(3) 5 Skill Groups	(4) MSAs	(5) Men Only	(6) OLS	(7) Urban Areas
1	-0.29	-0.15	-0.48	-0.47	-0.30	-0.04	-0.21
	(0.10)	(0.10)	(0.09)	(0.03)	(0.13)	(0.073)	(0.10)
2	-0.18	-0.12	–	-0.02	-0.21	-0.01	-0.17
	(0.03)	(0.02)		(0.07)	(0.03)	(0.01)	(0.04)
3	-0.06	-0.08	-0.04	-0.01	-0.09	-0.02	-0.06
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.01)	(0.02)
4	-0.03	-0.05	–	-0.07	-0.07	-0.01	-0.03
	(0.01)	(0.01)		(0.03)	(0.02)	(0.02)	(0.02)
5	-0.00	0.00	-0.01	-0.07	-0.03	0.00	-0.01
	(0.01)	(0.02)	(0.02)	(0.05)	(0.03)	(0.01)	(0.02)
6	0.01	0.04	–	-0.02	0.03	-0.01	-0.01
	(0.02)	(0.013)		(0.04)	(0.06)	(0.01)	(0.04)
7	-0.01	0.01	0.01	-0.03	-0.09	0.02	-0.04
	(0.02)	(0.03)	(0.05)	(0.14)	(0.06)	(0.02)	(0.05)
8	0.12	0.26	–	0.25	-0.03	0.04	0.06
	(0.07)	(0.06)		(0.10)	(0.10)	(0.02)	(0.09)
9	0.31	0.35	0.36	0.38	0.29	0.11	0.28
	(0.05)	(0.04)	(0.07)	(0.13)	(0.06)	(0.03)	(0.06)
10	0.72	0.63	–	0.60	0.80	0.33	0.66
	(0.10)	(0.10)		(0.13)	(0.11)	(0.13)	(0.10)
ark	✓	✓	✓	✓			

Notes: Each row shows an estimated coefficient γ_1 from equation (2) indicating the immigrants' impact on natives' wages at a separate point of the wage distribution, and each column presents a different specification. All estimates reflect a one percentage point increase in the share of immigrants and are hence interpreted as semi-elasticities. The outcome variable is log real weekly (hourly in Column 2) wages adjusted with a local price index. Standard errors are clustered by CZ and presented in parenthesis. The sample is the same as in Figure 1.

Table A5: Quantile Treatment Effects of the Impact of Immigrants on Natives' Wages

	Outcome Variable: Log Real Weekly Wage						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Decile / Skill Group	Baseline	Hourly Wages	5 Skill Groups	MSAs	Men Only	Year 2000	Urban Areas
1	-0.27	-0.30	-0.57	-0.27	-0.24	-0.24	-0.28
	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)
2	-0.13	-0.14	-0.44	-0.11	-0.11	-0.19	-0.13
	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
3	-0.08	-0.13	-0.14	-0.07	-0.11	-0.10	-0.08
	(0.02)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)
4	-0.08	-0.11	0.08	0.03	-0.04	-0.07	-0.08
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)
5	-0.03	-0.09	0.21	0.12	0.02	0.00	-0.04
	(0.01)	(0.01)	(0.01)	(0.03)	(0.00)	(0.01)	(0.01)
6	0.10	-0.08	0.29	0.13	0.13	0.08	0.09
	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
7	0.12	-0.00	0.31	0.15	0.08	0.11	0.11
	(0.02)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.02)
8	0.26	0.26	0.32	0.20	0.14	0.22	0.17
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
9	0.26	0.39	0.37	0.42	0.16	0.32	0.37
	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)
10	0.23	0.46	0.13	0.25	0.23	0.17	0.22
	(0.03)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)

Notes: Each entry is an estimated QTE at a specific point of the wage distribution, and each column is a different specification. These are constructed by comparing the 2015 wage distribution (2000 in Column 6) with a counterfactual one with lower immigration levels. See Section 3.3 for more details on the methodology. All regressions control for Bartik index for local labor demand shocks and include a control function based on the networks instrument. The first stage is estimated with 100 distributional regressions using a linear probability model, and the standard errors are estimated via 20 bootstrap replications. To account for correlation in earnings within cities, I use a cluster bootstrap method with 20 replications of the entire estimation. The outcome variable is log real weekly wages adjusted with a local price index. The sample is the same as in Figure 1.