

# Immigrants and the US Wage Distribution\*

Vasil I. Yasenov<sup>†</sup>

UC Berkeley, Stanford University and IZA

March 4, 2019

US 2050 Initiative Version

## Abstract

Since the 1980s the stock of immigrants to the US has been rapidly increasing potentially disrupting labor markets across the country. A large body of literature estimates the relative wage impact of immigration on high- and low-skill workers, but we know much less about how these effects map onto changes of the earnings structure. I begin with descriptively documenting the evolution of foreign-born workers in the natives' wage distribution, showing that, over time, they have become increasingly over-represented in the very bottom. I then undertake two distinct empirical approaches in deepening our understanding of the way foreign-born shape the earnings structure. First, I construct a counterfactual wage distribution with lower immigration levels and estimate reduced-form quantile treatment effects. Second, I build and estimate a standard theoretical model featuring Constant Elasticity of Substitution (CES) technology and skill types stratified across wage deciles. Both analyses uncover similar monotone effects: a one percentage point increase in the share of foreign-born leads to a 0.1-0.2 (0.2-0.3) percent wage decrease (increase) in the bottom (top) decile and asserts no significant pressure in the middle.

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

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

---

\*I would like to thank Marianne Bitler, George Borjas, Henry Brady, Colin Cameron, David Card, Domenico Depalo, Nicole Fortin, Hilary Hoynes, Patrick Kline, Adriana Kugler, Mark Lopez, Doug Miller, David Neumark, Giovanni Peri, Shu Shen, Chris Walters and seminar participants at UC Davis, UC Berkeley IRLE, and US2050 meetings in the Brookings Institution and West Palm Beach, FL. Much of the work on the current version was completed while I was a postdoctoral scholar in the Goldman School of Public Policy at UC Berkeley. I have benefited from data and code made public by Gaetano Basso, Blaise Melly and Evan Rose. This research was made possible by the US2050 project, supported by the Peter G. Peterson Foundation and the Ford Foundation and the W.E. Upjohn Institute for Employment Research Early Career Research Grant. The statements made and views expressed are solely my responsibility. All errors are my own.

<sup>†</sup>Address: Stanford University, Immigration Policy Lab, Encina Hall West, 616 Serra St., Stanford, CA 94305; Email: [yasenov@stanford.edu](mailto:yasenov@stanford.edu), Website: <https://sites.google.com/site/yasenov/>

# Contents

<b>1</b>	<b>Introduction</b>	<b>3</b>
<b>2</b>	<b>Theoretical Model</b>	<b>8</b>
<b>3</b>	<b>Empirical Strategy and Data</b>	<b>10</b>
3.1	Skill Groups and Concentration Measures . . . . .	10
3.1.1	Defining and Measuring Skill Groups . . . . .	10
3.1.2	Skill Downgrading . . . . .	11
3.1.3	Concentration Indexes . . . . .	12
3.2	Structural Method . . . . .	13
3.3	Counterfactual Distribution Method . . . . .	14
3.4	The Shift-Share Networks Instrument . . . . .	17
3.5	Data . . . . .	18
<b>4</b>	<b>Results</b>	<b>19</b>
4.1	Descriptive Findings . . . . .	19
4.2	The Effects of Immigrants on the Wage Distribution . . . . .	23
4.2.1	Structural Estimates . . . . .	23
4.2.2	Counterfactual Distribution Estimates . . . . .	25
<b>5</b>	<b>Discussion</b>	<b>26</b>
<b>6</b>	<b>Figures</b>	<b>31</b>
<b>7</b>	<b>Appendix: Figures and Tables</b>	<b>40</b>

# 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 (e.g., 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 impact of immigration on high- and low-skill native workers. While this analysis is motivated by theoretical considerations, economic theory itself does not give clear-cut classification of exactly which workers comprise each skill group. This choice turns out to have important implications on the empirically estimated effects of immigration.<sup>1</sup> Moreover, even if one knew the exact definition of each skill type, classification into correct types may be undermined by potential undervaluing of foreign workers' human capital attributes and credentials obtained abroad (Dustmann et al., 2013) and/or measurement error in schooling or labor market experience (e.g., 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 onto the observed wage structure. A main underlying theme throughout the analysis is stratification of skill types based on an unidimensional productivity measure - their location in the wage distribution (Dustmann et al., 2013). As explained below, this choice is designed to overcome 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 decile, which gives a first order hint as to which native skill groups ought to experience the largest competition on the labor market. I then test for skill downgrading among immigrants by comparing their position in the wage distribution with a prediction based on their skills being valued at the same rates as natives. Next, I zoom in on their geographic distribution and I calculate Herfindahl concentration and Duncan dissimilarity indexes for and between migrants and natives in the areas with largest stock of foreign-born. These indexes represent direct

---

<sup>1</sup> See Borjas et al. (2008); Ottaviano and Peri (2012) or Section 3.1 below.

measures of relative shares distortion, further indicating the possible relative wage deformation severity. I demonstrate that foreign workers' skills have indeed become less balanced over time, potentially placing pressure on the earnings structure.

In the second part of the paper I attempt to make progress towards 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 workers within multiple skill groups and constant elasticity of substitution (CES) production technology. Skill types are again defined by workers' position in the real wage distribution. I deflate all wages by a local price index following Moretti (2013) accounting for differential cost of living across localities. Using location in the wage distribution as a skill proxy 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 (e.g., Ashenfelter and Krueger (1994)). Moreover, using more disaggregate skill groups enables investigation of possibly important heterogeneous effects within, for instance, broadly defined low- and high-skill types. I proceed with two distinct empirical strategies.

First, 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* 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 quantile regressions (see Lee, 2007). Comparing the actual and counterfactual earnings distributions at various quantiles of interest yields estimates of the impact of immigration.

Second, I estimate the main prediction of the theoretical CES model relating local natives relative wages and immigration pressure. 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). 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 then the sum of the skill-specific probabilities across all workers employed in the labor market. 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 distribution.

Descriptively I find that, since 2000, the wave of foreign-born workers to the US has become increasingly over-represented in the bottom portions of the natives' wage distribution. While the foreign skill distribution was somewhat evenly spread in the 1980s, the US began receiving disproportionately more low-skill workers. Partially driving this pattern is skill downgrading - immigrants' human capital is undervalued relative to natives in the labor market. In terms of skill types and in the largest Commuting Zones, immigrants concentrate at higher rates than native-born workers. Nonetheless, in some localities they can significantly alter the pre-existing skill shares among natives thereby placing pressure on their economic outcomes.

The causal results uncover heterogeneous impacts of immigrants on the wage distribution whereby foreign-born exert pressure in the very bottom, leave largely unaffected the vast majority of the distribution and increase wages in the top. 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 0.2-0.1 (0.2-0.3) percentage points decrease (increase) in the bottom (top) decile of the wage structure. Although most of the estimated magnitudes are benign, they can certainly be masked when one focuses on two broadly defined skill groups. These findings are in line with, albeit smaller in magnitude than, Dustmann et al. (2013) who find a similar monotone pattern for the UK. The smaller elasticity magnitudes may partially be explained by the higher rates of labor mobility and lower rigidity in the US. All in all, the small magnitudes suggest foreign workers did not play a key role in the observed wage structure changes. The pattern I observe is consistent with a recent summary of the literature by the National Academy of Sciences . (2017) but sheds a new perspective on the “winners” and “losers” of immigration.

The data sources are the Integrated Public Use Microdata Samples (IPUMS) of the US Censuses in 1940, 1980, 1990 and 2000 and the American Community Surveys in 2008 and 2015. The outcome variable is real weekly wages among natives and spatial areas are Commuting Zones. Identification is based on (i) relying on predicted location in the national wage distribution, (ii) controlling for city-specific time-varying productivity shocks as proxied by a Bartik index and (iii) the migrant 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. With regards to the third strategy, a series of major geopolitical events throughout post-1940 including the end of World War II, the Bracero agricultural program, the Cuban Revolution, the Vietnam war as well as the passage of the extensive Immigration and Nationality Act of 1965 have sufficiently shuffled the local country

of origin mix among foreign workers, further shielding the analysis from confounding factors (see Jaeger et al. (2016)).<sup>2</sup> Throughout the paper I conduct a series of robustness checks such as focusing on native men, on the largest labor markets, using five or ten skill groups, using metropolitan areas and hourly wages. None of these choices plays a crucial role in the results.

The findings here have important implications for the future outlook of the US wage distribution. The current immigration system in the US is governed by the Immigration and Nationality Act of 1965. This legislation eliminated the longstanding quota system, replacing with a family-based US residency allocation. Hence, for the past fifty years, the majority of resident permits (i.e., green cards) are given to close relatives of US residents. On the other hand, some other Western countries such as Canada and Australia employ a system in which individuals are preferentially admitted based on their skills. Consequently, the foreign-born population in these countries tend to have higher education levels than the native workforce. Looking ahead, the Pew Research Center projects that immigration to the US would be a crucial population growth driver for the nation in the coming few decades Center (2015). At the same time, current policy debates about an overhaul of the immigration system often center around a shift towards focusing on admitting high skilled foreigners Griswold (2017). Even if such a change does not materialize, we are currently seeing a rise in immigrants' education levels Krogstad and Radford (2018). This pattern is mostly driven by (i) an increase in South and East Asian migrants and (ii) a decrease net migration from Mexico and Central America. These trends coupled with my findings imply, all else equal, immigration may play at most a modest role in exacerbating differences between the top and bottom wage distribution.

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 possible answers depending on the built-in adjustment mechanisms.<sup>3</sup> However, the simplest canonical version of a labor demand model with heterogeneous labor supply and a constant returns to scale world predicts that migrants distort relative wages among natives to the extent to which they alter their relative supply. That is, an exogenous flow of immigrants increases the marginal productivity of production inputs with most dissimilar characteristics and depress the

---

<sup>2</sup>Jaeger et al. (2018) argue this instrument conflates the short- and long-run adjustments to immigrants flows. If too slow to occur, general equilibrium adjustments leading to positive wage growth will bias estimates based on this shift-share IV. To overcome this issue they propose (i) adding a lagged value of the shift-share as a control variable and (ii) using 1940 as base year. While I am able to incorporate the second suggestion, the first one is too demanding and leaves insufficient first-stage power for some of the skill groups.

<sup>3</sup>These may include imperfect substitution between natives and foreign-born, voluntary unemployment, capital adjustment, product mix, open economy trade, demand effects, etc. See Borjas (2013); Dustmann et al. (2008); Gaston and Nelson (2000) for excellent discussions on the theoretical predictions on the impacts of immigration on wages and employment.

wages of the most similar ones. Average marginal products in the long run remain unchanged since capital stock adjusts.

Besides these studies focusing on mean wages, several papers analyze the effect of immigration on different points of the natives' wage distribution.<sup>4</sup> The overall findings are mixed. Most prominently, Dustmann et al. (2013) build a model in which skill groups are defined as workers' position 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 workers which further motivates my approach. Favre (2011) follows their analysis to study the wage structure in Switzerland finding no such significant effects. Next, Olney (2012) performs a similar empirical analysis across US states and incorporating 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 endogeneity, 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.<sup>5</sup> Labor markets in the US and Europe differ substantially in important aspects such as worker and capital mobility, wage rigidity, institutions and policies (e.g., collective bargaining coverage, replacement rates, etc). These differences may certainly impact the competition between native and foreign labor, requiring separate treatment. It is not immediately clear how their findings will 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. This type of analysis is entirely novel to the literature. My empirical specification motivated by the model uses variation of migrants across skill groups within each local labor market. This specification captures exposure to foreign labor more effectively than the overall share of immigrant, a crude measure used in most previous studies. The skill composition of foreign-workers varies widely across cities, hence their mere share in the labor market is an inadequate

---

<sup>4</sup>Related to this strand of studies, but still focusing on "low" (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 inequality.

<sup>5</sup>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.

measure of competition with foreign 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 predicting 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 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  $j = 1 \dots J$  skill types:

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

where  $\theta_j$  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 the 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  $\beta = 1$  and 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 an 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 of up 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  $\eta$ <sup>6</sup> such that  $\Delta \log L_j^{NAT} = \mu + \eta \Delta \log w_j + \delta_j$ , where  $\mu$  is an intercept common to all skill types and  $\delta_j$  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:

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

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

---

<sup>6</sup>More precisely,  $\eta$  measures the percentage change in the supply of native labor in response to a percentage change in their earnings.

## 3 Empirical Strategy and Data

### 3.1 Skill Groups and Concentration Measures

#### 3.1.1 Defining and Measuring Skill Groups

A starting point and a distinct feature common 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 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 immigrant 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 workers across a much larger segment of the labor market. Alternatively, assuming these education groups are distinct and non-substitutable inputs results in strongly concentrated competition and downward wage pressure among native dropouts.

A second advantage 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 are of worse quality (e.g., Card and Krueger, 1992). For instance, it is unclear whether a college graduate from Bulgaria "competes" for job opportunities with an otherwise similar US high school graduate, Associate's degree holder or a college student. This renders classifying foreign workers into skill groups potentially problematic. Dustmann et al. (2013) show evidence for skill downgrading in the UK whereby foreign workers are overrepresented in the bottom of the distribution relative to their skills. In the subsection below I describe the method I use to analyze skill downgrading in this context.

Third, this choice also avoids the possible misclassification due to skill downgrading or 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).<sup>7</sup> Lastly, the assumption that individuals' rank in the earning 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 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 in ordered probit regressions. Skill groups could be distinct deciles or quintiles of the wage distribution. This assignment cleans away part of the variation of labor types across spatial areas due to endogenous demand-pull factors. The sum of skill-specific probabilities across all workers within a locality is the expected skill-specific stock of labor in absence of local labor demand distortions. This mechanism can alternatively be viewed as assigning a probabilistic value of belonging to each 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 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 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 in 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 with constructing a predicted wage structure for natives based on their demographic characteristics. Next, I assign the estimated returns to these characteristics to foreign-born

---

<sup>7</sup>The approach I undertake is similarly prone to misclassification due to measurement error in wages e.g., (e.g. Bound and Krueger, 1991). However, this will be problematic only for individuals at the margins (i.e., around deciles/quintiles cutoff values).

workers and obtain their predicted location in this wage structure. That is, I construct predicted immigrants' earnings assuming their education and experience are valued as they are for natives. This procedure yields stock of foreign-born at each point in the predicted 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-/under-valued in the 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, estimate regressions separately for men and women and each time period in the sample.

### 3.1.3 Concentration Indexes

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

$$Herfindahl\ Index_k = \sum_{j=1}^J b_{jk}^2,$$

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/relative labor shares distortion. For instance, in the extreme case in which a particular group  $k$  is comprised only of low-skilled workers ( $b_{1k} = 1$  and hence  $Herfindahl\ Index_k = 1$ ), their presence will place strong downward wage pressure on low-skilled natives since their labor is more abundant.

The Herfindahl index measures the degree to which a particular group is concentrated relative to a completely even distribution. However, when interested in relative labor share distortions among native workers at the local labor market level, this may be an informative but not ideal measure. For instance, native workers in Washington, DC are disproportionately high skilled in which case a high-skilled 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 Duncan dissimilarity index measures the skill type evenness with which the two nativity groups are distributed within each labor market. It is defined as

$$Duncan\ Index_k = \frac{1}{2} \times \sum_{j=1}^J |b_{jk}^{IMM} - b_{jk}^{NAT}|,$$

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 higher degree of dissimilarity between the two nativity groups. It is interpreted as the percentage 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 which ensures no wage effects of immigration. This is indeed the index of interest when measuring native relative share distortion induced by foreign-born flows.

### 3.2 Structural 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 regression equation I estimate is:

$$\Delta \log w_{jrt} = \gamma_0 + \gamma_1 \Delta p_{jrt} + \gamma_2 \Delta \mathbf{X}_{jrt} + \Delta \delta_t \times \kappa_j + \Delta \epsilon_{jrt}, \quad (2)$$

where

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

This quantity measures the local change in the stock of immigrants between two time periods as a proportion of the initial labor force.<sup>8</sup> The outcome variable is the change in log real weekly wages among native workers. First-differencing eliminates all citywide skill-specific and time-invariant factors affecting labor markets (e.g.,  $\Delta \tilde{\psi}$ ). The term  $\Delta \delta_t \times \kappa_j$  captures skill-specific time trends accounting for differential national

---

<sup>8</sup>This specification avoids spurious endogeneity concerns of less careful specifications, such as differences in the share of foreign-born (see Card and Peri (2016)) in equation (2).

wage trajectories by skill type (e.g., the term  $\Delta\tilde{\phi}_j$  in equation (2)). Next,  $\Delta\mathbf{X}_{jrt}$  are time-varying control variables (e.g., Bartik growth index,<sup>9</sup> demographics) and  $\Delta\epsilon_{jrt}$  is an idiosyncratic mean-zero error term.

The coefficient of interest,  $\gamma_1$ , is a function of the elasticity of substitution between the labor types ( $\frac{1}{1-\beta}$ ) and the labor supply elasticity of natives ( $\eta$ ). It is interpreted as the percent change in natives' wages for a one percentage point increase in local immigration stock. Importantly, to obtain the effect of immigration on a specific skill type/part of the earnings distribution, I estimate this equation separately for each skill type  $j$ . In these models I include skill-specific time trends instead. 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 the Section 3.1 above, I use predicted rather than observed skill type  $j$ . In particular, skill-specific labor supply at 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 absence of market distortions.

Skill-specific wages ( $\log w_{jr}$ ) 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 distribution, the one for the second lowest is the 15th (30th) quantile, etc. I purge 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 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 pressure on the natives' wages distribution. The thought experiment is

---

<sup>9</sup>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  $t$ .

comparing the observed wage structure with one that would have prevailed with lower immigration levels. To construct this latter 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  $F_{\log w}(\cdot)$  and  $F_{\log w|p}(\cdot)$  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  $p$ . Let  $p$  stand for current immigration levels, while  $\tilde{p}$  denote lower immigration pressure by a single percentage point, so that the estimates have a semi-elasticity interpretation. I can decompose the counterfactual marginal wage distribution of interest,  $F_{\log w|\tilde{p}}^C(\cdot)$ , into a mixture of the observed wage structure and the foreign-born labor distribution as follows:

$$F_{\log w|\tilde{p}}^C(\cdot) \equiv \int F_{\log w|p}(\cdot) dF_{\tilde{p}}(\cdot).$$

Chernozhukov et al. (2013) propose tracing out  $F_{\log w|p}(\cdot)$  with a series of quantile regressions relying on the one-to-one relationship between the quantile function and the CDF. The second term,  $F_{\tilde{p}}(\cdot)$ , is a marginal distribution which could be estimated with standard density estimation methods. The authors establish bootstrap validity results and practical procedures for correctly estimating confidence intervals for this counterfactual distribution.

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

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

The QTEs are interpreted as the percent change in the  $\tau$ -th quantile of the wage structure for a ceteris paribus increase in immigration exposure by one percentage point. Note here  $\tau$  proxies for skill. For instance, If skill types are stratified across deciles, the impact on the 5th percentile ( $\tau = 5$ ) corresponds to the average wage impact on the bottom skill group.

I control for Mincerian-type characteristics and approximate natives' wages with the following relationship:

$$\log w_{irj} = \beta_0 + \beta_1 p_{rj} + \beta_2 \mathbf{X}_i + \beta_3 \mathbf{W}_{rj} + \epsilon_{irj}, \quad (3)$$

where  $i$  denotes worker,  $r$  labor market, and  $j$  skill group. The term  $p_{rj}$  meant to capture immigration 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 interactions included in the ordered probit regressions, while  $\mathbf{W}_{rj}$  includes Bartik index for employment growth controlling for local demand-pull shocks.

As discussed in the Section 3.4 below,  $p_{rj}^t$  is likely to be correlated with labor demand shocks simultaneously attracting foreign-born and raising wages. 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 controlling for endogenous variables in non-linear settings and quantile models in particular (Lee, 2007; Imbens and Newey, 2009). 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).

I model immigration exposure as follows:

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

where  $\hat{p}_{rj}$  is the shift-share instrumental variable described below and all other terms are defined as above. In this framework Lee (2007) shows the control function is in fact the estimated residual  $\hat{u}_{irj}$  and formally states the required identification assumption. Namely, a quantile independence between the structural error term ( $\epsilon_{irj}$ ) and the immigration share ( $p_{rj}$ ) conditional on the control function ( $\hat{u}_{irj}$ ) and all exogenous covariates. Note that this condition, although traditional, 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, 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 obtain the predicted residuals. They serve as the control function and are added to equation (3).<sup>10</sup> I then proceed in estimating the counterfactual wage distribution using and inverting quantile regressions. The conditional earnings distribution given the included controls,  $F_{\log w|p}^{-1}(\cdot)$ , is estimated by inverting 100 quantile regressions. To relieve computational burden associated with this task, I estimate this equation on a 20% random sample of the 2015 ACS data and use 20 bootstrap replications to obtain standard errors. All regressions are weighted by Census personal weight. To account for correlation

<sup>10</sup>Lee (2007) suggests that the control function enters equation (3) semi-parametrically to avoid assuming a strictly linear relationship between two unobserved variables (the error term  $\epsilon_{irj}$  and the control function  $\hat{u}_{irj}$ ). I ran the same model with the control function entering us  $B$ -splines of various degrees but this made little change to the results.



in earnings within cities, I use a cluster bootstrap method with 20 replications. Lastly, I obtain the  $QTE(\tau)$ 's of interest by juxtaposing the actual and counterfactual earnings structures.

### 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. 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 workers to booming markets. To go even 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 the ethnic goods and services, newly-arriving foreign-born are more likely to settle in areas with 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  $\rho_{cr}^{1940}$  denote their share located in city  $r$  in year 1940,  $\pi_{jc}$  denote their national share in skill group  $j$  and let  $\omega_{tc}$  be 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. They have reshuffled the country of origin mix among foreign-born workers to break the autocorrelation between unobserved demand

shocks (see Jaeger et al., 2016). Assuming each term is unrelated to *local* demand factors, I construct the instrumental variable  $\Delta\tilde{\rho}_{jrt}$  as follows:

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

where

$$\hat{L}_{jrt}^{IMM} = \sum_c \rho_{cr}^{1940} \times \pi_{jc} \times \omega_{tc}.$$

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, 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.<sup>11</sup>

The main sample consists of workers age 18-64, in the labor force, not in group quarters or self-employed and with positive reported earnings. I loosely refer to this group as “labor force” throughout the paper. All results are estimated on 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 citizen or not US citizen at all. To avoid issues with differential female labor force participation in the 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

---

<sup>11</sup>All MSA results exclude year 2015 because IPUMS’ *metarea* variable is unavailable for in this time period.

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 that fact that, for instance, a \$20 hourly wage does not carry the same purchasing power in Washington, DC and in Kentucky. It asserts that, in estimating nationally based wage bins, earnings across localities are comparable. I also use hourly real wages calculated by dividing the weekly wages by the reported usual hours worked per week.

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. I use year 1940 as a base time period in constructing the shift-share instrument. Note this is prior to a series of major events which disrupted the foreign-born source country mix - the end of World War II, the Vietnam and Korean Wars, the Cuban Revolution, the Bracero program and the enactment of the Immigration and Nationality Act of 1965. These historical events are meant to break the correlation between initial immigrant settlements and later labor demand shocks.

## 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. The stock of native workers in each quintile is, by construction, equal, so these 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 year 2000, the US started receiving disproportionately more low-skilled 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%. As predicted by the CES model, this concentration pattern may certainly place downward pressure on the wages of low skilled natives, while the high skilled worker is predicted to experience relative gains.

**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 these bins do not correspond to equal native labor force size and hence do not have a ratio interpretation. We do not observe a strong over-representation 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 (9.6 million) than high school graduates or workers with lower education (10.2 million). Assuming a strong relationship between the two distributions, 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 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' credentials and 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. A value greater than one indicates foreign-born are over-represented in that segment of the distribution. The figure shows that, regardless of the time period, foreign-born are over-represented in the bottom and in some years under-represented in the top. Put differently, among an otherwise identical native and foreign workers, the former is more likely to rank higher in the wage distribution. 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 expe-

rience inadequate and motivates the choice of using location in the wage distribution as a more direct skill proxy.

**Heterogeneity by Birthplace.** Next, I aim attention at which immigrant groups have contributed the most to the large and uneven immigration 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 immigrant group across skills sum 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 over-/under-representation. Foreign-born from Mexico and the rest of Latin America are predominantly low skilled, heavily represented in the bottom of the wage structure. Only 3.9% of them ranked in the top quintile while 41.8% were in the bottom 20 percentiles. On the other hand, immigrants from India are more likely to be high skilled - 40% of them fall in the top wage quintile. Lastly, foreign-born groups from China and Eastern Europe are the most evenly spread by skill type, minimally disrupting skill type shares among natives at the aggregate level.

Panel B of the same figure 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. 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 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 evenly distributed in 1980 as well. All in all, this figure illustrates that there is significant variation of skill types by country of origin. Immigrants from Mexico and Latin America are, on average, low skilled while foreign-born from China and India are more likely to fall in the top of the wage distribution. Appendix Table A1 shows more detailed related statistics and extends this figure to other areas of origin.

**Geographic Heterogeneity.** National trends are limited in giving insights relating to relative skill shares distortion because workers compete for jobs locally. To gain a better perspective of the competition between natives and foreign-born, I zoom in on local labor markets stratified across Commuting Zones. 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 while the Midwest and parts of the North had the largest groups of high-skilled immigrants. Panel B of Figure 5 shows the same numbers for 2015. Foreign-born skill groups are have grown more dispersed over time with an increase in within state variation of the most representative skill group. The two lowest skill types are the most representative in most cities. This is the case for most of the West and the entire state of California. On the other hand, high-skilled immigrants are most common in Seattle, WA, parts of Texas and the Midwest and the Northeast. Overall, the figure illustrates considerable variation in immigrant skill groups across localities, facilitating the estimation of their impact on the wage structure.

To zoom in on local skill shares distortions one degree further, Figure 6 presents skill group concentration indexes by nativity in the top immigrant receiving cities for years 1980 (Panel A) and 2015 (Panel B). Herfindahl concentration indexes for immigrants (natives) are displayed in black squares (blue circles). Higher values correspond to stronger concentration by skill group. Duncan dissimilarity index between the two nativity groups are shown in green diamonds. Higher values indicate more uneven skill distribution between immigrant and native workers hence stronger downward wage pressure on the most represented by immigrants skill group. Three features of this figure are noteworthy. First, foreign-born workers have become more concentrated over time. These concentration patterns are driven by low skilled only (e.g., in Los Angeles, CA and Miami, FL) or by low and high skilled immigrants (e.g., in New York, NY and Seattle, WA). Second, immigrants are now more concentrated by skill than natives in each CZ. 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 Duncan index. In a constant return to scale production technology, skill similarity implies a production expansion in which relative input prices are unaffected.

To summarize the descriptive evidence, (i) since the 1980s the US has received a large wave of foreign-born which over time has become disproportionately more low-skilled, 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, in the light of the increased college attainment of the native labor force over the same time period, these patterns suggest foreign workers have rendered low skill labor relatively more abundant, possibly placing downward wage pressure on its price. I now move on to using this geographic variation of immigrants across the US

to analyze their impact on the natives' wage distribution.

## 4.2 The Effects of Immigrants on the Wage Distribution

### 4.2.1 Structural Estimates

**Ordered Probits and Predicting Skill Types.** As explained in Section 3.1, I predict workers' location in the national earning structure with ordered probit regressions. A primary benefit of this approach is to purge local demand factors simultaneously attracting workers and raising input prices. I generate predicted probabilities for each individual and skill group which I use to calculate city-level skill-specific labor supply. Before proceeding to the estimating the 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 higher 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 and more married workers. Interestingly, 16% of all workers in the bottom quintile in 2015 were college graduates. This signals the inability of capturing productivity using education level alone and highlights the need of stratifying skill types along other dimensions. This panel asserts well-documented facts that whites, men, more educated and experienced workers earn higher wages in the labor market.

Panel B of the same table shows the same characteristics as predicted by the ordered probit regressions. That is, I assign every individual the quintile with highest predicted probability and summarize demographics by skill group. Note that this is a more stringent classification than the one I use to calculate labor supply where I use the variation in probabilities across all skill groups for each worker. 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 fewer women, more whites, higher educated, and more married individuals.

**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) 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 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. The coefficient from a pooled regression with all skill types indicating the effect of foreign labor on average wages is denoted with a dashed horizontal line. These regressions additionally control for national skill-specific time trends. All regressions control for Bartik employment growth, 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 0.10 (0.15) percentage points in the very bottom (top) of the distribution. The average effect, on the other hand, is very close to zero, masking this heterogeneity. Note these estimates control for endogenous self-selection of immigrants into localities by (i) estimating the local labor stock using nationally based skill-specific probabilities and (ii) controlling for Bartik Index measuring local productivity shocks and city fixed effects. In a series robustness check below I additionally use the shift-share instrument to further mitigate endogeneity concerns about immigrants' location choices.

**Robustness Checks.** Next, the six panels of Figure 8 show different robustness checks. All graphs and regressions follow the conventions of the previous figure. Panel A presents the results when using hourly wages as an outcome variable. These are constructed by dividing the respondents' weekly wages by the usual reported number of hours worked per week. The estimates remain very similar to the main results. In Panel B I use a specification with five (instead of ten) skill groups and each circle is interpreted as the effect of immigration on the respective quintile of the weekly wage distribution. The estimated effect in the very bottom is attenuated to -0.05. This is possibly explained by a stronger concentration of immigrant in the lowest than in the second lowest deciles and hence its impact is diffused when pooling the two into a single skill group. In Panel C I use metropolitan areas (MSAs) instead of CZs to define labor markets. All coefficients are estimated less precisely and the ones in the top are larger in magnitude. The semi-elasticity for the bottom (top) decile is -0.09 (0.22) while the mean is -0.03.

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 noisier due to the smaller sample from which wages are estimated but the (weakly) monotone pattern is virtually unchanged. Next, to further address potential endogeneity concerns, in Panel E I use



the shift-share networks instrument described in Section 3.4 and estimate (2) with 2SLS. The effects in the top and bottom are slightly magnified with the elasticity in the bottom (top) decile equal to -0.19 (0.35). Lastly, in Panel F I restrict the sample to CZs with above median rural-urban continuum code as defined by the United States 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. This choice does not affect the results significantly. Figure A1 mirrors Figure 8 by estimating every specification with 2SLS using the networks instrument. Most coefficients are less precisely estimated and slightly larger in magnitude but the general pattern remains the same.

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.** Table 1 presents the results from the counterfactual exercise described in Section 3.3. Each row shows the quantile treatment effect at a separate point of the wage distribution. These QTEs are interpreted as semi-elasticities as the results above. The columns represent different specifications and robustness checks following Figure 8. All regressions are weighted by Census sampling weight and control for individual characteristics (as in the ordered probit models), Bartik Index for local demand shocks, control function and city and skill fixed effects. Cluster bootstrapped standard errors accounting for within CZ residual correlation in wages are estimated based on Chernozhukov et al. (2013) and shown in parenthesis. The outcome variable is Mincerian log real weekly wages adjusted with a local price index and measured for native workers only.

Column 1 presents my baseline specification where I define 10 skill groups. The impact of immigration is monotone across the distribution, with negative values in the bottom, virtually insignificant effects in the large middle part and positive ones in the top. A one percentage point increase in the share of immigrants leads to 0.26 percent decrease in wages in the very bottom and 0.93 percent increase in the top.

**Robustness Checks.** The next six columns present robustness checks. In Column 2, I use five skill

groups along distribution quantiles to measure immigration exposure. As discussed earlier, this diffuses competition between native and foreign low-skilled workers into a much larger segment and hence attenuates the effects in the bottom (-0.21). The rest of the estimates are similar to the ones in Column 1. Next, in Column 3, I use MSAs to define local labor markets. The impact on the bottom decile is slightly larger in magnitude (-0.33) while there are no other significant changes throughout the distribution. In Column 4 I use hourly wages as an outcome variable and in Column 5 I analyze the effects only on men. The overall pattern of monotone effects remains unchanged and most of the estimates are not significantly different from the ones in Column 1. In Column 6 I focus on urban CZs as defined by CZs with below median rural-urban continuum code. Lastly, in Column 7 I use logistic distribution (rather than quantile) regressions to trace out the conditional wage distribution. Again, these choices do not change the results significantly.

Overall, similarly to the CES model results, the counterfactual analysis uncovers small, monotone treatment effects of foreign-born workers on natives' earnings. Immigrants place downward pressure on the very low skilled natives: a one percentage point increase in the share of foreign-born leads to -0.26 (0.53) percent decrease in natives' wages in the bottom (top) decile. This pattern is consistent across a series of robustness checks and subsamples.

## 5 Discussion

In this paper I study the location in and effect of immigrants on the US wage distribution. Descriptively, I find that since 1980 foreign-born workers are increasingly over-represented in the very bottom. Immigrants' skills are downgraded - i.e., there are more foreign-born in the bottom deciles than their education and experience imply, partially driving this over-representation in among the low-skilled workforce. In other words, comparing otherwise identical foreign and native workers, the latter are more likely to earn higher wages. Over time the immigrant population has increased its skill concentration in most major cities. Taken together, these patterns suggest foreign-born workers may place an increasingly intensifying downward wage pressure among the lowest skill native group.

I use two distinct approaches to estimate their impact across the wage structure - estimating a CES model and constructing a reduced-form counterfactual wage distribution. Both empirical approaches uncover weakly monotone effects. Across most specifications I estimate small negative effects the below the 10th percentile, larger positive ones above the 90th 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 0.1 percent wage decrease in the bottom decile and 0.3 percent wage increase in the top one. These magnitude imply the rise of immigration over the past few decades is unlikely to have played a major role in changing the earnings structure.

Several factors may explain this pattern. First, it is important to point out that, motivated by the simple theoretical model, I relate city- and skill-specific earnings and foreign-born induced pressure at the same aggregation level, which may omit cross skill-cell complementarity or productivity spillovers (see Ottaviano and Peri, 2012). In other words, I estimate direct partial wage impacts of immigration focusing on within skill competition and abstracting from spillover effects. Therefore, my estimates should be taken as lower bounds of the total wage impact of foreign-born workers. Second, the lack of strong competition effects in the bottom highlights the importance of adjustment mechanisms in absorbing local supply shocks. Key mechanisms previously shown to dampen the competition forces between native-born and foreign workers include complementarity in production (Ottaviano and Peri (2012)), productivity-enhancing specialization (Peri and Sparber (2009)), adjustments in technology (Clemens et al. (forthcoming); Lewis (2011)) and positive local demand impacts (Bodvarsson et al. (2008); Hong and McLaren (2015)). Lastly, I estimate strong complementarity effects in the top decile. As potential drivers of this result, previous studies have documented substantial contribution of foreign skilled labor to patented innovation (Alesina et al. (2016); Hunt and Gauthier-Loiselle (2010); Peri (2012)), the scientific process and productivity growth (Peri et al. (2015)). Moreover, these phenomena are likely to propagate and positively impact workers in the bottom of the distribution through, for instance, increased productivity and yet are unlikely to be captured in my analyses. These will likely further weaken the competition among low skilled with foreign-born workers.

## References

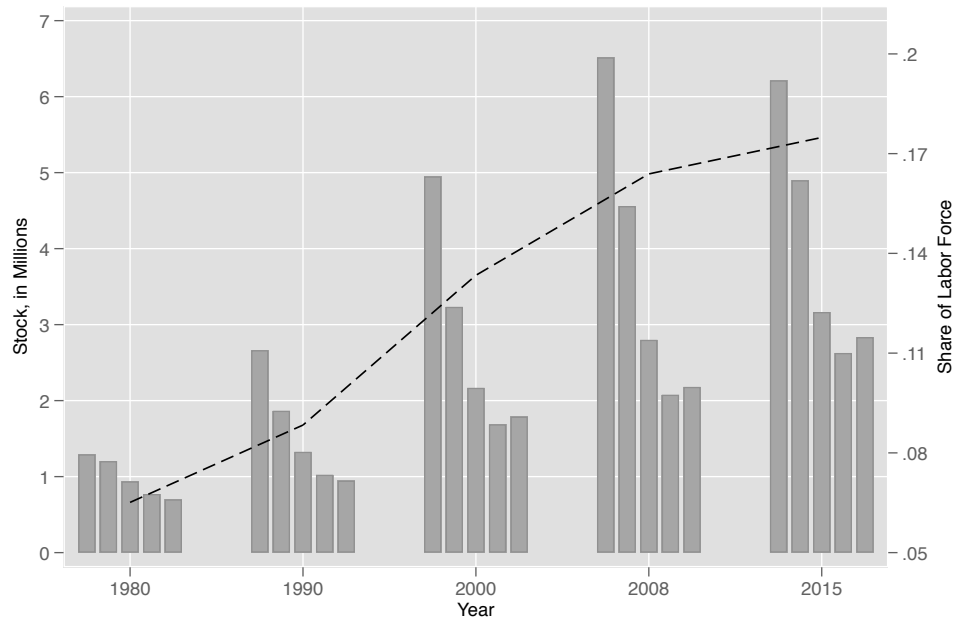
- ., *The economic and fiscal consequences of immigration*, National Academies Press, 2017.
- Acemoglu, Daron and David Autor**, “Skills, tasks and technologies: Implications for employment and earnings,” *Handbook of Labor Economics*, 2011, 4, 1043–1171.
- Alesina, Alberto, Johann Harnoss, and Hillel Rapoport**, “Birthplace diversity and economic prosperity,” *Journal of Economic Growth*, 2016, 21 (2), 101–138.
- Ashenfelter, Orley and Alan Krueger**, “Estimates of the Economic Return to Schooling from a New Sample of Twins,” *The American Economic Review*, 1994, 84 (5), 1157–1173.
- Bartel, Ann P**, “Where do the new US immigrants live?,” *Journal of Labor Economics*, 1989, 7 (4), 371–391.
- Bodvarsson, Örn B, Hendrik F Van den Berg, and Joshua J Lewer**, “Measuring immigration’s effects on labor demand: A reexamination of the Mariel Boatlift,” *Labour Economics*, 2008, 15 (4), 560–574.
- Borjas, George J**, “The Labor Demand Curve Is Downward Sloping: Reexamining the Impact of Immigration on the Labor Market,” *The Quarterly Journal of Economics*, 2003, 118, 1335–1374.
- , “The analytics of the wage effect of immigration,” *IZA Journal of Migration*, 2013, 2 (1), 22.
- , **Jeffrey Grogger, and Gordon H Hanson**, “Imperfect substitution between immigrants and natives: a reappraisal,” Technical Report, National Bureau of Economic Research 2008.
- Bound, John and Alan B Krueger**, “The extent of measurement error in longitudinal earnings data: Do two wrongs make a right?,” *Journal of Labor Economics*, 1991, 9 (1), 1–24.
- Cameron, A Colin and Pravin K Trivedi**, *Microeconometrics: methods and applications*, Cambridge university press, 2005.
- Card, David**, “Immigrant Inflows, Native Outflows, and the Local Labor Market Impacts of Higher Immigration,” *Journal of Labor Economics*, 2001, 19 (1), 22–64.
- , “Is the new immigration really so bad?,” *The Economic Journal*, 2005, 115 (507), F300–F323.
- , “Immigration and Inequality,” *The American Economic Review*, 2009, 99 (2), 1–21.
- **and Alan B Krueger**, “Does school quality matter? Returns to education and the characteristics of public schools in the United States,” *Journal of political Economy*, 1992, 100 (1), 1–40.
- **and Giovanni Peri**, “Immigration Economics by George J. Borjas: A Review Essay,” *Journal of Economic Literature*, 2016, 54 (4), 1333–1349.
- **and Thomas Lemieux**, “Can falling supply explain the rising return to college for younger men? A cohort-based analysis,” *The Quarterly Journal of Economics*, 2001, 116 (2), 705–746.
- Center, Pew Research**, “Modern Immigration Wave Brings 59 Million to U.S., Driving Population Growth and Change Through 2065,” 2015.
- Chernozhukov, Victor, Iván Fernández-Val, and Blaise Melly**, “Inference on counterfactual distributions,” *Econometrica*, 2013, 81 (6), 2205–2268.

- Choe, Chung and Philippe Van Kerm**, “Foreign workers and the wage distribution: Where do they fit in?,” 2014.
- Clemens, Michael A, Ethan G Lewis, and Hannah M Postel**, “Immigration restrictions as active labor market policy: Evidence from the mexican bracero exclusion,” Technical Report forthcoming.
- Cortes, Patricia**, “The Effect of Low-Skilled Immigration on US Prices: Evidence from CPI Data,” *Journal of political Economy*, 2008, 116 (3), 381–422.
- Dustmann, Christian, Albrecht Glitz, and Tommaso Frattini**, “The labour market impact of immigration,” *Oxford Review of Economic Policy*, 2008, 24 (3), 477–494.
- , **Tommaso Frattini, and Ian P Preston**, “The effect of immigration along the distribution of wages,” *The Review of Economic Studies*, 2013, 80 (1), 145–173.
- Favre, Sandro**, “The impact of immigration on the wage distribution in Switzerland,” 2011.
- Firpo, Sergio, Nicole M Fortin, and Thomas Lemieux**, “Unconditional quantile regressions,” *Econometrica*, 2009, 77 (3), 953–973.
- Foged, Mette and Giovanni Peri**, “Immigrants’ Effect on Native Workers: New Analysis on Longitudinal Data,” *American Economic Journal: Applied Economics*, 2016, 8 (2), 1–34.
- Fortin, Nicole M and Thomas Lemieux**, “Rank regressions, wage distributions, and the gender gap,” *Journal of Human Resources*, 1998, pp. 610–643.
- Gaston, Noel and Douglas Nelson**, “Immigration and labour-market outcomes in the United States: a political-economy puzzle,” *Oxford Review of Economic Policy*, 2000, 16 (3), 104–114.
- Goldin, Claudia Dale and Lawrence F Katz**, *The Race between Education and Technology*, Harvard University Press, 2009.
- Greenwood, Michael J, Gary L Hunt, and Ulrich Kohli**, “The factor-market consequences of unskilled immigration to the United States,” *Labour Economics*, 1997, 4 (1), 1–28.
- Griswold, Daniel**, “Reforming the US Immigration System to Promote Growth,” 2017.
- Heckman, James J and Guilherme Sedlacek**, “Heterogeneity, aggregation, and market wage functions: an empirical model of self-selection in the labor market,” *Journal of political Economy*, 1985, 93 (6), 1077–1125.
- Hong, Gihoon and John McLaren**, “Are Immigrants a Shot in the Arm for the Local Economy?,” *NBER Working Paper, No. w21123.*, 2015.
- Hunt, Jennifer and Marjolaine Gauthier-Loiselle**, “How much does immigration boost innovation?,” *American Economic Journal: Macroeconomics*, 2010, 2 (2), 31–56.
- Imbens, Guido W and Whitney K Newey**, “Identification and estimation of triangular simultaneous equations models without additivity,” *Econometrica*, 2009, 77 (5), 1481–1512.
- Jaeger, D, J Ruist, and J Stuhler**, “Are lagged immigrant shares valid as instruments,” 2016.
- Jaeger, David A, Joakim Ruist, and Jan Stuhler**, “Shift-share instruments and the impact of immigration,” Technical Report, National Bureau of Economic Research 2018.

- Krogstad, Jens Manuel and Jynnah Radford**, “Education levels of U.S. immigrants are on the rise,” 2018.
- Lee, Sokbae**, “Endogeneity in quantile regression models: A control function approach,” *Journal of Econometrics*, 2007, 141 (2), 1131–1158.
- Lewis, Ethan**, “Immigration, skill mix, and capital skill complementarity,” *The Quarterly Journal of Economics*, 2011, 126 (2), 1029–1069.
- Manacorda, Marco, Alan Manning, and Jonathan Wadsworth**, “The impact of immigration on the structure of wages: theory and evidence from Britain,” *Journal of the European Economic Association*, 2012, 10 (1), 120–151.
- Moretti, Enrico**, “Real wage inequality,” *American Economic Journal: Applied Economics*, 2013, 5 (1), 65–103.
- Olney, William W**, “Offshoring, immigration, and the native wage distribution,” *Canadian Journal of Economics/Revue canadienne d’économique*, 2012, 45 (3), 830–856.
- Ottaviano, Gianmarco IP and Giovanni Peri**, “Rethinking the effect of immigration on wages,” *Journal of the European Economic Association*, 2012, 10 (1), 152–197.
- Peri, Giovanni**, “The effect of immigration on productivity: Evidence from US states,” *Review of Economics and Statistics*, 2012, 94 (1), 348–358.
- **and Chad Sparber**, “Task Specialization, Immigration, and Wages,” *American Economic Journal: Applied Economics*, 2009, 1 (3), 135–69.
- **, Kevin Shih, and Chad Sparber**, “STEM workers, H-1B visas, and productivity in US cities,” *Journal of Labor Economics*, 2015, 33 (S1), S225–S255.
- Ruggles, Steven, Katie Genadek, Ronald Goeken, Josiah Grover, and Matthew Sobek**, “Integrated Public Use Microdata Series: Version 6.0. [Machine-readable database]. Minneapolis: University of Minnesota,” 2015.
- Wooldridge, Jeffrey M**, “Control function methods in applied econometrics,” *Journal of Human Resources*, 2015, 50 (2), 420–445.

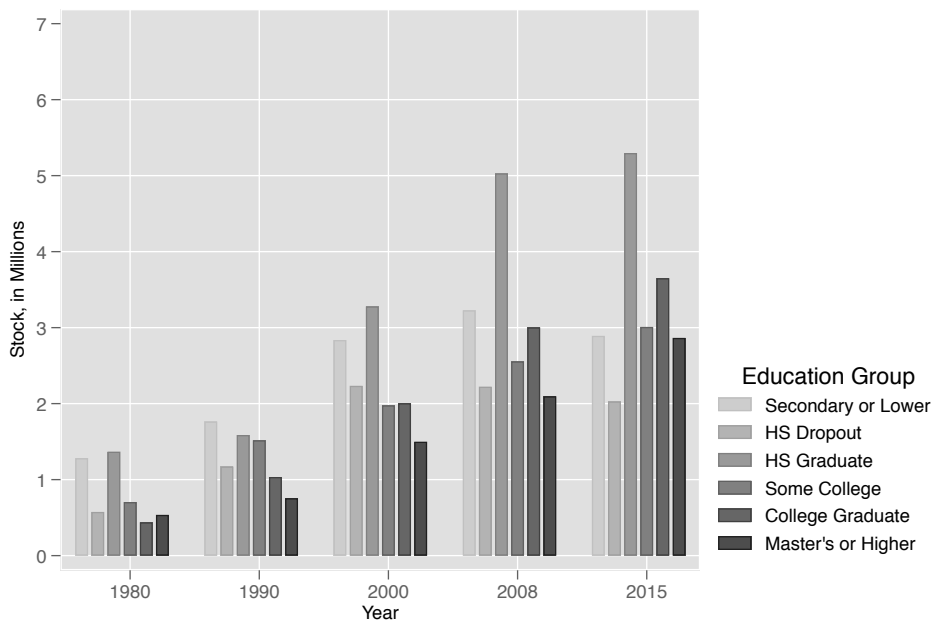
## 6 Figures

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.

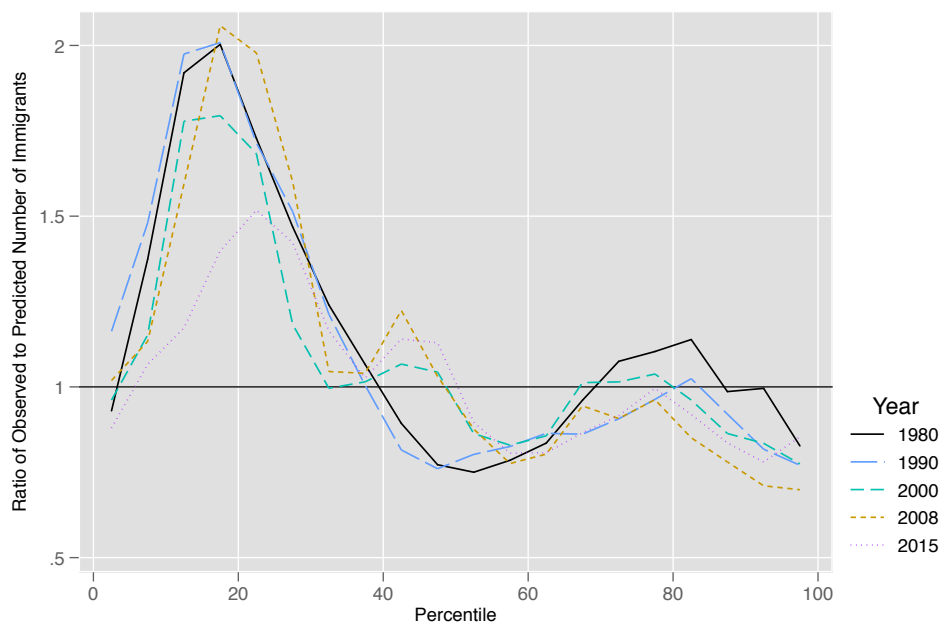
Figure 2: Number of Immigrants by Education Group, 1980-2015



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

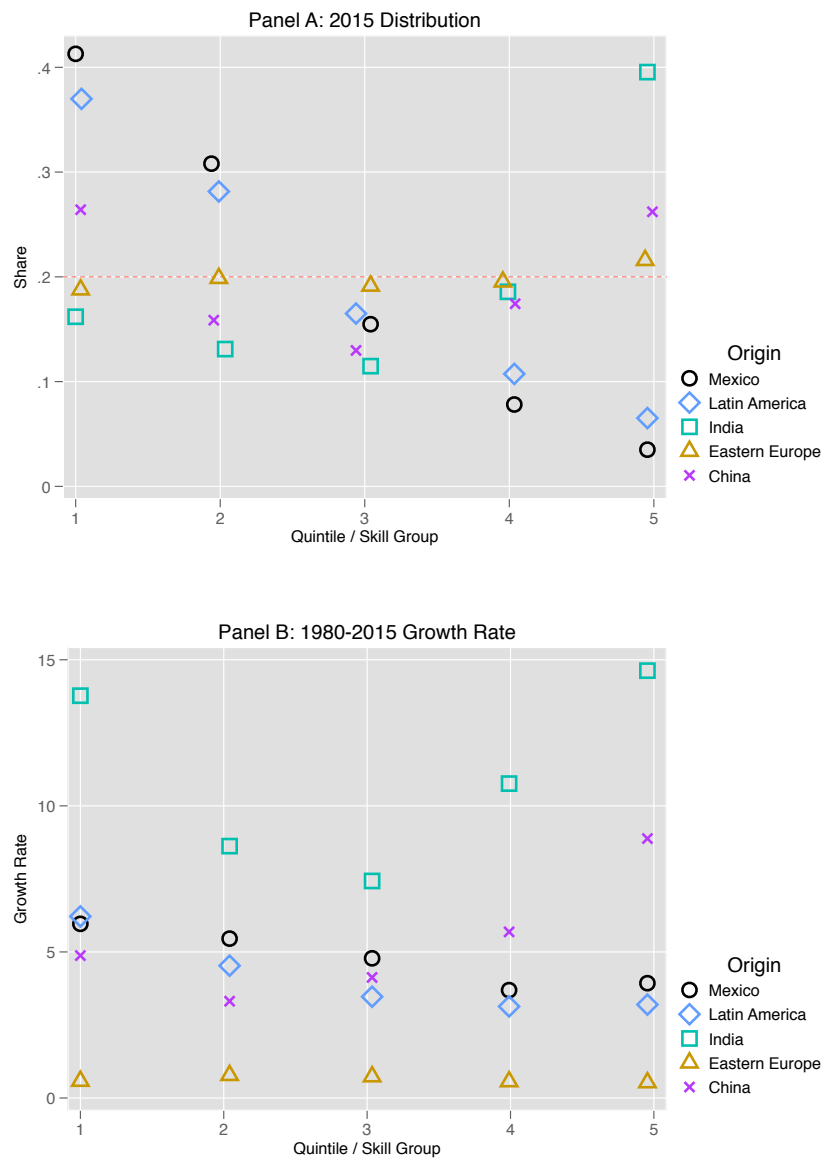


Figure 3: Observed and Predicted Number of Immigrants in the Natives' Wage Distribution, 1980-2015



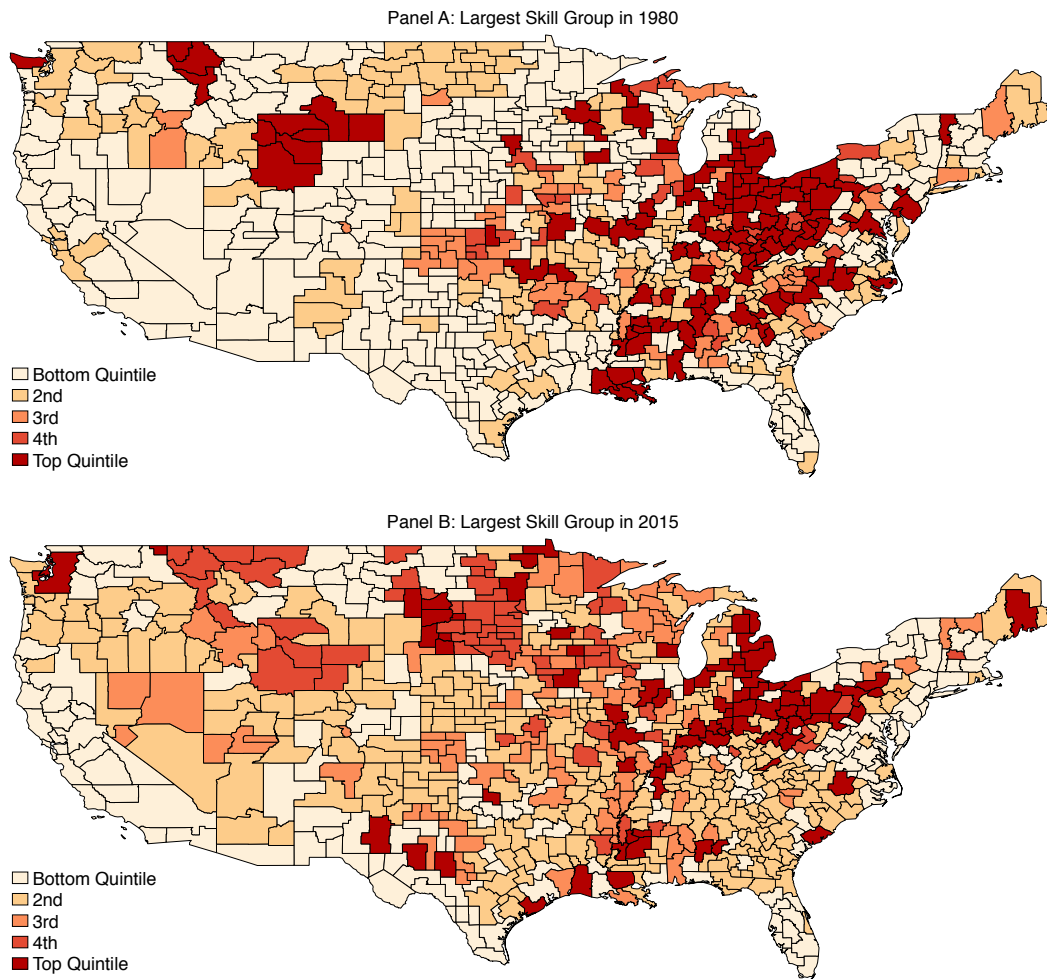
Notes: Each line shows the ratio of observed to predicted stock of foreign-born workers in the natives' wage distribution for a separate year. Predictions are based on immigrants' characteristics being valued at the same rate as natives'. Ratios greater than one correspond to immigrants being overrepresented in that segment of the wage distribution. 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 4: Skill Group Distribution of Immigrants by Area of Origin, 1980-2015



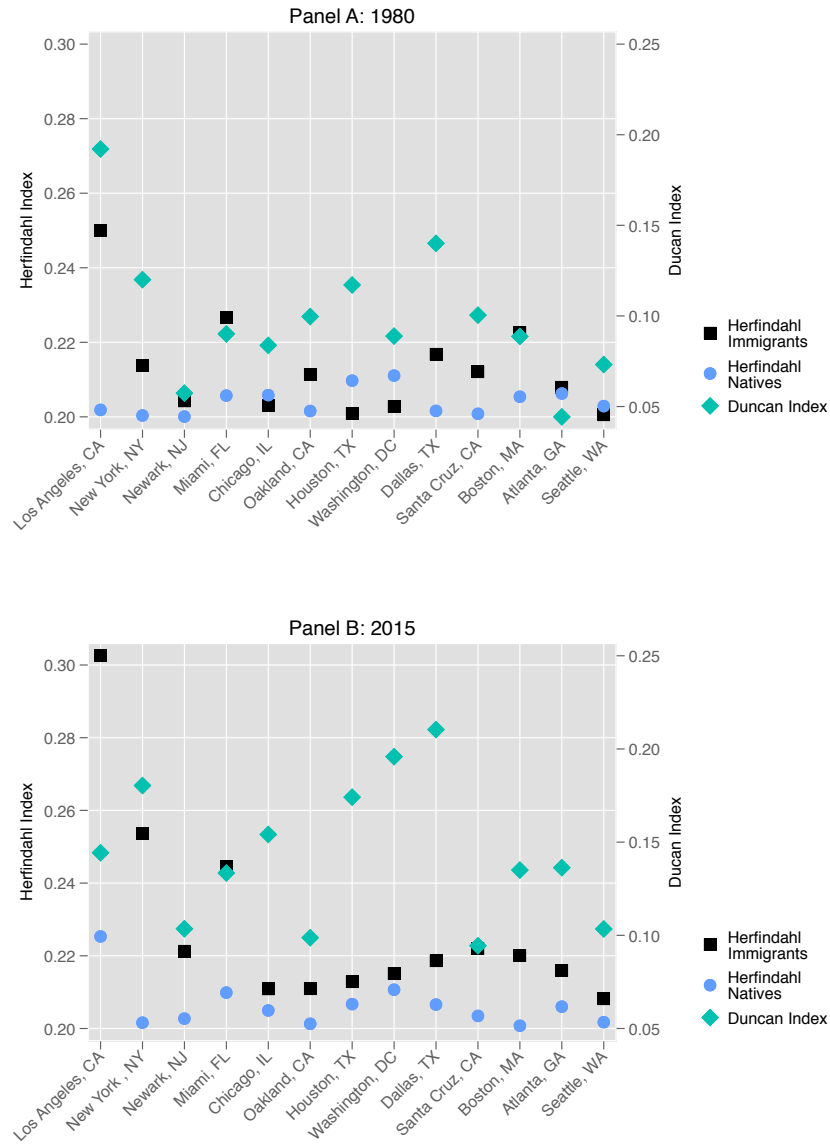
Notes: Panel A shows the 2015 immigrant skill distribution for the five largest areas of origin. All shares within an immigrant group sum to one. Panel B presents the 1980-2015 growth rate for each skill and origin group. The sample consists of all individuals age 18-64 with potential experience between 1 and 40 years, in the labor force, not self-employed, not in group quarter, not in school and with positive reported earnings.

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



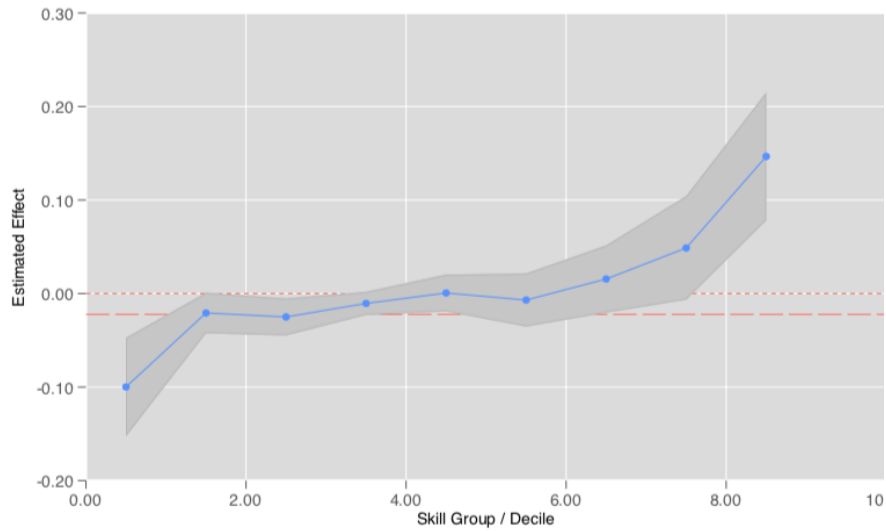
Notes: Panel A shows the largest immigrant skill group in 1980 for each Commuting Zone. Panel B does the same for year 2015. Darker shades of red correspond to higher quintile/skill group. The sample consists of all individuals age 18-64 with potential experience between 1 and 40 years, in the labor force, not self-employed, not in group quarter, not in school and with positive reported earnings.

Figure 6: Concentration Indexes by Nativity and Skill Group in the Top Immigrant Receiving Cities



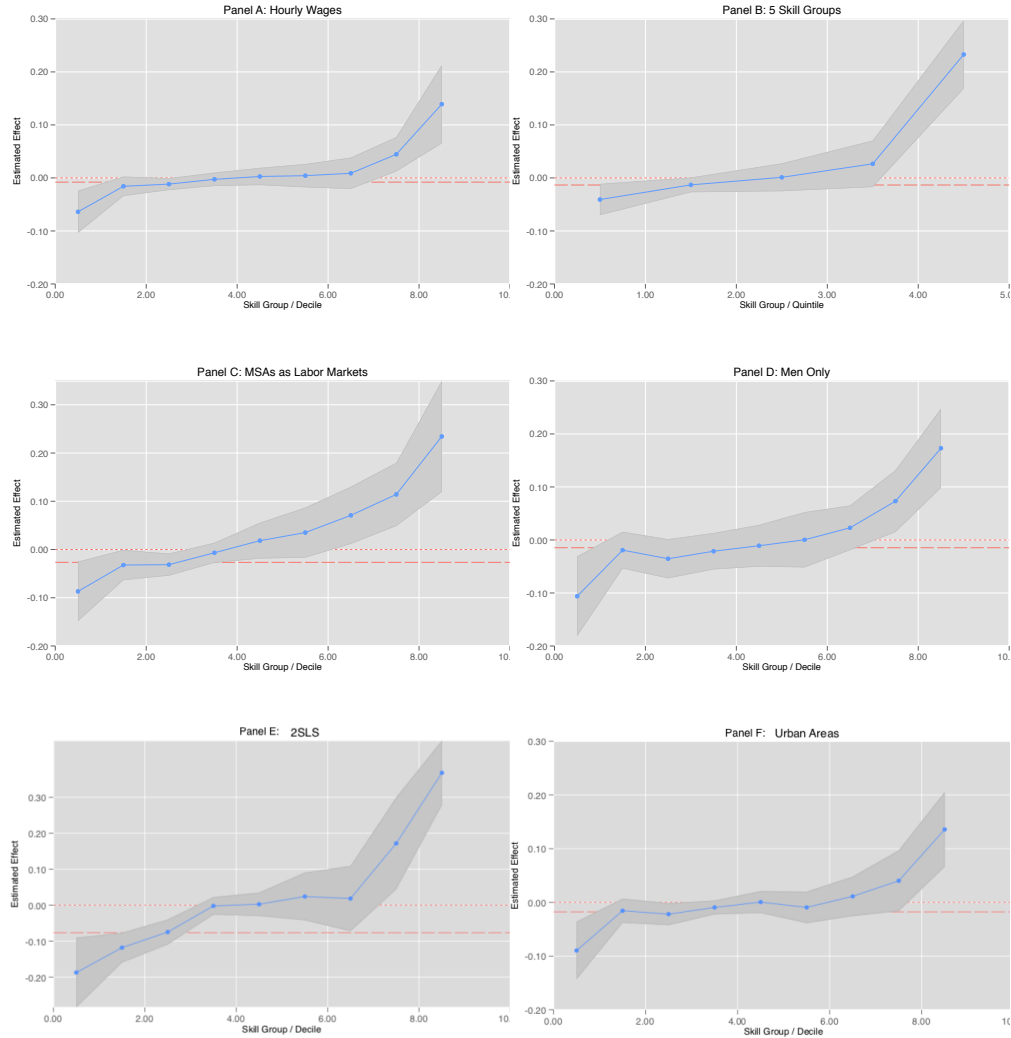
Notes: Concentration (Herfindahl, left axis) indexes for immigrants and natives and dissimilarity (Duncan, right axis) indexes for 1980 in Panel A and 2015 in Panel B in the largest immigrant receiving Commuting Zones. Higher Herfindahl (Duncan) index values correspond to stronger skill group concentration (dissimilarity with natives). 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 7: The Impact of Immigrants on the Natives' Wage Distribution: Main Result



Notes: Each point is an estimated coefficient  $\gamma_1$  from equation (2) 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 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 8: The Impact of Immigrants on the Natives' Wage Distribution: Robustness Checks



Notes: Each point is an estimated coefficient  $\gamma_1$  from equation (2) on a specific skill group (decile) denoted on the horizontal axis. 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.

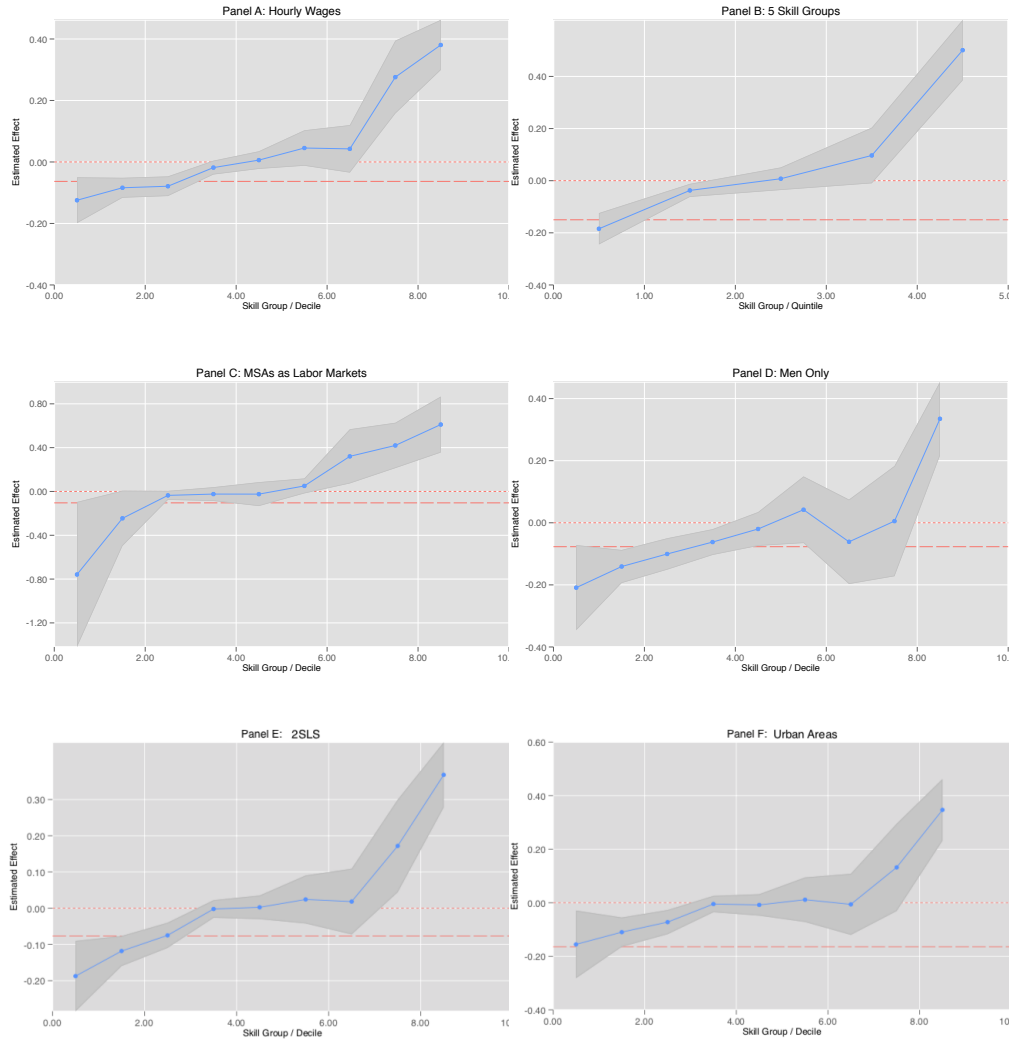
Table 1: Quantile Treatment Effects of Immigration on Natives' Wages

Decile / Skill Group	Outcome Variable: Log Real Weekly Wage						
	(1) Baseline	(2) 5 Skill Groups	(3) MSAs	(4) Hourly Wages	(5) Men Only	(6) Urban CZs	(7) Logit
1	-0.26 (0.09)	-0.21 (0.09)	-0.33 (0.09)	-0.22 (0.09)	-0.30 (0.09)	-0.29 (0.09)	-0.26 (0.09)
2	-0.09 (0.05)	-0.07 (0.05)	-0.08 (0.05)	-0.15 (0.05)	-0.08 (0.05)	-0.09 (0.05)	-0.08 (0.05)
3	-0.07 (0.05)	-0.03 (0.05)	-0.06 (0.05)	-0.17 (0.05)	-0.06 (0.05)	-0.08 (0.05)	-0.08 (0.05)
4	-0.05 (0.03)	-0.03 (0.03)	-0.04 (0.03)	-0.06 (0.03)	-0.05 (0.03)	-0.06 (0.03)	-0.06 (0.03)
5	-0.04 (0.03)	-0.03 (0.03)	-0.00 (0.03)	-0.01 (0.03)	-0.01 (0.03)	-0.04 (0.03)	-0.07 (0.03)
6	0.02 (0.03)	0.21 (0.03)	0.09 (0.03)	0.15 (0.03)	0.07 (0.03)	0.20 (0.03)	-0.02 (0.03)
7	0.04 (0.02)	0.28 (0.02)	0.15 (0.02)	0.14 (0.02)	0.11 (0.02)	0.05 (0.02)	0.01 (0.02)
8	0.15 (0.03)	0.42 (0.02)	0.16 (0.02)	0.16 (0.02)	0.17 (0.02)	0.14 (0.02)	0.09 (0.02)
9	0.53 (0.10)	0.56 (0.10)	0.51 (0.10)	0.43 (0.10)	0.52 (0.10)	0.52 (0.10)	0.53 (0.10)

Notes: Each row shows a treatment effect of immigrants 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 Panel A) wages adjusted with a local price index. The conditional wage distribution is estimated with 100 quantile regressions on a 20% random sample of the 2015 ACS data. The standard errors are cluster-bootstrapped with 20 replications following Chernozhukov et al. (2013). 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.

## 7 Appendix: Figures and Tables

Figure A1: The Impact of Immigrants on the Natives' Wage Distribution: More Robustness Checks



Notes: Each point is an 2SLS estimated coefficient  $\gamma_1$  from equation (2) on a specific skill group (decile) denoted on the horizontal axis. 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.



Table A1: Labor Force Shares and Growth Rates among Immigrants by Birthplace and Skill Group, 1980-2015

<i>Panel A: Shares, 2015</i>							
	Skill Group / Quintile					Count (in mil.)	Herfindahl Index
	1st	2nd	3rd	4th	5th		
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
Canada	0.13	0.13	0.14	0.22	0.38	0.3	0.25

<i>Panel B: Growth Rates, 1980 - 2015</i>							
	Skill Group / Quintile					Growth Rate	
	1st	2nd	3rd	4th	5th		
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	
Canada	-0.24	-0.22	-0.07	0.40	1.00	0.2	

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 Herfindahl 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 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.

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

	<i>Panel A: % Natives</i>						<i>Panel B: % Immigrants</i>					<i>Panel C: Nat - Imm</i>		
	Skill Group / Quintile					Herfindahl Index	Skill Group / Quintile					Herfindahl Index	Duncan Index	
	1st	2nd	3rd	4th	5th		1st	2nd	3rd	4th	5th			Herfindahl Index
Los Angeles-Long Beach, 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-MD-VA-WV	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
Santa Cruz-Watsonville, 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-Bellevue-Everett, 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 Herfindahl concentration index of the respective nativity group. Panel C displays the differences in the concentration index and the Duncan dissimilarity index between the two nativity groups. 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.

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

<i>Panel A: Observed</i>					
	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

<i>Panel B: Predicted</i>					
	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 year 2015. 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.