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Authors
Edwards, Ryan D.
Liu, Mao-Mei

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A new look at immigration and employment in the U.S. since 2005

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Ryan D. Edwards
Curriculum Coordinator,
Data Science Education Program
And Research Associate,
Berkeley Population Center
University of California, Berkeley
ryanedw@berkeley.edu

Mao-Mei Liu
Lecturer, Sociology Department
University of California, Berkeley
And Visiting Scholar,
Population Studies and Training Center
Brown University
mao-mei_liu@berkeley.edu

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Abstract

The foreign-born share of the U.S. population has been gradually rising in recent decades and is approaching its historic maximum. Areas that have not traditionally received immigrants have experienced greater increases in the foreign-born share than have other areas with persistently high levels of immigration. This raises clear questions about the macroeconomic impacts of immigration on native workers. Economic theory suggests that immigration shifts out labor supply, reducing wages for natives in the short run because labor demand is downward sloping, and raising unemployment among natives if wages do not fall. Although theoretically sound and widely cited in the U.S. immigration debate, this static view has received mixed support in the scientific literature. Researchers continue to debate whether influxes of immigrants like the Mariel Boatlift of 1980 reduced wages or employment among native workers in Miami, with a body of empirical evidence that often appears ambiguous.

We contribute to this debate by comparing recent trends in the employment rates of native workers in immigrant-receiving geographical areas to recent trends in other areas. We utilize the rich geographic resolution offered by the annual U.S. American Community Survey, which samples roughly 1 percent of the entire U.S. population and allows us to examine trends in public data within areas as small as 80,000 residents. The time period covered by the ACS, 2005-2016, provides us a unique look at employment outcomes during a period of much economic turbulence and differential immigration patterns across states and regions.

In contrast to the implication of the static model, we find that rising foreign-born shares of the local labor force are robustly associated with increases in native employment rates over 2005-2016. Our model predicts each percentage-point increase in the foreign-born share is associated with an increase in the native employment rate of 0.075 percentage point. Because the variation in the foreign-born share is large (SD = 0.15) relative to the variation in the native employment rate (SD = 0.04), our model implies that up to one quarter of the cross-sectional variation in native employment could be accounted for by variation in the foreign-born share of the labor force. By contrast, average annual changes in native employment and the foreign-born share are both about 0.1 percent, implying that a much smaller share of the typical annual change in native employment, only about 5 to 7 percent, might be attributable to changes in the foreign-born share of the labor force.

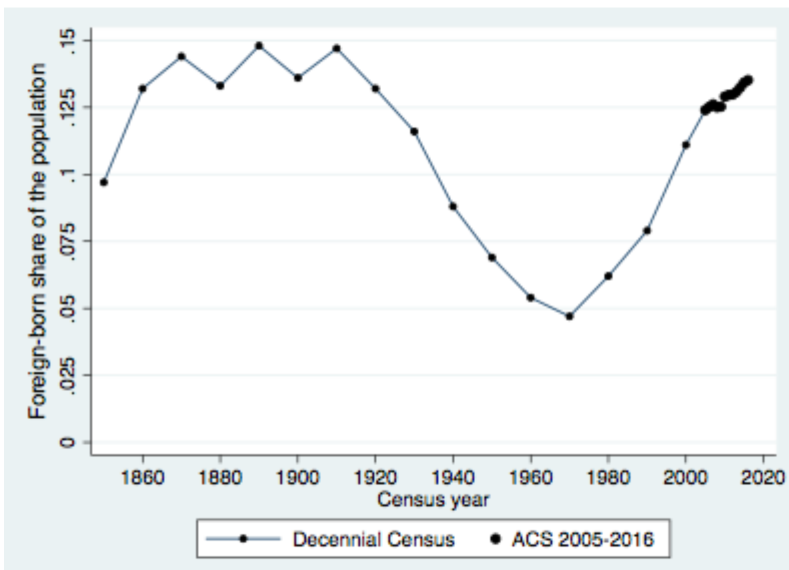
These results suggest that during the first two decades of the 21st century, the presence of foreign-born workers was not detrimental to the employment prospects of native workers and may have been a net benefit. Whether immigrant labor actually raises the employment of natives on its own or is a marker of third factors that are causal is less clear and remains the subject of future investigations.

1. Introduction

1.1. Trends in U.S. immigration

Estimates from the U.S. Census Bureau suggest there were nearly 44 million foreign-born U.S. residents in 2016, who represented 13.5 percent of the total population of 323 million (Lopez and Bialik, 2017). Historically speaking, this is a relatively high level but not unprecedented. As Waters and Pineau (2015) describe in a recent report of the National Academies of Sciences, the foreign-born share in the U.S. began to increase after the Immigration Act of 1965 and is currently hovering near the record high levels experienced during the last great waves of immigration in the late 19th and early 20th centuries. The time series of the foreign-born share of the population is depicted in Figure 1, which plots a hybrid series of Census data reported by Waters and Pineau combined with statistics compiled from the 2005-2016 waves of the American Community Survey (ACS) that we use in this study.

Figure 1: The foreign-born share of the U.S. population since 1850

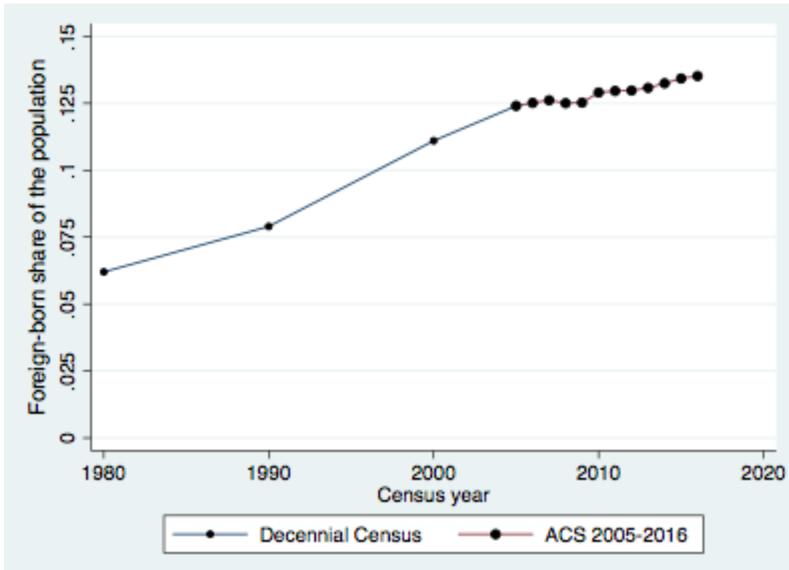


Notes: Data from the decennial Census waves up to 2000 are provided by Waters and Pineau (2015). Annual data from 2005-2016 are derived by the authors from the American Community Survey extracts provided by IPUMS (2018).

Figure 2 provides a closer look at trends in the series since 1980. As one might expect given the economic motivation to migrate, net immigration flows plateaued after the Great Recession of 2007 but then began to inch upward again by 2010. Overall, the foreign-born share increased by about 1 percentage point between 2005 and 2016, rising from 12.5 percent to 13.5 percent.[1]

[1] Trends in the foreign-born share of the labor force are similar, but the level and magnitude of the change are both higher, with an increase of about 2 percentage points from 15 percent to 17 percent over the sample period 2005-2016. This is because immigrants tend to be of working age, while the age structure of the native-born population is older. The stock of unauthorized immigrants fell slightly as a result of the recession and has not yet recovered (Passel and Cohn, 2017).

Figure 2: The foreign-born share of the U.S. population since 1980



Notes: Data from the decennial Census waves up to 2000 are provided by Waters and Pineau (2015). Annual data from 2005-2016 are derived by the authors from the American Community Survey extracts provided by IPUMS (2018).

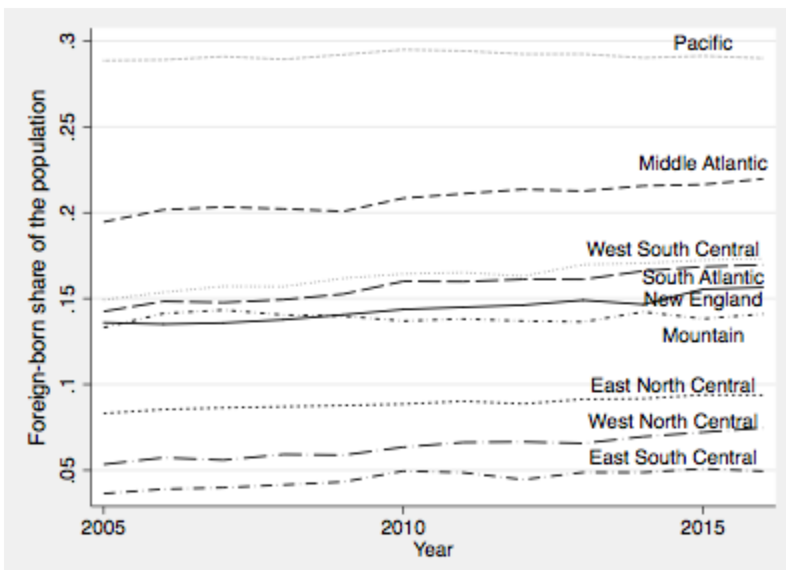
For understanding labor market outcomes, the foreign-born share of the labor force is a more proximate indicator than the overall foreign-born share, but these two measures are often different. Because new immigrants are usually of working age, there can be large differences in labor force participation rates between immigrants and natives at a given point in time, if the native population is not mostly of working age also. In modern advanced economies, where the demographic transition to lower fertility has universally occurred, native-born populations are older than new immigrants, and the foreign-born share of the labor force tends to be higher than the foreign-born share of the population. In the U.S. in 2016 for example, the labor force was 16.9% foreign born, while the total population was 13.5% foreign-born. Despite the differences in levels between these two indicators at a point in time, they have tended to move together over time.

Not all U.S. regions experienced the same gradual increase in the foreign-born share during this period. Figure 3 shows how foreign-born shares of the labor force differed greatly across U.S. Census divisions both in level and trend between 2005 and 2016. The Pacific division, which includes California, the most populous state, began this period with the highest foreign-born share of the labor force, 29 percent, and ended virtually unchanged. Similarly, the Mountain division, which extends from Arizona and New Mexico to Montana, experienced virtually no net change, remaining at about 14 percent foreign-born. But in the seven other U.S. division, the foreign-born share rose an average of 2 percentage points from 2005 to 2016. Measured relative to the baseline level at the start of the period, the percentage increase was largest for the West North Central division (including states like Minnesota, the Dakotas, Kansas and

Missouri), which experienced a 40 percent rise from 5.3 to 7.5 percent, and for the East South Central division (which includes states like Mississippi, Alabama, Kentucky, and Tennessee), where the foreign-born share rose 36 percent from 3.6 to 4.9 percent.

These differential patterns of change in the foreign-born share have sometimes been referred to as the "new geography" of immigration (Singer, 2009), which is often associated with the increase in productive activities in suburban as opposed to dense urban areas in the modern economy. By definition, the new geography of immigration implies that areas now receiving the most immigrants do not have as much experience as other areas where immigration had traditionally been higher. If these new patterns are indeed driven by the growth of employment opportunities in suburban areas, it would not be surprising to find that immigration trends hold a particular salience for native workers, employers, and industries in the new receiving divisions. Given these trends, it is perhaps not surprising that immigration has become a central focus of public interest and policy in the 21st century.

Figure 3: The foreign-born share of the labor force in U.S. divisions[2] since 2005



Notes: Annual data from 2005-2016 are derived by the authors from the American Community Survey extracts provided by IPUMS (2018).

[2] The Census Bureau-designated districts are New England (Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island and Vermont), Mid-Atlantic (New Jersey, New York, and Pennsylvania), East North Central (Illinois, Indiana, Michigan, Ohio, and Wisconsin), West North Central (Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota and South Dakota), South Atlantic (Delaware, Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia, District of Columbia and West Virginia), East South Central (Alabama, Kentucky, Mississippi, and Tennessee), West South Central (Arkansas, Louisiana, Oklahoma and Texas), Mountain (Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah and Wyoming) and Pacific (Alaska, California, Hawaii, Oregon and Washington).

1.2. Immigration, employment, and earnings

According to basic economic theory, labor demand is downward sloping, and thus an increase in labor supply caused by immigration should reduce the market-clearing wage, *ceteris paribus*. If wages are sticky and unable to adjust downward, then one would also expect immigration to lead to an increase in involuntary unemployment at least in the short run.

Although the simple theory permeates the immigration debate, in its basic form it omits other dynamics that we know are important, like the adjustment of capital and the reallocation of native labor, both of which may be made more productive by the presence of new immigrant labor. Capital — stocks of buildings and equipment used by workers — is an obvious complement to immigrant labor; but native labor might also enjoy complementarity with immigrant labor. And it might depend critically on the type or class of native worker and characteristics of the immigrant worker. Because the theoretical implications are not so cut and dried, the question of how U.S. immigration affects native employment and wages is ultimately an empirical one.

1.3. The literature in brief

The mechanisms through which immigration impacts the economy are complex, and thus most research examines the *reduced-form* relationship between immigration and native outcomes, sidestepping the mechanisms altogether. But the primary challenge for those seeking to estimate empirically the wage and employment impacts of immigration is a common one in social science: while we can observe wages and employment before and after immigration, we often cannot observe the counterfactual: what wages and employment would have become in the absence of immigration.

Scholars of the employment and wage impacts of immigration have developed three primary strategies for overcoming this challenge and constructing the counterfactual: spatial analyses, skill-cell approaches and the structural or production function approach. The recent National Academy of Sciences report *The Economic and Fiscal Consequences of Immigration* (Blau and Mackie 2017) review these approaches and discuss related conceptual issues: the short and long-term impacts of immigration (short-term impacts are expected to be larger); whether immigrants substitute or complement native labor and how much so; and how skill should be measured (e.g. education, occupation, percentile ranking in wage distribution).

Our study is a spatial (cross-area) study. Spatial studies contrast labor market outcomes among different geographic areas. To do so, they define labor markets – often as metropolitan areas – and then compare changes or differences in levels of wages and/or employment between areas with low or high immigration, all while controlling for other variables that capture the relevant characteristics of a particular area. Although not derived from experimental data, such studies attempt to identify the effect of immigration by comparing “control” and “treatment” groups, where the former are areas with low immigration and the latter are areas with high immigration. Because areas differ in many ways beyond immigration rates, the modeling challenge is to compare otherwise similar areas by controlling for other relevant variables, and then assess how outcomes among areas "treated" by immigration compare to similar areas that were not treated by immigration. Thus the control group proxies for the unobserved counterfactual, an untreated treatment group.

The empirical record for studies similar to ours is mixed. Recent spatial studies have used different data and analyzed different periods (see Appendix Table A below, which reprints a table from Blau and Mackie, 2017). They find that immigration's impact on the most vulnerable group – low-skilled workers – ranges from "negligible to at least modestly negative" (Blau and Mackie, 2017, p.217). Among low-skilled workers, certain sub-groups appear to experience larger negative wage impacts. These include prior migrants and their descendants: for example, Hispanic immigrants and Hispanic native-born (Cortes, 2008); as well as low-skilled previous immigrants - especially those with low English language skill - and low-skilled native-born Hispanics (Lewis, 2011).

In a recent study that is very similar to ours, Zavodny (2018) models unemployment and participation rates among native workers grouped by state, education, and sex as functions of the foreign-born share of the labor force in the annual American Community Survey from 2005 to 2013. She employs a two-stage least-squares approach to address concerns about the endogeneity of the key right-hand side variable: the foreign-born share of the labor force. Following a common practice in the literature (Borjas, Grogger, and Hanson, 2010), Zavodny first models the immigrant share of the labor force as a function of the immigrant share of the adult population. Contrary to what a simple model might imply, Zavodny's results suggest that a percentage point increase in the foreign-born share of the labor force reduces the native unemployment rate by 0.06 percentage point. Although this result is not robust within education groups or when education groups are combined, Zavodny also never finds evidence of a statistically significant positive relationship between immigration and native unemployment, as the simple model suggests might be the case.

When theory is ambiguous and the empirical record is mixed, further investigations are useful. They could in principle provide positive evidence supporting one view or another about the impact of immigration on native employment, or they might produce precisely estimated zero effects, or imprecise zeros. Whether our understanding ultimately improves depends on which of these types of results ultimately obtains.

2. The Data

2.1. The American Community Survey

For our study, we examine the 12 waves of the Census Bureau's annual American Community Survey (ACS) that are currently available: 2005 through 2016. The ACS was designed to replace the "long form" of the decennial Census, and it is a lengthy mailout survey that contains a large number of answers to questions about socioeconomic and sociodemographic status. Each ACS wave contains about 3 million observations of individuals in households for a roughly 1 percent sample of the resident population.

Although each ACS wave is quite large, they are not large enough to allow sufficient protection of privacy when combined with geographic identifiers in high resolution, for example across the roughly 3,000 U.S. counties. As a result, the Census Bureau only releases ACS data once it has been aggregated across either time or space or both. Two common geographic formats of ACS data are the Public-Use Microdata Areas (PUMAs), which are 1,078 agglomerations of counties no smaller than 80,000 people; and five-year averages at the county level.

2.2. Public-Use Microdata Areas

In this research note, we use Public Use Microdata Area (PUMA)-level data in single-year American Community Survey (ACS) data from 2005-2016 provided via the Integrated Public Use Microdata Series (IPUMS) by Ruggles et al. (2018). PUMAs are the most disaggregated level of geography identified in annual samples from the ACS.[3] There are 1,078 PUMAs consistently identified in the cross-wave IPUMS data, or about one third the number of U.S. counties.

Table 2.1 shows means, standard deviations, frequencies, and extrema of PUMA-level variables constructed from the pooled IPUMS extracts of the ACS waves from 2005 to 2016 that we use in this study. There is wide variation in most of the variables that we consider, most notably our y and x variables. The native employment rate was as low as 65.2 percent in the pooled sample and as high as 98.9 percent in the sample, and its average was 91.8 percent.[4] The foreign-born share of the labor force ranged between a minimum of 0 and a maximum of 84.9 percent, with an average of 15.8 percent.[5]

[3] Every 10 years, the Census Bureau redraws PUMA boundaries based on the information collected in the most recent census, and ACS then integrates the newly drawn boundaries within a few years of each census. The first ACS wave to use the 2010's PUMAs was 2012. In this analysis, we use the consistent PUMA series (cpuma0010) generated by the IPUMS project (Ruggles et al., 2018).

[4] In the data, native employment was below 70 percent in Flint, MI; part of Detroit, MI; part of Newark, NJ; and parts of the Bronx, New York City, NY. It was higher than 98.5 percent in parts of the District of Columbia and nearby parts of MD and VA; in the OK panhandle; in Erie County, NY, which includes Buffalo; in a suburban area of Minneapolis, MN; and in two nonmetro counties in WI.

[5] The maximum foreign-born share of the labor force was observed in central Los Angeles, CA, in a PUMA which includes Koreatown. PUMAs in the top 100 in foreign-born share are exclusively located in CA, FL, NJ, and NY.

Table 2.1. Characteristics of the PUMA sample from the 2005-2016 ACS

Variable	Observations	Mean	Std. Dev.	Min.	Max.
Employment rate of natives	12,936	0.918	0.038	0.652	0.989
Foreign-born share of the labor force	12,936	0.158	0.154	0.000	0.849
Share of LF aged 20-39	12,936	0.426	0.063	0.231	0.777
Share of LF aged 40-59	12,936	0.427	0.049	0.126	0.606
Share of LF aged 60-79	12,936	0.100	0.028	0.022	0.245
Share of LF aged 80+	12,936	0.003	0.002	0.000	0.027
Share of LF male	12,936	0.528	0.026	0.358	0.684
Share of LF non-Hispanic white	12,936	0.674	0.243	0.000	0.996
Share of LF non-Hispanic African American	12,936	0.115	0.148	0.000	0.966
Share of LF non-Hispanic Native American	12,936	0.006	0.023	0.000	0.511
Share of LF non-Hispanic Asian American	12,936	0.052	0.082	0.000	0.784
Share of LF Hispanic or Latino	12,936	0.137	0.163	0.000	0.985
Share of LF without a high school degree	12,936	0.112	0.059	0.002	0.567
Share of LF with a high school degree	12,936	0.272	0.082	0.014	0.519
Share of LF with some college	12,936	0.232	0.049	0.042	0.527
Share of LF with associate degree	12,936	0.085	0.026	0.004	0.220
Share of LF with bachelor’s degree	12,936	0.189	0.074	0.037	0.547
Share of LF with masters degree	12,936	0.075	0.043	0.002	0.315
Share of LF with professional degree	12,936	0.021	0.019	0.000	0.212
Share of LF in a metro area	12,936	0.777	0.398	0.000	1.000

Notes. Data are provided by the IPUMS database (Ruggles et al., 2018).

Table 2.2 shows means and standard deviations in the *first-differenced* dataset, to give a sense of typical change over time within the sample. For both our y and x variables, shown again in the top two rows, the average changes are of modest size, increases of 0.1 percentage point per year, while standard deviations in these annual changes are larger, 2.6 and 2.5 percentage points.

Table 2.2. Sample moments of annual changes in the PUMA sample from the 2005-2016 ACS

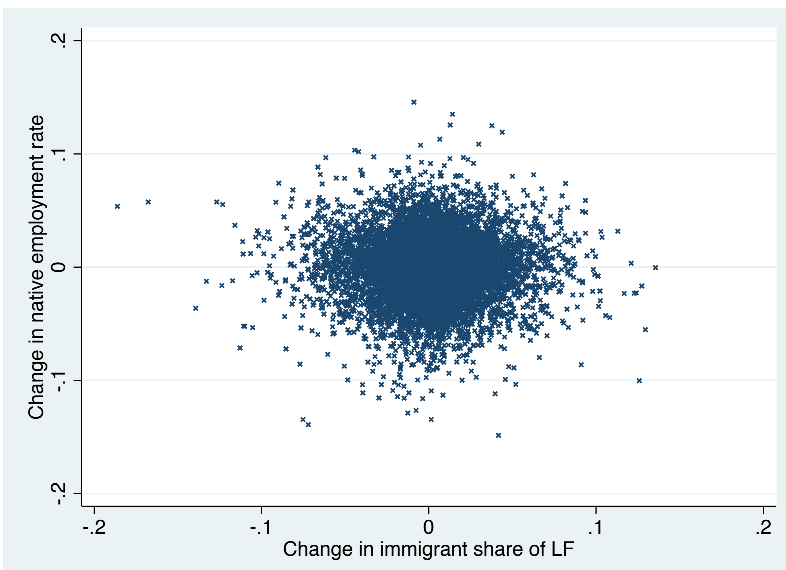
Annual change in variable	Observations	Mean	Std. Dev.	Min.	Max.
Employment rate of natives	11,858	0.001	0.026	-0.149	0.146
Foreign-born share of the labor force	11,858	0.001	0.025	-0.186	0.136
Share of LF aged 20-39	11,858	0.000	0.029	-0.130	0.212
Share of LF aged 40-59	11,858	-0.003	0.028	-0.169	0.114
Share of LF aged 60-79	11,858	0.004	0.016	-0.096	0.099
Share of LF aged 80+	11,858	0.000	0.003	-0.022	0.019
Share of LF male	11,858	-0.001	0.020	-0.126	0.132
Share of LF non-HIspanic white	11,858	-0.005	0.024	-0.149	0.140
Share of LF non-Hispanic African American	11,858	0.001	0.019	-0.132	0.167
Share of LF non-Hispanic Native American	11,858	0.000	0.004	-0.055	0.057
Share of LF non-Hispanic Asian American	11,858	0.001	0.014	-0.113	0.111
Share of LF Hispanic or Latino	11,858	0.002	0.020	-0.143	0.147
Share of LF without a high school degree	11,858	-0.003	0.022	-0.163	0.120
Share of LF with a high school degree	11,858	-0.003	0.032	-0.153	0.223
Share of LF with some college	11,858	0.001	0.029	-0.146	0.134
Share of LF with associate degree	11,858	0.001	0.018	-0.092	0.079
Share of LF with bachelor’s degree	11,858	0.002	0.025	-0.119	0.121
Share of LF with masters degree	11,858	0.001	0.016	-0.081	0.098
Share of LF with professional degree	11,858	0.000	0.008	-0.053	0.051
Share of LF in a metro area	11,858	0.002	0.057	-1.000	1.000

Notes. Data are provided by the IPUMS database (Ruggles et al., 2018).

It is also helpful to plot first differences in the y and x variables against one another in order to visually assess how they may be correlated. If the simple theory were true, one would expect to see a downward-sloping relationship between native employment (y) and the foreign-born share of the labor force (x). Zavodny (2018) does this for states in the ACS between 2005 and 2013 and finds little evidence of any correlation.

Figure 4 shows the relationship in our pooled dataset, where we have plotted the annual change in the native employment rate (y) against the annual change in the foreign-born share of the labor force (x) for each of the 1,078 PUMAs across 2006-2016. The Pearson correlation is practically zero at –0.0066, and the eye detects no obvious trend. Separately, we also examined scatterplots for specific Census divisions and for specific time spans in our sample. In no case did the scatterplot reveal any visual evidence of a relationship. Needless to say, this is not particularly strong evidence of a null effect of the treatment variable, immigration. PUMAs have not been randomly assigned the treatment, because many other variables might be correlated with immigration and could also affect native employment. We can conduct better inference in a multivariate setting, which we carry out below.

Figure 4: Annual changes in native employment rate and foreign-born share of labor force, 2005-2016



Notes: Annual data for 1,078 PUMAs are derived by the authors from the American Community Survey extracts provided by IPUMS (2018).

2.3. County-level tables from 5-year averages of the American Community Survey

Another possible approach is to evaluate county-level statistics reported in tabular form by the Census Bureau that are drawn from averages of five consecutive ACS waves. Although county lines change over time, they are more commonly recognized and understood than the more nebulous PUMA, which can be an agglomeration of counties where county populations are small.

For some applications, data that are 5-year averages at the county level are appropriate. For example, one could use these data to compare the foreign-born shares of the labor force across counties, and the result would be informative about typical geographic differences. In our study, as we detail more in the next section, we adopt a difference-in-differences approach to compare native employment rates across treatment and control groups. This requires precise, repeated observations on employment rates and immigration shares within geographic areas in order to examine how changes in native employment may be associated with changes in the foreign-born share of the labor force, holding other characteristics equal. Averaging over multiple years naturally attenuates the annual changes in key variables, and one would expect that using such data to analyze the difference-in-differences would likely dampen the signal in the data. This threatens to raise the probability of a Type-II error, a "false negative," in which we fail to reject the null hypothesis that there is no effect of immigration on native employment when we should have rejected it.

Unpublished exploratory work by Perales (2017) used 5-year averaged ACS data at the county level from 2009-2015. Perales reported a statistically insignificant coefficient on the foreign-born share of the population on the overall unemployment rate in the county. This null result is consistent with the raised probability of a Type-II error.

2.4. Level of aggregation

Theory offers no specific guidance about the appropriate unit of observation and thus the level of aggregation. The higher the aggregation, the more possible it is that important dynamics could be missed if they are occurring only within a portion of the aggregate, or if there are counterbalancing effects within units. For example, if immigration primarily affects rural employment and either causes native workers to relocate to urban areas or asymmetrically depresses employment below a rising trend felt elsewhere, then analyzing units that combine both types of areas is likely to miss this dynamic. Zavodny (2018) examines data aggregated at the state level, where this type of problem seems more likely to develop than at finer levels of disaggregation. But whether there is a problem with aggregation or not is up to the data.

3. Analytical Approach

3.1. Defining the treatment and outcomes

We are interested in measuring the impact of immigration on the employment outcomes of native workers. Thus we posit the following reduced-form relationship between native employment outcomes (y_{it}^N), the endogenous variable, and a measure of immigration (x_{it}^I), a vector of other controls (X_{it}), a set of common time dummy variables (d_t), and a white-noise error term (ϵ_{it}), all observed for unit i at time t:

$$y_{it}^N = \alpha_i + \beta\, x_{it}^I + B \cdot X_{it} + \textstyle\sum_{t=1}^{T} \gamma_t\, d_t + \epsilon_{it}, \qquad [1]$$

where α_i is a fixed effect for unit i. The tradition in labor economics is to measure average outcomes and treatments within geographic labor markets or specific subgroups of those labor markets, such as workers without a high school degree or workers with other characteristics like identifying as White or African-American. In this approach, i indexes groups, areas, or groups within areas rather than individuals.[6] An advantage to this strategy is that the treatment variable x^I is well defined at the geographic level: it measures the local presence of immigrant labor. An alternative design would be to estimate equation (1) using individual-level data on outcomes combined with local-level data on the treatment, and to cluster standard errors at the geographic level.

In our preferred specification, we set y_{it}^N equal to the *employment rate of native workers* in Census division i at time *t*; while we set x_{it}^I equal to the foreign-born share of the entire labor force in that region i at time *t*:

$$y_{it}^N = \frac{employed\ natives_{it}}{native\ labor\ force_{it}}, \qquad [2]$$

$$x_{it}^I = \frac{foreign{-}born\ workers_{\ it}}{total\ labor\ force_{it}}. \qquad [3]$$

Given these definitions, β is the percentage-point change in the employment rate of natives that is associated with a percentage-point change in the foreign-born share of the labor force.

There are other possible ways of defining *x* and *y*, but equations (2) and (3) exhibit several desirable properties:

A change in the immigrant labor force does not mechanically affect the *y*-variable. We are probing for changes in the employment probability faced by native workers. Restricting the *y*-variable to natives alone means that changes in the availability of immigrant workers does not affect either the numerator nor the denominator in the construction of *y* unless it exerts a real change on labor supply or demand.

The *x*-variable captures the relative prevalence of immigrant labor in the local market. While the elements of the left-hand-side variable cannot include immigrant labor without embedding a mechanical response that we wish to avoid, by contrast the right-hand-side variable should rise when immigrant labor becomes more plentiful and fall when it becomes more scarce. The foreign-born share of the total labor force in the area is the most logical choice.

We believe the measures described in equations (2) and (3) are the best indicators of labor market impacts, but we are also cognizant of a key shortcoming inherent to both: the possibility that **native workers might become discouraged** and transition out of the labor force. The Great Recession of 2007-2009 brought large declines in especially male labor force participation, with

[6] Examining group-level averages raises the specter of the ecological fallacy, where conclusions are made about the micro, usually individual, level based on some macro-level, in this case group-level, analysis. The literature has traditionally dealt with this potential problem by checking for robustness across different definitions of the groups.

a drop in the aggregate employment-to-population ratio among ages 16+ from 63 percent before the recession to 58 percent by 2010, before rising to 60 percent by the end of 2016. The most likely explanation for this decline was the recession itself, which impacted most U.S. divisions and sectors. In that case, including year fixed effects in the regression equation (1) is an appropriate and sufficient modeling strategy. But we are concerned about differential rates of discouragement and attrition between natives and immigrants, and the potential that the arrival of immigrant labor could increase discouragement among natives. To address this concern, we estimate models using x's and y's defined over the prime-age working population aged 25-54:

$$y_{it}^{N*} = \frac{employed\ natives\ aged\ 25\text{–}54_{it}}{native\ population\ aged\ 25\text{–}54_{it}}, \qquad [2*]$$

$$x_{it}^{I*} = \frac{foreign\text{–}born\ population\ aged\ 25\text{–}54_{it}}{total\ population\ aged\ 25\text{–}54_{it}}. \qquad [3*]$$

If native workers become discouraged, y_{it}^{N*} as defined here will fall, while our original variable y_{it}^{N} would probably rise.[7] The right-hand-side variable x_{it}^{I*} is unaffected by discouragement of natives or of immigrants.

How to construct the controls (X_{it}) is a subjective choice when i indexes divisions. In an individual-level regression, *y* indexes a native worker's employment, while *X* would measure his or her characteristics. When i indexes divisions, we could choose *X*'s that measure the characteristics of native workers only, matching *y* with *X*; or we could select *X*'s that are relevant for the total labor force, matching *X* with x^I. We choose the latter, achieving some uniformity among the covariates, and we measure in X_{it} the average characteristics of the total labor force within Census division i at time t.

3.2. Identification and estimation strategy

The most rigorous source of identification for $\hat{\beta}$ would derive from a real or natural experiment in which a policy change increased the supply of foreign-born labor. The canonical example is the Mariel Boatlift of 1980, in which 125,000 Cuban immigrants arrived in Miami by boat and ultimately increased the city's labor force by 7 percent (Card, 1990). In addition to strong identification, a convenient advantage to a natural experiment such as the Mariel Boatlift is that the researcher could define the treatment variable very simply, as a binary measure of being in the treatment group when the experiment began.

There are other natural experiments in immigration besides the Mariel Boatlift, most of which stem from changes in immigration policy. Bohn, Loftstrom, and Raphael (2015) and Orrenius and Zavodny (2015) examine the labor market effects of the 2007 imposition of E-Verify

[7] We imagine discouraged workers are probably disproportionately unemployed rather than "underemployed," thus their exit from the labor force would likely push the unemployment rate down.

requirements in Arizona. Other studies have assessed the effects of refugee flows (Tumen, 2016).

Studies that leverage the strong identification of natural experiments often employ a difference-in-differences (DID) approach to reveal the effect of the immigration treatment, *x*, on an outcome of interest, *y*. In its most basic form, the DID estimator is the differential change over time in *y* between treatment and control groups divided by the (differential) change in the treatment *x*:

$$\hat{\beta}^{DID} = \frac{\Delta y^T - \Delta y^C}{\Delta x^T - \Delta x^C}. \qquad [4]$$

When the treatment variable *x* is randomly assigned, $\hat{\beta}^{DID}$ is strongly identified by the randomization. Differencing equation (1) reveals that the DID estimator $\hat{\beta}^{DID}$ is analogous to either the **panel fixed effects** estimator of $\hat{\beta}$ run on the levels regression in equation (1), or to an ordinary least-squares estimator that is run on first differences.[9]

In this paper, we apply these standard estimation methods to a broad empirical question: were changes in the foreign-born share of the labor force during the period covered by the American Community Survey (ACS) associated with increases or decreases in native employment rates? We analyze the rich synthetic panel data of the ACS series using the panel fixed effects estimator, a generalization of the difference-in-differences approach that provides the foundation for much applied empirical research.

4. Panel Fixed-Effects Results

4.1. Full sample main results

We first estimate the marginal effect on native employment of a change in the foreign-born share of the labor force, $\hat{\beta}$ in equation (1), using a standard panel fixed-effects estimator on PUMA-level averages in the entire ACS sample period from 2005 to 2016. These results appear across the columns in Table 4.1, where we begin on the left with few covariates in X_{it} and build up to our preferred specification in Model 1F at far right.

In our most basic framework, Model 1A, with only the foreign-born share of the labor force (x_{it}^I), PUMA fixed effects, and year fixed effects, we recover a negative but statistically insignificant coefficient on the foreign-born share equal to $\hat{\beta} = -0.012$. In Model 1B in the second column, we add indicator variables for the proportion of the PUMA labor force that is male and the proportions in several age categories; there too, $\hat{\beta}$ is negative but statistically insignificant.

[9] If the coefficients on the time dummies are allowed to vary in the level regression, as they do in equation (1), the first-differences regression here also requires time dummies.

When we add controls for racial and ethnic shares of the labor force in the PUMA, in Model 1C, we recover a positive estimate of $\hat{\beta} = 0.038$ that is statistically significant at the 1 percent level. Compared to the models without racial and ethnic shares, the model R^2 increases roughly 75 percent, from about 0.25 to 0.44. This magnitude of $\hat{\beta}$ implies that for every percentage point increase in the foreign share of the labor force, this model predicts that the native employment rate will *rise* by roughly 0.04 percentage points. This is not a huge effect, but it is substantial. As shown in Table 2.1, the mean and standard deviation in the foreign-born share of the labor force within the full ACS sample here are $\mu_x = 0.158$ and $\sigma_x = 0.154$, while the mean and standard deviation in the native employment rate are $\mu_y = 0.918$ and $\sigma_y = 0.038$. According to this estimate, a shock to x_{it}^I of one standard deviation would increase y_{it}^N by

$$\hat{\beta}\ \sigma_x = 0.04\ \times 0.154 = 0.006$$

or about one-sixth of a standard deviation in the native employment rate.

As Table 2.2 reveals, the typical experience within a PUMA is quite different than implied by the full-sample standard deviations. The average annual change in the foreign-born share of the labor force is about 0.1 percent, and that is also the average annual change in the native employment rate. Viewed this way, our model attributes a very small amount, only about 4 or 5 percent, of the annual change in native employment to the annual change in the foreign-born share of the labor force.

In Model 1D, we remove the race/ethnic shares and insert covariates for population shares of educational attainment instead, to assess whether controlling for education might produce similar results on its own. We find this is not the case; although compared to Model 1B, $\hat{\beta}$ becomes positive in Model 1D, it also remains insignificant. When we control for race/ethnicity and education in Model 1E, the model R^2 rises above 0.5, and $\hat{\beta}$ rises to 0.054 and is significant at the 1 percent level. That level of $\hat{\beta}$ implies that the foreign-born share could account for about one-fifth of the total sample variation in native employment. In the final column, Model 1F adds a control for the percent of the labor force in metropolitan areas, which raises the R^2 slightly but barely affects $\hat{\beta}$.

Table 4.1. The marginal effect of percent foreign-born on native employment in the full ACS sample, 2005-2016, with evolving covariate lists

	Model 1A	Model 1B	Model 1C	Model 1D	Model 1E	Model 1F
Coefficient on percent foreign-born, $\hat{\beta}$	–0.012 (0.011)	–0.017 (0.011)	0.038*** (0.012)	0.017 (0.011)	0.054*** (0.013)	0.053*** (0.013)
PUMA fixed effects	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes
Sex and age structure covariates	no	yes	yes	yes	yes	yes
Race and ethnicity covariates	no	no	yes	no	yes	yes
Education covariates	no	no	no	yes	yes	yes
Metro share covariate	no	no	no	no	no	yes
Time span	2005-2016	2005-2016	2005-2016	2005-2016	2005-2016	2005-2016
Number of PUMAs	1,078	1,078	1,078	1,078	1,078	1,078
N	12,936	12,936	12,936	12,936	12,936	12,936
R^2	0.2327	0.2512	0.4395	0.3822	0.5228	0.5245
Population weights	no	no	no	no	no	no

Notes: Each column shows results from a separate panel fixed-effects regression where the endogenous variable (y) is the employment rate among native workers in a PUMA and the key exogenous variable (x) is the percent of the PUMA labor force that is foreign-born. We measure age structure using indicator variables for ages 20 to 39, 40 to 59, 60 to 79, and 80 and over. Race and ethnicity are measured by indicator variables for non-Hispanic whites, African Americans, Native Americans, and Asian Americans; and for Hispanics. We measure education with indicator variables for 7 levels of attainment. All these covariates (X) are expressed as shares of the total PUMA labor force in the group. Data are provided by the IPUMS database (Ruggles et al., 2018). Robust standard errors are clustered at the PUMA level. Asterisks denote significance at the 1% (***), 5% (**), and 10% (*) levels.

Our main findings in this section are threefold. Contrary to what the static economic theory of immigration would predict, we recover evidence that increases in the foreign-born share of the local labor force are associated with *increases* in native employment in the U.S. during the sample period of 2005 to 2016. The relationship is substantial but not so large as to be implausible; one standard deviation in the percent foreign born might explain between one-seventh and one-fifth of a standard deviation in the employment rate of natives. And it appears that controlling for the racial and ethnic composition of the PUMA is important for identifying this result. Because PUMAs vary considerably in their racial and ethnic composition, and their composition appears to be correlated with immigration patterns, this last result is perhaps not surprising.

4.2. Initial robustness checks

Table 4.2 shows our initial robustness checks: population weights, restrictions to working-age populations, and checking first differences. In our main results above (Table 4.1), we do not employ population weights, but we know that PUMAs have different sizes. When we do not account for differences in populations across PUMAs, small PUMAs have a larger effect on the results, larger than they arguably should compared to a study where the level of observation is an individual, and thus could shift our results away from the "true effect." We include population weights in Models 2A, 2B and 2C (2005, 2010 and 2016 population weights, respectively), and find that weighting by population appears to amplify the chief result. Once population weights are included, the size of the positive effect of foreign-born share on native employment increases. It appears that whatever was driving the original results is stronger within larger PUMAs than within small PUMAs. Given traditional patterns of immigration, in which more populous urban areas are the usual receivers, this may be evidence of a nonlinear and increasing "dose-response" effect.

Our research question and main results focus on labor market participation broadly. However, people of all ages are not equally likely to participate in the labor market, and we are also concerned about the potential for immigrant labor to differentially affect the labor force participation choices of natives. To look at this, we restrict both our endogenous variable and key exogenous variable to the prime working-age population, ages 25-54 (Model 2D). The magnitude and statistical significance of our main findings endures this change; our estimate of $\hat{\beta}$ rises to 0.055 and remains significant at the 1 percent level.

We also run ordinary least squares on the first differences or changes in both our endogenous and exogenous variables, with year fixed effects. As differencing equation (1) reveals, this approach is equivalent to running a panel fixed effects estimator and should in principle return the same estimate of $\hat{\beta}$. Results are shown in Model 2E. The magnitude of $\hat{\beta}$ decreases slightly, to 0.036, but it remains statistically significant.

Table 4.2. Robustness checks: population weights, employment-to-population ratios, and first differences

	Model 2A	Model 2B	Model 2C	Model 2D	Model 2E
Outcome (y) is:	native employment rate	native employment rate	native employment rate	native employment-to-population ratio aged 25-54	change in the native employment rate
Foreign-born variable (x) is:	foreign-born share of the labor force	foreign-born share of the labor force	foreign-born share of the labor force	foreign-born share of the population aged 25-54	change in the foreign-born share of the labor force
Coefficient on percent foreign-born, $\hat{\beta}$	0.075*** (0.014)	0.075*** (0.014)	0.076*** (0.014)	0.055*** (0.016)	0.036*** (0.011)
PUMA fixed effects	yes	yes	yes	yes	no
Year fixed effects	yes	yes	yes	yes	yes
Sex and age structure covariates	yes	yes	yes	yes	changes
Race/ethnicity covariates	yes	yes	yes	yes	changes
Education covariates	yes	yes	yes	yes	changes
Metro share covariate	yes	yes	yes	yes	changes
Time span	2005-2016	2005-2016	2005-2016	2005-2016	2006-2016
Number of units	1,078	1,078	1,078	1,078	1,078
N	12,936	12,936	12,936	12,936	11,858
R^2	0.4889	0.4878	0.4871	0.4990	0.2814
Population weights	2005	2010	2016	none	none

Notes: See notes to Table 4.1. In Model 2D, the endogenous (y) variable is the native employment-to-population ratio among those aged 25-54, and the key exogenous variable (x) is the foreign-born share of the total employment-to-population ratio for ages 25-54. In Model 2E, the endogenous (y) variable is the change in the native employment rate, and the key exogenous variable (x) is the change in the foreign-born share of the labor force.

4.3. Results stratified by education of native workers

As discussed above, previous studies have found evidence that the impact of immigration on native-born workers may be different for workers of different skill or education. Certain sub-groups of native-born workers — the low-skilled in some cases, the native Hispanic in others — may fare especially poorly when competing with immigrant workers, who are not exclusively Hispanic and/or low-skill but often are. In this third set of robustness results, we stratify the analysis by level of education of the native workers.

Table 4.3 reveals that positive and statistically significant effects of the foreign-born share on the employment rates of natives with some college education (Model 3C) and of natives who are college graduates (Model 3D). But we find null results for natives with less than a high school degree (Model 3A) or native high school graduates (Model 3B). For natives with less than a high school degree, we find a relatively large negative effect that is estimated imprecisely.

Statistics in Table 2.1 show that about 60 percent of the labor force has above a high school degree education. Results in this section suggest that share is driving the main result. These findings are broadly consistent with a story about worker complementarity, in which native workers with more education benefit from the arrival of immigration, who tend to have less education than natives on average, although immigrant workers are diverse with varying levels of education and skills. But it is striking that the largest employment gains accrue to native workers with some college and not a bachelor's degree, revealing nonmonotonic employment gains to immigration through education. These findings relate to previous study of immigrant employment patterns by occupation which reveals that language skills are both variable and important in how businesses allocate different types of workers to different tasks.[10] Firms might approach the challenge of heterogeneous skills among workers as an opportunity, by combining the unique services of immigrant workers with the unique skills of new hires of native-born workers.

[10] Kenneth Megan (2015) "Immigration and the Labor Force, Part II," *Bipartisan Policy Institute Blog Post*, September 21.

Table 4.3. The marginal effect of percent foreign-born on native employment stratified by education

	Model 3A	Model 3B	Model 3C	Model 3D
Outcome is employment rate of natives with:	Less than high school degree	High school degree	Some college	College graduate and more
Coefficient on percent foreign-born, $\hat{\beta}$	–0.046 (0.057)	0.027 (0.025)	0.043** (0.018)	0.028** (0.012)
PUMA fixed effects	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
Sex and age structure covariates	yes	yes	yes	yes
Race/ethnicity covariates	yes	yes	yes	yes
Education covariates	yes	yes	yes	yes
Metro share covariate	yes	yes	yes	yes
Time span	2005-2016	2005-2016	2005-2016	2005-2016
Number of units	1,078	1,078	1,078	1,078
N	12,936	12,936	12,936	12,936
R^2	0.2065	0.3338	0.3162	0.1829
Population weights	no	no	no	no

Notes: See notes to Table 4.1. In each column of this table, the panel fixed-effects regression includes a different y variable that measures the employment rate among natives in the PUMA within one of four classes of educational attainment, which are shown along the first row. The right-hand-side variables are unchanged.

4.4. Robustness across time periods

The time period of our analysis, 2005-2016, was a tumultuous and eventful span of time that included the lead-up to the Great Recession, the Great Recession itself and its recovery. Here, we check that our results are robust to different time specifications within the primary analysis. To do so, we examine six different time spans (three models that include the years leading up to the Great Recession and varying end years, as well as three models that included varying start years and the years of the recovery). While the results are robust in terms of the sign and statistical significance of $\hat{\beta}$ to the varying time specifications that included the Great Recession (Model 4A-Model 4D), it appears to be impossible to recover the result in any contiguous time subsamples measured *after* the Great Recession. We have null effects of percent foreign-born on native employment for both the 2008-2016 (Model 4E) and 2009-2016 (Model 4F) time periods. The question this naturally raises is whether our results are unique to a period of generally declining employment rates. We devise an alternative method to assess this in the next section.

4.5. Robustness over signed changes in the foreign-born share and native employment

While the main results were robust to some changes in the time period, our inability to reproduce them when omitting data from 2007 and earlier raises the question of why those earlier years might be special. Given the prominent role of the Great Recession in employment during the sample period, it is plausible that it may be driving our main result. Although symmetry is certainly not at odds with theory, it is qualitatively different for a study to report that the data indicate employment fell as immigration fell, rather than rising as immigration rose, and thus we would like to know which of those two stories appears to be driving the results.

To investigate this, we run a fourth set of robustness checks where we split the sample into pieces where either the y or the x variable was either nonnegative or negative, producing four additional models. Results are shown in Table 4.5.

Our estimate of $\hat{\beta}$ maintains sign across all four models, but its size and significance vary. In Model 5A, when we restrict our analysis to observations where the foreign-born share is unchanging or increasing, we find $\hat{\beta} = 0.057$ and significant at the 1 percent level. But in Model 5B, when we examine observations where the foreign-born share is falling, we find a null result. When we look at subsamples chosen according to whether the change in native employment is nonnegative or negative, we see more uniformity of results, but still some evidence that it is the observations where there has been positive change that are driving the main result.

Table 4.4. The marginal effect of percent foreign-born on native employment in various time periods since 2005

	Model 4A	Model 4B	Model 4C	Model 4D	Model 4E	Model 4F
Coefficient on percent foreign-born, $\hat{\beta}$	0.048* (0.027)	0.065*** (0.021)	0.084*** (0.017)	0.039*** (00.14)	0.018 (0.014)	0.012 (0.015)
PUMA fixed effects	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes
Sex and age structure covariates	yes	yes	yes	yes	yes	yes
Race and ethnicity covariates	yes	yes	yes	yes	yes	yes
Education covariates	yes	yes	yes	yes	yes	yes
Metro share covariate	yes	yes	yes	yes	yes	yes
Time span	2005-2007	2005-2009	2005-2012	2007-2016	2008-2016	2009-2016
Number of PUMAs	1,078	1,078	1,078	1,078	1,078	1,078
N	3,234	5,390	8,624	10,780	9,702	8,624
R^2	0.3507	0.2355	0.5047	0.5299	0.5410	0.5316
Population weights	no	no	no	no	no	no

Notes: See notes to Table 4.1. In each column of this table, the panel fixed-effects regression includes a different time span, which are shown along the fifth to last row. Other variables are unchanged.

Table 4.5. The marginal effect of percent foreign-born on native employment in samples restricted to signed changes in x or y

	Model 5A	Model 5B	Model 5C	Model 5D
Restriction on the change in x or y, Δx_{it}^{I} or Δy_{it}^{N}	change in foreign-born share is nonnegative: $\Delta x_{it}^{I} \geq 0$	change in foreign-born share is negative: $\Delta x_{it}^{I} < 0$	change in native employment is nonnegative: $\Delta y_{it}^{N} \geq 0$	change in native employment is negative: $\Delta y_{it}^{N} < 0$
Coefficient on percent foreign-born, $\hat{\beta}$	0.057*** (0.027)	0.029 (0.021)	0.054*** (0.014)	0.039** (0.018)
PUMA fixed effects	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
Sex and age structure covariates	yes	yes	yes	yes
Race and ethnicity covariates	yes	yes	yes	yes
Education covariates	yes	yes	yes	yes
Metro share covariate	yes	yes	yes	yes
Time span	2005-2016	2005-2016	2005-2016	2005-2016
Number of PUMAs	1,078	1,078	1,078	1,078
N	7,330	5,606	7,582	5,354
R^2	0.5062	0.5416	0.4986	0.5551
Population weights	no	no	no	no

Notes: See notes to Table 4.1. In each column of this table, the panel fixed-effects regression is restricted to different signed changes in x (native employment) or y (foreign-born share), which are shown along the first row. Other variables are unchanged.

To summarize, we find that the main result of $\hat{\beta} \approx 0.05$ appears to be somewhat more driven by concomitant increases in native employment and the foreign-born share of the labor force in the sample. The expansion years of 2005 through 2007 prior to the onset of the Great Recession in December 2007 appear to be important for identifying the main result. We do not find evidence supporting the notion that the Great Recession per se is driving our main results "in reverse" as it were.

4.6. Robustness across geographic regions

Our main results rely on an analysis of trends in PUMAs across the entire United States. As we showed early on, we know, however, that significant heterogeneity exists among Census divisions, and it is possible that a few divisions may be driving our results. For example, as mentioned in the introduction, there was substantive variation in how percent foreign-born changed across the time period of our study. Some divisions like the Pacific and Mountain experienced no net change between 2005-2016, but nearly all others experienced some increase. Of these, the West North Central division (including states like Minnesota, the Dakotas, Kansas and Missouri) and the East South Central division (which includes states like Mississippi, Alabama, Kentucky, and Tennessee experienced the largest percentage increases of 40 and 36 percent, respectively. It is also possible that the relationship between foreign-born share and native employment in some divisions is opposite to what we have found in the main findings. Our final set of robustness checks are geographic robustness checks that can help verify the stability of our results and potentially enhance our understanding of the driving factors underneath them.

First, we examine whether our main results hold with each of the nine different Census divisions (Models 6A-6I). We find that increases in foreign-born share are associated with increases in native employment in the Pacific division (Alaska, California, Hawaii, Oregon and Washington), with a regional $\hat{\beta}$ equal to 0.055 and significant at the 5 percent level. We recover a $\hat{\beta}$ = 0.093 in the East North Central division (Illinois, Indiana, Michigan, Ohio, and Wisconsin); a $\hat{\beta}$ = 0.079 in the West North Central division (Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota and South Dakota); a $\hat{\beta}$ = 0.095 in the West South Central division (Arkansas, Louisiana, Oklahoma and Texas); and a $\hat{\beta}$ = 0.094 in the Mountain division (Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah and Wyoming). All of these coefficients are significant at the 5% level or lower.

However, we find no statistically significant association between foreign-born share and native employment in the division-stratified models for New England (Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island and Vermont); for the Middle Atlantic (New Jersey, New York, and Pennsylvania); for the South Atlantic (Delaware, Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia, District of Columbia and West Virginia); and for the East South Central (Alabama, Kentucky, Mississippi, and Tennessee).

We also investigate whether the main results hold once fixed effects for Census division (Model 6J) or division and division-year fixed effects are introduced (Model 6K). Fixed effects for divisions absorb static variation between geographic regions that could be driving some of the main result but is likely already absorbed by PUMA fixed effects. Division-year fixed effects allow there to be differential, flexible time trends in employment rates across regions that the model nets out of the data, in addition to a single national time trend.

Neither of these inclusions changes the results very much. As one might expect, division fixed effects do not change the results at all, because PUMAs do not cross state lines and thus are constant within divisions. When we include division-year fixed effects, we find that $\hat{\beta}$ becomes slightly attenuated, to 0.044, but it maintains significance at the 1 percent level.

Table 4.6. The marginal effect of percent foreign-born on native employment within the 9 Census divisions

	Model 6A	**Model 6B**	**Model 6C**	**Model 6D**	**Model 6E**
Coefficient on percent foreign-born, $\hat{\beta}$	–0.026 (0.044)	0.008 (0.023)	0.093** (0.040)	0.079** (0.039)	0.041 (0.040)
PUMA fixed effects	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes
Sex and age structure covariates	yes	yes	yes	yes	yes
Race and ethnicity covariates	yes	yes	yes	yes	yes
Education covariates	yes	yes	yes	yes	yes
Metro share covariate	yes	yes	yes	yes	yes
Time span	2005-2016	2005-2016	2005-2016	2005-2016	2005-2016
Census division	New England	Middle Atlantic	East North Central	West North Central	South Atlantic
Number of PUMAs	56	216	180	73	178
N	672	2,592	2,160	876	2,136
R^2	0.7302	0.6656	0.6350	0.6139	0.6056
Pop. weights	no	no	no	no	no

Table 4.6 cont.

	Model 6F	Model 6G	Model 6H	Model 6I	Model 6J	Model 6K
Coefficient on percent foreign-born, $\hat{\beta}$	0.005 (0.080)	0.095*** (0.036)	0.094* (0.049)	0.055** (0.027)	0.053*** (0.013)	0.044*** (0.012)
PUMA fixed effects	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes
Sex and age structure covariates	yes	yes	yes	yes	yes	yes
Race and ethnicity covariates	yes	yes	yes	yes	yes	yes
Education covariates	yes	yes	yes	yes	yes	yes
Metro share covariate	yes	yes	yes	yes	yes	yes
Time span	2005-2016	2005-2016	2005-2016	2005-2016	2005-2016	2005-2016
Census division	East South Central	West South Central	Mountain	Pacific	All, with division fixed effects	All, with division and division-year fixed effects
Number of PUMAs	76	87	51	161	1,078	1,078
N	912	1,044	612	1,932	12,936	12,936
R^2	0.4991	0.2632	0.4737	0.6094	0.5245	0.5792
Pop. weights	no	no	no	no	no	no

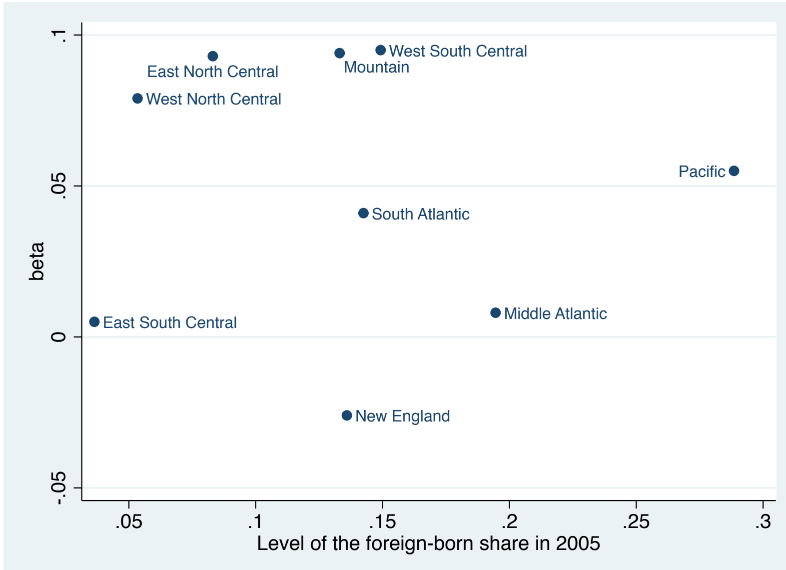
Notes: See notes to Table 4.1. In each column of this table, the panel fixed-effects regression are restricted to one or more Census divisions, which are shown along the sixth to last row. All other variables are unchanged. Model 6A examines New England (Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island and Vermont. Model 6B examines Mid-Atlantic (New Jersey, New York, and Pennsylvania). Model 6C examines East North Central (Illinois, INdiana, Michigan, Ohio, and Wisconsin). Model 6C examines West North Central (Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota and South Dakota). Model 6D examines South Atlantic (Delaware, Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia, District of Columbia and West Virginia). Model 6E examines East South Central (Alabama, Kentucky, Mississippi, and Tennessee). Model 6F examines West South Central (Arkansas, Louisiana, Oklahoma and Texas. Model 6G examines Mountain (Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah and Wyoming). Model 6H examines Pacific (Alaska, California, Hawaii, Oregon and Washington).

Heterogeneity in the results across geographic regions is striking and deserving of further inquiry. One might infer that regional characteristics must be important for the marginal effect of immigration on native employment, which is to some extent tautologically true if we leave aside the issue of varying statistical power across differently sized divisions and believe the null results are real. Whether we can identify the salient characteristics of regions is an open question, of course. Obvious candidates are the foreign-born share of the labor force, which is a proxy for the history of immigrant absorption, and the change in the foreign-born share, which measures how much absorption has increased.

In Figures 5 and 6, we plot the regression coefficients across Census divisions from Models 6A-6K against the foreign-born share and then against the change in the foreign-born share to see whether we can visually identify any relationships. Figure 5 plots the level of the foreign-born share at the beginning of the period (x) against the marginal effect of immigration on native employment (y). There is no evident linear nor non-linear relationship, and the simple correlation coefficient is small at –0.05. Divisions with the smallest foreign-born shares in 2005, shown at left in the figure, have a very wide range of regression coefficients, which run from near 0 to close to the maximum near 0.1. The same is true for the districts with intermediate levels of the foreign-born share: their respective regression coefficients also range from below 0 to close to the maximum near 0.1. The initial amount of immigrant within a Census division does not seem to explain the marginal effect of immigration on native employment. When the metric is the effect of immigration on native employment, traditional receiving areas were neither systematically "better" nor "worse" than other areas at absorbing immigration.

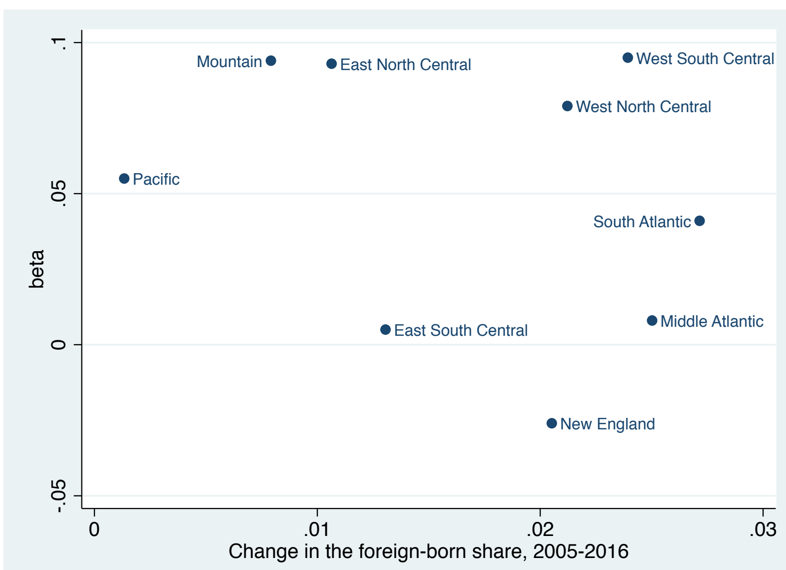
Because the geography of immigration has changed so much, it might also make sense to examine how the division coefficients vary according to either the ending level of the foreign-born share or the change in the share. But examining the former produces a picture that is nearly indistinguishable from what appears in Figure 5. In Figure 6, we look at the change in the foreign-born share during the 2005-2016 study period rather than its level. Once again, there is not much evidence of an obvious relationship between the two variables. Here the simple correlation coefficient is somewhat larger in magnitude, at –0.26, than it was in Figure 5. But the larger magnitude of the correlation implies more knowledge than the eye reveals; five divisions are shown stacked here at the right-hand side of the graph, with similar changes in the foreign-born share but with vastly different $\hat{\beta}$'s. We are left, as before, with a picture of great and unexplained geographic heterogeneity. Needless to say, there are many other characteristics of regions that might be important for assimilating immigrant labor, but it is striking that the level and change in immigration do not seem to matter much.

Figure 5: Effect of immigration on native employment (2005-2016) and 2005 foreign-born share



Notes: The unit of observation is Census division, for each of which we plot the marginal effect of the immigrant share on native employment ($\hat{\beta}$, vertical axis) against the foreign-born share in 2005 (horizontal axis). Statistics are derived from authors' calculation using the 2005-2016 ACS samples from Ruggles et al. (2018).

Figure 6: Effect of immigration on native employment and Change in foreign-born share, 2005-2016



Notes: See notes to Figure 5. Here, the horizontal axis shows the total change in the foreign-born share between 2005 and 2016.

5. Discussion

In this paper, we applied standard estimation methods to a broad empirical question: were changes in the foreign-born share of the labor force associated with changes in native employment rates between 2005 and 2016 in the United States? Specifically, we employed a panel fixed effects estimator, which is a generalization of the difference-in-differences approach used in much applied empirical research, to the rich synthetic panel data of the American Community Survey series.

In contrast to what the static theoretical model predicts, we find that rising foreign-born shares of the local labor force are robustly associated with increases in native employment rates over the 2005-2016 time period. Our models predict that each percentage-point increase in the foreign-born share would raise the native employment rate by 0.055 to 0.075 percentage point. Whether immigrant labor actually raises the employment of natives on its own or is a marker of third factors that are causal is less clear and remains the subject of future investigations.

We ran a variety of robustness checks. We implemented population weights to probe for asymmetries between large and small PUMAs; we checked employment-to-population ratios to assess whether differential rates of worker discouragement and dynamics in participation might be important; and we also estimated the model in first differences. None of these affected our primary finding.

We also stratified our results by educational level of the native-born workers, and we recovered differences in the main effect across these groups that fit our understanding of U.S. immigration patterns. Native employment rates among workers with less than a high school education did not rise with immigration and may have fallen, but the coefficient was statistically insignificant. Workers with more education fared better, with the interesting result that workers with some college experience but not a bachelor's degree fared the best.

We also restricted our results by time period and across signed changes in the endogenous and exogenous variables, and by geographic region. The main results endured most of these tests but also revealed interesting patterns of heterogeneity. We found that the early years of the ACS sample, 2005 through 2008, were important for the main result, but we cannot conclude that it was the Great Recession per se that is driving our result. Rather, the evidence is more consistent with the hypothesis that the later years of the Bush-43 Administration were a special time for growth in native employment and in the foreign-born share of the labor force. We also found interesting variance in the main result across geographic regions, and we think these patterns deserve future study.

Like other spatial studies, our study faces two challenges to validity: endogeneity, and labor market responses to immigration, such as out-migration of native labor or capital. The size of immigrant inflows is likely correlated with an area's economic and wage growth. Some studies overcome the endogeneity issue use an instrumental variables strategy. The most common instrument for studies like ours – one that is highly correlated with inflows of foreign-born workers into a certain area, but hopefully uncorrelated with other factors that determine wages or job growth there – is some measure of co-nationals or migrant networks (Altonji & Card, 1991; Bartel, 1989; Card, 2001). Orrenius and Zavodny (2007: 11) use a variable of "immigrants who are admitted to the United States in a given year as the spouse of a U.S. citizen by occupation group, area and year" for their analysis of metropolitan statistical areas. In a study very similar to ours, Zavodny (2018) uses the foreign-born share of the total population to instrument for the foreign-born share of the labor force. Strikingly, Zavodny reports estimates that are nearly identical to our own, despite her using an instrumental variables approach and state-level observations. Alternative instruments include distance between origin and destination countries (Llull, 2016). We leave further exploration of identification strategies to future studies.

Second, our study, like other area studies, does not formally model the possibility that as immigrants flow into a geographical area, natives can respond to the increased competition for jobs by moving out. Previous empirical findings for immigration and native out-migration are mixed: many studies find no relationship or that both international and domestic migrants move to the same areas (Card, 2001; Card & DiNardo, 2000; Kritz & Gurak, 2001; Peri, 2007), but other find some association between high immigration and higher native out-migration (Borjas, 2006), in-migration of foreign-born associated with out-migration of native (Kritz & Gurak, 2001) and heterogeneity by place and group.

All in all, in a context where theory is ambiguous and previous empirical findings are mixed, empirical studies can strengthen understanding of how immigration is associated with native employment. Neither our work nor other recent work that uses the American Community Survey data (Zavodny, 2018) finds evidence of a statistically significant negative relationship between immigration and native employment, as would be suggested by the simple theory. Instead, both this prior state-level analysis and our own analysis disaggregated at the PUMA find a modest positive relationship between immigration and native employment overall. When we examine trends in employment rates of native U.S. workers compared to trends in foreign-born shares of the local labor force between 2005 and 2016, we find that employment rates for native workers rose by a small amount when more immigrants arrived.

References

Altonji, Joseph G., and David Card (1991) "The Effects of Immigration on the Labor Market Outcomes of Less-Skilled Natives." In *Immigration, Trade, and the Labor Market*, 201–234. University of Chicago Press.

Bartel, Ann P. (1989) "Where Do the New US Immigrants Live?" *Journal of Labor Economics* 7 (4): 371–391.

Blau, Francine D. and Christopher Mackie (2017) *The Economic and Fiscal Consequences of Immigration*. National Academies of Sciences, Engineering, and Medicine. Washington: National Academies Press.

Bohn, Sarah, Magnus Lofstrom, and Steven Raphael (2015) "Do E-verify mandates improve labor market outcomes of low-skilled native and legal immigrant workers?" *Southern Economic Journal*, 81(4): 960–979. doi:10.1002/soej.12019

Borjas, George J. (2006) "Immigration in High-Skill Labor Markets: The Impact of Foreign Students on the Earnings of Doctorates." National Bureau of Economic Research.

Borjas, George J., Jeffrey Grogger, and Gordon H. Hanson (2010) "Immigration and the Economic Status of African-American Men." *Economica* 77: 255-282.

Card, David (1990) "The Impact of the Mariel Boatlift on the Miami Labor Market," *Industrial and Labor Relations Review* 43(2): 245-257.

Card, David (2001) "Immigrant Inflows, Native Outflows, and the Local Labor Market Impacts of Higher Immigration." *Journal of Labor Economics* 19 (1): 22–64.

Card, David, and John DiNardo. (2000). "Do Immigrant Inflows Lead to Native Outflows?" *American Economic Review* 90 (2): 360–367.

Cortes, Patricia. (2008). "The Effect of Low-Skilled Immigration on US Prices: Evidence from CPI Data." *Journal of Political Economy* 116 (3): 381–422.

Kritz, Mary M., and Douglas T. Gurak. (2001). "The Impact of Immigration on the Internal Migration of Natives and Immigrants." *Demography* 38 (1): 133–145.

Lewis, Ethan G. (2011). "Immigrant-Native Substitutability: The Role of Language Ability." National Bureau of Economic Research.

Llull, Joan. (2016). "Understanding International Migration: Evidence from a New Dataset of Bilateral Stocks (1960–2000)." *SERIEs* 7 (2): 221–255.

López, Gustavo and Kristen Bialik (2017) "Key findings about U.S. immigrants," *Pew FactTank*, May 3. http://pewrsr.ch/2qz2zvx

Kenneth Megan (2015) "Immigration and the Labor Force, Part II" Bipartisan Policy Institute Blog Post, September 21 https://bipartisanpolicy.org/blog/immigration-and-the-labor-force-part-ii/

Orrenius, Pia M., and Madeline Zavodny (2007) "Does Immigration Affect Wages? A Look at Occupation-Level Evidence." *Labour Economics* 14 (5): 757–773.

Orrenius, Pia. M. and Madeline Zavodny (2015) "*The impact of E-Verify mandates on labor market outcomes,*" Southern Economic Journal, 81: 947–959. doi:10.1002/soej.12023

Passel, Jeffrey S. and D'Vera Cohn (2017) "As Mexican share declined, U.S. unauthorized immigrant population fell in 2015 below recession level" *Pew FactTank,* April 25. http://pewrsr.ch/2qavmFK

Perales, E. Jose (2017) "An Analysis on the Effect of Immigration on Employment," unpublished working paper, Bipartisan Policy Center, June 26.

Peri, Giovanni. (2007) "Immigrants' Complementarities and Native Wages: Evidence from California." National Bureau of Economic Research.

Ruggles, Steven, Katie Genadek, Ronald Goeken, Josiah Grover, and Matthew Sobek (2018) Integrated Public Use Microdata Series: Version 7.0 [dataset]. Minneapolis: University of Minnesota. https://doi.org/10.18128/D010.V7.0.

Singer, Audrey (2009) "The New Geography of United States Immigration," *Brookings Immigration Series*, No. 3, July.

Smith, James P. and Barry Edmonston, eds. (1997) *The New Americans: Economic, Demographic, and Fiscal Effects of Immigration*. Panel on the Demographic and Economic Impacts of Immigration, Committee on Population and Committee on National Statistics Commission on Behavioral and Social Sciences and Education, National Research Council. Washington: National Academy Press.

Tumen, Semi (2016) "The Economic Impact of Syrian Refugees on Host Countries: Quasi-experimental Evidence from Turkey," *American Economic Review*, 106(5): 456-60.

Waters, Mary C. and Marisa Gerstein Pineau, eds. (2015) *The Integration of Immigrants into American Society*. Panel on the Integration of Immigrants into American Society, Committee on Population, Division of Behavioral and Social Sciences and Education, National Academies of Sciences, Engineering, and Medicine. Washington: National Academies Press.

Zavody, Madeline (2018) “Immigration, Unemployment, and Labor Force Participation in the United States,” *NFAP Policy Brief,* May.

Appendix Table A
Recent Empirical Studies, Table 5-3 excerpt from Blau and Mackie (2017: 270-273)

TABLE 5-3 Recent Studies Using Cross-Area, Occupation, or Industry Approaches

Study	Sample, Analysis Unit	Methods	Findings
Altonji and Card (1991)	U.S. men and women, 1970-1980, MSA	Spatial correlation, first differences, IV	1 percentage (pctg.) point increase in immigrant share lowers native wages by 0.3% to –1.2%; employment and participation effects negligible.
LaLonde and Topel (1991)	U.S. men, 1970-1980, MSA	Spatial correlation, first differences	Negative wage effects for new immigrants, effects die out for earlier immigrant cohorts, no effects for natives.
Card (2001)	U.S. men, 1990 cross-section; natives and earlier immigrants by MSA × broad skill/occupation/ gender group	Spatial correlation, IV, analysis across cities and skill levels simultaneously to remove bias from omitted variables	Immigrants lower wages of less skilled natives—wages 0.99 pctg. points (male natives), 2.5 pctg. points (female earlier immigrants), 0 (other groups). 10% labor supply increase reduces employment rate 2.02 pctg. points (male natives), 0.81 pctg. points (female natives), 0.96 pctg. points (male earlier immigrants), 1.46 pctg. points (female earlier immigrants).
Cortés (2008)	U.S. men and women, 1980-2000, MSA	Spatial correlation, IV, country	Low-skilled immigrants don't affect native wages overall. Previous immigrant and Hispanic wages lowered (1-1.5%).
Peri et al. (2014)	U.S. city × period (periods: 1990-2000, 2000-2005, 2005-2010)	Estimated H-1B–driven rise in STEM workforce, based on 1990 foreign STEM workforce by city and sending country and national-level distribution of H-1B visas by sending country	1 pctg. point increase in foreign share in STEM workers raises native STEM wages 7-8%.
Borjas (2003)	Education level × experience level × U.S. census survey, 1960-2000	Number of foreign-born workers in each education-experience-year group	~10% migration-induced labor growth in 1980-2000 cut wages for native non-high school completers 8.9%.
Camarota (1998)	Cross-section (1991) for U.S.	Wages of all workers	Wages: –0.5% overall; wages for workers in low-skilled occupations –0.8%.
Card (2001)	Cross-section (1990), IV for U.S.	Relative wages and employment of low-skilled natives	No effect on relative wages, small negative impact on relative employment.
Card (1990)	Miami men and women, 1980-1985	Spatial correlation; measured impact of increase in low-skilled labor supply shock associated with Mariel boatlift	No effect on wages or unemployment of unskilled workers.
Dustmann et al. (2005)	UK men and women, 1983-2000 (pooled cross-sections)	Spatial correlation, IV methods; first-differences with IV (1983-2000); participation rate, (un)employment rate, and hourly wages of the working population by education	Immigration has statistically insignificant effect on wage of each skill group.
Dustmann et al. (2013)	UK men and women, 1997-2005	Spatial correlation by wage percentile, IV method	Immigration lowers wages at 5th and 10th percentiles, raises average and above median wages.
Clemens (2013)	58 employment offices × 66 months, North Carolina, Feb. 2005-May 2011	Great Recession–caused unemployment jump, 2008-2009	Even after total unemployed in studied counties rose from 283,000 to 490,000, and with 6,500 job openings, only 7 native workers took and held farm jobs for the 2011 season—the rest were filled by migrants.

TABLE 5-3 Continued

Study	Sample, Analysis Unit	Methods	Findings
Smith (2012)	U.S. youth and adults	Spatial correlation, IV	10% increase in immigrants with high school degree or less reduced average number of hours worked by 3-3.5% for native teens; less than 1% for less educated adults.
Kerr and Lincoln (2010)	U.S. cities × year, 1995-2007	Estimated number of H-1B holders in a city, by ethnicity, based on national-level H-1B ethnic breakdown and number of H-1B applications in 2001-2002	Among top quintile of cities in H-1B dependence, 10% increase in national H-1B population associated in same year with 6-12% increase in patent filing by people with Indian or Chinese names and 0-2% rise overall.
Peri (2012)	U.S. states × U.S. Decennial Census, 1960-2006	Distance to Mexican border; estimates of migrant stocks based on 1960 stocks by state and sending country; national-level growth rates by sending country	Immigration increases productivity (output per units of labor and capital input).
Borjas and Doran (2012)	U.S. and Soviet mathematicians who published in 1970-1989	Arrival of ~336 Soviet émigré mathematicians in U.S. just after collapse of Soviet Union	American mathematicians in subfields with active émigrés were published and cited less after 1992 and more likely to leave profession, indicating zero-sum displacement by new immigrants.
Moser et al. (2014)	166 chemistry subfields × year, U.S., 1920-1970	Starting in 1933, arrival of 26 Jewish émigré chemists from Nazi Germany & Austria, distinguishing their pre-departure subfields from ones with active German/Austrian researchers who did not leave	American inventors in subfields with émigrés recorded an extra 170 patents/year in 1933-1970 in total, 70% over pre-1933 level.