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Chapter 6

The Short-Run Impacts of Immigration on Native Workers: A Sectoral Approach

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6.1 Introduction

Labor economists have long been interested in the impacts of immigration on the labor market outcomes of native-born workers in the United States (US), starting with the seminal work of Grossman (1982), followed by influential contributions by Card (1990, 2001, 2009), Altonji and Card (1991), Friedberg and Hunt (1995), Borjas *et al.* (1997), Borjas (2003), Peri and Sparber (2009), Ottaviano and Peri (2012), and Dustmann *et al.* (2017), to name a few.

While the wealth of estimates produced by this literature has failed to paint a consensual picture of immigration effects (Basso and Peri, 2015), recent work by Dustmann *et al.* (2016) helps rationalize some of the empirical discrepancies found across wage studies, elucidating how different sources of variation in fact identify different structural parameters. While the "national skill-cell approach" of Borjas (2003) and the "mixture approach" of Card (2001) identify *relative* wage effects (across education–experience groups and education groups, respectively), the "pure spatial approach" potentially identifies a total effect, and is therefore the method of choice according to Dustmann *et al.* (2016).

Building upon the spatial approach, this chapter proposes new estimates of the short-run impacts of immigration on the employment conditions of US-born workers based on a fixed-effects panel regression of US metropolitan areas spanning the years 1990–2011, a period during which the US experienced a remarkable increase in immigration. We use a novel partial identification strategy that has not been exploited in the related literature

Table 6.1: Educational Attainment of the Native-Born Workforce by Sector

Sector	High-school or less (%)	Bachelor's degree or more (%)
Food service	65.4	7.1
Maintenance	72.3	5.1
Personal services	50.8	13.4
Construction	67.2	5.6
Manufacturing	67.1	5.7
Transportation	68.2	6.2
Computers	8.7	59.4
Engineering	6.7	69.8
Science	9.9	73.2

Notes: The native-born workforce is defined by individuals who are between the ages of 18–64, neither in school, nor living in group quarters, and who were both employed at the time of the survey and had worked a positive number of weeks during the previous year.

to date. Our approach requires estimating immigration impacts at a sectoral, rather than economy-wide, level. While this restriction may be seen by some as a weakness, it allows us to paint a contrasted picture of immigration impacts across nine sectors of the US economy with high immigrant worker penetration: construction, transportation, manufacturing, maintenance, food service, personal services, computers, engineering, and science. Not counting agriculture, these nine sectors are the ones with highest immigrant shares over the period 1990–2011.[1] Taken together, they have employed 34.9% of the total native workforce and 50.3% of the low-skilled native workforce.[2] While the first six sectors employ predominantly low-skilled workers, the last three employ predominantly high-skilled workers. Table 6.1 shows the percentages of workers having no more than a high-school diploma and those having at least a Bachelor's degree in each of these nine sectors.

The sectoral approach delivers upper bounds on the short-run impacts of immigration on native workers' earnings, occupational levels, and sectoral employment rate. In the personal services, food service, and construction sectors, upper bounds on earnings are typically negative, statistically significant, and of much larger magnitude than recently published estimates for the US economy as a whole, suggesting that there exist transitory costs to immigration for part of the native population. We find that a 10% point

[1]We do not look at agriculture because our dataset focusses on workers located in large metropolitan areas, and because the share of immigrants in that sector calculated using our dataset grossly understates the actual prevalence of immigrants, as inferred from other sources like the National Agricultural Workers Survey, which uses a nationally representative sample of agricultural workers.
[2]Here we define "low-skilled" as having no more than a high-school diploma or equivalent. Our empirical analysis includes native workers with any level of educational achievement.

increase in the share of immigrant workers in personal services (resp., food service; resp., construction), which is less than the increases that occurred over the period of investigation, causes at least a 6.6% (resp., 6.0%; resp., 2.9%) drop in the annual earnings of natives. These effects are generally more pronounced for occupations within these sectors most exposed to immigrant inflows. For example, when focussing on workers within personal services (resp., construction) in occupations with the highest immigrant shares, we find effects about twice as large as those for the sector as a whole.

Earnings results in the remaining sectors are more nuanced. Although our point estimates suggest negative effects on the annual earnings of natives in maintenance and transportation, these effects are only statistically significant once we focus on more disaggregated portions of these sectors. In the maintenance sector, we find significantly negative effects for natives in occupations related to landscaping; interestingly, the effect on these workers is of comparable magnitude as that found in the immigrant-exposed occupations of the construction sector such as roofers or painters.

In the transportation sector, which employs a variety of workers such as aircraft pilots, boat operators, or garbage collectors, we find significantly negative effects in immigrant-exposed occupations like those of drivers or loaders. We do not find significant earnings effects in the manufacturing sector, likely due to the traded nature of the goods produced. Nor do we find effects in the three higher-skill sectors considered, perhaps due to complementarities between native and immigrant labor in these sectors (Ottaviano and Peri, 2012; Manacorda *et al.*, 2012).

An important insight of our analysis is that annual earnings effects, where present, may be partly driven by reductions in the occupational levels of natives, i.e., fewer weeks worked per year. This is particularly true for construction occupations, as well as immigration-exposed personal service occupations such as child and personal care. In these occupations, income is often earned "per job" and workers compete for jobs, sometimes through a formal bidding process. Such occupations also have high rates of self-employment, and work may be undeclared. To the extent that immigrant workers, some of whom work illegally, have a preference for work unreported to the government or are willing to accept lower pay, they cost less to employers and may be in a position to outcompete natives.[3]

[3]The construction sector, in particular, is notorious for having high rates of "under the table" employment (i.e., workers paid in cash without reporting employment to the government). Contractors engaging in this type of employment have a competitive advantage over others who strictly employ workers "on the books" because of the additional cost of workers' compensation, unemployment insurance, and other payroll taxes, which must be factored into bids (Fishman, 2013).

In line with earlier literature, our results on earnings are derived conditional on workers earning a strictly positive income (among other criteria). Our analysis shows that immigration has also had sizable effects on native workers' employment rates in the six low-skill sectors considered, including manufacturing. Again, the largest effects are found in the construction (resp., food service; resp., personal services) sector where a 10% point increase in the share of immigrants causes at least a 2.3% point (resp., 1.8% point; resp., 1.7% point) decrease in the employment rate of natives when considering the entire sector, and a 3.6% point (resp., 1.8% point; resp., 3.0% point) decrease when focussing on immigrant-exposed occupations. In the three higher-skill sectors, there is no discernible effect of immigration on sectoral employment, suggesting that natives are either not displaced, or are displaced but find employment in another sector.

Although the definition of economic sectors we use is quite broad and accommodates within-sector mobility, immigration in one sector could plausibly cause some natives to shift to other sectors, raising concerns that our sectoral estimates could be partly driven by compositional effects. To address this concern, we pool lower-skill sectors into a composite sector and estimate effects at the level of the composite sector. The results confirm negative effects of immigration on annual earnings, occupational levels, and the employment rate.

The sectoral approach proposed here relies on comparisons of immigration shocks across regions and thus belongs to the "spatial approach" literature pioneered by Card (1990) and Altonji and Card (1991). As explained by Dustmann *et al.* (2016), the spatial approach can, from a structural perspective, capture the total effect of immigration on native outcomes, at least under the assumption that immigration into one city does not indirectly affect outcomes in others, e.g., through the displacement of natives.[4] Similarly, applying the spatial approach at the sectoral level implicitly assumes that native workers within a sector are principally affected by immigration into that sector, and not into others.

A critical issue facing analyses that rely on spatial comparisons is identification. Immigrants sort into locations, supposedly following employment opportunities. Locations with better opportunities for immigrant workers are plausibly those where demand for labor is higher, potentially confounding

[4]In addition to out-migration of natives, movement of goods and capital across cities can cause the spatial approach to fail to detect the effects of immigration on native outcomes (Borjas, 2003). See Appendix B for a formal argument.

the effect of immigration on native wages or employment. The literature has resorted to instrumental variable approaches in order to address this issue, the most popular instrument being a shift-share instrument constructed by interacting the fraction of immigrants from a country who are observed living in a city in a prior reference period with the *national* inflow of immigrants from that country in the current period (and then summing up across origin countries). The instrument thus represents the total influx of immigrants in the current period that would be obtained if new influxes were perfectly correlated with the geographical distribution in the reference period. Nonetheless, many authors have questioned the validity of the shift-share instrument due to the possible spatial correlation between initial immigrant settlement patterns and subsequent growth in employment opportunities (e.g., Reed and Danziger, 2007; Borjas, 2014; Basso and Peri, 2015, and more recently Goldsmith-Pinkham *et al.*, 2019).

Perhaps more importantly, a recent paper by Jaeger *et al.* (2018) demonstrates that estimates obtained from the shift-share instrument conflate short-run (negative) impacts with long-run recovery processes whenever there is limited change in the composition of immigrant inflows at the national level over time, as has been the case in the US since the 1980s. According to the authors, the only time period in the US when the shift-share instrumental variable approach — or the improved strategy they propose — may be successfully leveraged is the decade 1970–1980, which saw a considerable shift in the country-of-origin composition of US immigrant inflows due to the enactment of the Immigration and Nationality Act of 1965. Although they find evidence of negative short-run impacts of immigration on natives' wages based on this earlier period, it is not clear whether these impacts can be extrapolated to current conditions, due, for example, to the secular increase in immigration and the fact that effects may not be globally linear.

In this chapter, we leverage a novel partial identification method formalized by Nevo and Rosen (2012) to address the effect of increased immigration on the employment opportunities of native-born workers in the context of the spatial correlation approach. Our partial identification strategy relies on the use of a series of so-called "imperfect instruments:" instruments for the sectoral immigrant share in a given city and year that, although still potentially correlated with the error term (unobserved demand shocks about city and year averages), are plausibly less correlated with it than the regressor itself, albeit in the same direction. In this sense, they represent imperfect instrumental variables or IIVs. Because of the remaining correlation, which violates the exclusion restriction, the IIV estimate is biased. However, Nevo and Rosen (2012) show that under certain conditions, the IIV estimate can be used as a lower or upper bound on the coefficient of interest.[5] We use their insights to derive upper bounds on the negative effects of immigration on native employment conditions over the period 1990–2011. Because our approach relies on spatial differences, it delivers estimates that are also possibly subject to spatial-arbitrage bias. But since both sources of bias (imperfect instrument and spatial arbitrage) work in the same direction, our estimates are conservative in nature. Nonetheless, we find that in the food service and personal service sectors, immigration impacts are negative, statistically significant, and larger in magnitude than comparable estimates derived in the US context for recent decades. Once we focus on immigrant-exposed occupations, we also find evidence of large negative effects in the construction sector. In these sectors, our estimates for earnings effects are consistent with the latest figures derived by Jaeger *et al.* (2018) for the earlier decade 1970–1980. Our estimate for the construction sector appears consistent with that derived by Bratsberg and Raaum (2012) for the Norwegian constructor sector.[6]

In terms of empirical implementation, the dual requirement that the correlation between the IIV and the error term be of the same sign as, but of a lower magnitude than, the correlation between the regressor and the error term does have a cost.[7] Our approach focusses on one sector of the economy at a time in order to use as an IIV for the sectoral share of immigrants the share of immigrants *across all sectors*, or *across all other sectors*. These instruments are plausibly correlated with demand pulls that affect native employment/earnings in the sector of interest in the same direction as the sectoral immigrant share: economic booms attract immigrants across all sectors, and they increase employment opportunities for natives in any given

[5]They also show how one may derive two-sided bounds, but for reasons highlighted in what follows, our setting does not allow such derivation.

[6]Bratsberg and Raaum (2012) rely on differences in immigrant shares *across* construction trades, rather than intercity comparisons. As such, the interpretation of their estimate differs from ours: whereas our estimate can be interpreted as capturing the *total* sectoral effect of immigration on native outcomes — assuming away spatial arbitrage — theirs represents a *relative* effect across construction trades. Following the argument of Dustmann *et al.* (2016), our estimate is closer to the relevant effect because it encompasses effects of immigration that are common to all construction trades.

[7]One may argue that the shift-share instrument discussed above already constitutes an IIV. In some studies, like Dustmann *et al.* (2005), the use of the shift-share instrument actually results in a less negative impact of immigration. In others (e.g., Reed and Danziger, 2007; Basso and Peri, 2015; Jaeger *et al.*, 2018) the estimate becomes more negative but the change is minimal, suggesting that the IIV correlation with the error term remains high in comparison with that of the regressor.

sector. However, since the immigrant share pertains to the entire economy (or the rest of the economy), it is likely less correlated with the sectoral demand pulls than the sectoral immigrant share itself. Our IIV estimates, which are typically much more negative than the ordinary least squares (OLS) estimates, confirm this intuition. Our finding that the immigrant share has a negative effect on natives' employment rate across all six low-skill sectors also provides some evidence that labor may not be completely mobile across sectors in the short run, underscoring the relevance of a sectoral approach.

This chapter contributes to the literature on the impacts of immigration on the employment conditions of natives in several ways. First, we deploy a novel instrumental variable strategy that represents an alternative to the much criticized shift-share instrument in the context of the spatial correlation approach. Our strategy acknowledges the inherent remaining correlation between our instrument and unobserved sectoral demand shocks, but leverages it to derive an upper bound on the negative impacts of immigration on natives' employment conditions. Second, we are able to produce estimates of immigration impacts for a relatively recent period; Jaeger *et al.* (2018) show that the shift-share instrument approach may only produce reliable impacts for the period 1970–1980 in the US context. Third, in spite of the fact that spatial correlation estimates may mask larger national effects (Borjas, 2003), several of our estimated effects are larger in magnitude than most recent estimates for the US, suggesting that natives can be hurt by immigration in the short run. Fourth, the sectoral approach allows us to provide a nuanced picture of immigration impacts across the economic sectors most exposed to immigration.[8] We relate our findings to critical differences across sectors and occupations regarding goods tradability, immigrant penetration, and skill requirements.

The rest of the chapter is organized as follows. Section 6.2 discusses recent immigration trends in the sectors we investigate. Section 6.3 describes our data sources. Section 6.4 describes the IIV strategy we deploy, building upon the work of Nevo and Rosen (2012). Section 6.5 discusses our results, and Section 6.6 concludes.

[8]The idea that the effects of immigration on native workers may be more pronounced in industries with high immigrant share was recently explored by Dustmann *et al.* (2017) in their study of a commuting policy along the German–Czech border. Their main analysis considers all industries together as the spatial variation in immigrant inflows that they exploit cannot address the selection of immigrant workers into industries experiencing positive labor demand shocks. Nonetheless, the results they report in Appendix D.V suggest larger negative effects on employment in immigrant-exposed industries.

6.2 Background

Since the enactment of the Immigration and Nationality Act of 1965, the US has experienced a remarkable increase in immigration, with the share of foreign-born individuals in the total population increasing from 4.7% in 1970 to 13.4% in 2015 (López and Bialik, 2017). There were 27,400,000 foreign-born (immigrant) individuals in the US labor force in 2017, representing 17.1% of the total labor force (US Department of Labor, 2018). Construction and extraction occupations attracted 9.3% of employed immigrant workers, making these occupations the single category with the highest number of immigrants, and one with an immigrant share of 30.4%. Building and grounds cleaning and maintenance occupations employed 8.4% of immigrant workers, and the immigrant share in that sector reached 37.4%.

Low-skill sectors of the economy with high immigrant penetration, as defined in this chapter, have seen a remarkable increase in the share of immigrant workers in the sectoral workforce (Figure 6.1). According to our data (see Section 6.3), between 1990 and 2011 the share of immigrants in the construction sector has increased from 10% to 26%, while that in the maintenance sector has increased from 18% to 37%. Other sectors have seen

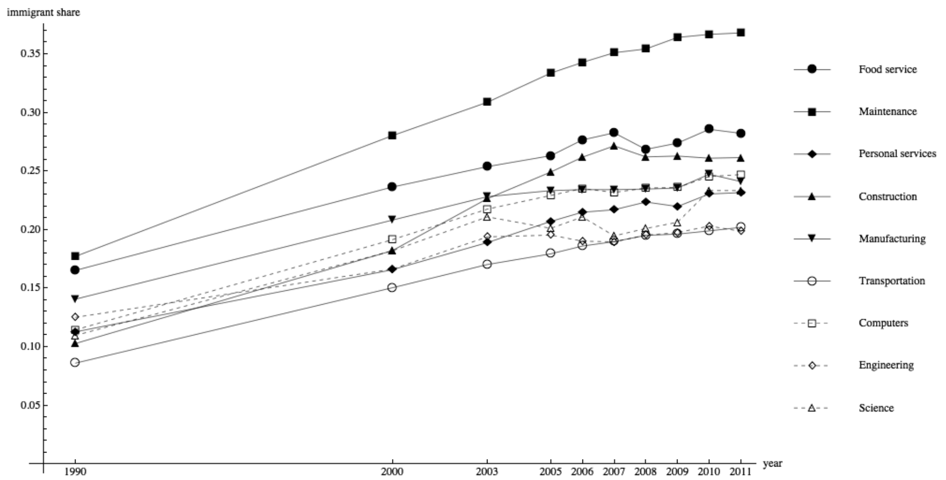

Fig. 6.1: Evolution of the Immigrant Share by Sector

Notes: Figure was created in the program Mathematica. The immigrant share is calculated over individuals aged 18–64, neither living in group quarters, nor in school, and in the labor force. Individuals are considered not to be in the labor force if they report being unemployed at the time of the survey and having worked zero weeks during the previous year.

Source: IPUMS data processed by the authors.

comparable trends. To the extent that the increase in the sectoral share of immigrant workers has not been uniform across geographical labor markets, this pronounced trend represents an opportunity to empirically identify immigration impacts on the employment conditions of native workers while controlling for common national shocks such as recessions or business cycles.

The evolution of annual earnings of native workers at the national level is depicted in Figure 6.2 for the period 1990–2011. The figure shows a clear clustering of earnings across the nine sectors considered. Of the nine sectors we analyze, workers in the computers, engineering, and science sectors are at the top of the income distribution. Their average annual earnings fall between the \$60,000 and \$80,000 range. Workers in the construction, transportation, and manufacturing sectors have annual earnings that cluster around \$40,000. At the bottom of the income distribution are the maintenance, food service, and personal service workers, who have annual earnings that cluster around \$20,000. As depicted in Figure A.1 in Appendix A, trends in estimated weekly earnings tell a very similar story.

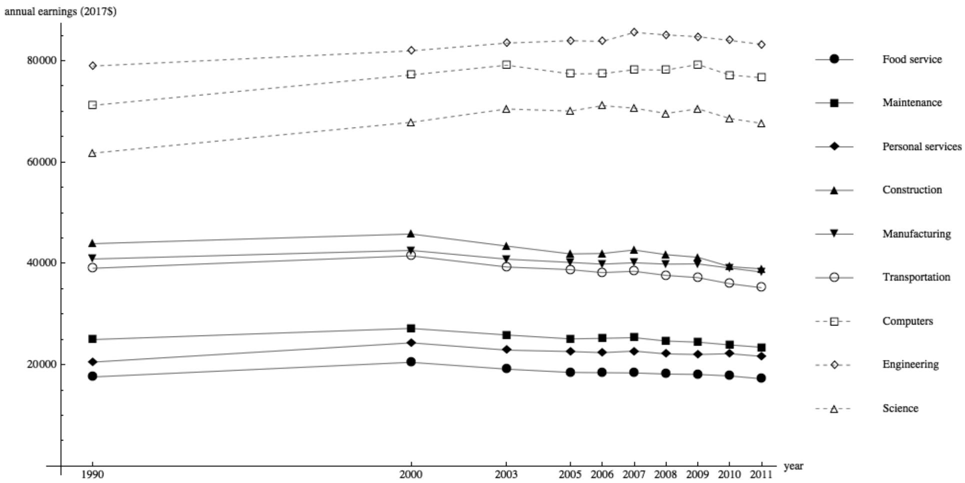

Fig. 6.2: Evolution of Annual Earnings of Natives by Sector, All Occupations

Notes: Figure was created in the program Mathematica. Earnings are calculated over natives aged 18–64, neither living in group quarters, nor in school, in the labor force, and with annual earnings above zero and below \$300,000 (in 2017\$). Individuals are considered not to be in the labor force if they report being out of the labor force at the time of the survey and having worked zero weeks during the previous year. Annual earnings include wage income and income from a person's own business or farm.

Source: IPUMS data processed by the authors.

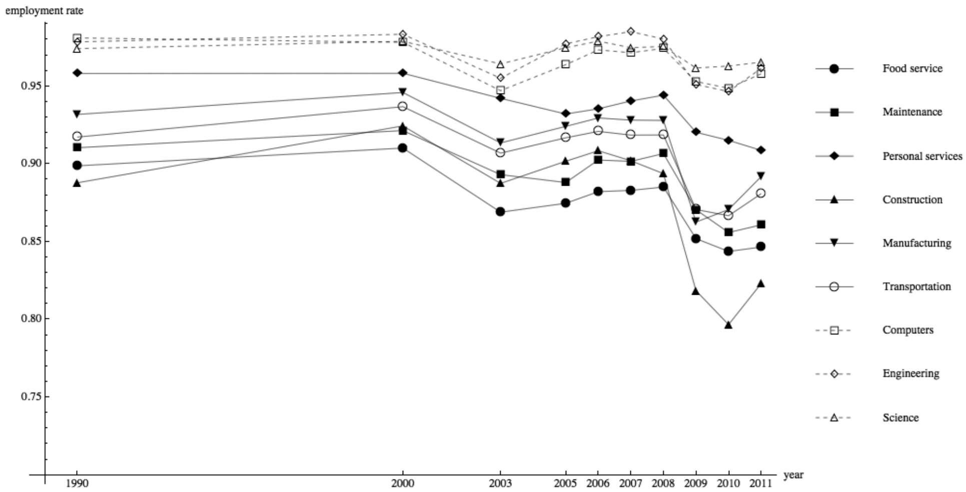

Fig. 6.3: Evolution of the Native Employment Rate by Sector

Notes: Figure was created in the program Mathematica. The employment rate is calculated over natives aged 18–64, neither living in groups, nor in school, and in the labor force at the time of the survey.

Source: IPUMS data processed by the authors.

Figure A.2 depicts annual earnings for native workers in occupations with the highest immigrant shares, by sector. When compared to Figure 6.2, the figure shows that immigrants tend to select into lower-paying occupations within each of the low-skill sectors. The opposite holds for high-skill sectors.

Figure 6.3 depicts the evolution of employment by sector over the period 1990–2011. The figure shows the early effects of the US subprime mortgage crisis on employment in the construction sector, followed by cascading effects on employment in other sectors during the Great Recession.

Note that it is difficult to relate the immigrant share to native earnings or employment by simply looking at national-level aggregates. The immigrant share shows a clear upward trend over the period. Earnings appear relatively stable, while employment seems to be mostly driven by macroeconomic factors. Indeed, Figure 6.4 shows the unemployment rate over time for the entire US economy from the Bureau of Labor Statistics. Consistent with our sectoral data, unemployment increased after 2001, and then again after 2008. Importantly, our empirical strategy nets out any common national effects through year fixed effects and relies on differences across metropolitan statistical areas (MSAs) in the evolution of the immigrant share about the MSA average.

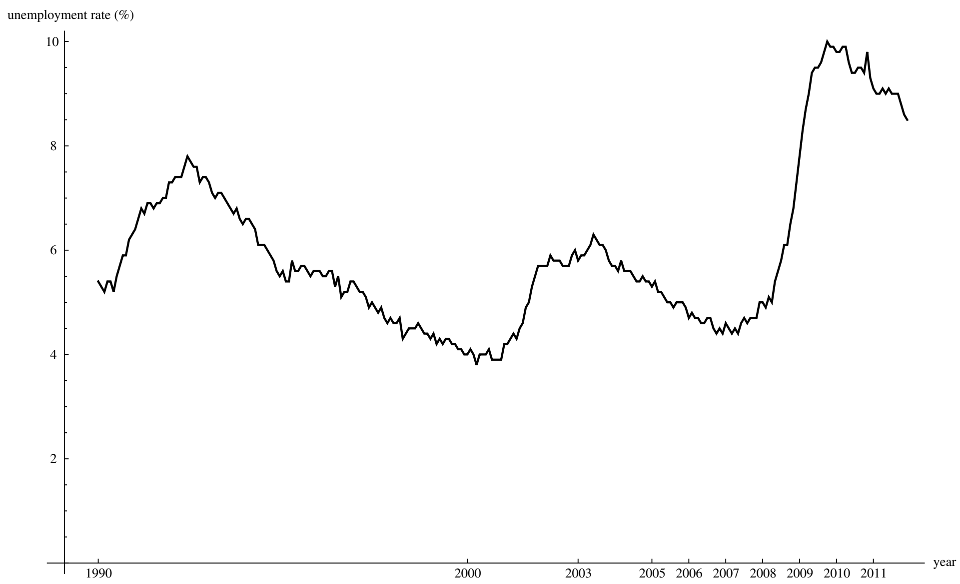

Fig. 6.4: Evolution of the National Unemployment Rate

Note: Figure was created in the program Mathematica.

Source: Bureau of Labor Statistics, seasonally adjusted monthly unemployment rate for individuals 16 years and older.

6.3 Data

The data used for this analysis were obtained from the Integrated Public Use Microdata Series (IPUMS) provided by the University of Minnesota (Ruggles *et al.*, 2017). These data include US Census data from the 1990 5% State sample and 2000 5% sample as well as American Community Survey (ACS) data between the years 2001 and 2011. Due to a missing geographic variable ("metarea") used to assign a location to workers, the years 2001, 2002, and 2004 are excluded from our dataset and our analysis does not extend beyond 2011. Our analysis is conducted separately for several sectors of the economy as identified by the Census Bureau's 2010 classification using the variable "occ2010." This variable provides a "consistent, long-term classification of occupations" (Ruggles *et al.*, 2017), which identifies sectors of the labor market as well as individual occupations within each sector.

Our analysis is conducted on the following sectors of the US economy: Food Preparation and Serving ("food service"), Building and Grounds

Cleaning and Maintenance ("maintenance"), Personal Care and Service ("personal services"), Construction, Production ("manufacturing"), Transportation and Material Moving ("transportation"), Computers and Mathematics ("computers"), Life, Physical, and Social Science ("science"), and Architecture and Engineering ("engineering"). These sectors are selected because, excluding agriculture, they have the highest immigrant worker penetration across all the economic sectors in the US (see Figure 6.1).

To reduce attenuation bias caused by measurement error, our analysis is conducted on the largest 150 MSAs in terms of population. Smaller MSAs are likely to include only a few surveyed individuals from a given sector in a given year, which can lead to noisy measures of our regressor of interest (the sectoral share of immigrants working in each MSA).

The dataset we use is a repeated cross-section of individual-level data that includes the annual earnings of the individual during the preceding year, the number of weeks worked in the preceding year, the employment status (employed/unemployed/out of the labor force), the MSA where the individual lives (taken to be the relevant labor market), their birthplace, as well as information about educational attainment, race, gender, and marital status. This last set of variables is used to construct "residualized" dependent variables that are purged of potentially confounding demographic factors (see Section 6.4.1). The birthplace variable is used to select natives and to construct the sectoral and multi-sectoral immigrant shares. Between 2008 and 2011, the variable identifying the number of weeks worked ("wkswork2") is only available as a categorical variable that assigns individuals to time intervals (e.g., 50–52 weeks). We transform this variable into a continuous one by assigning the midpoint of the relevant interval as the number of weeks worked.

The income amounts reported in the surveys are nominal values. We convert these values to constant 2017 dollars using the CPI provided by the Bureau of Labor Statistics for all items (US city average, all urban consumers) at https://www.bls.gov/data. The income values for the 1990 and 2000 Census years represent income from the previous calendar year, and the ACS data between 2001 and 2011 report income from the previous 12 months. We adjust the 1990 (resp., 2000) income values using the corresponding 1989 (resp., 1999) CPI values, but we use the CPI values corresponding to the sample years for the ACS samples.[9] We define an individual's

[9]Because the ACS is administered throughout the year, income amounts reported by individuals surveyed in January will represent mostly income generated in the previous calendar year, and they

annual earnings as the sum of their wage income and the income from their own business or farm.[10] We compute weekly earnings by dividing annual earnings by the number of weeks worked.

To avoid outliers, when generating regional averages of the earnings variable we exclude workers reporting annual earnings of \$300,000 or more. Since our dependent variable is the logarithm of earnings, we also exclude individuals reporting zero earnings and those for which the reported value is \$1 (a code for "breaking even"). When generating the weekly earnings variable, we exclude workers making at least \$300,000/52 = \$5,769.23 per week and those making \$50 per week or less.

To make sure that we capture the effect of immigration on individuals who are actually in the workforce, we follow the literature by including only working-age adults (18–64 years of age) who are not in school and do not live in group quarters (e.g., jails or other institutions). Because we perform our analysis at the MSA-year level, our analysis only considers individuals that are identified in the data as living in a specific MSA.[11] In addition, we exclude individuals whose birthplace is not identified and those who report both being out of the labor force at the time of the survey and having worked zero weeks during the previous year.

The individual-level data samples used in our analysis are "weighted," and as such IPUMS recommends using weighted averages to construct variables that are representative at the regional level. We follow this recommendation by applying the personal weights (variable "perwt") provided in the data sample to generate our immigrant share regressors and instruments. The resulting MSA-panel datasets in each sector are unbalanced as some MSAs are not represented in the year 2003.[12]

Table 6.2 summarizes our data. Note that the mean and standard deviations are calculated across MSAs and years. Since MSAs have different population sizes, the mean values are representative of an average MSA included in our analysis rather than national averages.

will represent income generated mostly during the current year for those surveyed in December. Although the Census Bureau provides a variable that attempts to adjust for this, the adjustments are imperfect, and Ruggles *et al.* (2017) find that the adjusted and unadjusted income values are essentially perfectly correlated. As a result, Ruggles *et al.* (2017) do not recommend using the adjustment variable, hence we refrain from using it.

[10] That is, we use the variable "incearn" provided in the IPUMS dataset.

[11] That is, we ignore individuals for which the MSA identifier is missing in the data.

[12] Our results are robust to removing the year 2003 from the sample.

Table 6.2: Summary Statistics

			All occ.		Exposed occ.	
Sector	Variable	Unit	Mean	S.D.	Mean	S.D.
Personal services	Annual earnings (natives)	2017$	21,433	4,666	16,756	4,927
	Weekly earnings (natives)	2017$	511	96	430	105
	Employment rate (natives)		0.934	0.048	0.919	0.073
	Share of immigrant workers		0.157	0.142	0.190	0.173
	Share of immigrant workers in all other sectors		0.137	0.113		
Food service	Annual earnings (natives)	2017$	17,909	3,843	16,763	3,866
	Weekly earnings (natives)	2017$	444	82	424	86
	Employment rate (natives)		0.877	0.055	0.871	0.064
	Share of immigrant workers		0.218	0.172	0.243	0.188
	Share of immigrant workers in all other sectors		0.134	0.112		
Construction	Annual earnings (natives)	2017$	40,261	7,504	32,412	7,189
	Weekly earnings (natives)	2017$	944	158	811	155
	Employment rate (natives)		0.871	0.069	0.839	0.087
	Share of immigrant workers		0.194	0.176	0.246	0.211
	Share of immigrant workers in all other sectors		0.134	0.111		
Maintenance	Annual earnings (natives)	2017$	24,136	4,840	22,003	4,622
	Weekly earnings (natives)	2017$	581	101	543	98
	Employment rate (natives)		0.891	0.057	0.884	0.061
	Share of immigrant workers		0.262	0.222	0.273	0.230
	Share of immigrant workers in all other sectors		0.132	0.109		
Transportation	Annual earnings (natives)	2017$	36,474	4,972	33,297	4,758
	Weekly earnings (natives)	2017$	825	103	764	98
	Employment rate (natives)		0.904	0.047	0.892	0.053
	Share of immigrant workers		0.152	0.149	0.165	0.161
	Share of immigrant workers in all other sectors		0.137	0.112		

Manufacturing	Annual earnings (natives)	2017$	40,050	6,735	33,370	6,053
	Weekly earnings (natives)	2017$	884	136	764	127
	Employment rate (natives)		0.912	0.048	0.894	0.062
	Share of immigrant workers		0.217	0.180	0.264	0.209
	Share of immigrant workers in all other sectors		0.132	0.111		
Computers	Annual earnings (natives)	2017$	70,659	11,937	73,577	13,439
	Weekly earnings (natives)	2017$	1,450	237	1,508	267
	Employment rate (natives)		0.966	0.043	0.968	0.045
	Share of immigrant workers		0.148	0.116	0.166	0.129
	Share of immigrant workers in all other sectors		0.137	0.114		
Engineering	Annual earnings (natives)	2017$	79,959	11,846	85,681	13,884
	Weekly earnings (natives)	2017$	1,630	235	1,736	278
	Employment rate (natives)		0.970	0.042	0.976	0.049
	Share of immigrant workers		0.144	0.119	0.155	0.144
	Share of immigrant workers in all other sectors		0.137	0.114		
Science	Annual earnings (natives)	2017$	65,118	14,197	67,607	18,958
	Weekly earnings (natives)	2017$	1,343	272	1,389	370
	Employment rate (natives)		0.972	0.052	0.970	0.076
	Share of immigrant workers		0.149	0.123	0.201	0.175
	Share of immigrant workers in all other sectors		0.138	0.114		

Notes: These figures are based on the 150 most populous MSAs and are representative of an average MSA in our sample during the period 1990–2011. Figures will differ from national averages due to differences in MSA populations. The statistics for the Personal Services, Food Service, Construction, Maintenance, Transportation, and Manufacturing sectors are calculated with 1,387 observations. The number of observations used to generate the statistics in the Computers, Engineering, and Science sectors varies between 1,363 and 1,386 depending on the variable and sector. To define immigrant-exposed occupations ("Exposed occ."), we select occupations with the highest immigrant shares within a sector, until the total number of native workers in those occupations exceeds 50% of the total native workforce in the sector.

6.4 Methodology

The main difficulty in measuring the effect of immigration on the labor market outcomes of native-born workers in a sector $s = 1, \ldots, S$ of the economy is that increases in immigration in sector s are likely correlated with unobserved demand-pull factors in that sector that also affect natives' earnings and employment. We use the imperfect instrumental variable approach described in what follows to partially identify the effect of immigration on the labor market outcomes of native-born workers by economic sector.

6.4.1 *Model specification and instrument choice*

We estimate a sectoral regression of the form

$$y_{it}^{s} = \beta p_{it}^{s} + \alpha_i + \phi_t + \epsilon_{it}^{s}, \tag{6.1}$$

where i denotes a metropolitan statistical area, t denotes a year, α_i and ϕ_t are fixed effects, p_{it}^{s} is the immigrant share in sector s, and y_{it}^{s} is the outcome of interest.

Our outcome variables include the natural logarithm of the annual or weekly earnings of native-born workers, the proportion of native-born workers working full time, and the proportion of natives in the labor force who are employed — our measure of the native sectoral employment rate.[13] To identify the effect of immigration on the distribution of native workers across occupational levels, we use several definitions of "full-time" workers: workers who worked 48 weeks or more, 40 weeks or more, 27 weeks or more, 14 weeks or more, and 1 week or more.[14]

To address MSA-specific changes in the composition of the native sectoral workforce over time, for each choice of dependent variable (say the logarithm of annual earnings) we first regress individual-level observations around a set of observable individual characteristics related to gender, marital status, race, education, and work experience as well as a full set of MSA-year fixed

[13] The sectoral employment rates are estimated with samples of natives who are in the labor force (i.e., employed in the previous week or having been looking for a job during the previous four weeks).

[14] These cutoffs are chosen to match the categories defined by the variable "wkswork2," which identifies a range of weeks worked for each individual (instead of the actual number of weeks worked) in the IPUMS data starting in 2008.

effects. The estimated MSA-year fixed effects are then used as the dependent variable in the IIV regression on immigrant shares (see Appendix C).[15]

Our main regressor is a measure of immigration defined as the fraction of foreign-born workers in sector s relative to the total workforce in that sector in each MSA and year, p_{it}^{s}. Apart from the fact that we focus on one sector at a time and do not differentiate by skill, this is the same regressor as that used by Altonji and Card (1991), Borjas (2003, 2014), or Llull (2017), and it is directly related to the one used in Dustmann *et al.* (2005) (the ratio of immigrant to native workers) or Bratsberg and Raaum (2012) (a transformation thereof).

In a recent review of George Borjas's *Immigration Economics*, Card and Peri (2016) criticize the use of the immigrant share regressor on the grounds that due to possible *native* inflows correlated with demand pulls that affect native wages, the regressor might be negatively correlated with the error term, resulting in *negative* bias on the correlation of interest. If both immigrants *and* natives are attracted to areas with positive demand pulls, whether the immigrant share is positively or negatively correlated with the error term ultimately depends on whether natives or immigrants are more responsive to these pulls. It seems reasonable to believe that the immigrant population would respond more promptly to local demand shocks than natives, so that the net bias, in fact, remains positive. A basic reason why the immigrant population would be more responsive is that in any given period, part of this population is migrating from abroad (current inflow), i.e., it is already mobile (Borjas, 2001). In addition, Card's (2001) results suggest little migratory response of natives to immigration shocks, while Cadena and Kovak (2016) show that low-skilled Mexican-born immigrants respond much more strongly to local labor demand shocks than natives, even after arrival. Card and Peri's (2016) preferred regressor, used in a regression where the dependent variable is the growth in wages rather than the current wage, is defined as the ratio of the *current inflow* of immigrants to the *previous workforce* (including natives and previously arrived immigrants). Our specification reflects the idea that it is the stock of foreign-born workers, rather than the current inflow, that may affect native wages.[16]

[15] This technique mirrors that used by Reed and Danziger (2007) in a cross-sectional context. We get very similar results if instead we average the dependent variable over observations in each MSA-year cell using the personal weights provided in IPUMS.

[16] Card and Peri (2016) also argue that their regressor better captures Borjas's "relevant wage elasticity", defined as the derivative of the log wage of a given skill group with respect to the "immigration-induced percent increase in the labor supply of (the) group". Borjas defines the

Our instruments are variables that measure the proportion of immigrants across many sectors of the economy, including (resp., excluding) sector s itself (p_{it}^{S}, resp., p_{it}^{S-s}). The instrument p_{it}^{S} is calculated across all economic sectors and corresponds to the regressor used in a spatial correlation approach that considers all sectors of the economy rather than one in isolation. The instrument p_{it}^{S-s} removes the contribution of sector s itself to the immigrant share and is our preferred instrument. We also use two alternative instruments in our analysis for comparison. The first one, denoted p_{it}^{10}, is a variant of the instrument p_{it}^{S} constructed using the 10 economic sectors with the highest proportions of immigrants. The second one, denoted $p_{it}^{S-s\,\mathrm{Pop}}$, is a variant of the instrument p_{it}^{S-s} that uses the share of immigrants in the entire sectoral population, which includes individuals who are not part of the active workforce at the time of the survey but identify as belonging to the sector.

Although p_{it}^{S} and p_{it}^{S-s} are likely correlated with unobservable labor demand shocks in sector s, perhaps due to macroeconomic shocks that affect all sectors,[17] they are plausibly less correlated with the sectoral error term than the sectoral regressor p_{it}^{s}, making them good candidates for an imperfect instrument. Still, the ability of imperfect instruments constructed using information from other economic sectors to improve on OLS estimates of the immigrant share–outcome relationship partially hinges on whether labor demand shocks about MSA (α_i) and year (ϕ_t) effects are sufficiently heterogeneous across sectors. That is, if labor demand shocks were perfectly correlated across sectors, there would be no reason to expect much bias reduction from the use of the imperfect instrument. Fortunately, this seems not to be the case in our data. For instance, a regression of the log annual earnings of natives at the MSA by year by sector level (using the six low-skill economic sectors that are the main focus of this study) on a set of sector and MSA-by-year fixed effects has an R-squared of 0.73, meaning that a

immigration-induced percent increase in the labor supply as the ratio of *current foreign-born workers* to *current US-born workers*. With this definition, the relevant wage elasticity can be directly deduced from the estimate of the coefficient on the immigrant share (Borjas, 2003), whereas it cannot be deduced from Card and Peri's (2016) regression (unless there are only two periods, no immigrants in the first period, and no change in the native workforce between periods, see Appendix D). An important difference between the two specifications is that Borjas's specification considers that immigrants affect native outcomes in levels irrespective of the timing of their arrival, whereas Card and Peri's (2016) specification identifies effects from changes in outcomes using the most recent inflow, measured relative to the previous workforce irrespective of its immigrant–native composition. The fact that we exploit year-to-year variation to identify short-run effects, coupled with the fact that our panel is missing some years, makes the latter approach less justifiable in our context.

[17] Another reason why p_{it}^{S} may be correlated with sectoral demand pulls is that sector s itself is included in the calculation of the immigrant share.

significant amount of variation remains in the outcome after netting out common shocks.

In addition to the fact that common macroeconomic shocks may result in a correlation between the overall immigrant share (say p_{it}^S) and sectoral labor demand shocks (ϵ_{it}^s), overall immigration may have a direct effect on native labor demand in a given sector. In particular, one may worry that although sectoral immigration may hurt natives in that sector because native and immigrant labor are substitutable, immigration as a whole may affect the economy in ways that improve natives' employment conditions.[18] In that case, our instrument would be an omitted variable of the following underlying immigration–native outcome relationship:

$$y_{it}^s = b_1 p_{it}^s + b_2 p_{it}^S + a_i + f_t + e_{it}^s.$$

While our framework does not allow identification of a causal relationship between *overall* immigration and *sectoral* outcomes, it can speak to the sign of the bias that would be caused on the estimate of the sectoral effect b_1. Denoting by $\tilde{p}_{it}^s$ the residuals of a regression of p_{it}^s on location and time fixed effects, our IIV estimate of b_1 has a probability limit equal to

$$\beta_{p^S}^{\mathrm{IV}} = b_1 + b_2 \frac{\mathrm{var}(p^S)}{\mathrm{cov}(\tilde{p}^s, p^S)} + \frac{\mathrm{cov}(p^S, e^s)}{\mathrm{cov}(\tilde{p}^s, p^S)}.$$

It is natural to assume that $\mathrm{cov}(\tilde{p}^s, p^S) > 0$. It is then clear that if overall immigration improves sectoral native labor outcomes ($b_2 > 0$), then our estimate of b_1 will be biased upwards. That is, our IIV strategy provides a conservative estimate of the sectoral impact of sectoral immigration.

We provide results for all IPUMS occupations within each sector, as well as results pertaining to what we call "immigrant-exposed occupations" within a sector. To define immigrant-exposed occupations, we select occupations with the highest immigrant shares within a sector, until the total number of native workers in those occupations exceeds 50% of the total native workforce in the sector. Notably, we do not redefine our regressor of interest (or the imperfect instruments) when focussing on immigrant-exposed occupations, that is, we look at the effect of the overall sectoral immigrant share on outcomes for workers in occupations with the highest immigrant penetration.

[18] This situation can be thought of as a variant of Ottaviano and Peri's (2012) argument that immigration-induced shocks to a skill group have effects on wages in other skill groups.

6.4.2 *The IIV strategy*

We use the results contained in Proposition 2 of Nevo and Rosen (2012). This proposition provides us with a one-sided bound given by the IIV estimate.

For the purpose of this section, let us adopt the same notation as Nevo and Rosen (2012). We write the DGP underlying model (6.1) as

$$Y = X\beta + \mathbf{W}\boldsymbol{\delta} + U, \tag{6.2}$$

where Y is the dependent variable, X is the sectoral immigrant share, $\mathbf{W}$ is a row vector of covariates comprising dummy variables for each MSA and dummy variables for each year, and U is the error term, which satisfies $\mathbb{E}[\mathbf{W}'U] = 0$. We denote by Z (or Z_1, when necessary to avoid confusion) our preferred instrument, p_{it}^{S-s}. We denote by Z_2 an alternative instrument, for instance, the instrument constructed as the share of immigrant workers in sectors with the 10 highest shares of immigrant workers. For two random variables, say X and Y, σ_{xy} denotes the covariance between X and Y. We use σ_x to denote the standard deviation of X. We denote the correlation between X and Y as ρ_{xy}. We further denote by β^{OLS} (resp., β_z^{IV}) the probability limits of the OLS estimator (resp., the IV estimator using instrument Z) of parameter β in Equation (6.2).

We denote by $\tilde{X}$ (resp., $\tilde{Y}$) the errors from the OLS regression of X (resp., Y) on $\mathbf{W}$, that is,

$$\begin{cases} \tilde{X} = X - \mathbf{W}\mathbb{E}[\mathbf{W}'\mathbf{W}]^{-1}\mathbb{E}[\mathbf{W}'X] \\ \tilde{Y} = Y - \mathbf{W}\mathbb{E}[\mathbf{W}'\mathbf{W}]^{-1}\mathbb{E}[\mathbf{W}'Y]. \end{cases} \tag{6.3}$$

$\tilde{X}$ (resp., $\tilde{Y}$) represents the error term from a regression of the regressor (resp., outcome variable) on the MSA and year fixed effects. Nevo and Rosen (2012) show that $\tilde{Y} = \tilde{X}\beta + U$. Using the Frisch–Waugh–Lovell theorem (Frisch and Waugh, 1933; Lovell, 1963) and its extension to IV estimation (Giles, 1984), it is straightforward to show that

$$\begin{cases} \beta^{\text{OLS}} = \beta + \dfrac{\sigma_{\tilde{x}u}}{\sigma_{\tilde{x}}^2} \\ \beta_z^{\text{IV}} = \beta + \dfrac{\sigma_{zu}}{\sigma_{\tilde{x}z}}. \end{cases} \tag{6.4}$$

To fix ideas, consider the case where the dependent variable represents the annual earnings of natives, which implies that $\sigma_{\tilde{x}u} = \sigma_{xu} > 0$ since unobserved demand pulls would tend to increase native earnings and the immigrant share. Given Equation (6.4), we would expect the OLS estimate to be asymptotically biased upwards. That is, $\beta \leq \beta^{\text{OLS}}$. We now make the following two-part assumption, referred to as Assumptions 3 and 4 in Nevo and Rosen (2012):

Assumption 1 $0 \leq \rho_{zu} \leq \rho_{xu}$.

Assumption 1 implies that the direction of correlation with the error term in (6.2) is the same for the regressor and the instrument, but the "intensity" of the correlation is lessened when using the instrument. In that sense, the instrument is "less endogenous" than the regressor. It is also natural in our setting (and we systematically test this condition) to expect that $\sigma_{\tilde{x}z} = \sigma_{\tilde{x}\tilde{z}} > 0$, that is, the shocks in the immigrant share about city and year means are positively correlated across a given sector and the rest of the economy.[19] Because $\sigma_{zu} \geq 0$ from Assumption 1, Equation (6.4) implies that the IV estimate is also asymptotically biased, in the same direction as the OLS estimate, that is, $\beta \leq \beta_z^{\text{IV}}$. In addition, $\beta_z^{\text{IV}} < \beta^{\text{OLS}} \Leftrightarrow \sigma_{zu}\sigma_{\tilde{x}}^2 - \sigma_{\tilde{x}u}\sigma_{\tilde{x}z} < 0 \Leftrightarrow \rho_{zu} < \rho_{\tilde{x}u}\rho_{\tilde{x}z} = \rho_{xu}\rho_{\tilde{x}z}$. Importantly, the fact that the instrument be less endogenous than the regressor in the sense of Assumption 1 is necessary, but not sufficient, for the IV estimate to improve on the OLS estimate. In particular, if the correlation between the residualized sectoral immigrant share and its economy-wide counterpart is positive but weak, it could be the case that $\beta^{\text{OLS}} < \beta_z^{\text{IV}}$ even if Assumption 1 holds.

Nevo and Rosen's (2012) analysis suggests that under our Assumption 1, the verified assumption that $\sigma_{\tilde{x}z} > 0$, and the additional assumption that $\sigma_{\tilde{x}x}\sigma_z - \sigma_x\sigma_{\tilde{x}z} > 0$ (which is also satisfied in our setting), one may be able to improve on the upper bound β_z^{IV} by using a combined instrument defined as $V(1) = \sigma_x Z - \sigma_z X$.[20] The probability limit of the corresponding IV estimator can be derived as

$$\beta_{V(1)}^{\text{IV}} = \beta + \frac{\sigma_x\sigma_{zu} - \sigma_z\sigma_{xu}}{\sigma_x\sigma_{\tilde{x}z} - \sigma_z\sigma_{\tilde{x}x}}. \tag{6.5}$$

Under the above assumptions, it turns out that $\beta_{V(1)}^{\text{IV}} < \beta_z^{\text{IV}} \Leftrightarrow \beta^{\text{OLS}} < \beta_z^{\text{IV}} \Leftrightarrow \beta_{V(1)}^{\text{IV}} < \beta^{\text{OLS}}$. Therefore, the use of $V(1)$ as an instrument does not improve on either β_z^{IV} or even β^{OLS} when $\beta_z^{\text{IV}} < \beta^{\text{OLS}}$. In cases where $\beta^{\text{OLS}} < \beta_z^{\text{IV}}$, however, $\beta_{V(1)}^{\text{IV}}$ improves on β^{OLS}.

Finally, Nevo and Rosen's (2012) analysis suggests a way to derive a lower bound for our effect of the immigrant share on annual income. The idea, developed in Proposition 5 and Lemma 2 of their paper, is that if the

[19] $\tilde{Z}$ denotes the error from the regression of Z on $\mathbf{W}$.

[20] This instrument $V(1)$ is a limit value of the set of instruments $V(\lambda) = \sigma_x Z - \lambda\sigma_z X$. The authors show that for $\lambda = \lambda^* = \frac{\rho_{zu}}{\rho_{xu}}$, a value unknown to the analyst, the instrument $V(\lambda)$ is valid. Assumption 1 essentially implies that $\lambda^* \in [0, 1]$, which is used to derive bounds on β.

analyst has not only one, but two IIVs, say Z_1 and Z_2, he or she may be able to construct a weighted difference, say $\omega(\gamma) = \gamma Z_2 - (1-\gamma)Z_1$, with $\gamma \in (0,1)$, that satisfies $\sigma_{\omega(\gamma)u} \geq 0$ and $\sigma_{\tilde{x}\omega(\gamma)} < 0$. That is, by differencing the two IIVs, one may be able to obtain a new IIV that is still positively correlated with the error term, but is now negatively correlated with the regressor. The probability limit of the corresponding IV estimator is

$$\beta^{\mathrm{IV}}_{\omega(\gamma)} = \beta + \frac{\sigma_{\omega(\gamma)u}}{\sigma_{\tilde{x}\omega(\gamma)}}, \tag{6.6}$$

implying that $\beta^{\mathrm{IV}}_{\omega(\gamma)}$ constitutes a lower bound for β. Nevo and Rosen (2012) even provide a testable sufficient condition for $\omega(\gamma)$ to meet these requirements for some unknown value $\gamma^* \in (0,1)$, namely that $\sigma_{\tilde{y}z_1}\sigma_{\tilde{x}z_2} - \sigma_{\tilde{y}z_2}\sigma_{\tilde{x}z_1} < 0$. Even if this condition, which guarantees the existence of a value γ^* from which a lower bound can be derived, is satisfied in our analysis, we have no guidance as to what this value of γ^* should be. In fact, without an additional assumption on γ^* (besides $\sigma_{\tilde{x}\omega(\gamma)} < 0$, which, given $\sigma_{\tilde{x}z_j} > 0$, is equivalent to $\gamma < \bar{\gamma} \equiv \frac{\sigma_{\tilde{x}z_1}}{\sigma_{\tilde{x}z_1}+\sigma_{\tilde{x}z_2}}$), one can only deduce that $-\infty = \beta^{\mathrm{IV}}_{\omega(\bar{\gamma})} < \beta$, that is, the lower bound is uninformative. In what follows, we therefore only report the values of β^{OLS} and the upper bound $\beta^{\mathrm{IIV}} = \min(\beta^{\mathrm{IV}}_z, \beta^{\mathrm{IV}}_{V(1)})$. In the vast majority of regressions we report, the IV estimate does improve on the OLS estimate and therefore the estimate we usually report is $\beta^{\mathrm{IIV}} = \beta^{\mathrm{IV}}_z$.

6.5 Results

We begin by presenting results pertaining to the short-run impact of immigration on the earnings of natives, organized by sector of the economy. We report earnings results for the manufacturing sector and the three higher-skill sectors in Appendix E, as none of them are statistically significant. We then report short-run effects of immigration on natives' employment rates across all six low-skill sectors. Employment effects for the three higher-skill sectors are generally negative, but never significant. They are reported in Appendix F. To address the possibility that the negative effects we uncover in low-skill sectors may be driven by compositional effects (i.e., more productive workers leaving a sector in response to the immigration shock), we then report results for a composite sector defined as the aggregate of these sectors. All of the first-stage coefficients on our preferred instrument have the correct sign (that is, $\sigma_{\tilde{x}z} > 0$), and all of the partial first-stage F-statistics, which are not reported, are larger than 70.

6.5.1 *Earnings effects*

6.5.1.1 *Personal services, food service, and construction*

We first report results for the effect of the immigrant share on the annual earnings of native-born workers. We provide results for all occupations within a sector, as well as results pertaining to immigrant-exposed occupations.

Table 6.3 shows that the annual earnings of native workers in the personal services, food service, and construction sectors are negatively affected by the sectoral share of immigrants. Although the OLS estimate is never statistically significant, the IIV estimates often are, and they are much larger in magnitude.

Importantly, the move from the IIV constructed from the share of immigrants in immigration-exposed sectors ("IIV-10") to that constructed from

Table 6.3: Effect of Immigration on the Annual Earnings of Native-Born Workers

		(1) OLS	(2) IIV-10	(3) IIV-All	(4) IIV-All but	(5) IIV-All but Pop
Personal services	All occ.	−0.011	−0.114	−0.499**	−0.658**	−0.591*
		(0.127)	(0.254)	(0.234)	(0.287)	(0.340)
	Exposed occ.	−0.105	−0.597*	−0.955***	−1.233***	−1.231***
		(0.177)	(0.358)	(0.307)	(0.375)	(0.425)
Food service	All occ.	0.056	−0.280**	−0.386***	−0.598***	−0.510***
		(0.066)	(0.136)	(0.131)	(0.202)	(0.196)
	Exposed occ.	0.122	−0.249*	−0.347**	−0.585***	−0.401**
		(0.093)	(0.129)	(0.139)	(0.218)	(0.199)
Construction	All occ.	0.019	−0.029	−0.158	−0.293*	−0.294*
		(0.068)	(0.098)	(0.116)	(0.160)	(0.157)
	Exposed occ.	−0.162**	−0.308***	−0.487***	−0.689***	−0.699***
		(0.082)	(0.116)	(0.135)	(0.194)	(0.200)
N		1,387	1,387	1,387	1,387	1,387

Notes: All regressions include MSA and year fixed effects. Standard errors are clustered at the MSA level. Column (1) reports the OLS estimate of β in Equation (6.1). Column (2) reports the IV estimate obtained by using the immigrant share across the 10 sectors with the highest immigrant share. Column (3) reports the IV estimate obtained by using the immigrant share across all sectors. Column (4) reports the IV estimate obtained by using the immigrant share across all other sectors. Columns (2)–(4) use instruments constructed from individuals who were between the ages of 18–64, neither in school, nor living in group quarters, and who were both employed at the time of the survey and had worked a positive number of weeks during the previous year. Column (5) reports the IV estimate obtained by using the immigrant share of the entire population across all other sectors of the economy. "All occ." refers to the analysis conducted on all occupations within the sector. "Exposed occ." refers to the analysis conducted on the immigrant-exposed occupations within the sector. * (resp., **, resp., ***) denotes statistical significance at the 10% (resp., 5%, resp., 1%) level.

the share of immigrants across all sectors ("IIV-All") and across all other sectors ("IIV-All but") has the expected effect on the point estimate: the effect systematically becomes more negative as the correlation between the IIV and the error term is attenuated. Personal services, food service, and construction all belong to the 10 sectors with the highest immigrant shares and each is therefore included in the calculation of the "IIV-10".[21] The attenuation in the correlation between the error term and the series of imperfect instruments likely comes from the fact that in sectors less prone to immigration, a positive shock in labor demand (which we assume would be positively correlated with a positive shock in the demand for labor in the sector of interest, say construction) may not correlate as much with an increase in the share of immigrant workers as in sectors with larger immigrant shares.[22] In addition, since the correlation of interest is with sectoral demand pulls, the fact that the share of immigrants is calculated across a broader set of industries mechanically "dilutes" the correlation with any sectoral-specific shock in labor demand, and completely eliminates it when the immigrant share is calculated for all other sectors.

As suggested by Equation (6.4), the tightness of the upper bound afforded by the IIV estimate relative to the OLS estimate is also inversely related to the correlation between the sectoral immigrant share and the instrument. Our results suggest that this effect either reinforces, or at least does not supersede, the changing strength of correlation between the error term and the various instruments. In Appendix G, we formally derive a testable condition that can be used to determine the relative endogeneity of the imperfect instruments used in our analysis. We use this test to show that the "IIV-10" instrument (p_{it}^{10}) is, in fact, the most endogenous instrument used in our analysis and that our preferred instrument, the "IIV-All but" variable (p_{it}^{S-s}), is the least endogenous.

As explained in Section 6.4.2, the preferred IIV estimate should be interpreted as an upper bound. That is, the true underlying parameter is likely more negative. Our preferred estimates, given by the "IIV-All but" estimate, imply that a 10% point increase in the share of immigrants is associated with at least a 6.6% (resp., 6.0%; resp., 2.9%) decrease in the annual earnings of native workers in the personal services (resp., food service; resp., construction) sector. Table 6.3 further shows that in the personal service and

[21]The other sectors are the other three low-skill sectors we study, plus agriculture, computers, engineering, and science.

[22]An alternative explanation may be that labor-demand shocks are more correlated among immigration-exposed sectors than between immigration-exposed and immigration-poor sectors.

construction sectors, the effect is almost doubled for workers in occupations where the share of immigrants is higher.

On balance, these upper bounds appear large relative to recent econometric estimates reported in the literature. Estimates obtained from location-year or location-year-skill comparisons of average wages across *all occupations* range from –0.22 (Borjas, 2003) to positive values (Basso and Peri, 2015). Borjas (2014) reports an estimate of –0.21 for the period 1990–2010 (–0.24 for males) using the same data source as ours, an MSA-year-skill regression, and a shift-share instrumental variable approach. Card (2001) reports that city comparisons typically estimate the effect of a 10% point increase in the fraction of immigrants to correlate with a less than 1% decrease in native wages.[23]

There are two essential channels by which the annual earnings of native-born workers may be affected by immigration flows: their wage rate may decrease and/or they may work fewer weeks per year (none in the extreme). The second channel is particularly relevant for the construction sector because construction workers are typically paid per "job". A year's worth of earnings is made up of earnings from a potentially large number of jobs. If workers have difficulty filling in their schedule due to increased competition from cheaper, and perhaps illegal immigrant labor, they may end up with lower annual earnings even if their weekly earnings (annual earnings divided by the number of weeks worked) do not change. A similar remark may hold in certain personal service occupations with high immigrant penetration, like child and personal care, where self-employment is high.

Table 6.4 reports weekly earnings effects. Weekly earnings are constructed by dividing annual earnings by the number of weeks worked. Weekly (or hourly) effects partially mask annual earnings effects insofar as one margin of response to increased immigration may be the reduction in the quantity of labor supplied by natives. Indeed, a general rule here is that point estimates for weekly effects are smaller in magnitude than for annual earnings effects. For instance, we find that a 10% point increase in the share of immigrant workers causes at least a 3.5% (resp., 3.0%) decrease in the weekly earnings of native personal service (resp., food service) workers. Effects are again more pronounced in the immigration-exposed occupations. Weekly earnings

[23]Admittedly, our upper bounds fall short of the larger effect on lower-skilled natives' earnings found in Altonji and Card (1991), a 12% decrease for each 10% point increase in the immigrant share. On balance, they are also less negative than the estimate derived for the decade 1970–1980 by Jaeger *et al.* (2018).

Table 6.4: Effect of Immigration on the Weekly Earnings of Native-Born Workers

		(1) OLS	(2) IIV-10	(3) IIV-All	(4) IIV-All but	(5) IIV-All but Pop
Personal services	All occ.	−0.034	−0.036	−0.275*	−0.353*	−0.277
		(0.067)	(0.076)	(0.149)	(0.186)	(0.209)
	Exposed occ.	−0.069	−0.163	−0.409**	−0.525**	−0.496*
		(0.117)	(0.208)	(0.203)	(0.249)	(0.278)
Food service	All occ.	0.052	−0.162*	−0.190**	−0.296**	−0.137
		(0.048)	(0.083)	(0.085)	(0.129)	(0.130)
	Exposed occ.	0.085	−0.167*	−0.191*	−0.325**	−0.086
		(0.063)	(0.091)	(0.103)	(0.158)	(0.143)
Construction	All occ.	0.026	0.020	0.002	−0.037	−0.053
		(0.045)	(0.061)	(0.074)	(0.100)	(0.096)
	Exposed occ.	−0.080	−0.153**	−0.217**	−0.300**	−0.298***
		(0.059)	(0.075)	(0.090)	(0.125)	(0.115)
N		1,387	1,387	1,387	1,387	1,387

Notes: All regressions include MSA and year fixed effects. Standard errors are clustered at the MSA level. Column (1) reports the OLS estimate of β in Equation (6.1). Column (2) reports the IV estimate obtained by using the immigrant share across the 10 sectors with the highest immigrant shares. Column (3) reports the IV estimate obtained by using the immigrant share across all sectors. Column (4) reports the IV estimate obtained by using the immigrant share across all other sectors. Columns (2)–(4) use instruments constructed from individuals who were between the ages of 18–64, neither in school, nor living in group quarters, and who were both employed at the time of the survey and had worked a positive number of weeks during the previous year. Column (5) reports the IV estimate obtained by using the immigrant share of the entire population across all other sectors of the economy. "All occ." refers to the analysis conducted on all occupations within the sector. "Exposed occ." refers to the analysis conducted on the immigrant-exposed occupations within the sector. * (resp., **, resp., ***) denotes statistical significance at the 10% (resp., 5%, resp., 1%) level.

effects are not statistically significant for the construction sector as a whole, although they are for immigration-exposed occupations, with an estimated effect of at least minus 3.0%.

Looking at impacts on occupational levels confirms a redistribution of natives away from full-time and high-time work toward part-time work. Table 6.5 shows the effects on the share of native construction workers having worked at least a certain number of weeks in the past year. Effects are shown for all construction occupations and for immigrant-exposed construction occupations. Preferred IIV estimates (based on p^{S-s}) are statistically significant, and the pattern of increasingly negative effect as the instrument becomes likely less endogenous is maintained. Overall, the estimates suggest that immigration has a negative effect on the occupational level

Table 6.5: Effect of Immigration on the Distribution of Weeks Worked Among Native-Born Construction Workers

	(1) OLS	(2) IIV-10	(3) IIV-All	(4) IIV-All but	(5) IIV-All but Pop
All occ.					
48 weeks or more	0.021	−0.024	−0.098*	−0.183**	−0.181**
	(0.034)	(0.041)	(0.051)	(0.073)	(0.075)
40 weeks or more	0.034	−0.032	−0.113**	−0.212***	−0.208***
	(0.029)	(0.037)	(0.048)	(0.072)	(0.073)
27 weeks or more	0.025	−0.020	−0.094**	−0.175***	−0.157***
	(0.024)	(0.029)	(0.038)	(0.058)	(0.057)
14 weeks or more	0.005	−0.023	−0.079***	−0.138***	−0.122***
	(0.018)	(0.021)	(0.026)	(0.041)	(0.039)
One week or more	0.010	−0.014	−0.037**	−0.072***	−0.070***
	(0.012)	(0.014)	(0.016)	(0.024)	(0.026)
Exposed occ.					
48 weeks or more	−0.033	−0.121**	−0.211***	−0.328***	−0.323***
	(0.047)	(0.059)	(0.076)	(0.109)	(0.104)
40 weeks or more	−0.034	−0.151***	−0.254***	−0.394***	−0.372***
	(0.038)	(0.051)	(0.069)	(0.102)	(0.099)
27 weeks or more	−0.007	−0.096**	−0.202***	−0.327***	−0.263***
	(0.032)	(0.043)	(0.057)	(0.087)	(0.083)
14 weeks or more	−0.035	−0.085***	−0.147***	−0.224***	−0.213***
	(0.029)	(0.031)	(0.038)	(0.058)	(0.051)
One week or more	0.007	−0.035*	−0.064***	−0.114***	−0.101***
	(0.016)	(0.019)	(0.021)	(0.032)	(0.033)
N	1,387	1,387	1,387	1,387	1,387

Notes: All regressions include MSA and year fixed effects. Standard errors are clustered at the MSA level. Column (1) reports the OLS estimate of β in Equation (6.1). Column (2) reports the IV estimate obtained by using the immigrant share across the 10 sectors with the highest immigrant shares. Column (3) reports the IV estimate obtained by using the immigrant share across all sectors. Column (4) reports the IV estimate obtained by using the immigrant share across all other sectors. Columns (2)–(4) use instruments constructed from individuals who were between the ages of 18–64, neither in school, nor living in group quarters, and who were both employed at the time of the survey and had worked a positive number of weeks during the previous year. Column (5) reports the IV estimate obtained by using the immigrant shares of the entire population across all other sectors of the economy. "All occ." refers to the analysis conducted on all occupations within the sector. "Exposed occ." refers to the analysis conducted on the immigrant-exposed occupations within the sector. * (resp., **, resp., ***) denotes statistical significance at the 10% (resp., 5%, resp., 1%) level.

of native construction workers. For instance, a 10% point increase in the share of immigrants is predicted to result in at least a 2.1% point decrease in the share of native construction workers working at least 40 weeks.

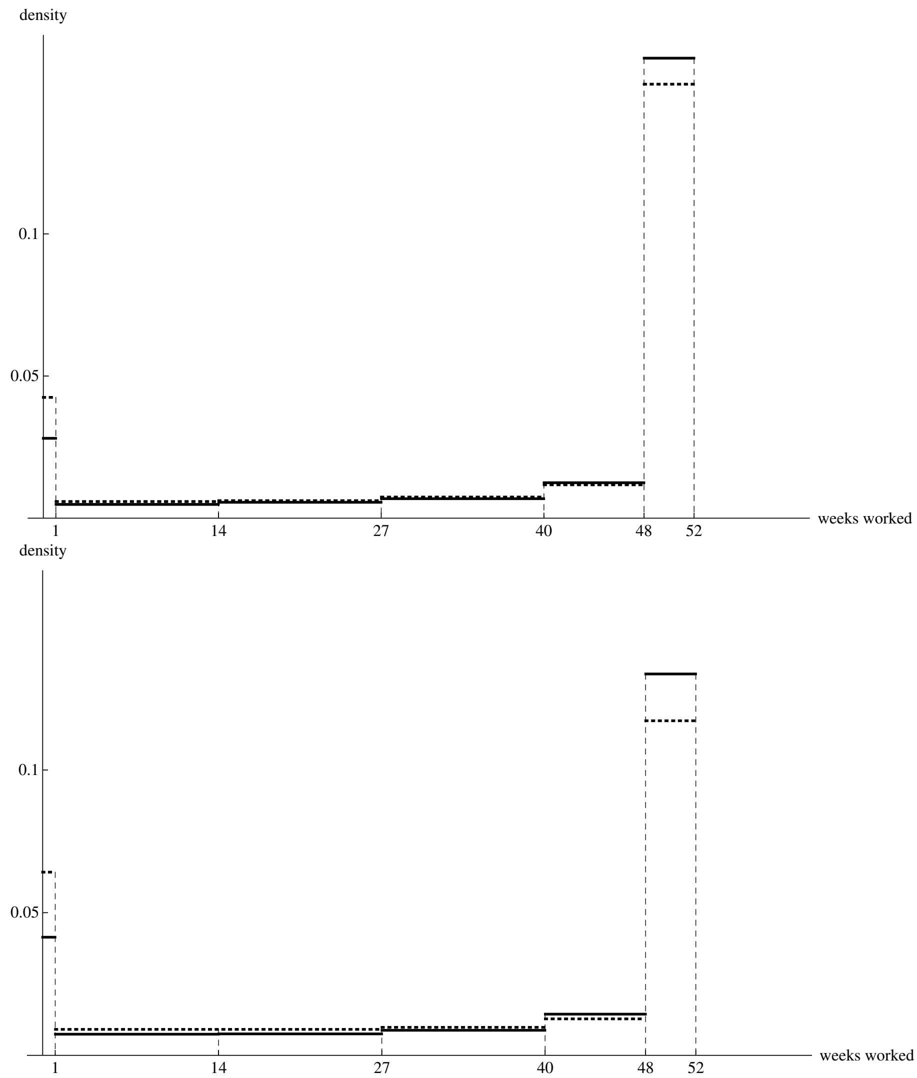

Fig. 6.5: Effect of a 20% Point Increase in the Immigrant Share on Native Workers' Occupational Levels in the Construction Sector (top panel: All Occupations; bottom panel: Immigrant-Exposed Occupations)

Notes: Figure was created in the program Mathematica. The solid (resp., dashed) line represents the distribution of native workers across occupational levels before (resp., after) the increase in immigration.

For exposed construction trades, the effects are more pronounced (3.9% points).

To get a better idea of the effect of immigration on the occupational level of natives, Figure 6.5 uses the estimates reported in Table 6.5 to depict the shift in the distribution of native construction workers across occupation levels, from unemployed to full-time workers, induced by a 20% point increase in the share of immigrant workers in construction.[24] The initial distribution is constructed by using occupational shares averaged across sample years and MSAs.

We also find that occupational levels of native workers are affected negatively by the immigrant share in the food service sector (Table 6.6) and, for exposed occupations, in the personal service sector (Table 6.7), thereby contributing to the negative annual earnings effects reported earlier.

6.5.1.2 *Maintenance and transportation*

The results from the maintenance and transportation sectors are much less clear-cut than those from the sectors analyzed in Section 6.5.1.1, at least when considering all occupations within each sector together. Although we find small negative effects on the employment rate of natives (see Section 6.5.2), we do not find significant effects on annual or weekly earnings. However, once we focus on occupations within these sectors with higher immigrant penetration and/or lower skill requirements, we uncover significant negative effects that were masked when these occupations were grouped with higher-skill occupations. For example, the transportation sector includes aircraft pilots as well as laborers who load freight trucks. One would not expect to find low-skilled immigrants competing with aircraft pilots, so including pilots in the analysis is not very informative.

In the transportation sector, which includes many occupations, we select occupations with a high immigrant share. The occupations selected include taxi drivers, truck drivers, vehicle cleaners, packers, etc. In IPUMS, the maintenance sector as a whole only includes four broad occupations: janitors (and supervisors), landscapers (and supervisors), housekeepers, and pest control workers. Among those, the occupations with highest immigrant penetration are landscapers (34.9%) and housekeepers (44.7%). The next high-immigrant occupation is that of janitorial workers (25.8%). Our data indicate that landscapers and housekeepers also have the lowest average educational attainment in the maintenance sector. We explore immigration impacts for each of the four maintenance occupations, but, perhaps surprisingly, only find significant effects for landscapers. While housekeeping has a high immigrant penetration, housekeepers have by far the lowest annual and weekly earnings of all occupations in the maintenance sector.[25] Therefore, it is plausible that the absence of an effect is due to earnings having reached a floor below

[24] We choose 20% rather than 10% so that the change in the distribution is more legible.

[25] For instance, our data indicate that housekeepers' weekly earnings are about one-third lower than those of landscapers.

Table 6.6: Effect of Immigration on the Distribution of Weeks Worked Among Native-Born Food Service Workers

	(1) OLS	(2) IIV-10	(3) IIV-All	(4) IIV-All but	(5) IIV-All but Pop
All occ.					
48 weeks or more	−0.010	−0.083	−0.109	−0.161	-0.221^{**}
	(0.038)	(0.057)	(0.072)	(0.111)	(0.091)
40 weeks or more	−0.010	-0.134^{**}	-0.164^{**}	-0.239^{**}	-0.241^{***}
	(0.034)	(0.056)	(0.065)	(0.096)	(0.091)
27 weeks or more	−0.015	-0.099^{**}	-0.138^{**}	-0.208^{**}	-0.182^{**}
	(0.027)	(0.048)	(0.061)	(0.096)	(0.087)
14 weeks or more	0.001	−0.002	−0.015	−0.035	−0.047
	(0.018)	(0.035)	(0.040)	(0.055)	(0.057)
One week or more	−0.005	−0.007	−0.007	−0.006	−0.006
	(0.014)	(0.024)	(0.019)	(0.019)	(0.017)
Exposed occ.					
48 weeks or more	0.004	−0.060	−0.091	−0.143	-0.178^{*}
	(0.036)	(0.055)	(0.066)	(0.100)	(0.094)
40 weeks or more	−0.017	-0.131^{***}	-0.159^{***}	-0.230^{***}	-0.199^{**}
	(0.038)	(0.050)	(0.058)	(0.086)	(0.088)
27 weeks or more	−0.012	−0.076	−0.088	−0.139	−0.113
	(0.027)	(0.057)	(0.073)	(0.108)	(0.098)
14 weeks or more	0.017	0.012	0.014	−0.002	−0.022
	(0.024)	(0.045)	(0.058)	(0.081)	(0.082)
One week or more	−0.001	−0.001	−0.004	−0.002	−0.003
	(0.021)	(0.035)	(0.033)	(0.031)	(0.049)
N	1,387	1,387	1,387	1,387	1,387

Notes: All regressions include MSA and year fixed effects. Standard errors are clustered at the MSA level. Column (1) reports the OLS estimate of β in Equation (6.1). Column (2) reports the IV estimate obtained by using the immigrant share across the 10 sectors with the highest immigrant shares. Column (3) reports the IV estimate obtained by using the immigrant share across all sectors. Column (4) reports the IV estimate obtained by using the immigrant share across all other sectors. Columns (2)–(4) use instruments constructed from individuals who were between the ages of 18–64, neither in school, nor living in group quarters, and who were both employed at the time of the survey and had worked a positive number of weeks during the previous year. Column (5) reports the IV estimate obtained by using the immigrant shares of the entire population across all other sectors of the economy. "All occ." refers to the analysis conducted on all occupations within the sector. "Exposed occ." refers to the analysis conducted on the immigrant-exposed occupations within the sector. * (resp., **, resp., ***) denotes statistical significance at the 10% (resp., 5%, resp., 1%) level.

which native workers would stop supplying labor. It is also plausible that as we focus on more narrowly defined occupations, too few individuals are left in the IPUMS dataset to construct the MSA averages of immigrant penetration, causing attenuation bias.

Table 6.7: Effect of Immigration on the Distribution of Weeks Worked Among Native-Born Personal Service Workers

	(1) OLS	(2) IIV-10	(3) IIV-All	(4) IIV-All but	(5) IIV-All but Pop
All occ.					
48 weeks or more	0.006	−0.022	−0.007	−0.008	−0.008
	(0.040)	(0.047)	(0.043)	(0.043)	(0.044)
40 weeks or more	0.012	0.010	−0.001	−0.001	−0.005
	(0.035)	(0.044)	(0.078)	(0.099)	(0.114)
27 weeks or more	0.006	−0.046	−0.065	−0.087	−0.102
	(0.031)	(0.066)	(0.068)	(0.085)	(0.093)
14 weeks or more	0.009	−0.046	−0.072	−0.099	−0.115
	(0.030)	(0.047)	(0.046)	(0.061)	(0.079)
One week or more	−0.007	−0.036	−0.035	−0.044	−0.057
	(0.012)	(0.028)	(0.028)	(0.036)	(0.044)
Exposed occ.					
48 weeks or more	−0.031	−0.101	−0.077	−0.086	−0.176
	(0.063)	(0.155)	(0.167)	(0.210)	(0.225)
40 weeks or more	−0.028	-0.255^{**}	-0.229^{*}	-0.290^{*}	-0.362^{**}
	(0.056)	(0.130)	(0.123)	(0.153)	(0.174)
27 weeks or more	−0.021	-0.298^{**}	-0.294^{**}	-0.382^{***}	-0.461^{***}
	(0.054)	(0.122)	(0.116)	(0.145)	(0.161)
14 weeks or more	0.021	-0.145^{*}	-0.144^{*}	-0.200^{**}	-0.289^{**}
	(0.046)	(0.081)	(0.077)	(0.099)	(0.131)
One week or more	−0.012	-0.086^{*}	-0.089^{*}	-0.115^{*}	-0.193^{**}
	(0.021)	(0.052)	(0.049)	(0.063)	(0.084)
N	1,387	1,387	1,387	1,387	1,387

Notes: All regressions include MSA and year fixed effects. Standard errors are clustered at the MSA level. Column (1) reports the OLS estimate of β in Equation (6.1). Column (2) reports the IV estimate obtained by using the immigrant share across the 10 sectors with the highest immigrant shares. Column (3) reports the IV estimate obtained by using the immigrant share across all sectors. Column (4) reports the IV estimate obtained by using the immigrant share across all other sectors. Columns (2)–(4) use instruments constructed from individuals who were between the ages of 18–64, neither in school, nor living in group quarters, and who were both employed at the time of the survey and had worked a positive number of weeks during the previous year. Column (5) reports the IV estimate obtained by using the immigrant shares of the entire population across all other sectors of the economy. "All occ." refers to the analysis conducted on all occupations within the sector. "Exposed occ." refers to the analysis conducted on the immigrant-exposed occupations within the sector. * (resp., **, resp., ***) denotes statistical significance at the 10% (resp., 5%, resp., 1%) level.

Table 6.8: Landscaping, Housekeeping, and Exposed Transportation Occupations

		(1) OLS	(2) IIV-10	(3) IIV-All	(4) IIV-All but	(5) IIV-All but Pop
Landscaping	Annual earnings	−0.011	−0.544**	−0.586**	−0.750**	−0.673*
		(0.106)	(0.251)	(0.289)	(0.376)	(0.365)
	Weekly earnings	−0.039	−0.208	−0.193	−0.221	−0.140
		(0.064)	(0.143)	(0.156)	(0.214)	(0.174)
	Employment rate	0.036	−0.130**	−0.181***	−0.264***	−0.151**
		(0.027)	(0.057)	(0.054)	(0.079)	(0.069)
	N	1,386	1,386	1,386	1,386	1,386
Housekeeping	Annual earnings	−0.074	−0.177	−0.106	−0.099	−0.099
		(0.157)	(0.182)	(0.166)	(0.166)	(0.166)
	Weekly earnings	0.025	−0.004	0.006	0.013	0.013
		(0.081)	(0.095)	(0.094)	(0.093)	(0.092)
	Employment rate	0.045	−0.080	−0.071	−0.098	−0.088
		(0.028)	(0.070)	(0.073)	(0.090)	(0.081)
	N	1,382	1,382	1,382	1,382	1,382
Exposed transportation	Annual earnings	−0.187*	−0.201	−0.261*	−0.274	−0.212
		(0.098)	(0.145)	(0.142)	(0.167)	(0.165)
	Weekly earnings	−0.060	−0.107	−0.081	−0.084	−0.076
		(0.067)	(0.087)	(0.085)	(0.100)	(0.082)
	Employment rate	−0.053	−0.075*	−0.104***	−0.119***	−0.154***
		(0.032)	(0.038)	(0.036)	(0.044)	(0.044)
	N	1,387	1,387	1,387	1,387	1,387

Notes: All regressions include MSA and year fixed effects. Standard errors are clustered at the MSA level. Column (1) reports the OLS estimate of β in Equation (6.1). Column (2) reports the IV estimate obtained by using the immigrant share across the 10 sectors with the highest immigrant shares. Column (3) reports the IV estimate obtained by using the immigrant share across all sectors. Column (4) reports the IV estimate obtained by using the immigrant share across all other sectors. Columns (2)–(4) use instruments constructed from individuals who were between the ages of 18–64, neither in school, nor living in group quarters, and who were both employed at the time of the survey and had worked a positive number of weeks during the previous year. Column (5) reports the IV estimate obtained by using the immigrant share of the entire population across all other sectors of the economy. "Exposed transportation" refers to the analysis conducted on the immigrant-exposed occupations within the transportation sector. *(resp., **, resp., ***) denotes statistical significance at the 10% (resp., 5%, resp., 1%) level.

Table 6.8 shows selected results for landscaping, housekeeping, and immigrant-exposed transportation activities.[26] We find that a 10% point increase in the share of immigrants causes at least a 7.5% (resp., 2.6%, column (3)) decrease in the annual earnings of landscaping (resp., exposed transportation) workers. This earnings effect appears to be channeled through lower rates of employment in both sectors, as well as a reduced

[26]Results for other maintenance occupations are not statistically significant and are available upon request.

Table 6.9: Effect of Immigration on the Distribution of Weeks Worked in Immigration-Exposed Transportation Occupations

	(1) OLS	(2) IIV-10	(3) IIV-All	(4) IIV-All but	(5) IIV-All but Pop
48 weeks or more	−0.092**	−0.119*	−0.109*	−0.119*	−0.140**
	(0.036)	(0.062)	(0.058)	(0.069)	(0.061)
40 weeks or more	−0.078**	−0.123**	−0.112**	−0.122*	−0.151***
	(0.032)	(0.056)	(0.052)	(0.063)	(0.057)
27 weeks or more	−0.072**	−0.086*	−0.073*	−0.075*	−0.102**
	(0.032)	(0.049)	(0.043)	(0.043)	(0.051)
14 weeks or more	−0.060**	−0.063	−0.063	−0.060	−0.060*
	(0.028)	(0.039)	(0.043)	(0.051)	(0.031)
One week or more	−0.006	−0.010	−0.021	−0.025	−0.038
	(0.018)	(0.023)	(0.021)	(0.026)	(0.029)
N	1,387	1,387	1,387	1,387	1,387

Notes: All regressions include MSA and year fixed effects. Standard errors are clustered at the MSA level. Column (1) reports the OLS estimate of β in Equation (6.1). Column (2) reports the IV estimate obtained by using the immigrant share across the 10 sectors with the highest immigrant shares. Column (3) reports the IV estimate obtained by using the immigrant share across all sectors. Column (4) reports the IV estimate obtained by using the immigrant share across all other sectors. Columns (2)–(4) use instruments constructed from individuals who were between the ages of 18–64, neither in school, nor living in group quarters, and who were both employed at the time of the survey and had worked a positive number of weeks during the previous year. Column (5) reports the IV estimate obtained by using the immigrant share of the entire population across all other sectors of the economy. * (resp., **, resp., ***) denotes statistical significance at the 10% (resp., 5%, resp., 1%) level.

incidence of full-time employment in immigration-exposed transportation occupations (see Table 6.9). For example, in exposed transportation occupations, a 10% point increase in the share of immigrants leads to at least a 1.2% point decrease in the share of workers working at least 40 weeks/year and a 1.2% point decrease in the employment rate.[27] For landscapers, the same change in the share of immigrants leads to a 2.6% point decrease in the native employment rate. This evidence suggests that immigrants are displacing native workers, causing them to work less in some of the occupations in the maintenance and transportation sectors, which is likely attributable to low skill requirements and, subsequently, a high substitutability between natives and immigrants.

[27]For a precise definition of the employment rate, see Section 6.5.2.

6.5.2 *Effects on the sectoral employment rate*

Table 6.10 reports estimates of the effect of immigration on natives' self-reported employment status. The sectoral employment rate is defined as the share of the active population (those in the sector reporting working the

Table 6.10: Effect of Immigration on the Employment Rate of Native-Born Workers

		(1) OLS	(2) IIV-10	(3) IIV-All	(4) IIV-All but	(5) IIV-All but Pop
Personal services	All occ.	−0.043	−0.136***	−0.139***	−0.168***	−0.197**
		(0.028)	(0.050)	(0.050)	(0.064)	(0.078)
	Exposed occ.	−0.070	−0.217***	−0.239***	−0.296***	−0.397***
		(0.046)	(0.072)	(0.077)	(0.101)	(0.153)
Food service	All occ.	0.012	−0.082**	−0.113**	−0.179**	−0.195**
		(0.027)	(0.039)	(0.047)	(0.074)	(0.076)
	Exposed occ.	0.014	−0.075	−0.106*	−0.176*	−0.203**
		(0.033)	(0.049)	(0.061)	(0.095)	(0.094)
Construction	All occ.	−0.054**	−0.099***	−0.158***	−0.234***	−0.223***
		(0.025)	(0.034)	(0.039)	(0.058)	(0.057)
	Exposed occ.	−0.099***	−0.173***	−0.249***	−0.355***	−0.320***
		(0.033)	(0.045)	(0.052)	(0.078)	(0.074)
Transportation	All occ.	−0.037	−0.061**	−0.076***	−0.087**	−0.112***
		(0.028)	(0.031)	(0.028)	(0.034)	(0.035)
	Exposed occ.	−0.053	−0.075*	−0.104***	−0.119***	−0.154***
		(0.032)	(0.038)	(0.036)	(0.044)	(0.044)
Maintenance	All occ.	−0.011	−0.035	−0.049*	−0.062*	−0.067*
		(0.019)	(0.026)	(0.027)	(0.034)	(0.035)
	Exposed occ.	−0.017	−0.044	−0.062**	−0.075**	−0.089**
		(0.020)	(0.028)	(0.028)	(0.035)	(0.038)
Manufacturing	All occ.	−0.036	−0.078**	−0.098**	−0.118**	−0.146***
		(0.024)	(0.036)	(0.041)	(0.050)	(0.048)
	Exposed occ.	−0.045	−0.082*	−0.109**	−0.124*	−0.101*
		(0.028)	(0.048)	(0.055)	(0.067)	(0.059)
N		1,387	1,387	1,387	1,387	1,387

Notes: All regressions include MSA and year fixed effects. Standard errors are clustered at the MSA level. Column (1) reports the OLS estimate of β in Equation (6.1). Column (2) reports the IV estimate obtained by using the immigrant share across the 10 sectors with the highest immigrant shares. Column (3) reports the IV estimate obtained by using the immigrant share across all sectors. Column (4) reports the IV estimate obtained by using the immigrant share across all other sectors. Columns (2)–(4) use instruments constructed from individuals who were between the ages of 18–64, neither in school, nor living in group quarters, and who were both employed at the time of the survey and had worked a positive number of weeks during the previous year. Column (5) reports the IV estimate obtained by using the immigrant share of the entire population across all other sectors of the economy. "All occ." refers to the analysis conducted on all occupations within the sector. "Exposed occ." refers to the analysis conducted on the immigrant-exposed occupations within the sector. * (resp., **, resp., ***) denotes statistical significance at the 10% (resp., 5%, resp., 1%) level.

previous week or having been in search of a job for the previous four weeks) who reported working the previous week. It is therefore equal to one minus the sectoral unemployment rate. Results show that the immigrant share has a negative effect on natives' employment rate. In some sectors, these effects are relatively large. For instance, in construction (resp., food service; resp., personal services), a 10% point increase in the share of immigrants causes at least a 2.3% point (resp., 1.8% point; resp., 1.7% point) decrease in the employment rate, and larger effects among workers in exposed construction and personal service occupations. The mean unemployment rate in our sample of MSA-years lies between 7% for native personal service workers and 13% for native construction workers, so these effects are not trivial. Importantly, we find negative and statistically significant effects in all six sectors, including manufacturing. Overall, these employment effects contrast with the zero to positive correlations reported by Basso and Peri (2015) for the period 1970–2010.

6.5.3 *Results for pooled low-skill sectors*

Results for the six low-skill sectors suggest that native workers are affected by immigration through various channels. One concern when focussing on sectoral effects is that native workers may sort across sectors in response to immigration shocks, raising concerns that the estimates may be partly driven by compositional effects. There are at least two reasons to believe that this should not be too much of a concern in our case. First, our immigration effects are derived after residualizing outcomes on a series of observables that include education, race, work experience, gender, and marital status. To the extent that mobility is driven by these observables, our estimates should reflect average net effects.[28] Second, mobility within a sector is already implicitly accounted for in our sectoral estimates, and the definition of our sectors is quite broad. Because individuals who change occupations tend to seek employment in occupations that require a set of skills similar to the one they already have, it is likely that movement between occupations occurs intra-sectorally. Our sectoral definitions are also broad enough to account for potential task specialization and upgrading (Peri and Sparber, 2009). For example, our construction sector includes first-line supervisors of construction trades and our maintenance sector includes first-line supervisors of housekeeping and janitorial workers.

[28] We also ran the sectoral analysis without residualizing outcomes on observables. The estimates were comparable to those reported earlier.

Nonetheless, to further address cross-sectoral mobility of natives, we pool the six low-skill sectors into a composite sector and re-estimate immigration impacts for that sector. Given that these six sectors are all low-skill, in addition to being high-immigrant, it seems unlikely to us that natives working in these sectors could be displaced outside of the composite sector. Therefore, compositional effects should be less of a concern for that sector. In the IPUMS classification, there are two additional sectors that employ primarily workers with a high-school degree or less: extraction (mining and oil drilling) and technical maintenance (mechanics, electrical or equipment repairers, etc.). Although the occupations within these sectors typically appear to require some field knowledge and technical training,[29] which may help explain why their immigrant share is smaller,[30] it is plausible that natives working in our six low-skill sectors could be displaced into them. Therefore, we also report results for a composite sector that includes extraction and technical maintenance, in addition to the other six low-skill sectors.

Table 6.11 reports the upper bounds on the effects of immigration on native outcomes for the composite low-skill sectors. All upper bounds are negative and statistically significant (except for the weekly earnings effect, which is negative but not significant). When considering the six low-skill, high-immigrant sectors, the estimates reveal that a 10% point increase in the share of immigrants causes at least a 3.0% decrease in the annual earnings of low-skill native workers. The results also demonstrate that the decrease in the annual earnings is channeled through lower employment rates and fewer weeks of work per year. Each 10% point increase in the share of immigrants causes at least a 1.5% point decrease in the employment rate and a 1.1% point (resp., 1.4% point) decrease in the proportion of low-skilled natives who work at least 48 (resp., 40) weeks per year. When including the extraction and technical maintenance sectors, we find very similar results. If the negative impacts presented in the sectoral analysis were entirely driven by compositional effects due to inter-sectoral mobility, we would expect them to disappear when aggregating the low-skill sectors. Instead, the results in Table 6.11 suggest that significant negative effects persist even after allowing for plausible occupational mobility.

[29] In the technical maintenance sector, the share of workers having an AA degree is about twice as high as the average share in the six high-immigrant, low-skill sectors.

[30] In particular, the extraction sector has an immigrant share of only 7.8%.

Table 6.11: Pooled Low-Skill Sector Results

	Six sectors		Eight sectors	
	(1) OLS	(2) IIV-All but 6	(3) OLS	(4) IIV-All but 8
Annual earnings	0.057	-0.302^{**}	0.086	-0.294^{*}
	(0.084)	(0.149)	(0.082)	(0.152)
Weekly earnings	0.100^{*}	-0.059	0.118^{**}	-0.054
	(0.056)	(0.098)	(0.057)	(0.099)
Employment rate	-0.058^{***}	-0.154^{***}	-0.062^{***}	-0.148^{***}
	(0.019)	(0.038)	(0.019)	(0.038)
48 weeks or more	-0.004	-0.105^{*}	0.006	-0.110^{*}
	(0.028)	(0.055)	(0.027)	(0.058)
40 weeks or more	-0.023	-0.140^{***}	-0.020	-0.144^{***}
	(0.025)	(0.048)	(0.025)	(0.050)
27 weeks or more	-0.016	-0.126^{***}	-0.015	-0.134^{***}
	(0.020)	(0.040)	(0.020)	(0.042)
14 weeks or more	-0.001	-0.114^{***}	0.000	-0.119^{***}
	(0.017)	(0.031)	(0.017)	(0.033)
One week or more	0.001	-0.047^{**}	-0.001	-0.048^{**}
	(0.010)	(0.021)	(0.010)	(0.020)
N	1,387	1,387	1,387	1,387

Notes: All regressions include MSA and year fixed effects. Standard errors are clustered at the MSA level. Columns (1) and (2) pool the six low-skill, high-immigrant sectors previously analyzed in the sectoral results. Columns (3) and (4) additionally include the extraction and technical maintenance sectors into the pooled analysis. Column (1) (resp., (3)) reports the OLS estimate of β in Equation (6.1) while pooling the six (resp., eight) low-skill sectors together. Column (2) (resp., (4)) reports the IV estimate obtained by using the immigrant share across all sectors of the economy excluding the six (resp., eight) low-skill sectors used in the analysis. * (resp., **, resp., ***) denotes statistical significance at the 10% (resp., 5%, resp., 1%) level.

6.6 Conclusion

Economists have long sought to understand the impacts of immigration on the employment conditions of natives. Recently, there has been renewed interest in this question from policymakers and the general public. While most economists would agree that in the long run, any wage effects of immigration-induced labor supply shocks will be buffered by capital adjustments, there has been disagreement in the empirical literature about whether short-run impacts should even be of concern. Admittedly, the question is difficult to answer. Exogenous labor supply shocks rarely happen in practice, and the use of observational data on wages and employment limits the range and usefulness of the effects that can be estimated empirically (Borjas, 2003; Ottaviano and Peri, 2012; Dustmann *et al.*, 2016) while potentially affecting the reliability of the estimates (Jaeger *et al.*, 2018).

The present study does not purport to completely resolve these fundamental tradeoffs. However, it offers a novel approach to the problem — a sectoral analysis that relies on imperfect instruments — as well as meaningful bounds on short-run immigration impacts in important sectors of the US economy for a recent period. We find negative effects of immigration on native earnings in sectors where we would most expect to find them: low-skill sectors that produce non-traded goods where immigrant penetration has been high in recent decades. The negative effects that we find are perhaps best exemplified by looking at the construction sector, which employs a sizable share of the native and immigrant workforce over the period of our study (an average of 5.9% and 9.4%, respectively, according to our data). In that sector, we find that a 10% point increase in the share of immigrants, which falls short of the historical increase over the period 1990–2011, causes at least a 6.9% (resp., 3.6% point; resp., 3.9% point) decline in the annual earnings (resp., employment rate; resp., full-time occupational rate) of native workers when we focus on immigration-exposed occupations such as those of painters and roofers. We find qualitatively similar results in other low-skill sectors of the US economy such as personal services and food service. Our estimated impacts should be interpreted as upper bounds (meaning that the true effect is larger in magnitude) for at least two reasons: first, our strategy does not entirely correct for endogeneity bias, and second, the area-year variation we exploit may mask larger effects due to spatial arbitrage by native workers or capital flows across areas.

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Appendices

A. Background Figures

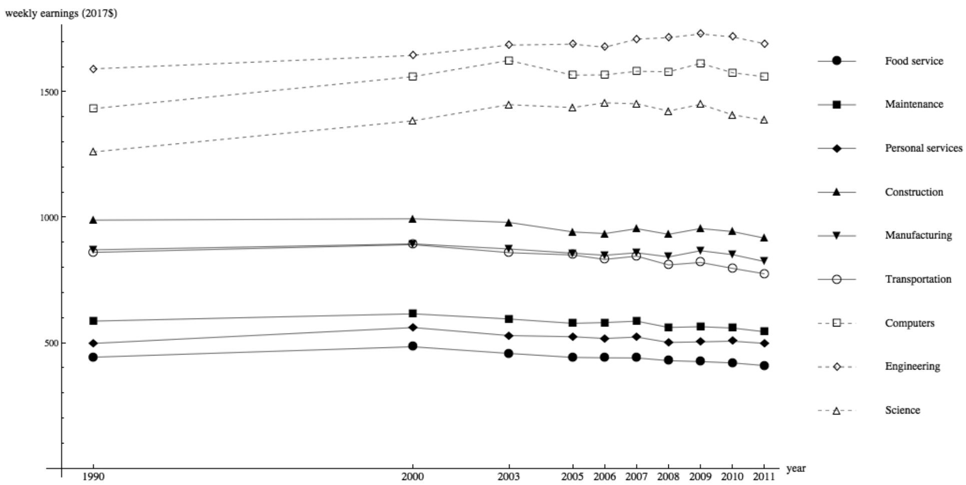

Fig. A.1: Evolution of Weekly Earnings of Natives by Sector, All Occupations

Notes: Weekly earnings are calculated for natives aged 18–64, neither living in group quarters, nor in school, in the labor force, and with weekly earnings above $50 and below $5,769.23 (in 2017$). Individuals are considered not to be in the labor force if they report being unemployed at the time of the survey and having worked zero weeks during the previous year. Weekly earnings include wage income and income from a person's own business or farm.

Source: IPUMS data processed by the authors.

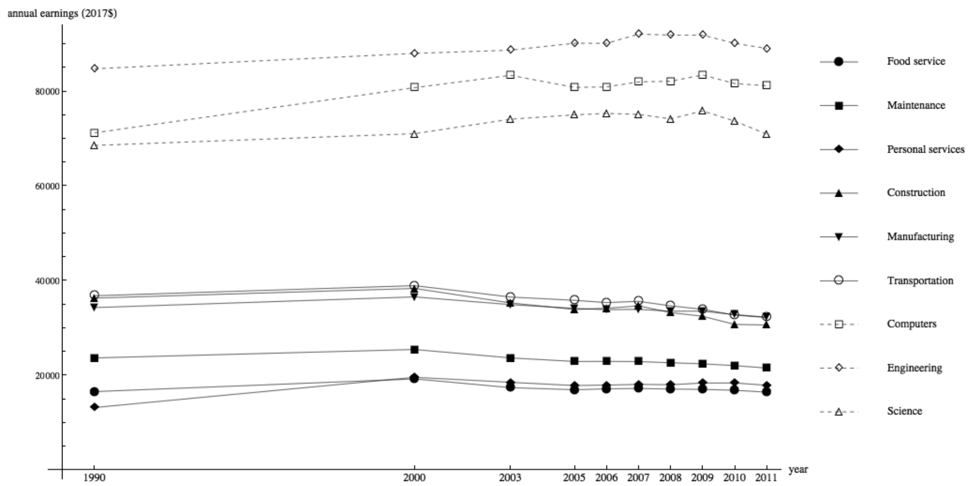

Fig. A.2: Evolution of Annual Earnings of Natives by Sector, Immigration-Exposed Occupations

Notes: Earnings are calculated over natives aged 18–64, neither in school, nor living in group quarters, in the labor force, and with annual earnings above zero and below \$300,000 (in 2017\$). Individuals are considered not to be in the labor force if they report being unemployed at the time of the survey and having worked zero weeks during the previous year. Annual earnings include wages or income from a person's own business or farm. To define immigrant-exposed occupations, we select occupations with the highest immigrant shares within a sector, until the total number of native workers in those occupations exceeds 50% of the total native workforce in the sector.

Source: IPUMS data processed by the authors.

B. City Comparisons and the Short-Run Wage Effects of Immigration

This section shows that in the presence of trade in capital between cities, the spatial correlation approach tends to underestimate the overall impact of immigration on wages, even if there is no trade in goods across cities.

Consider two cities, A and B. In the short run, capital is mobile between cities, but fixed in the aggregate at $\bar{K}$. Labor L_i, $i \in \{A, B\}$, is immobile. For the sake of the argument, here we assume that immigrant and native labor are perfectly substitutable and that labor is supplied perfectly inelastically. Each city uses the same constant-returns-to-scale technology to produce a homogeneous good Q_i: $Q_i = f(L_i, K_i)$. The production function satisfies the law of diminishing marginal returns. The associated unit cost function is denoted $c(w, r)$, with w the wage rate and r the rental on capital. The labor endowment of City B is assumed to be fixed at $\bar{L}_B$, while City A experiences an increase in its labor endowment due to immigration, $\Delta L_A > 0$. For simplicity, we assume that demand in City A is unaffected by immigration, and we write the demand functions as $Q_i = D_i(p_i)$, with $D_i' < 0$ and p_i denoting the local price of the good.

We are interested in the comparative statics $\frac{\partial w_i}{\partial L_A}$, for $i = A, B$, and also in the difference between them, which is what would be identified by exploiting city comparisons in a spatial correlation approach.

B.1. *Scenario 1: Traded good*

If the good is traded between cities, then in equilibrium we have $p_A = p_B$. Under constant returns to scale, we also have $p_i = c(w_i, r)$. Therefore, we must have $w_A = w_B$ (the cost function is monotonically increasing in input prices), and as a result the wage is equalized between cities. Intercity comparisons will reveal an absence of a wage effect.

Nonetheless, the wage decreases in both cities. To see why, note that in equilibrium the wage-to-output-price ratio must be equal to the marginal product of labor in each city, i.e., $\frac{w_i}{p_i} = \frac{\partial f}{\partial L}\left(\frac{L_i}{K_i}, 1\right)$, where we have used the fact that the marginal product of labor is homogeneous of degree zero. Since total labor increases in the aggregate due to $\Delta L_A > 0$, while total capital is fixed, the ratio $\frac{L_i}{K_i}$ increases in each city. Because the marginal product of labor decreases in the labor argument, the ratio $\frac{w_i}{p_i}$ declines. Since demand slopes down in each city and the additional labor results in more output in each city, output prices must decline. As a result, wages w_i decline as well.

In this scenario with traded good and traded capital between cities, intercity comparisons of wages would thus reveal *none* of the short-run wage effects of immigration. Note that if the good was traded internationally rather than just between cities, the same conclusion would obtain as long as capital is fixed in the aggregate. If capital and the good were traded internationally, then there would be no wage effect of immigration.

B.2. *Scenario 2: Non-Traded good*

If the good is not traded between cities, then the equilibrium can be described by the following set of equations:

$$D_A(p_A) = f(L_A, K_A), \tag{B.1}$$

$$D_B(p_B) = f(\bar{L}_B, K_B), \tag{B.2}$$

$$\frac{w_A}{p_A} = \frac{\partial f}{\partial L}\left(\frac{L_A}{K_A}, 1\right), \tag{B.3}$$

$$\frac{w_B}{p_B} = \frac{\partial f}{\partial L}\left(\frac{\bar{L}_B}{K_B}, 1\right), \tag{B.4}$$

$$p_A \frac{\partial f}{\partial K}\left(1, \frac{K_A}{L_A}\right) = p_B \frac{\partial f}{\partial K}\left(1, \frac{K_B}{\bar{L}_B},\right), \tag{B.5}$$

$$K_A + K_B = \bar{K}, \tag{B.6}$$

which constitute a system of six equations with six unknowns: p_A, p_B, K_A, K_B, w_A, and w_B. We are interested in the effect of a change in L_A, $\Delta L_A > 0$, on these equilibrium variables, specifically the wages w_i.

- **Case 1: Gross complements**

First, assume that in each city, labor and capital are *gross complements*: that is, an increase in the labor endowment results in an increase in the derived demand for capital. As shown, for instance, in Muth (1964), labor and capital are gross complements whenever the substitution elasticity in production is lower than the (absolute) output demand elasticity. This happens if capital and labor are not too substitutable and output demand is not too inelastic.

Under the assumption of gross complements, the demand for capital rises in City A, which leads to a transfer of capital from City B to City A: $\Delta K_A = -\Delta K_B > 0$. Because labor and capital are gross complements, the outflow of capital from City B results in a reduction in the derived demand for labor, and therefore a reduction in the wage w_B. Output declines in City B, and thus output price increases: $\Delta p_B > 0$. But then, condition (B.5) together with the fact that the marginal product of capital decreases in the capital-to-labor ratio implies that either p_A increases or the ratio $\frac{K_A}{L_A}$ decreases or both. Since $\Delta L_A > 0$ and $\Delta K_A > 0$, output increases in City A and therefore $\Delta p_A < 0$. Therefore, $\Delta\left(\frac{K_A}{L_A}\right) < 0$, and condition (B.3) implies that the wage-to-output-price ratio declines in City A. Since $\Delta p_A < 0$, $\Delta w_A < 0$.

Summarizing, the wage w_i declines in both cities. If we relax the assumption that the inflow of labor into City A does not change the output demand, the conclusion that w_B declines still holds because capital still flows to City A due to the combined effects of labor–capital gross complementarity and the increase in output demand. The conclusion that w_A declines holds as long as it is still the case that $\Delta p_A < 0$, that is, the increase in output demand is not so high as to result in an output price increase. This will hold if the immigrant inflow makes local goods cheaper.

- **Case 2: Gross substitutes**

Now assume that labor and capital are gross substitutes in both cities. If the immigrant inflow does not shift the output demand in City A (or not too much), then the derived demand for capital decreases and capital flows toward City B. In City B, the derived demand for labor declines due to gross substitutability, hence the wage rate decreases. Output increases and output price decreases. Condition (B.5) then implies that p_A decreases. Condition (B.3) implies that $\frac{w_A}{p_A}$ decreases, and therefore w_A decreases as well.

Because the spatial correlation approach identifies the effect of immigration from comparing wage changes between City A (the treatment city) and City B (the control city), and the wage declines in both cities, this approach underestimates the total effect and might even predict a positive wage effect if the wage decline in City A is less than in City B.

C. Residualized Dependent Variables

As explained in Section 6.4.1, the dependent variables used in our analysis are generated by running sector-specific regressions with individual-level outcomes on a full set of MSA-year fixed effects as well as a set of individual observables.[31] Following Reed and Danziger (2007), we use the MSA-year effects to construct "residualized" dependent variables that are used in our final analysis, the difference being that we construct MSA-year effects separately for each economic sector considered. The regressions we use to residualize our dependent variables are commonly referred to as Mincer models, named after Mincer (1958) who is credited with pioneering the use of factors other than school, such as work experience, to explain differences in individual labor market outcomes. Our model controls for educational attainment, race, potential work experience, gender, and marital status, as follows (to alleviate notation, there is no explicit index to denote the sector):

$$\begin{aligned}\mathrm{O}_{kit} = y_{it} &+ \gamma_1 \mathrm{HS}_{kit} + \gamma_2 \mathrm{AA}_{kit} + \gamma_3 \mathrm{Black}_{kit} + \gamma_4 \mathrm{Other}_{kit}\\ &+ \gamma_5 \mathrm{Exp}_{kit} + \gamma_6 \mathrm{Exp}^2_{kit} + \gamma_7 \mathrm{Fem}_{kit} + \gamma_8 \mathrm{Mar}_{kit} + \psi_{kit},\end{aligned}$$

where O_{kit} is the outcome for individual k in MSA i in survey year t, HS_{kit} is a dummy variable that identifies individuals who have at least a high school

[31] This is not a panel regression. Although the sample contains multiple time periods, we are not able to identify individuals over time. For each sector, we pool the individual observations from each cross-section into a single sample and run the regression on the sample of pooled cross-sections.

education but not an Associate's (or higher) degree, AA_{kit} is a dummy variable for having at least an Associate's degree, Black_{kit} is a dummy variable that identifies black individuals, Other_{kit} is a dummy variable that identifies individuals who are neither white or black, Exp_{kit} is an individual's potential work experience (assumed to be non-negative), which is defined as the individual's age minus their years of schooling minus six (the typical age for starting school), Exp^2_{kit} is potential work experience squared, Fem_{kit} is a dummy variable for being female, Mar_{kit} is a dummy variable for being married, and ψ_{kit} is the error term. The MSA-year fixed effects from these regressions y_{it} are then used as the dependent variables in our main sectoral analysis. For a given sector, y_{it} effectively captures the average outcome for each MSA in each year after controlling for a set of individual-level observables.

D. Borjas's "Relevant Wage Elasticity"

In his book *Immigration Economics*, as well as in earlier work (Borjas, 2003), George Borjas defines the "relevant wage elasticity" as the percentage change in native wages associated with a percent change in labor supply attributable to immigration (past and present). Denote by w the native wage, by $m = \frac{M}{N}$ the ratio of the immigrant to native workforce, and by $p = \frac{M}{M+N}$ the share of immigrants in the workforce. Borjas's relevant elasticity is then $\eta = \frac{\partial \ln w}{\partial m}$, while the elasticity given by the coefficient on the immigrant share in a regression of the log wage is $\beta = \frac{\partial \ln w}{\partial p}$. Because $p = \frac{m}{1+m}$, it follows that $\eta = \frac{\beta}{(1+m)^2} = \beta\,(1-p)^2$. Therefore, Borjas's "relevant wage elasticity" is directly deducible from the regression of log wage on the immigrant share.

Card and Peri (2016) (and other authors) choose to regress the first difference of the log wage, $\Delta \ln w$, on the regressor $\frac{\Delta M}{M_{-1}+N_{-1}}$, where $\Delta M = M - M_{-1}$ is the (net) immigrant inflow between the prior and current periods and N_{-1} is the number of native workers in the prior period. Although this specification is sometimes referred to as a first-difference model in the literature, it cannot be obtained by first-differencing any underlying data generating process (DGP) for the determination of wages. Rather, it is a *sui generis* DGP that specifies wage growth as a function of the relative inflow of immigrants. The wage elasticity in Card and Peri's (2016) model is $\epsilon = \frac{\partial \Delta \ln w}{\partial \left(\frac{\Delta M}{M_{-1}+N_{-1}}\right)}$. Only if $N_{-1} = N$ and $M_{-1} = 0$ can ϵ be related to η. In that case, $\frac{\Delta M}{M_{-1}+N_{-1}} = \frac{M}{N} = \frac{M}{N} - \frac{M_{-1}}{N_{-1}} = \Delta\left(\frac{M}{N}\right)$ and Card and Peri's (2016) regression becomes the first-differenced version of a regression with m as the regressor, which implies $\epsilon = \eta$.

E. Annual Earnings Results for the Manufacturing and Higher-Skill Sectors

See Table E.1.

Table E.1: Effect of Immigration on the Annual Earnings of Native-Born Workers

			(1) OLS	(2) IIV-10	(3) IIV-All	(4) IIV-All but	(5) IIV-All but Pop
Computers	All occ.		0.137*	0.122	0.108	0.108	0.103
			(0.077)	(0.078)	(0.077)	(0.076)	(0.079)
		N	1,386	1,386	1,386	1,386	1,386
	Exposed occ.		0.181*	0.149	0.137	0.139	0.139
			(0.102)	(0.095)	(0.097)	(0.096)	(0.099)
		N	1,386	1,386	1,386	1,386	1,386
Engineering	All occ.		0.056	0.029	0.022	0.023	0.028
			(0.053)	(0.054)	(0.057)	(0.057)	(0.054)
		N	1,385	1,385	1,385	1,385	1,385
	Exposed occ.		−0.046	−0.105	−0.114	−0.112	−0.096
			(0.105)	(0.113)	(0.116)	(0.116)	(0.110)
		N	1,377	1,377	1,377	1,377	1,377
Sciences	All occ.		−0.060	−0.085	−0.080	−0.080	−0.085
			(0.090)	(0.094)	(0.091)	(0.091)	(0.092)
		N	1,382	1,382	1,382	1,382	1,382
	Exposed occ.		−0.081	−0.134	−0.121	−0.120	−0.130
			(0.174)	(0.180)	(0.181)	(0.180)	(0.179)
		N	1,363	1,363	1,363	1,363	1,363
Manufacturing	All occ.		0.057	0.053	0.026	0.049	0.003
			(0.083)	(0.136)	(0.149)	(0.195)	(0.168)
		N	1,387	1,387	1,387	1,387	1,387
	Exposed occ.		0.040	−0.060	−0.101	−0.127	−0.127
			(0.113)	(0.171)	(0.193)	(0.272)	(0.220)
		N	1,387	1,387	1,387	1,387	1,387

Notes: All regressions include MSA and year fixed effects. Standard errors are clustered at the MSA level. Column (1) reports the OLS estimate of β in Equation (6.1). Column (2) reports the IV estimate obtained by using the immigrant share across the 10 sectors with the highest immigrant shares. Column (3) reports the IV estimate obtained by using the immigrant share across all sectors. Column (4) reports the IV estimate obtained by using the immigrant share across all other sectors. Columns (2)–(4) use instruments constructed from individuals who were between the ages of 18–64, neither in school, nor living in group quarters, and who were both employed at the time of the survey and had worked a positive number of weeks during the previous year. Column (5) reports the IV estimate obtained by using the immigrant share of the entire population across all other sectors of the economy. "All occ." refers to the analysis conducted on all occupations within the sector. "Exposed occ." refers to the analysis conducted on the immigrant-exposed occupations within the sector. * (resp., **, resp., ***) denotes statistical significance at the 10% (resp., 5%, resp., 1%) level.

F. Employment Results for the Higher-Skill Sectors

See Table F.1.

Table F.1: Effect of Immigration on the Employment Rate of Native-Born Workers

			(1) OLS	(2) IIV-10	(3) IIV-All	(4) IIV-All but	(5) IIV-All but Pop
Computers	All occ.		0.022	0.002	0.015	0.016	−0.030
			(0.025)	(0.067)	(0.069)	(0.088)	(0.087)
		N	1,386	1,386	1,386	1,386	1,386
	Exposed occ.		0.012	0.010	0.009	0.009	−0.025
			(0.026)	(0.064)	(0.027)	(0.027)	(0.081)
		N	1,386	1,386	1,386	1,386	1,386
Engineering	All occ.		−0.018	−0.042	−0.092	−0.119	−0.084
			(0.020)	(0.064)	(0.072)	(0.096)	(0.093)
		N	1,385	1,385	1,385	1,385	1,386
	Exposed occ.		−0.021	−0.092	−0.168*	−0.215	−0.165
			(0.027)	(0.093)	(0.100)	(0.136)	(0.119)
		N	1,377	1,377	1,377	1,377	1,377
Sciences	All occ.		−0.019	−0.020	−0.040	−0.049	−0.204
			(0.023)	(0.023)	(0.103)	(0.142)	(0.137)
		N	1,382	1,382	1,382	1,382	1,382
	Exposed occ.		−0.021	−0.022	−0.103	−0.136	−0.042
			(0.043)	(0.041)	(0.162)	(0.219)	(0.235)
		N	1,363	1,363	1,363	1,363	1,363

Notes: All regressions include MSA and year fixed effects. Standard errors are clustered at the MSA level. Column (1) reports the OLS estimate of β in Equation (6.1). Column (2) reports the IV estimate obtained by using the immigrant share across the 10 sectors with the highest immigrant shares. Column (3) reports the IV estimate obtained by using the immigrant share across all sectors. Column (4) reports the IV estimate obtained by using the immigrant share across all other sectors. Columns (2)–(4) use instruments constructed from individuals who were between the ages of 18–64, neither in school, nor living in group quarters, and who were both employed at the time of the survey and had worked a positive number of weeks during the previous year. Column (5) reports the IV estimate obtained by using the immigrant share of the entire population across all other sectors of the economy. "All occ." refers to the analysis conducted on all occupations within the sector. "Exposed occ." refers to the analysis conducted on the immigrant-exposed occupations within the sector. * (resp., **, resp., ***) denotes statistical significance at the 10% (resp., 5%; resp., 1%) level.

G. Relative Endogeneity of Imperfect Instruments

In this section, we derive a testable condition that, when met, can be used to determine the relative endogeneity of each imperfect instrument. We use this test to provide evidence that our preferred instrument, the "IIV-All but" (p_{it}^{S-s}) variable, is plausibly the least endogenous. Let $\tilde{x}$ denote the residuals from a regression of p_{it}^{s} on a set of year and MSA fixed effects. Let ρ_{vw} (resp., σ_{vw}) denote the correlation coefficient (resp., covariance) between two random variables v and w. Let σ_v denote the standard deviation of a random variable v. Define $z_1 \equiv p_{it}^{10}$, $z_2 \equiv p_{it}^{S}$, and $z_3 \equiv p_{it}^{S-s}$. Suppose that $\beta_{z_1}^{IV} > \beta_{z_2}^{IV} > \beta_{z_3}^{IV}$, as is the case for the majority of the effects we estimate. By Equation (6.4) in the main text,

$$\beta_{z_1}^{IV} > \beta_{z_2}^{IV} > \beta_{z_3}^{IV} \iff \frac{\sigma_{z_1 u}}{\sigma_{\tilde{x} z_1}} > \frac{\sigma_{z_2 u}}{\sigma_{\tilde{x} z_2}} > \frac{\sigma_{z_3 u}}{\sigma_{\tilde{x} z_3}}$$
$$\iff \rho_{z_1 u}\frac{\sigma_{z_1}}{\sigma_{\tilde{x} z_1}} > \rho_{z_2 u}\frac{\sigma_{z_2}}{\sigma_{\tilde{x} z_2}} > \rho_{z_3 u}\frac{\sigma_{z_3}}{\sigma_{\tilde{x} z_3}}. \tag{G.1}$$

Therefore, assuming that the instruments are indeed "imperfect instruments" in the sense that $\rho_{z_j u} \geq 0 \; \forall j$, a sufficient condition for $\rho_{z_1 u} > \rho_{z_2 u} > \rho_{z_3 u}$, that is, the instruments become progressively "less endogenous", is that

$$\frac{\sigma_{z_1}}{\sigma_{\tilde{x} z_1}} < \frac{\sigma_{z_2}}{\sigma_{\tilde{x} z_2}} < \frac{\sigma_{z_3}}{\sigma_{\tilde{x} z_3}}. \tag{G.2}$$

In our case, (G.1) generally holds, while (G.2) always holds (see Table G.1). As a result, when considering these three imperfect instruments, it is plausible that z_1 (p_{it}^{10}) is the most endogenous, z_2 (p_{it}^{S}) falls in the middle, and z_3 (p_{it}^{S-s}) is the least endogenous.

Table G.1: Sample Values for Condition (G.2), by Sector

	(1) $\frac{\hat{\sigma}_{z_1}}{\hat{\sigma}_{\tilde{x} z_1}}$	(2) $\frac{\hat{\sigma}_{z_2}}{\hat{\sigma}_{\tilde{x} z_2}}$	(3) $\frac{\hat{\sigma}_{z_3}}{\hat{\sigma}_{\tilde{x} z_3}}$	(4) $\frac{\hat{\sigma}_{z_4}}{\hat{\sigma}_{\tilde{x} z_4}}$
Food service	223.2	300.8	432.0	460.7
Maintenance	160.7	196.9	246.4	279.8
Personal services	298.8	335.3	417.4	529.2
Construction	166.4	211.2	288.1	331.3
Manufacturing	232.0	292.9	371.3	414.6
Transportation	246.4	272.2	327.4	386.1
Computers	380.0	412.3	534.7	622.2
Engineering	471.4	526.1	675.1	732.3
Science	553.5	754.2	1,084.7	1,251.5

Defining $z_4 \equiv p_{it}^{S-sPop}$, we also show in Table G.1 that $\frac{\sigma_{z_3}}{\sigma_{\tilde{x}z_3}} < \frac{\sigma_{z_4}}{\sigma_{\tilde{x}z_4}}$ in all nine sectors. However, the use of z_4 improves upon z_3 in less than one half of the cases (that is, in the majority of cases $\beta_{z_3}^{IV} < \beta_{z_4}^{IV}$). Because $\beta_{z_3}^{IV} < \beta_{z_4}^{IV} \iff \rho_{z_3 u}\frac{\sigma_{z_3}}{\sigma_{\tilde{x}z_3}} < \rho_{z_4 u}\frac{\sigma_{z_4}}{\sigma_{\tilde{x}z_4}}$, when $\frac{\sigma_{z_3}}{\sigma_{\tilde{x}z_3}} < \frac{\sigma_{z_4}}{\sigma_{\tilde{x}z_4}}$ the relative endogeneity between z_3 and z_4 cannot be determined. Therefore, we rely on the "IIV-All but" (p_{it}^{S-s}) instrument as our preferred instrument.