The Impacts of Agricultural Minimum Wage on US Agricultural Employment

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December 31, 2021

Abstract

Over the past 30 years, agricultural employers have been required to pay their workers at least a minimum wage, called the Adverse Effect Wage Rates (AEWRs). These wage rates were established to protect the American workforce from any adverse effects potentially caused by foreign workers, but its economic effects on labor markets are not yet explored. By using the Temporary Agricultural Worker data from the US Department of Labor (DOL) along with the 2005-2019 American Community Survey (ACS), I assess the impact of the AEWRs on US agricultural employment and on different groups of farmworkers. The AEWR policy leads to reduction in agricultural employment, especially for less-educated workers. The estimation results also indicate that the AEWRs have a negative relationship with the employment of less-educated domestic non-Hispanic Whites and unauthorized workers, but a positive relationship with the employment of less-educated domestic Hispanics and foreign workers (H-2A workers). However, the jobs left by one group are not sufficiently filled by the other groups. This finding suggests that the AEWRs tend to shorten job opportunities especially for domestic agricultural workers which is unintended consequence of the AEWR policy.

Keywords: Agricultural employment, Adverse effect wage rate

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1 Introduction

Since temporary agricultural workers were first invited to the US in 1986 under the H-2A visa program, farm employers hiring H-2A workers have been required to pay all their employees not less than the agricultural minimum wage; this wage rate is known as the Adverse Effect Wage Rates (AEWRs). While the federal and state minimum wages were established to keep America's workers out of poverty, the AEWRs were created to keep the American agricultural workforce out of low wage rates potentially caused by foreign workers. Although the economic literature on minimum wages is longstanding, the analysis of agricultural minimum wages is not yet started. Do the AEWRs bring gains to American agricultural workers in accordance with policy objectives? Do we see the disadvantaged groups among them due to this policy? Do the AEWRs affect farm employers' demand for labor? Many questions are left unanswered for this policy.

Many papers in labor economics document the employment effect of federal and state minimum wages. They has focused on workers in lower-wage industries such as the fast food and restaurant industries (Card & Krueger (1993); Neumark & Wascher (1995); Neumark & Wascher (2000); Dube et al. (2010)) or on teenagers (Neumark & Wascher (1992); Card (1992); Allegretto et al. (2011); Neumark et al. (2014)) who are most affected by a minimum wage increase. One strand of the existing literature on the minimum wage and the labor market finds that there is an disemployment effect of the minimum wage since employers will demand less labor as the price of labor increases (Neumark & Wascher (1992); Neumark & Wascher (2000); Orrenius & Zavodny (2008)). Another strand of the literature finds that because demand for low-wage labor is inelastic, the minimum wage has very small to no adverse employment effects (Card (1992); Dube et al. (2010); Zavodny

(2000); Giuliano (2013)). These mixed results have shed considerable light on the importance of industry-specific analysis because employers and employees in each industry respond differently to the minimum wage increase.

I believe this study is the first to examine the impact of the agricultural minimum wage on the hired agricultural labor market. Only a handful of studies look at the impacts of federal and state minimum wages on agricultural labor markets. In 1966, the federal minimum wage started applying to agricultural workers and thus Gardner (1972) and Lianos (1972) analyze this policy change and find its disemployment effects in the agricultural sector. Another recent study by Kandilov & Kandilov (2020) analyzes the state minimum wage on agricultural employment and reports disemployment effects on seasonal agricultural employment. Other studies look at the impacts of federal and state minimum wages on farm wages. Moretti & Perloff (1999) find that a dollar increase in the federal minimum wage leads to about \$0.065 increase in the average farm wage. Similarly, Buccola et al. (2012) find a positive relationship between Oregon minimum wages and the mean wage in the nursery industry.

Although the previous studies analyze the federal and state minimum wages, these wages are different from the agricultural minimum wage in terms of policy objectives as mentioned above. Also, the AEWRs are around 40-50% higher than the state minimum wages in almost all states, which implies that the federal and state minimum wages have no direct impacts on agricultural employment. Thus, the AEWRs are the appropriate indicator when analyzing the agricultural labor market, and it is essential to explore the agricultural minimum wage specifically in order to uncover its impact on the agricultural labor market.

How agricultural minimum wages affect the US agricultural employment is an important question. The answers to this question are of great importance in the US agriculture industry for three reasons. First, increased farm labor costs tend to be absorbed by the price of food we eat every day. More importantly, as Engel's law says, poor families spend a large portion of their income on food, which means if the food price goes up due to high labor costs, poor families have to limit their consumption of food as well as other non-agricultural products. Second, the minimum wage is closely related to an agricultural labor shortage issue. The higher wages may attract more workers and thus increase labor supply. However, considering that farmers are experiencing a widespread labor shortages in their fields (Hertz & Zahniser (2013*a*); Fisher & Knutson (2013)), it is questionable whether the minimum wages bring more workers to farms and mitigate shortage of labor in agriculture. Third, if farm employers have no choice but to sell their products at higher prices due to labor costs, their products lose price competitiveness in international markets. Unlike the fast-food industry, farm employers would not be able to pass the burden to consumers by raising the prices of their goods because they have to compete with suppliers in other countries. Since the US farm export substantially contributes to the US economy[1], losing a competitive edge in international agricultural markets due to high labor costs can harm farm employers as well as the US economy.

In this paper, I study the relationship between the AEWRs and agricultural employment. I narrow agricultural employment down to the employment of less-educated workers who are most likely affected by the AEWRs; they are less-educated domestic farmworkers, unauthorized farmwworkers, and H-2A worker. In analysis, this paper evaluates the impact of the AEWRs on the employment of these three groups of workers. One might ask whether all domestic farmworkers are

[1] About 25% of US farm production is exported each year (USDA (2018)), and it was valued at $140 billion in 2018 (USDA (2019))

affected by the AEWRs or only specific groups of them are adversely/favorably affected. Thus I provide analysis of the effect of the the AEWRs on employment of four subgroups of less-educated domestic farmworkers by race/ethnicity; 1) non-Hispanic White, 2) non-Hispanic Black, 3) non-Hispanic other races, and 4) Hispanic.

To do so, I use a panel data set which includes 15 years (2005-2019) and 2,331 PUMAs (Public Use Microdata Areas) across the 49 states, excluding Alaska. In the case of unobserved heterogeneity, I include PUMA fixed effects and year fixed effects in regression along with PUMA-specific time trends, all in an effort to ensure that the results are robust to different specifications. Given the dynamic nature of the data, within-year spillovers may occur when farmworkers migrate across states due to an AEWR increase. Although this potential endogeneity issue is not ignorable, given that the US has experienced a decline in interstate migration since the 1990s and the interstate residential migration rate was around 2 percent in mid-2010, this issue may not substantially cause biased estimates.

The analysis shows a negative and statistically significant relationship between the AEWRs and the employment of total agricultural workers and those with less education. I also find a similar relationship between the AEWRs and the employment of unauthorized workers, but find a positive and statistically significant, albeit less robust, association between the AEWRs and the employment of H-2A workers. Among less-educated domestic farmworkers, the employment of non-Hispanic White is negatively associated with the AEWRs while the employment of Hispanic workers is positively associated with the AEWRs. The agricultural minimum wages can lead to low agricultural employment levels and bring adverse effects to less-educated domestic farmworkers.

The remainder of this paper is organized as follows. Section 2 provides background information about the AEWRs. Section 3 describes data and provides descriptive statistics. In Section 4, the empirical framework is presented. Section 5 presents the empirical results, and Section 6 concludes with a discussion of the findings and limitations of the study.

2 Institutional Background

Foreign workers have been long utilized in the agricultural sector as an essential labor resource. During World Wars I and II, Mexican workers were brought into the US to replace American workers mobilized for the war effort abroad. The Bracero program started in 1942 to fill farm labor shortages with Mexican workers, and employers had to pay them at the minimum wage. As American farms increased dependence on Mexican labor even after the end of World War II, growing concerns had been raised that the Bracero program depressed the wages and employment of American workers in the agriculture sector (Borjas & Katz (2007)). To alleviate these concerns, the US government raised the minimum wage to make Mexican workers less attractive to farmers (Craig (2014)), and finally ended the Bracero program in 1964 (See Clemens et al. (2018) for information on the Bracero program).

With termination of the Bracero program, some jobs were taken by unauthorized workers who remained in the US or newly crossed the border without the appropriate documentation (Sosnick (1978)). To control the volume of undocumented immigration, Immigration Reform and Control Act (IRCA) was enacted in 1986. Under this Act, temporary agricultural workers again were invited to the US with H-2A visas (henceforth H-2A workers). This visa program has no numerical cap on the number of visas issued annually.

Although H-2A workers have been an important labor resource in agriculture, they are viewed as an economic threat to American farmworkers. As H-2A workers are willing to accept low wages or difficult working conditions, employers prefer to hire them to reduce labor costs (Whittaker (2008)). Echoing labor concerns about the Bracero program, a new generation of American laborers demanded a way to protect themselves from wage depression.

To mitigate any "adverse effects" for the American workforce, legislators developed a system of wage floors that applies both to H-2A and citizen workers. This is known as the Adverse Effect Wage Rate (AEWR). Under the H-2A program, H-2A workers must be paid either the AEWR, the state or federal minimum wage, or the locally prevailing wage for their occupation, whichever is higher. The AEWR is normally higher than the federal and state minimum wages. For example, the 2019 AEWR was, on average, 50% higher than the state minimum wage in every state (Farm Bureau (2019)). The employers who hire H-2A workers have to pay at least AEWR to them as well as domestic farmworkers while the employers who do not engage any H-2A worker are not required to pay their workers a wage that equals or exceeds the AEWR (Whittaker (2008)).

The AEWRs vary by state and have changed over years. An AEWR has been developed for each state except Alaska and is announced early each year (around February) prior to the growing season. The AEWR is released annually by the Department of Labor (DOL). Figure 1 maps the AEWRs across states in 2019 and shows the AEWRs differ between states and some states share the same wage rates. The AEWRs in the West and Midwest are relatively higher than those in the South. Figure 2 illustrates that the average AEWRs have been increasing over time even after adjusting for inflation. A table of real AEWRs is available in Appendix D.

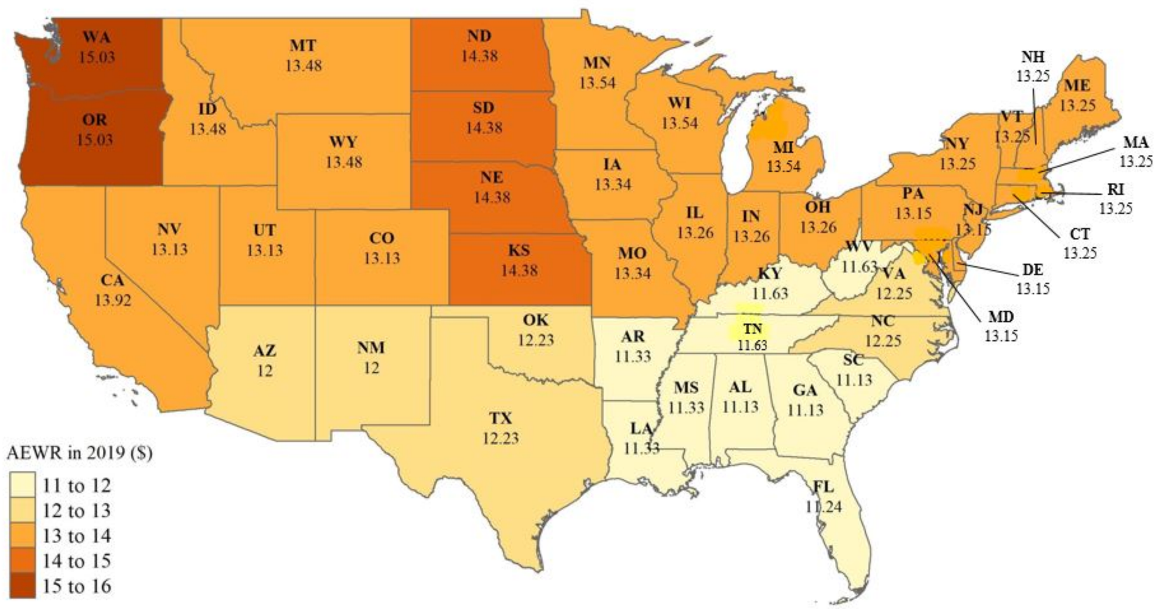

FIGURE 1: Adverse Effect Wage Rates by State, 2019

Notes: Hawaii is excluded from the figure.

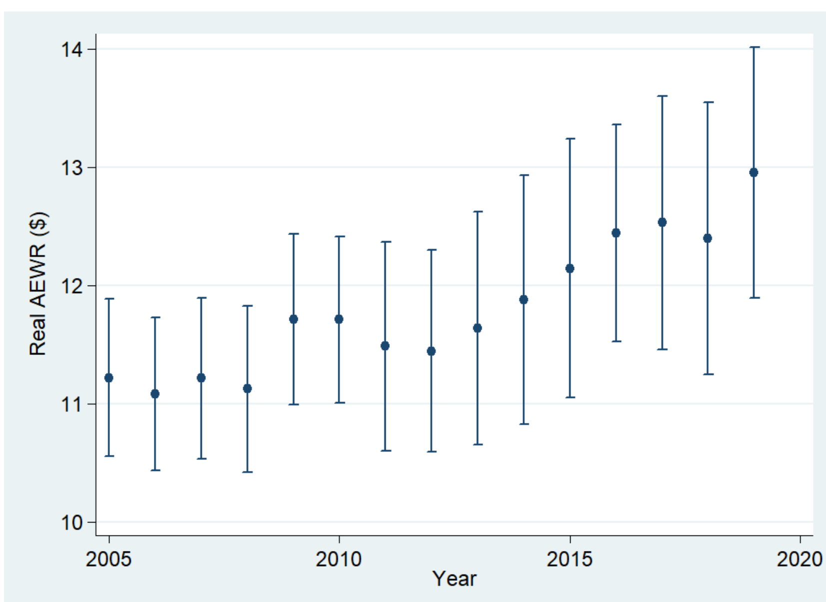

FIGURE 2: Trends in the Adverse Effect Wage Rates, 2005-2019

Notes: Bars represent standard deviation of the mean.

3 Data and Descriptive Statistics

To test for an effect of Adverse Effect Wage Rates (AEWRs) on employment in the agriculture sector, the data from the annual 2005-2019 American Community Survey (ACS) and H-2A program data from the Department of Labor (DOL) are used. These data sets come along with state-level data on AEWRs obtained from the DOL and Congressional Research Service (CRS) reports.

3.1 Agricultural Employment

The American Community Survey (ACS) accessed using the Integrated Public Use Microdata Series (IPUMS) provides individual-level data collected by the US Census Bureau yearly. It is nationally representative data, randomly selecting about 3.5 million households (US Census Bureau (2020)) and thus covering approximately 3.1 million persons per annum. Although several sources of data on US agricultural labor market are available, including the Farm Labor Survey (FLS), National Agricultural Workers Survey (NAWS), Current Population Survey (CPS), or Quarterly Census of Employment and Wages (QCEW), the ACS dataset is better suited for the purposes of this paper for two reasons, which I will describe below.[2]

First, unlike FLS, NAWS, CPS, and QCEW data, the ACS reports respondents' residential areas at the lower geographic level than state-level using the Public Use Microdata Areas (PUMAs). PUMAs are sufficiently represent low geographic areas considering that 49 states consist of 2,334 PUMAs in total. PUMAs are statistical geographic areas that partition each state into geographic areas containing no fewer than 100,000 people each (US Census Bureau (2020)). The PUMA-level

[2]National sources of agricultural labor market data are well introduced in Hertz & Zahniser (2013*b*)

allows me to better analyze local labor market conditions, and it is especially essential for agricultural labor market analysis due to its substantial heterogeneity across PUMAs which cannot be determined at the state-level analysis.

A second advantage of using the ACS is its inclusion of a rich set of socio-demographic and work-related variables. These variables allow me to identify different groups of persons employed in the agriculture sector, distinguishing citizen workers from unauthorized workers as well as their race and education levels. The definition of unauthorized workers is explained in the following Section 3.1.1

In 2005, the ACS began to provide the residents' PUMA codes. The configuration of PUMAs changed in 2010, and these 2010-based PUMA codes were first used in the 2012 ACS. To make the geographic areas comparable across all years from 2005 to 2019, the PUMA codes used between 2005 and 2011 are converted to the 2010-based PUMAs through two steps: 1) I count the number of respondents of interest residing in each PUMA; 2) I distribute the number of corresponding respondents in 2000-based PUMAs proportionally into new PUMAs based on the population ratios in new PUMAs.[3] See Appendix A for the detailed process of how the crosswalk is conducted.

The numbers of agricultural workers used for the dependent variables are estimated combining with the ACS one-year estimates assessed from the Census Bureau. While the ACS assessed using the IPUMS (ACS-IPUMS) provides individual-level data, the ACS assessed from the Census Bureau (ACS-CB) releases estimates of the PUMA-level population. In the ACS-IPUMS, I first obtain the ratios of agri-

[3]For example, old PUMAs with population growth were likely divided into two or more new PUMAs, and the number of corresponding respondents in those old PUMAs is allocated into new ones based on their population in 2010. On the other hand, old PUMAs with population decline were likely merged into one new PUMA, so I merely sum the number of respondents in the old PUMAs to determine the number in the new one. This 2000 to 2010 PUMA conversion can be undertaken using the crosswalk file named 'Geocorr 2018' from the Missouri Census Data Center.

cultural workers of interest in each PUMA by dividing the numbers of agricultural workers by the total number of respondents in each PUMA. I then multiply these ratios by population totals obtained from ACS-CB, which returns the estimated number of agricultural workers of interest.

3.1.1 Unauthorized Workers

Ideally, I would know the actual number of illegal migrant farmworkers working in the United States; however, the Office of Immigration Statistics in the Department of Homeland Security has no official record of illegal migrant entry at the US border. To overcome this data limitation, I first define undocumented farmworkers following previous studies on undocumented workers (Amuedo-Dorantes & Bansak (2012); Bohn et al. (2014); Good (2013)). This strand of literature measures undocumented workers in the US by identifying a subgroup population with the following characteristics: Hispanic, non-US citizen, ages 15–65, education of high school or less. In this analysis, I narrow this undocumented worker group to those employed in agriculture.[4] In the robustness checks, I also experiment with alternative definitions of the sample by replacing Hispanic with Mexican and ages 15–65 with ages 15–45. to more accurately capture the population that is unauthorized. Results prove robust through use of these alternative sample definitions (see Appendix E.1).

3.1.2 Temporary H-2A Visa Workers

This study uses data on the actual number of H-2A temporary agricultural workers for the years 2006-2019 obtained from the Department of Labor, Office of Foreign

[4]An occupation group in agriculture industry is an employment group with NAICS code 11 (Agriculture, Forestry, Fishing, and Hunting).

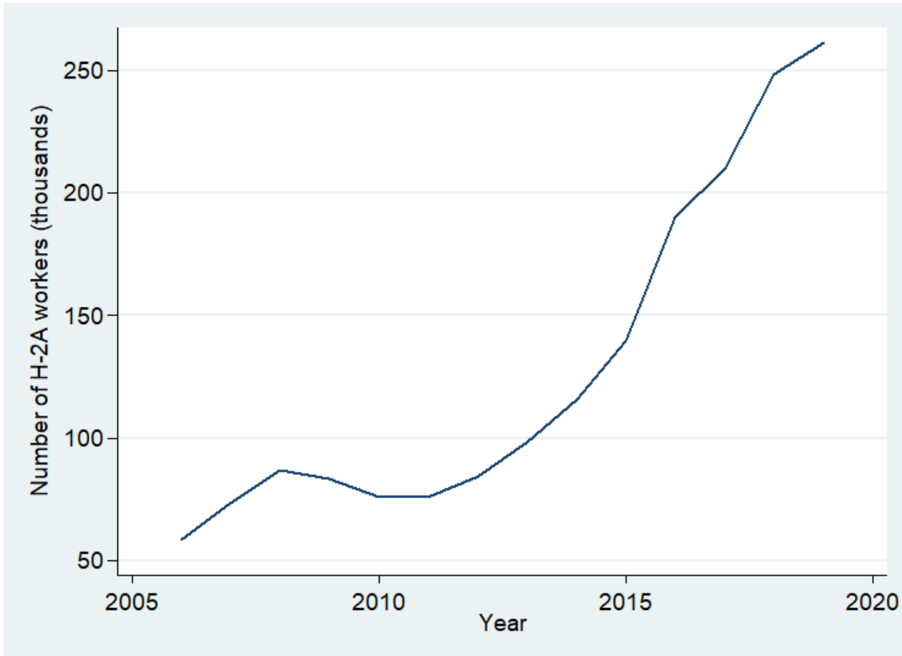

FIGURE 3: H-2A positions certified in the US, 2006-2019

Labor Certification (OFLC). We need to consider this group of workers when analyzing the agricultural labor market because: 1) employers who need to substitute for citizen workers or unauthorized workers can partially fill the positions with H-2A workers and 2) the inflow of H-2A workers has increased remarkably over the past decade (see in Figure 3). In 2019, the number of H-2A workers was 261,383 3.5 times more than in 2010. The detailed description of data and cleaning procedure is available in Appendix C.

3.1.3 Summary Statistics

Using the aforementioned datasets, I create a balanced panel of 2,334 PUMAs and 15 years throughout the sample, providing 35,010 observations. Table 1 presents descriptive statistics for all 2,334 PUMAs in 49 states, excluding Alaska, for the years 2005-2019. The table includes the dependent variables (i.e. the estimated

TABLE 1: **Descriptive Statistics for All 2,331 PUMAs, 2005-2019**

Variables	Mean	Std. Dev.
Total agricultural workers	862.732	(1516.730)
Less-educated workers	563.721	(1073.638)
Unauthorized workers	133.142	(589.137)
Domestic workers	422.200	(715.875)
Non-Hispanic White	342.376	(646.787)
Non-Hispanic Black	14.807	(64.932)
Non-Hispanic other	12.671	(59.347)
Hispanic	52.347	(191.780)
H-2A workers	53.349	(317.083)
Observations	35,010	

Notes: Summary statistics across 2,331 PUMAs in the 49 states, excluding Alaska. For the 'H-2A workers' variable, the number of observations is 32,676 for the years 2006-2019, and this data comes from the Department of Labor (DOL). The rest of the variables is from the American Community Survey (ACS).

numbers of workers in the agriculture sector and their subgroups by citizenship status and race/ethnicity as well as the actual numbers of H-2A workers).

The average PUMA-year reports 863 workers in the agricultural sector, and around 65 percent of those workers are less-educated (564 workers). Among the less-educated workers, an average of 133 workers (26 percent) are likely unauthorized workers. Of the average 422 less-educated domestic farmworkers, 342 workers are non-Hispanic Whites (81 percent), 15 workers are non-Hispanic Blacks (4 percent), 13 workers are non-Hispanic other race groups (3 percent), and 52 workers are Hispanic (12 percent). On average, each PUMA has a total of 53 H-2A workers per year. The maps illustrating the variation of employment levels by PUMA in 2019 are available in Appendix B.

3.2 Adverse Effect Wage Rate

The data on Adverse Effect Wage Rates (AEWRs) is collected from the Department of Labor (DOL) and Congressional Research Service (CRS)[5]. The inflation adjustments to the AEWRs are made using the regional Consumer Price Index for Urban Wage Earners and Clerical Workers (CPI-W) from the Bureau of Labor Statistics. This index is better suited for this study because it seeks to track retail prices as they affect urban hourly wage earners who are more likely to be affected by minimum wage changes. To account for the inflation by region, regional CPI-W is used.[6] I convert nominal AEWRs into real AEWRs by dividing by the CPI-W. Real values of the AEWRs are expressed in terms of 2019 dollars. The data shows the average AEWR is $11.73 (standard deviation = .95) for the years 2005-2019.

3.3 Other Control Variables

Continuing to use the ACS-IPUMS data source, I include a broad set of the PUMA-level demographic and socioeconomic covariates to control the effects of other factors that may influence agricultural employment. To control for labor market conditions, I include the labor force participation rate and employment rate at the PUMA level. To control for demographics and socioeconomic composition, I include population shares by age group, gender, race, ethnicity, educational attainment, and family income group. Summary statistics for all control variables are reported in Table 2.

[5] Information on AEWRs is collected from the Department of Labor (DOL (2021)), along with previously published information from the CRS report (Whittaker (2008)) and Federal Register (DOL (2009-2013))

[6] Regions are defined using the four Census regions (Northeast, Midwest, South, and West).

TABLE 2: **Descriptive Statistics: Control Variables for All 2,331 PUMAs, 2005-2019**

Control variables	Mean	Std. Dev.
Labor force participation rate[a]	.495	(.053)
Employment rate[b]	.931	(.032)
Population share, Age 15-24	.126	(.033)
Population share, Age 25-34	.118	(.031)
Population share, Age 35-44	.125	(.020)
Population share, Age 45-54	.143	(.020)
Population share, Age 55-64	.136	(.024)
Population share, Age 65 and over	.169	(.051)
Population share, Female	.513	(.017)
Population share, White	.764	(.184)
Population share, Black	.107	(.146)
Population share, Asian	.050	(.077)
Population share, Hispanic	.145	(.179)
Population share, High school graduate	.292	(.072)
Population share, Some college or higher education	.401	(.108)
Population share, Total household income less than 25k	.187	(.083)
Population share, Total household income 25k-35k	.093	(.031)
Population share, Total household income 35k-50k	.131	(.034)
Population share, Total household income 50k-75k	.179	(.036)
Population share, Total household income 75k-100k	.131	(.031)
Population share, Total household income 100k-150k	.144	(.055)
Population share, Total household income 150k-200k	.058	(.040)
Observations	34,965	

[a] The rate is calculated by dividing the number of respondents in the labor force by the total respondents for each PUMA.
[b] The rate is calculated by dividing the number of respondents employed by the total respondents in the labor force for each PUMA.

4 Empirical Framework

The first stage of the analysis tests whether AEWRs affect the employment of total agricultural workers and less-educated agricultural workers. If demand for agricultural labor is inelastic, we would observe no disemployment effect because employers are willing to pay their workers at or above the AEWR even though it increases. As an adjustment, employers may reduce their employees' working hours but it will not be captured in this analysis. On the other hand, if demand for agricultural labor is not inelastic and employers substitute farm machinery for human labor, the AEWR increase yields disemployment effects.

One might argue that US farms could hire fewer domestic farmworkers to pay H-2A workers or could hire more unauthorized farmworkers to avoid hiring H-2A workers. If employers risk higher penalties for hiring unauthorized workers, they would keep hiring H-2A workers unless they pay less for domestic farmworkers. To address substitution effects between workers, the second stage of my analysis investigates whether AEWRs increase or decrease agricultural employment of less-educed domestic farmworkers, unauthorized farmworkers, and H-2A workers.

In the third stage, I investigate whether specific groups of domestic farmworkers are disadvantaged due to the AEWR increase. It is possible for employers to prefer certain groups of domestic farmworkers because of their characteristics, average wages, and unobserved attributes.

To estimate the effect of AEWRs on agricultural employment, I explore the variation in the AEWRs over time and across states. Specifically, the two-way fixed effects regression is estimated as follows:

$$y_{ist} = \alpha + \gamma AEWR_{st} + \beta x_{ist} + \delta_i + \phi_t + \delta_i t + \epsilon_{ist} \tag{1}$$

where y_{ist} is one of the outcome variables of interest (i.e. agricultural employment broadly and agricultural employment of workers grouped by citizenship and race in PUMA i in state s in year t), $AEWR$ is the treatment variable (i.e. real adverse effect wage rates), x includes the PUMA-level control variables, and ϵ_{ist} is an error term.

To account for omitted variable biases induced by the regional and macroeconomic components possibly correlated to the employment of different groups of workers and the AEWRs by state, the empirical specification includes PUMA and year fixed-effects. The PUMA fixed effects (δ_i) leave out the correlation between the error term and the treatment variable due to factors that are constant over the years for a given PUMA (e.g. each PUMA has lower or higher AEWRs due to the state's propensity to keep lower or higher minimum wages). Year fixed effects (ϕ_t) eliminate the correlation between the error term and the treatment variable due to factors that are constant across all PUMAs in a given year (e.g. PUMA-wide lowering AEWRs during an economic downturn or PUMA-wide raising AEWRs due to economic prosperity or calls for better wages from farmworker unions).

The identifying assumption is that whatever unobserved heterogeneity is left does not bias the coefficient of interest,γ. But it is implausible to rule out the possibility of existence of unobserved heterogeneity in my data. Thus I also estimate specifications that include PUMA-specific time trends ($\delta_i t$). If a PUMA that exhibits higher employment levels over time (i.e. stronger employment growth) is more likely to increase its AEWR, then this confounding variation may be properly controlled for by including PUMA-specific time trends.

In an effort to eliminate the potential bias caused by unobserved heterogeneity, I estimate separate regressions with: (1) PUMA fixed effects, (2) PUMA fixed effects with linear time trends, (3) PUMA fixed effects with state-specific time trends, (4) PUMA fixed effects with PUMA-specific time trends, (5) PUMA fixed effects and year fixed effects, (6) PUMA fixed effects and year fixed effects with state-specific time trends, and (7) all four components (PUMA fixed effects, year fixed effects, state-specific time trends, and PUMA-specific time trends). Regression (1) is the most parsimonious approach, regression (7) is the least parsimonious approach, and regressions (2)-(6) are in between.

Last, standard errors are clustered at the PUMA level to account for arbitrary within-unit correlation in the error term (i.e. autocorrelation). Each PUMA is weighted using the estimated number of workers employed in agriculture, forestry, fishing, hunting, or mining industries obtained from the 2012 five-year American Community Survey (ACS).

One threat to identification is a violation of the stable unit treatment value assumption (SUTVA). In this context, the SUTVA states that the AEWR in a given PUMA-year should not affect the agricultural employment in another PUMA-year. A potential limitation for this study is that within-year spillovers may exist in case an AEWR increase in a given PUMA induces farmworkers to move to another PUMA to look for agricultural work. Since the AEWR is identical across all PUMAs in a given state, within-year spillovers only occur when farmworkers migrate across states. H-2A workers cannot work in another farm not specified in the contract and thus we need to pay attention to the migration of domestic and unauthorized farmworkers. Since the first decade of the twenty-first century, the US has experienced a decline in interstate migration.[7] Although we cannot ignore within-year spillovers caused by migration, the interstate residential migration rate is fairly low (around two percent in mid-2010 (Hyatt et al. (2018)) which may not substantially cause bias.

[7]Between 2000 and 2010, the economic migration rate fell from 0.9% to 0.5% in the Current Population Survey, whereas it fell from 0.8% to 0.5% in the administrative records data (Hyatt et al. (2018)).

5 Results and Discussion

Tables 3 to 5 present regression estimates of employment of nine groups of agricultural workers: 1) all workers, 2) less-educated workers, 3) less-educated domestic workers, 4) unauthorized workers, 5) H-2A workers; among less-educated domestic workers 6) non-Hispanic White, 7) non-Hispanic Black, 8) non-Hispanic other races, and 9) Hispanic. The means of these outcome variables are provided in the tables. Each coefficient is estimated from different regressions, and each column represents seven different regressions explained in Section 4.

5.1 Agricultural Employment of Total Workers and Those with Less Education

Table 3 shows that the AEWR is negatively associated with employment of all agricultural workers, and this relationship is statistically significant in six out of seven specifications. It means that one dollar increase in the real AEWR is associated with a reduction of 105 to 150 agricultural workers on average in a PUMA. This reduction accounts for 12 to 17 percent of the mean. This result implies that an increase in the minimum wage can raise labor costs to farm employers, and thus, reduce their demand for labor.

Among those employed in the agriculture sector, less-educated workers are also negatively associated with real AEWR increase, and this relationship is statistically significant in all specifications. A reduction of 104 to 147 less-educated workers, on average, in a PUMA (columns 2 to 7) accounts for 18 to 26 percent of the mean for that group. Considering that the coefficients for all agricultural workers account for only 12 to 17 percent of their mean, the less-educated work-

TABLE 3: **Impact of AEWRs on the Employment of Agricultural Workers**

Dependent variable	Mean	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Total agricultural workers	863	-51.806	-136.888***	-147.195***	-149.636***	-108.147**	-105.531***	-110.030***
		(35.089)	(40.273)	(43.867)	(44.318)	(42.187)	(38.343)	(39.689)
R^2		0.148	0.162	0.214	0.394	0.169	0.221	0.401
Less-educated workers	564	-66.047**	-146.521***	-132.669***	-130.547***	-135.564***	-103.517***	-106.125***
		(28.437)	(34.094)	(39.783)	(39.599)	(33.395)	(31.939)	(32.946)
R^2		0.188	0.204	0.255	0.423	0.211	0.262	0.429
PUMA fixed effects		Yes	Yes	Yes	Yes	Yes	Yes	Yes
Linear time trend			Yes					
Year fixed effects						Yes	Yes	Yes
State-specific time trends				Yes			Yes	Yes
PUMA-specific time trends					Yes			Yes
Observations		34,965	34,965	34,965	34,965	34,965	34,965	34,965

Notes: Estimation results of the seven models across 2,331 PUMAs in the 49 states, excluding Alaska for the years 2005-2019. Relevant control variables are included in all regressions which consist of the population shares by age group (15-24, 25-34, 35-44, 45-54, 55-64, 65+), by gender (female), by race (White, Black, and Asian), by ethnicity (Hispanics), by educational attainment (high school graduate, some college or higher education), by family income group (less than 25k, 25k-35k, 35k-50k, 50k-75k, 75k-100k, 100k-150k,150k-200k); and the labor force participation rate and the employment rate. Standard errors are clustered at the PUMA level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

ers are disproportionately affected by the AEWR increase. As expected, the real AEWR lowers the likelihood of being employed especially for less-educated workers whose income is more affected by the AEWR increase.

5.2 Agricultural Employment of Less-Educated Domestic, Unauthorized, and H-2A Workers

Table 4 presents estimation results for three groups of agricultural workers: less-educated domestic workers, likely unauthorized workers, and H-2A workers. Results indicate that working in a PUMA with a high AEWR is negatively associated with agricultural employment of domestic workers with less education. The coefficients ranging from 70 to 93 are statistically significant at the 1% level in two out of seven specifications, accounting for 17 to 22 percent of the mean. These statistically significant results are found only when I additionally control for linear time trends or time fixed effects. For the first, the time trends would potentially include the increasing employment of domestic farmworkers related to the trend of rising AEWRs[8]. Similarly, the PUMA-invariant factors within each year would potentially include the positive relationships between employment levels and the AEWRs[9].

TABLE 4: **Impact of AEWRs on the Agricultural Employment of Less-educated Domestic, Unauthorized, and H-2A Workers**

Dependent variable	Mean	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Domestic workers	422	-35.771*	-69.907***	-19.512	-23.248	-92.816***	-25.070	-27.769
		(20.639)	(22.019)	(17.054)	(17.177)	(25.913)	(21.681)	(22.302)
R^2		0.128	0.135	0.219	0.371	0.141	0.224	0.376
Unauthorized workers	133	-30.141*	-74.063***	-110.756***	-104.924***	-41.337**	-78.166***	-78.103***
		(18.297)	(24.729)	(32.047)	(31.198)	(19.314)	(23.778)	(24.515)
R^2		0.190	0.200	0.218	0.403	0.208	0.225	0.409
H-2A workers	53	43.482**	23.933	38.995***	35.904***	3.591	19.614	16.383
		(19.380)	(22.334)	(11.989)	(11.784)	(34.896)	(12.304)	(11.689)
R^2		0.089	0.091	0.230	0.800	0.094	0.233	0.803
PUMA fixed effects		Yes	Yes	Yes	Yes	Yes	Yes	Yes
Linear time trend			Yes					
Year fixed effects						Yes	Yes	Yes
State-specific time trends				Yes			Yes	Yes
PUMA-specific time trends					Yes			Yes
Observations		34,965	34,965	34,965	34,965	34,965	34,965	34,965

Notes: Estimation results of the seven models across 2,331 PUMAs in the 49 states, excluding Alaska for the years 2005-2019. For the 'H-2A workers' outcome variable, the number of observations is 32,676 for the years 2006-2019. Relevant control variables are included in all regressions which consist of the population shares by age group (15-24, 25-34, 35-44, 45-54, 55-64, 65+), by gender (female), by race (White, Black, and Asian), by ethnicity (Hispanics), by educational attainment (high school graduate, some college or higher education), by family income group (less than 25k, 25k-35k, 35k-50k, 50k-75k, 75k-100k, 100k-150k,150k-200k); and the labor force participation rate and the employment rate. Standard errors are clustered at the PUMA level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 4 sheds light on the negative association between the employment of unauthorized workers and the AEWRs. The coefficients range from 74 to 111, statistically significant at the 1% level. Considering that the mean of undocumented farmworkers is 133, the reduction of employment is large. This negative and large association is the opposite of what would be expected assuming farm employ-

[8]The coefficient of linear time trends is 28.969 with 4.719 standard error.

[9]The coefficients of year fixed effects are all positive and statistically significant at the 1% level except for the year 2008.

ers substitute domestic farmworkers or H-2A workers for unauthorized workers without being concerned about paying higher wages. The result may imply that the overall level of wage rates including those for unauthorized workers increases, and farm employers have little choice but to unhire unauthorized workers and try to avoid the risk of hiring them.

Using the alternative definitions of likely unauthorized workers, I conduct a robustness check which is reported in Appendix E.1. While unauthorized workers in Table 4 are defined; 1) Hispanic noncitizens 15-65 years olds with a high school education or less, they are defined in three alternative ways as 1) Hispanic noncitizens 15-45 years olds with a high school education or less, 2) Mexican noncitizens 15-45 years olds with a high school education or less, and 3) Mexican noncitizens 15-65 years olds with a high school education or less. The magnitudes of point estimates are different across alternative definitions, but the negative association between the employment of unauthorized workers and the AEWRs is consistent with my main results.

In addition to alternative definitions, I conduct additional robustness checks including the immigration policy as a control variable. A potentially omitted variable is immigration policies which prevent farm employers from hiring unauthorized workers and are potentially correlated with the AEWRs. That being said, E-verify program is a good proxy to represent these types of policies. This program was adopted by 23 states between 2008 and 2012, and these states require all employers to verify the legal eligibility of newly hired employees prior to employment. I create a dummy variable which is 1 if state i mandated the use of E-verify in year t and 0 otherwise. As can be seen in Appendix E.2, the point estimates are slightly smaller but of similar magnitudes and statistically significant.

Results for H-2A workers show that H-2A workers would be hired more with the rise of the AEWR. The coefficients range from 36 to 40, statistically significant at the 1% level in two out of seven specifications. These results may imply that farmers are inclined to prefer hiring temporary agricultural workers to less-educated domestic farmworkers or unauthorized workers when facing a rise in labor costs. They suggest that farmers may discharge domestic farmworkers initially paid higher than the AEWR in order to keep or increase the number of H-2A workers, or the AEWR increase exerts more upward pressure on domestic farmworkers' pay and thus farmers are reluctant to hire them. Another scenario is that employers may view the availability of H-2A workers as a device through which to deter unionization among domestic agricultural workers (Whittaker (2008)). With the ready accessibility of foreign workers and upward pressure on labor costs, employers may want to avoid bargaining collectively with American workers over issues of wages and hours.

To investigate the mechanism of how AEWRs change the employment of less-educated domestic, undocumented, and H-2A farmworkers, we need to know how wages changed for less-educated domestic farmworkers and undocumented farmworkers which is unfortunately not plausible to be obtained. As mentioned above, the AEWR increase can attract more American workers but employers cannot hire them because American workers expect higher wages than employers would pay. If employers risk higher penalties for hiring unauthorized workers, the wage plus the cost of the risk is higher when hiring unauthorized workers than H-2A workers. Thus employers tend to employ more H-2A workers as the AEWR increases.

Here, we learned that the AEWRs can reduce the employment of less-educated domestic farmworkers and increase the employment of H-2A workers but its absolute change is relatively smaller than that of less-educated domestic farmworkers.

This result implies that the substitutability between native, unauthorized, and foreign farmworkers is small although their education levels are similar to each other. These findings imply that the AEWRs can bring unintended consequences in agricultural labor markets; adverse effects on less-educated domestic farmworkers and lower agricultural employment. A rural PUMA with higher real AEWRs also can suffer from a fewer employees who can work in the fields.

5.3 Agricultural Employment of Less-Educated Domestic Workers by Race/Ethnicity

In Section 5.2, we found a negative association between the employment of less-educated domestic farmworkers and the AEWRs for the specifications where it is statistically significant. Do the AEWRs reduce the employment of these workers differently by their race and ethnicity? Table 5 answers this question by reporting estimation results for four mutually exclusive race/ethnic groups: 1) Non-Hispanic White, 2) Non-Hispanic Black, 3) Non-Hispanic other, and 4) Hispanic.

A one dollar increase in the real AEWR appears to have negative and statistically significant associations with the employment of non-Hispanic Whites at the 1% level (columns 1, 2, 5) — decreasing the number of workers by 77 to 127. This reduction comprises 23 to 37 percent of their mean. On the other hand, a one dollar increase in the real AEWR has a positive and statistically significant association with the employment of Hispanic workers at the 1% level (columns 1, 2, 5) — increasing the number of workers by 25 to 38 which comprises 48 to 73 percent of their mean. The estimation results for the employment effects on non-Hispanic Black and non-Hispanic other races are not statistically significant except for a small and statistically significant increase in the employment of non-Hispanic

TABLE 5: **Impact of AEWRs on the Agricultural Employment of Less-educated Domestic Workers by Race/Ethnicity**

Dependent variable	Mean	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Non-Hispanic White	342	-76.858***	-96.482***	-17.929	-20.604*	-126.877***	-20.914	-22.729
		(17.110)	(18.559)	(11.349)	(11.951)	(22.784)	(16.101)	(16.471)
R^2		0.176	0.179	0.246	0.384	0.189	0.253	0.393
Non-Hispanic Black	15	1.517	2.087*	-0.613	-0.503	3.958***	0.815	0.983
		(1.089)	(1.233)	(1.206)	(1.239)	(1.423)	(1.376)	(1.426)
R^2		0.025	0.025	0.063	0.190	0.027	0.065	0.191
Non-Hispanic other	13	1.645	-0.96	-1.996	-1.828	-1.038	-3.272	-3.293
		(2.441)	(2.711)	(2.542)	(2.687)	(3.524)	(3.813)	(3.953)
R^2		0.019	0.021	0.049	0.153	0.024	0.053	0.157
Hispanic	52	37.926***	25.448***	1.026	-0.313	31.141***	-1.698	-2.731
		(9.298)	(9.272)	(10.626)	(9.859)	(8.270)	(9.833)	(10.148)
R^2		0.133	0.138	0.235	0.425	0.140	0.236	0.427
PUMA fixed effects		Yes	Yes	Yes	Yes	Yes	Yes	Yes
Linear time trend			Yes					
Year fixed effects						Yes	Yes	Yes
State-specific time trends				Yes			Yes	Yes
PUMA-specific time trends					Yes			Yes
Observations		34,965	34,965	34,965	34,965	34,965	34,965	34,965

Notes: Estimation results of the seven models across 2,331 PUMAs in the 49 states, excluding Alaska for the years 2005-2019. Relevant control variables are included in all regressions which consist of the population shares by age group (15-24, 25-34, 35-44, 45-54, 55-64, 65+), by gender (female), by race (White, Black, and Asian), by ethnicity (Hispanics), by educational attainment (high school graduate, some college or higher education), by family income group (less than 25k, 25k-35k, 35k-50k, 50k-75k, 75k-100k, 100k-150k,150k-200k); and the labor force participation rate and the employment rate. Standard errors are clustered at the PUMA level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Black in columns 2 and 5. This result suggests that a real AEWR increase would reduce job opportunities for non-Hispanic Whites, whereas Hispanic workers may have a chance to be hired.

6 Summary and Concluding Remarks

Over the past 30 years, employers seeking to hire foreign agricultural workers under the H-2A program have been required to pay them as well as domestic farmworkers at the Adverse Effect Wage Rates (AEWRs) or more. However, this policy is not yet analyzed in terms of its impact on the agriculture labor market. Using data on employment levels for different groups of agricultural workers and their subgroups by race/ethnicity along with real AEWRs over the years 2005-2019, this study explores the relationships between employment changes in the agriculture sector and the minimum wages imposed in this sector. The results indicate that real AEWRs can reduce agricultural employment overall. Real AEWRs also significantly curtail the employment likelihood of less-educated domestic farmworkers, especially for non-Hispanic White, whereas employment levels of less-educated Hispanic domestic farmworkers and H-2A workers increase.

While the estimation results suggest that the AEWRs are negatively associated with agricultural employment, this study has some limitations in interpreting the policy impact on the agricultural labor market. First, analyzing the employment cannot fully cover the stories in the labor market because the AEWRs would have different impacts on diverse work-related components such as wage rates, the number of hours worked, or working conditions for different groups of workers. Some workers would be better off receiving higher wage rates, working longer hours to earn more income, or working in better environments. Second, the study cannot explore the effects of the AEWRs on seasonal agricultural employment but year-round agricultural employment. Considering that many agricultural workers are employed during growing and harvesting seasons, analysis at monthly or quarterly employment can reveal seasonal hiring fluctuations that occur in local markets. Third, due to data constraints, the analysis is limited to the period 2005-2019 although the AEWR policy has been implemented since late 1980.

Although the AEWR policy is designed not to adversely affect the wages, job opportunities, and working conditions of native workers similarly employed with foreign workers, it raises concerns about its negative consequences of harming job opportunities for less-educated domestic agricultural workers. Moreover, an increase in farmers' labor costs disproportionally affects job opportunities for non-Hispanic White. However, the jobs left by them appear not to be sufficiently filled by other workers such as H-2A workers or domestic Hispanic farmworkers. Thus, it is important to be aware of possible low employment rate in the agricultural sector due to high AEWRs. In future research, it is worth exploring whether farm employers substitute their labor for capital coping with high labor costs and whether small farms and labor-intensive industries are disproportionally affected by high labor costs.

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Appendix

A Crosswalk from 2000-based to 2010-based PUMAs for 2005-2011 ACS

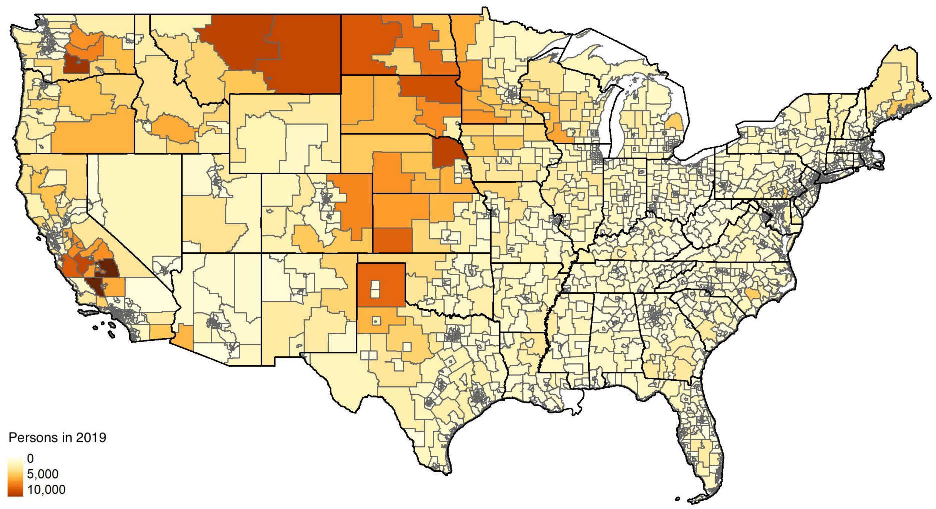
Each PUMA contains a total population of 100,000 or more, and the Census Bureau redraws PUMA boundaries every 10 years based on population information from the most recent decennial census. The 2000-based PUMAs were applied to the ACS 2005-2011, while the 2010-based PUMAs were first used in the ACS 2012 and beyond. The Missouri Census Data Center provides a crosswalk file for the conversion from 2000-based to 2010-based PUMAs.

A few PUMAs in Louisiana are omitted from the data, particularly those in the city of New Orleans and the surrounding areas. Due to population displacement following Hurricane Katrina, persons living in Louisiana PUMAs 01801, 01802, and 01905 are coded as living in Louisiana PUMA 77777 in the 2006-2011 ACS. The crosswalk file does not take this change into account, and thus I eliminate those PUMA codes and their associated 2010-based codes to reduce measurement errors. The following codes in Louisiana are omitted: 01801, 01802, 01803, 01804, 01901, 01902, 01903, 01904, 01905, and 77777 for the 2000-based PUMAs; and 02400, 02401, 02402, 02300, 02301, 02302, and 02500 for the 2010-based PUMAs.

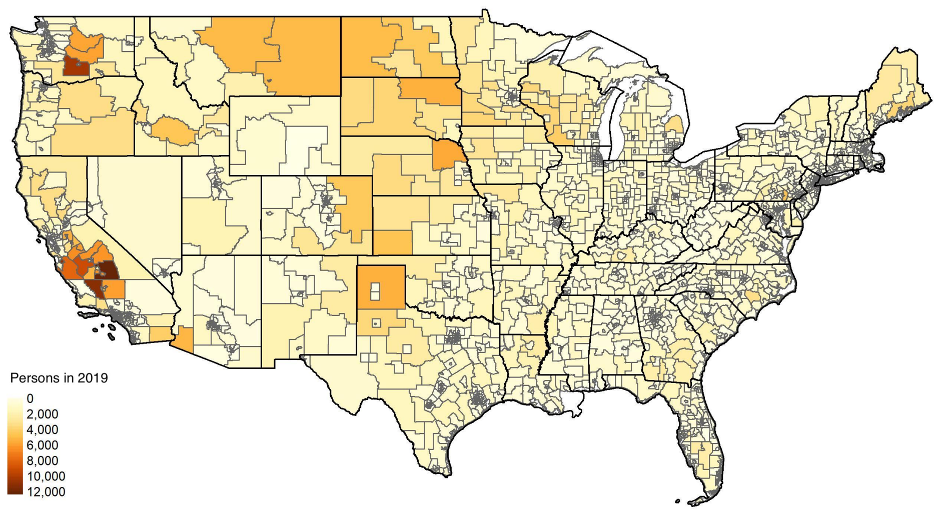
The Missouri Census Data Center's crosswalk file for 2000-based to 2010-based PUMA conversion uses the 2010 Census population as a weighting variable. In the file, the population is indicated in a cell for each 2010-based PUMA which is linked to one or more 2000-based PUMAs. It is possible because the decennial census in 2010 releases the total population at the lower geographic unit than PUMA, called a block, and the population at a PUMA is the sum of the population for all the blocks included in that PUMA. Based on population, the Missouri Census Data Center generates the allocation factors which indicate a portion of a 2010-based PUMA in a 2000-based PUMA. For example, if a 2010-based PUMA includes only one 2000-based code, the allocation factor is one, while if a 2010-based PUMA includes two 2000-based codes, the allocation factor is the share of people who reside in that 2000-based PUMA. By multiplying this allocation factor with the number of respondents in each PUMA for 2005-2011 ACS, I can obtain the number of respondents in terms of 2010-based PUMAs. Finally, I add all the number of respondents in the same 2010-based PUMA.

B Employment of agricultural workers by PUMA, 2019

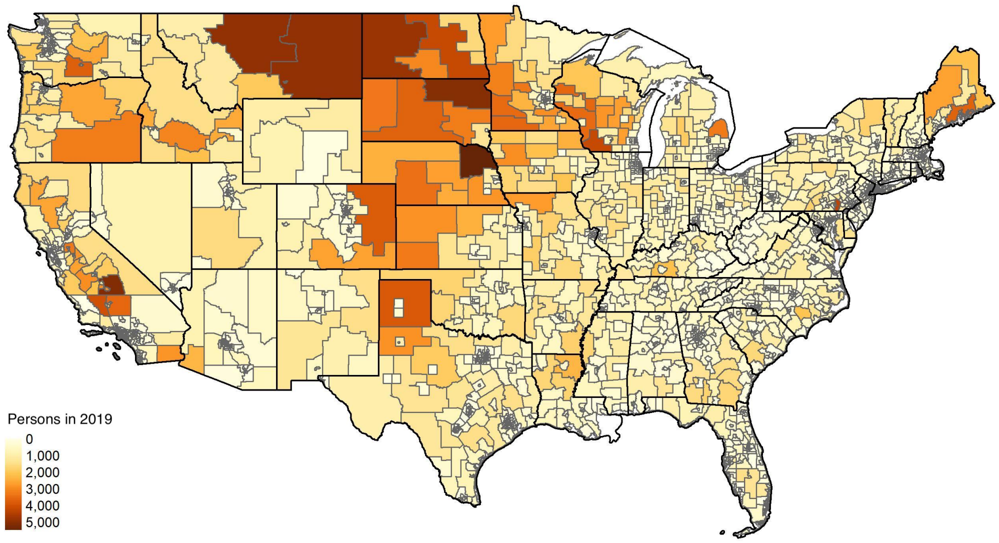
A. Estimated number of agricultural workers



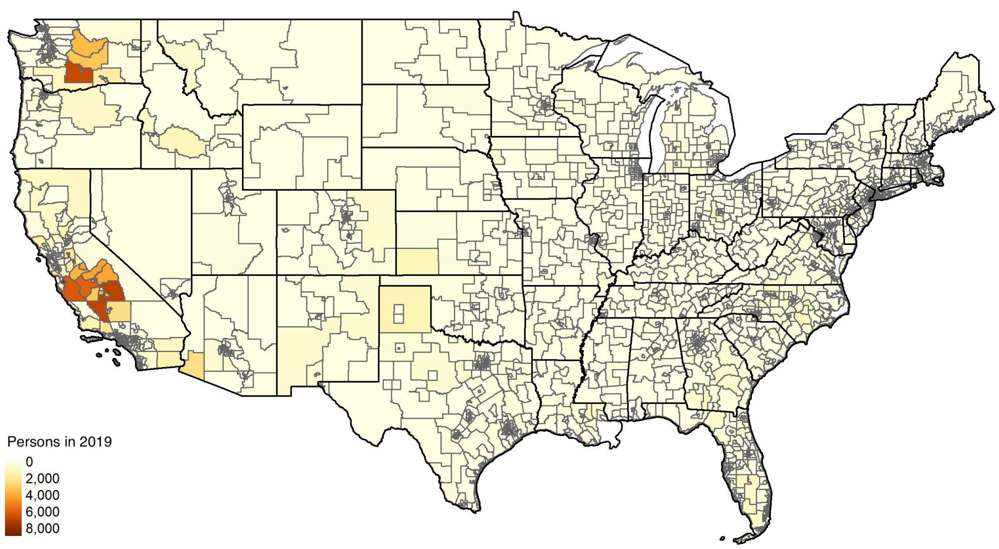
B. Estimated number of agricultural workers with a high school education or less

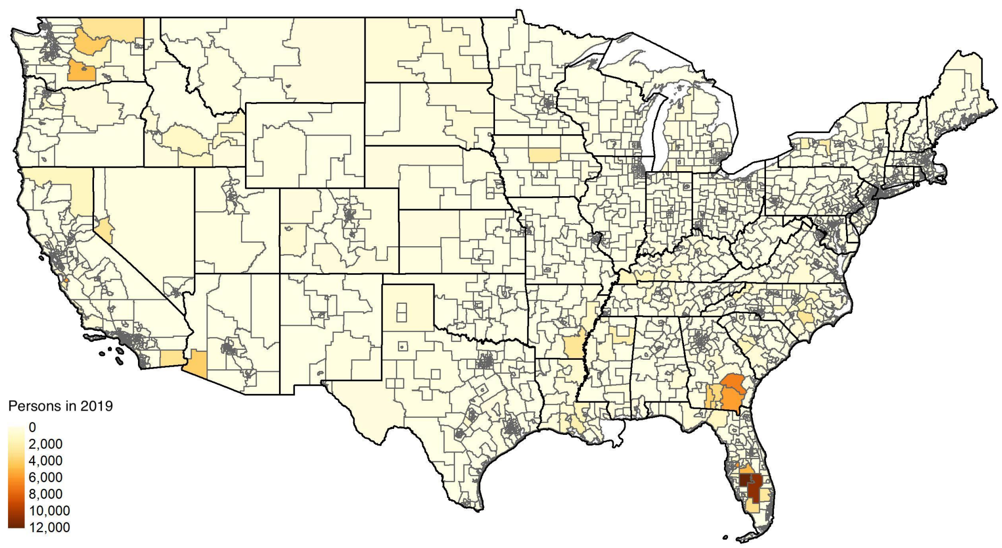


D. Estimated number of domestic agricultural workers with a high school education or less



C. Estimated number of unauthorized agricultural workers





C Description of H-2A data and cleaning procedure

The H-2A data comes from the Department of Labor (DOL), Office of Foreign Labor Certification (OFLC). This administrative data combine the employers' H-2A applications and the certification determinations issued between October 1 in the previous calendar year and September 30 in the current calendar year, based on when these processes are completed. Employers, on average, file an H-2A application in May. Considering that the AEWRs are released around February every year, most employers are aware of new AEWRs when they submit an H-2A application.

Using the H-2A data, which include each employer's address with a postal code and the number of H-2A workers certified, I converted zip codes to PUMA codes using the crosswalk file obtained from the Missouri Census Data Center [10]. The procedure is almost the same as that for the 2000-based to 2010-based PUMA

[10] Some missing zip codes are recovered using employers' addresses, but missing zip codes without employers' addresses or with Canadian addresses are dropped. The dropped cases constitute only 0.39 percent of the data. The crosswalk file is available from https://mcdc.missouri.edu/cgi-bin/uexplore?/data/corrlst/zip2_xxx, and the file name is 'zip2puma12.csv'

conversion, which is explained in Appendix A. The crosswalk file also includes allocation factors which allow me to distribute the number of H-2A workers in one zip code to one or multiple PUMA codes based on the 2010 Census population.

In addition to the zip-to-PUMA conversion, only sub records in the data files are used, to avoid double-counting. The data files contain both master and sub-records. If two or more employers jointly employ workers, they are recorded under the same case number. But the number of H-2A workers certified for each employer is reported as the sub-record, and the sum of the number of workers for all employers under the same case number is entered as the master record. To prevent double-counting, I deleted the master records from my data.

D Real AEWRs, 2005-2019

TABLE 6: **Real Adverse Effect Wage Rates by State, 2005-2019**

State	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Alabama	10.52	10.54	10.42	10.00	10.38	10.55	10.17	10.25	10.52	10.59	10.66	11.20	11.00	11.09	11.13
Arizona	10.30	10.45	10.48	10.63	12.08	11.78	11.29	11.45	11.06	11.14	11.70	12.23	11.63	10.73	12.00
Arkansas	10.17	9.55	9.81	9.86	10.55	10.54	10.00	10.15	10.22	10.45	10.86	11.30	10.76	10.87	11.33
California	11.55	11.76	11.65	11.87	12.50	12.43	12.13	11.80	12.21	12.31	12.58	12.99	13.35	13.52	13.92
Colorado	12.05	10.93	10.94	11.51	12.16	12.20	12.33	12.02	11.46	12.17	12.62	12.31	11.69	10.97	13.13
Connecticut	11.78	11.50	11.63	11.38	11.97	11.64	11.36	11.47	11.70	11.89	12.00	12.41	12.84	13.01	13.25
Delaware	11.06	11.27	11.37	11.38	11.24	11.51	11.82	11.29	11.69	11.71	12.04	12.33	12.63	12.21	13.15
Florida	10.52	10.78	10.48	10.34	10.74	10.65	10.59	10.41	10.72	10.86	10.87	11.31	11.52	11.44	11.24
Georgia	10.52	10.54	10.42	10.00	10.38	10.55	10.17	10.25	10.52	10.59	10.66	11.20	11.00	11.09	11.13
Hawaii	13.16	13.05	13.07	13.26	13.61	13.89	14.12	14.12	14.46	14.43	14.41	13.81	13.96	14.74	14.73
Idaho	11.06	11.06	11.10	10.68	11.86	12.01	11.64	11.74	11.35	11.95	12.37	12.83	12.39	11.93	13.48
Illinois	11.61	11.35	11.85	11.43	12.17	11.96	11.90	11.93	12.46	12.17	12.28	12.70	13.47	13.11	13.26
Indiana	11.61	11.35	11.85	11.43	12.17	11.96	11.90	11.93	12.46	12.17	12.28	12.70	13.47	13.11	13.26
Iowa	11.29	11.69	11.94	12.05	12.55	12.36	12.11	12.36	12.11	12.79	13.35	12.80	13.59	13.61	13.34
Kansas	11.35	11.37	11.46	11.43	12.10	12.13	12.65	12.48	13.08	14.04	14.37	14.52	14.28	13.83	14.38
Kentucky	10.65	10.38	10.59	10.71	11.13	11.24	10.57	10.24	10.54	10.69	10.96	11.47	11.32	11.33	11.63
Louisiana	10.17	9.55	9.81	9.86	10.55	10.54	10.00	10.15	10.22	10.45	10.86	11.30	10.76	10.87	11.33
Maine	11.78	11.50	11.63	11.38	11.97	11.64	11.36	11.47	11.70	11.89	12.00	12.41	12.84	13.01	13.25
Maryland	11.06	11.27	11.37	11.38	11.24	11.51	11.82	11.29	11.69	11.71	12.04	12.33	12.63	12.21	13.15
Massachusetts	11.78	11.50	11.63	11.38	11.97	11.64	11.36	11.47	11.70	11.89	12.00	12.41	12.84	13.01	13.25
Michigan	11.58	11.62	11.58	11.56	12.38	12.03	11.66	11.59	11.99	12.03	12.23	12.65	13.20	13.24	13.54
Minnesota	11.58	11.62	11.58	11.56	12.38	12.03	11.66	11.59	11.99	12.03	12.23	12.65	13.20	13.24	13.54
Mississippi	10.17	9.55	9.81	9.86	10.55	10.54	10.00	10.15	10.22	10.45	10.86	11.30	10.76	10.87	11.33
Missouri	11.29	11.69	11.94	12.05	12.55	12.36	12.11	12.36	12.11	12.79	13.35	12.80	13.59	13.61	13.34
Montana	11.06	11.06	11.10	10.68	11.86	12.01	11.64	11.74	11.35	11.95	12.37	12.83	12.39	11.93	13.48
Nebraska	11.35	11.37	11.46	11.43	12.10	12.13	12.65	12.48	13.08	14.04	14.37	14.52	14.28	13.83	14.38

Table6 – continued from previous page

State	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Nevada	12.05	10.93	10.94	11.51	12.16	12.20	12.33	12.02	11.46	12.17	12.62	12.31	11.69	10.97	13.13
New Hampshire	11.78	11.50	11.63	11.38	11.97	11.64	11.36	11.47	11.70	11.89	12.00	12.41	12.84	13.01	13.25
New Jersey	11.04	11.24	11.37	11.38	11.15	11.39	11.75	11.23	11.66	11.72	12.03	12.33	12.64	12.22	13.15
New Mexico	10.30	10.45	10.48	10.63	12.08	11.78	11.29	11.45	11.06	11.14	11.70	12.23	11.63	10.73	12.00
New York	11.78	11.50	11.63	11.38	11.97	11.64	11.36	11.47	11.70	11.89	12.00	12.41	12.84	13.01	13.25
North Carolina	10.74	10.72	11.04	10.38	11.05	11.10	10.37	10.59	10.41	10.45	11.00	11.34	11.68	11.61	12.25
North Dakota	11.35	11.37	11.46	11.43	12.10	12.13	12.65	12.48	13.08	14.04	14.37	14.52	14.28	13.83	14.38
Ohio	11.61	11.35	11.85	11.43	12.17	11.96	11.90	11.93	12.46	12.17	12.28	12.70	13.47	13.11	13.26
Oklahoma	10.29	10.48	10.60	10.58	10.97	11.32	10.76	10.78	10.95	11.50	11.04	11.79	12.01	12.02	12.23
Oregon	12.18	11.77	12.38	12.14	12.45	13.16	12.47	12.58	13.64	13.27	13.79	13.86	14.21	14.49	15.03
Pennsylvania	11.04	11.24	11.37	11.38	11.15	11.39	11.75	11.23	11.66	11.72	12.03	12.33	12.64	12.22	13.15
Rhode Island	11.78	11.50	11.63	11.38	11.97	11.64	11.36	11.47	11.70	11.89	12.00	12.41	12.84	13.01	13.25
South Carolina	10.52	10.54	10.42	10.00	10.38	10.55	10.17	10.25	10.52	10.59	10.66	11.20	11.00	11.09	11.13
South Dakota	11.35	11.37	11.46	11.43	12.10	12.13	12.65	12.48	13.08	14.04	14.37	14.52	14.28	13.83	14.38
Tennessee	10.65	10.38	10.59	10.71	11.13	11.24	10.57	10.24	10.54	10.69	10.96	11.47	11.32	11.33	11.63
Texas	10.29	10.48	10.60	10.58	10.97	11.32	10.76	10.78	10.95	11.50	11.04	11.79	12.01	12.02	12.23
Utah	12.05	10.93	10.94	11.51	12.16	12.20	12.33	12.02	11.46	12.17	12.62	12.31	11.69	10.97	13.13
Vermont	11.78	11.50	11.63	11.38	11.97	11.64	11.36	11.47	11.70	11.89	12.00	12.41	12.84	13.01	13.25
Virginia	10.74	10.72	11.04	10.38	11.05	11.10	10.37	10.59	10.41	10.45	11.00	11.34	11.68	11.61	12.25
Washington	12.18	11.77	12.38	12.14	12.45	13.16	12.47	12.58	13.64	13.27	13.79	13.86	14.21	14.49	15.03
West Virginia	10.65	10.38	10.59	10.71	11.13	11.24	10.57	10.24	10.54	10.69	10.96	11.47	11.32	11.33	11.63
Wisconsin	11.58	11.62	11.58	11.56	12.38	12.03	11.66	11.59	11.99	12.03	12.23	12.65	13.20	13.24	13.54
Wyoming	11.06	11.06	11.10	10.68	11.86	12.01	11.64	11.74	11.35	11.95	12.37	12.83	12.39	11.93	13.48

Notes: I convert nominal AEWRs into real AEWRs by dividing the former by the regional Consumer Price Index for Urban Wage Earners and Clerical Workers (CPI-W). All values are expressed in 2019 dollars.

E Robustness checks testing for effects on employment of unauthorized workers

E.1 Estimates using three alternative definitions of unauthorized workers

TABLE 7: **Impact of AEWRs on the Agricultural Employment of Unauthorized Workers defined in three different ways**

Dependent variable	Mean	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Unauthorized workers [a]	97	-58.746***	-84.237***	-62.169***	-67.521***	-66.446***	-95.147***	-89.041***
		(15.760)	(20.329)	(16.557)	(18.596)	(19.218)	(24.039)	(23.700)
R^2		0.149	0.154	0.161	0.175	0.372	0.168	0.366
Unauthorized workers [b]	88	-59.098***	-80.676***	-61.906***	-66.309***	-65.308***	-89.158***	-83.898***
		(15.187)	(19.228)	(16.361)	(17.204)	(17.765)	(21.660)	(21.507)
R^2		0.143	0.147	0.153	0.170	0.362	0.164	0.357
Unauthorized workers [c]	122	-31.069*	-69.825***	-40.051**	-75.695***	-75.675***	-103.915***	-98.602***
		(17.402)	(23.177)	(19.034)	(21.834)	(22.460)	(28.708)	(27.915)
R^2		0.184	0.192	0.200	0.216	0.395	0.211	0.389
PUMA fixed effects		Yes	Yes	Yes	Yes	Yes	Yes	Yes
Linear time trend			Yes					
Year fixed effects						Yes	Yes	Yes
State-specific time trends				Yes			Yes	Yes
PUMA-specific time trends					Yes			Yes
Observations		34,965	34,965	34,965	34,965	34,965	34,965	34,965

a: Hispanic, noncitizen, 15-45 year olds with a high school education or less

b: Mexican, noncitizen, 15-45 year olds with a high school education or less

c: Mexican, noncitizen, 15-65 year olds with a high school education or less

Notes: Estimation results of the seven models across 2,331 PUMAs in the 49 states, excluding Alaska for the years 2005-2019. Relevant control variables are included in all regressions which consist of the population shares by age group (15-24, 25-34, 35-44, 45-54, 55-64, 65+), by gender (female), by race (White, Black, and Asian), by ethnicity (Hispanics), by educational attainment (high school graduate, some college or higher education), by family income group (less than 25k, 25k-35k, 35k-50k, 50k-75k, 75k-100k, 100k-150k,150k-200k); and the labor force participation rate and the employment rate. Standard errors are clustered at the PUMA level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

E.2 Estimates after controlling for immigration policy

TABLE 8: **Impact of AEWRs on the Agricultural Employment of Unauthorized Workers with Controlling for E-verify**

Dependent variable	Mean	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Unauthorized workers	133	-26.627	-71.620***	-110.796***	-104.913***	-39.501**	-74.498***	-74.097***
		(18.228)	(25.178)	(32.047)	(31.193)	(19.790)	(23.284)	(23.879)
PUMA fixed effects		Yes	Yes	Yes	Yes	Yes	Yes	Yes
Linear time trend			Yes					
Year fixed effects						Yes	Yes	Yes
State-specific time trends				Yes			Yes	Yes
PUMA-specific time trends					Yes			Yes
Observations		34,965	34,965	34,965	34,965	34,965	34,965	34,965

Notes: Estimation results of the seven models across 2,331 PUMAs in the 49 states, excluding Alaska for the years 2005-2019. Relevant control variables are included in all regressions which consist of the population shares by age group (15-24, 25-34, 35-44, 45-54, 55-64, 65+), by gender (female), by race (White, Black, and Asian), by ethnicity (Hispanics), by educational attainment (high school graduate, some college or higher education), by family income group (less than 25k, 25k-35k, 35k-50k, 50k-75k, 75k-100k, 100k-150k,150k-200k); and the labor force participation rate and the employment rate. Standard errors are clustered at the PUMA level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$