The Agricultural Minimum Wage, Guest Workers, and US Workers

SongYi Paik*

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Abstract

American agricultural employers have relied on guest workers but are required to pay them at least the minimum wage, known as the Adverse Effect Wage Rates (AEWRs). Using a border discontinuity approach, I find that the AEWRs led to an increased employment of less-educated agricultural workers, especially for citizen Hispanics but had insignificant effects on other groups of agricultural workers. Further analysis indicates a consistent pattern in the outcomes for hours of work and hourly wages. This suggests that higher AEWRs do not adversely affect American workers and may attract less-educated citizen Hispanics who were previously receiving lower wages. Moreover, higher AEWRs are unlikely to discourage the hiring of guest workers, potentially due to a lack of viable substitution options for employers. While employers can hire more workers, they need to bear higher labor costs.

Keywords: Agricultural employment, Adverse effect wage rate, Guest workers

*Ph.D. Candidate, Applied Economics, University of Minnesota. Email: songyi@umn.edu.

1 Introduction

Since 1986, agricultural employers have been employing guest workers through the H-2A visa program, and their numbers have surged since the early 2010s. Employers hiring guest workers are required to pay all their employees at least the agricultural minimum wage, known as the Adverse Effect Wage Rates (AEWRs). The AEWRs consistently surpass the state minimum wages in all states, averaging 52% higher in 2019.[1] While federal and state minimum wages were established to lift American workers out of poverty, AEWRs were designed to protect the American agricultural workforce from potential low wage rates caused by guest workers. Despite the extensive economic literature on minimum wages, there is a notable gap in the analysis of agricultural minimum wages. Do AEWRs have adverse effects on American agricultural workers in alignment with policy objectives? Do we see the disadvantaged groups among them due to this policy? Do the AEWRs affect farm employers' demand for labor? Numerous questions remain unanswered regarding this policy.

The existing literature in labor economics has extensively examined the effects of federal and state minimum wages on employment. Previous studies have primarily concentrated on workers in lower-wage industries, such as the fast food and restaurant sectors (Card and Krueger (1993); Neumark and Wascher (1995); Neumark and Wascher (2000); Dube et al. (2010)) or on teenagers (Neumark and Wascher (1992); Card (1992); Allegretto et al. (2011); Neumark et al. (2014)) who are most affected by increases in minimum wage. One strand of this literature on the minimum wage suggests a disemployment effect of the minimum wage, asserting that as the cost of labor rises, employers reduce their demand for labor (Neumark

[1] The AEWRs are 70% higher than state minimum wages on average in 2024.

and Wascher (1992); Neumark and Wascher (2000); Orrenius and Zavodny (2008)). Another strand of the literature argues that, due to the inelastic demand for low-wage labor, the minimum wage has minimal to no adverse employment effects (Card (1992); Dube et al. (2010); Zavodny (2000); Giuliano (2013)). These mixed results underscore the significance of industry-specific analysis because employers and employees in each industry respond differently to increases in the minimum wage.

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 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 48 states, excluding Alaska and Hawaii. 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.

This positive employment effect is also reported in previous studies, especially for low-wage industries Card and Krueger (1994); Dube et al. (2010); Wang et al. (2019). As Neumark and Shirley (2022) comment, the disemployment effect is unlikely observed when there are fewer other workers in the group to whom employers could substitute.

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 contribution of this paper is threefold. First, I extend the analysis to the agricultural labor market, which has been relatively underexplored in previous minimum wage studies. Agricultural jobs, as reported by Neumark and Shirley (2022), are characterized by low pay, with approximately 60% of workers in farming earning below $10 in 2010. While existing minimum wage papers often analyze this sector in an extension section or one among many industries (Bailey et al., 2021; Even and Macpherson, 2019; Tauchen, 1981), I conduct a comprehensive analysis of the minimum wage effect specifically within the agricultural industry.

Second, I analyze the AEWRs, which are more relevant as minimum wages when examining the agricultural labor market. Previous studies have analyzed the effects of federal and state minimum wages on agricultural employment instead of AEWRs (Buccola et al., 2012; Gardner, 1972; Kandilov and Kandilov, 2020; Lianos, 1972; Moretti and Perloff, 1999; Smith et al., 2022). However, the share of workers affected by the minimum wage in the farming industry is low, approximately 6% (Neumark and Shirley, 2022). Considering that AEWRs are, on average, more than 50% higher than state minimum wages, it suggests that AEWRs could potentially serve as binding minimum wages and are more pertinent to explore.

Third, I conduct an analysis of AEWRs, a key aspect of ongoing political debates. One perspective argues that AEWRs are excessively high, deterring growers from utilizing the H-2A program and disproportionally impacting small farmers (Bureau, 2023). Advocates of this view contend that guest workers and similar jobs pose minimal competition for American workers, who generally avoid such tasks. They propose that lowering hand-harvest wages would not harm American workers and would enable growers to hire more guest workers. On the opposing side, proponents argue that AEWRs serve to protect farmworkers, including both US workers and guest workers from economically disadvantaged countries (Farmworker justice, 2023). Notably, during the pandemic shutdown in 2020, the Trump Administration proposed freezing AEWRs to assist farmers facing financial losses, but this initiative was halted by judicial intervention. My study provides valuable policy implications for this debatable policy landscape.

The remainder of this paper is organized as follows. Section 2 provides background information about the AEWRs. In Section 3, the empirical framework is presented. Section 4 describes data and provides descriptive statistics. Section 5 presents the empirical results, and Section 6 reports the results of a number of robustness checks. Section 7 concludes with a discussion of the findings and their policy implications.

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 and 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 the 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, the Immigration Reform and Control Act (IRCA) was enacted in 1986. Under this Act, temporary agricultural workers were once again invited to the US with H-2A visas (henceforth guest workers). This visa program has no numerical cap on the issuance of visas annually.

Although guest workers have been an important labor resource in agriculture, they are viewed as an economic threat to American farmworkers. As guest 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 guest and citizen workers. This is known as the Adverse Effect Wage Rate (AEWR). Under the H-2A program, guest 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 guest workers have to pay at least AEWR to them as well as citizen and non-citizen agricultural workers while the employers who do not engage any guest 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 A.

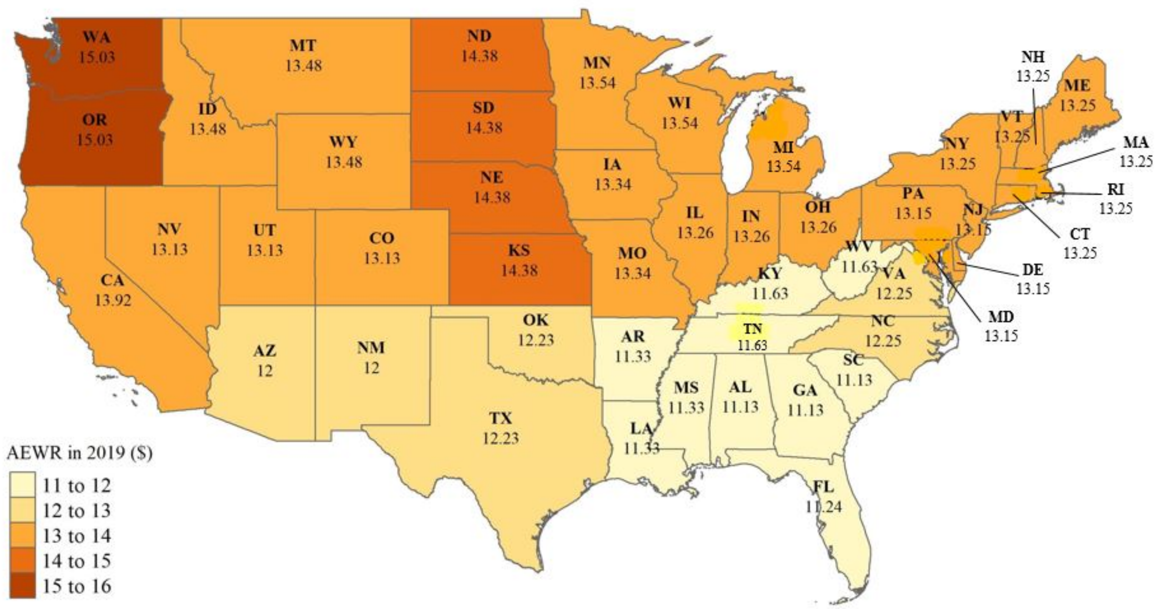


FIGURE 1: Adverse Effect Wage Rates by State, 2019
Notes: Alaska and Hawaii are excluded from the figure.

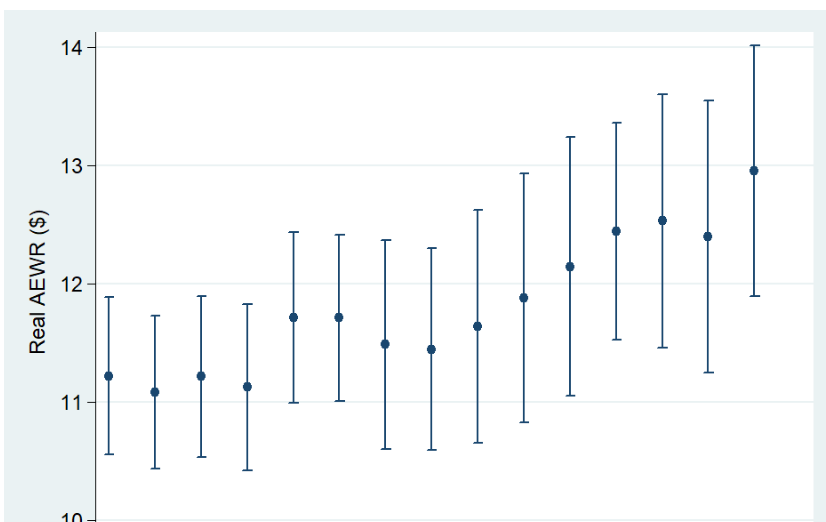


FIGURE 2: Trends in the Adverse Effect Wage Rates, 2005-2019
Notes: Bars represent standard deviation of the mean.

3 Empirical Framework

To estimate the effect of AEWRs on agricultural employment, working hours, and hourly wage, I explore the variation in the AEWRs over time and across states. Specifically, analogous to Dube et al. (2010), the border discontinuity approach is used as follows:

$$y_{ipt} = \alpha + \beta AEWR_{it} + \gamma x_{it} + \delta_i + \phi_{pt} + \epsilon_{ipt} \tag{1}$$

where y_{ipt} represents employment, working hours, and hourly wage for agricultural workers, with each group categorized based on their education level, citizenship, and race/ethnicity in PUMA i within its corresponding PUMA-pair p in year t. $AEWR_{it}$ is the treatment variable (i.e. real adverse effect wage rates) in PUMA i and year t, and x_{it} represents PUMA-year-level control variables. δ_i and ϕ_{pt} denote PUMA and pair-year fixed-effects, and ϵ_{ipt} is an error term.

PUMA-year-level control variables (x_{it}) are incorporated to address PUMA characteristics changing over years, which may be correlated with the employment of agricultural workers and AEWRs. These variables encompass the number of persons distributed by age, gender, race, education attainment, and family income group. In addition, log-transformed variables, including log(employment) and log(population), have been included to further capture relevant aspects of the employment landscape and overall population dynamics.

I also take into account the immigration policies that are potentially correlated with agricultural employment and AEWRs. The E-verify program serves as a good proxy to represent these types of policies by compelling employers to refrain from hiring undocumented workers, who constitute an important source of agricultural labor. This program, applied to both public and private employers, was adopted by 9 states between 2008 and 2012, and I created a dummy variable that is set to 1 if PUMA i is in a state that mandated the use of E-Verify in year t, and 0 otherwise.

The specification includes PUMA and pair-year fixed-effects to account for omitted variable biases induced by local and macroeconomic components that may be correlated with the employment of agricultural workers and AEWRs. The PUMA fixed-effects (δ_i) leave out the correlation between the error term and the treatment variable due to factors that remain constant over years for a given PUMA (e.g., Each PUMA consistently tends to maintain higher wages for agricultural workers, driven by factors such as the high cost of living, historical economic patterns, industry composition, or cultural influences).

The inclusion of pair-year fixed-effects sweeps out all the variation between local areas p, and only uses variation within local areas surrounding a state border. For example, shifts in market demand for specific crops or agricultural products can lead to changes in production and employment patterns across local areas. Events such as wildfires, droughts, or pest outbreaks can also vary over time and have disruptive effects on agricultural production, influencing employment and wage dynamics. Pair-year fixed-effects enable me to take the mean difference of all features within each pair-year group, and thus I use only the variation in AEWRs within each contiguous border PUMA-pair.

Standard errors are clustered at both the state and border segment levels. Within a state, multiple PUMAs exist, potentially leading to non-independent residuals ($E(e_{ipt}, e_{i'p't'}) \neq 0$ where i, $i' \in$ state S). Clustering standard errors at the state level addresses the potential correlation or dependence between PUMAs within the same state.

Due to the sample construction nature, a single PUMA can appear in multiple pairs along a border segment, sharing the state border with several other PUMAs.

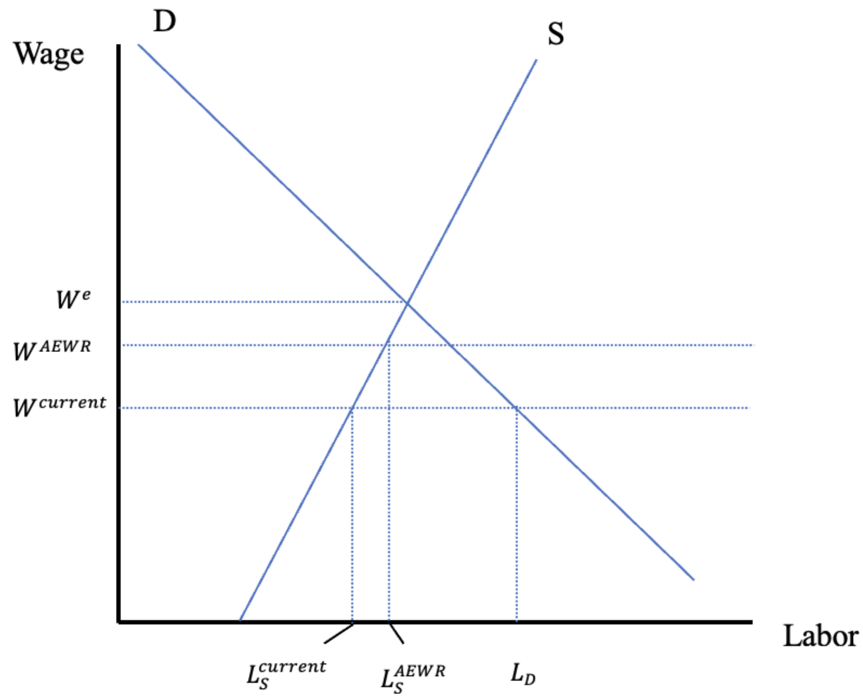
Consequently, there can be a correlation between PUMA-pairs along the same border segment ($E(e_{ipt}, e_{i'p't'}) \neq 0$ where p, $p' \in$ border segment B). Clustering at the border segment level allows for the appropriate adjustment to account for correlation in the residuals.

The coefficient of interest (β) estimates the changes in employment, working hours, or hourly wages in response to a one dollar increase in real AEWR. In the competitive market, a minimum wage set above the equilibrium wage can lead to a decrease in employment ($\beta < 0$) due to a shortage of labor demand and an excess of labor supply.

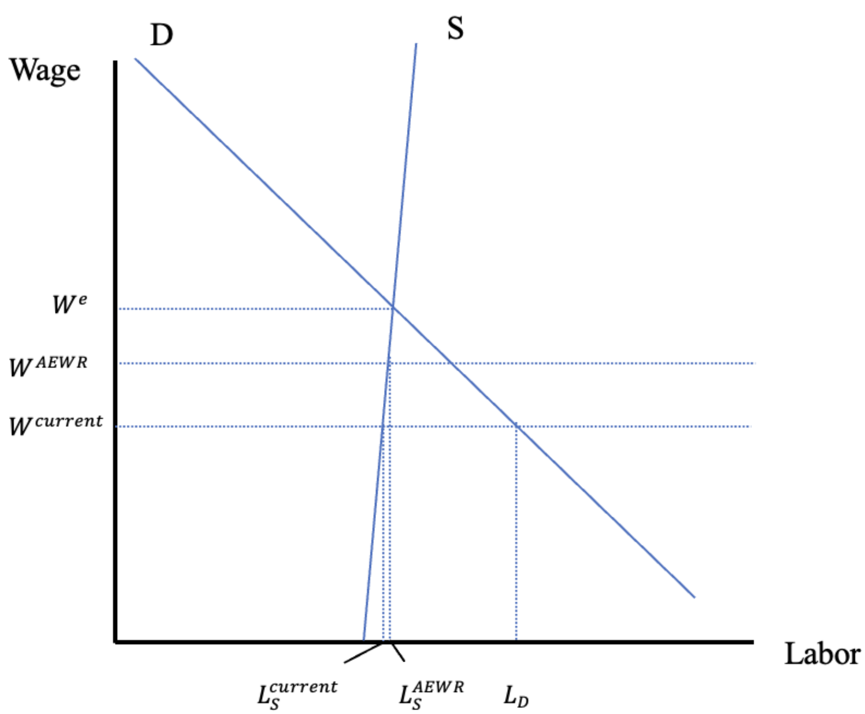
However, the agricultural sector is unlikely to operate in a purely competitive market. Farmers and ranchers often experience labor scarcity, reporting difficulties in finding enough workers available at the required time and location. This suggests that current wages offered by farmers and ranchers are below the reservation wage of workers, indicating that the current wages ($W^{current}$) are below the equilibrium wage (W^e) (see Figure 3). Thus, the difference between the labor demand and supply ($L_D - L_S^{current}$) represents a labor shortage.

Even with the existence of AEWR, which requires employers to pay all workers at least the minimum wage if they hire guest workers, it has not been high enough to attract non-guest workers. Consequently, employers continue to face labor shortages, suggesting that the AEWR is likely set below the equilibrium wage ($W^{AEWR} < W^e$). This result in excess labor demand, even with the existence of AEWR, as the difference between labor demand and supply indicates a shortage ($L_D - L_S^{AEWR}$). This unique agricultural labor market situation leads to the hypothesis that a higher AEWR attracts more workers, increasing their labor supply ($\beta >$ o).

The magnitude of β depends on the elasticity of labor supply. If a particular



(A) Elastic labor supply



(B) Inelastic labor supply

FIGURE 3: Labor supply and demand

Notes: The difference ($L^{AEWR} - L^{current}$) indicates the increased employment due to AEWR.

group of agricultural workers has a relatively elastic labor supply (Figure 3 (A)), an increase in AEWR will result in a relatively large positive coefficient ($L_S^{AEWR} - L_S^{current} > 0$). Conversely, if another group of agricultural workers has an inelastic labor supply (Figure 3 (B)), the increase in AEWR may have little to no impact on their labor supply, resulting in an insignificant coefficient ($L_S^{AEWR} - L_S^{current} \approx 0$).

The first stage of the analysis tests whether AEWRs affect the employment, working hours, and hourly wages of total agricultural workers and less-educated agricultural workers. The former will caputure overall impacts of AEWR on the agricultural labor market while the latter will do the impacts of AEWR on workers who are expected to be affected if their current wages received below the AEWR and it is enough to be attractive to chang their labor supply.

In the second stage of the analysis, I analyze three different groups of agricultural workers: 1) less-educated citizens, 2) less-educated non-citizens, and 3) guest workers. One might argue that farmers and ranchers could either hire more guest workers by reducing the hiring of citizen workers whose wages are higher than those of guest workers or hire more non-citizen workers to avoid employing guest workers and paying the AEWR. Unauthorized workers are also an important workforce in the agricultural sector and are included in the category of non-citizen workers (Fisher and Knutson, 2013; USDA, 2023). If employers face higher penalties for hiring unauthorized workers, they are more likely to continue hiring guest workers. To address substitution effects between workers, the second stage of my analysis investigates whether AEWRs increase or decrease agricultural employment for less-educated citizen workers, non-citizen workers, and guest workers.

In the third stage, I investigate whether specific groups of less-educated citizen workers are disadvantaged due to the AEWR increase. Employers may prefer certain groups of citizen workers based on their characteristics, average wages, and unobserved attributes.

4 Data and Descriptive Statistics

To test for the impact of AEWRs on agricultural labor market outcomes, I use data from the annual 2005-2019 American Community Survey (ACS) and H-2A program data from the Department of Labor. These datasets are supplemented with state-level information on AEWRs obtained from the DOL and Congressional Research Service (CRS) reports.

4.1 Agricultural Employment, Working Hours, and Hourly Wages

The American Community Survey (ACS), accessed through the Integrated Public Use Microdata Series (IPUMS), provides individual-level data collected annually by the US Census Bureau. This nationally representative dataset randomly selects approximately 3.5 million households, covering around 3.1 million individuals each year (US Census Bureau, 2020). While various sources offer data on the US agricultural labor market, such as 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 particularly well-suited for the purposes of this paper for two reasons, as elaborated below.[2]

First, the ACS uses the Public Use Microdata Areas (PUMAs) to capture respondents' residential locations at a more granular geographic level than the state, affording an examination of local variations. PUMAs, designed to encompass no fewer than 100,000 individuals per area (US Census Bureau, 2020), offer a compre-

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

hensive representation of lower geographic locales, with a total of 2,334 PUMAs across 48 states excluding Alaska and Hawaii. It's noteworthy that despite these states also comprising 3,113 counties, PUMAs can effectively capture lower geographic levels, adding an extra layer of granularity to counties, encompassing those with higher populations, and amalgamating those with lower populations.

In contrast to the ACS, both the FLS and NAWS do not provide information on an individual's location at a level of detail lower than the state level. Meanwhile, the CPS does provide data at the county level, but the limited sample size of approximately 100,000 per month (CPS, 2018), restricts its effectiveness in adequately representing individuals engaged in the agricultural sector at the local level.

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 individuals engaged in the agriculture sector into distinct groups, enabling differentiation between citizen and non-citizen workers and by their racial and educational backgrounds.

The outcome variables of interest are the number of agricultural workers employed, the total amount of hours worked in a year, and the hourly wage at the PUMA level. The construction of each outcome variable for distinct groups of agricultural workers, categorized by their citizenship status and race, is as follows.

First, since ACS provides weighted samples, I use the personal weight variable (PERWT) to generate the aggregate and average statistics following the Katz and Murphy (1992) tradition. The PERWT variable indicates how many persons in the US population are represented by a given person. To count the number of agricultural workers employed at the PUMA level for each citizenship-race group, I calculate weighted sums by summing the person weight (PERWT) of each individual employed in the agricultural sector for each group and aggregating the counts for each PUMA i in year t. It contains people aged 16 and older who worked in the previous 12 months as the reference period[3].

Second, the total hours worked for each PUMA in a year are determined as follows. I calculate individual working hours by multiplying the usual weekly hours by the weeks worked in a year. The ACS reports weeks worked in the last 12 months using intervals. Following the approach of Ottaviano and Peri (2008), the median value is selected for each interval to represent the weeks worked. Then, individual working hours are multiplied by the personal weight (PERWT) and summed over all individuals within each PUMA for a given year. I use these aggregated values for total hours worked to measure the total labor supplied to the US agricultural labor market by individuals within each group (Katz and Murphy, 1992).

Third, the average hourly wages are calculated as annual wage and salary incomes divided by the individual working hours as defined above and averaging them for each PUMA in a year using weights, which are determined by multiplying individual working hours by the individual's personal weight. Individual working hours are also used when computing weights to accommodate their contribution to the average hourly wage by their labor supply. The average hourly wages are adjusted to 2019 dollars. A detailed step-by-step description of how each variable has been constructed can be found in Appendix C.

To address concerns regarding measurement error, I employ two additional variables as robustness checks. Rather than using the total hours worked in a year, I employ the mean usual hours worked per week, excluding considerations for weeks in a year to avoid dependence on the median value within their intervals.

[3]The ACS collects data year-round, and the reference timeframe for work and income related variables is the twelve months preceding the month of response (US Census Bureau, 2023).

Likewise, instead of using hourly wages, I utilize yearly wages and salary incomes without dividing them by usual hours per week and the number of weeks in a year. I aggregate wages and salary incomes for agricultural workers within each group in the PUMA and for a given year.

4.2 Guest Workers through the H-2A Visa Program

I use data on the actual number of guest workers employed in the agricultural sector through the H-2A visa program for the years 2006-2019. This data is obtained from the Department of Labor, Office of Foreign Labor Certification (DOL-OFLC). Including this group of workers in my analysis of the agricultural labor market is essential for two primary reasons: 1) Employers seeking to substitute for citizen or non-citizen workers can partially fill positions with guest workers, and 2) the influx of guest workers has experienced a significant increase over the past decade, as depicted in Figure 4. In 2019, the number of guest workers reached 261,383, marking a 3.5-fold increase compared to the figure in 2010. A detailed description of the data, the cleaning procedure, and the conversion of zip codes in the OFLC data to PUMA codes is provided in Appendix E.

4.3 Adverse Effect Wage Rates

The AEWR data, collected from the DOL and Congressional Research Service (CRS) [4], represents a nominal hourly wage. To account for inflation, adjustments are made using the CPI99 variable in the ACS dataset, denoting the Consumer Price Index for all urban consumers (CPI-U) by the Bureau of Labor Statistics. This con-

[4] 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)

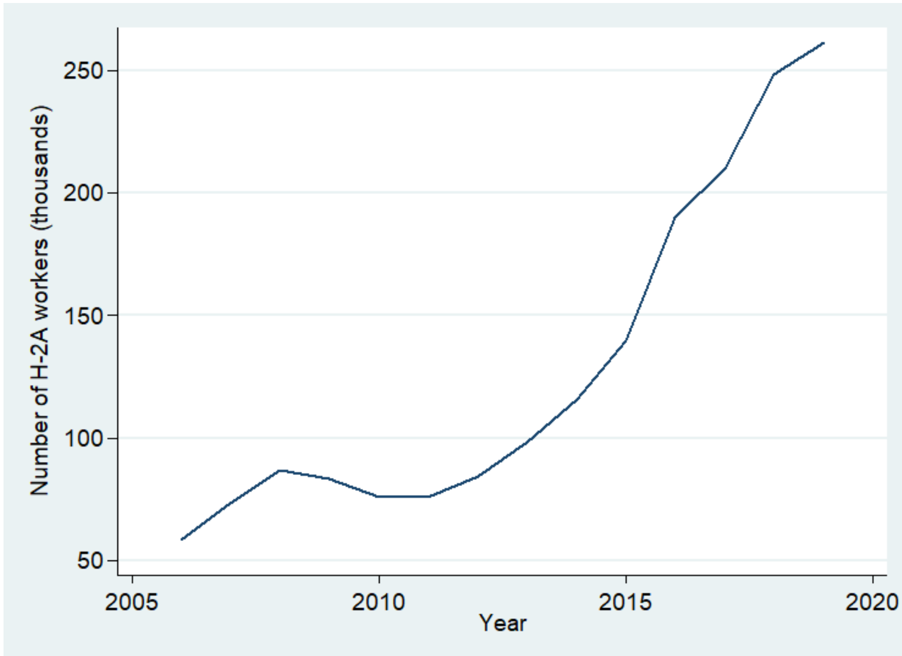


FIGURE 4: H-2A positions certified in the US, 2006-2019

version to constant 1999 dollars is achieved by multiplying AEWRs by CPI99. For conversion to constant 2019 dollars, a multiplier of 1.535, as suggested in IPUMS, is applied. Consequently, the real values of AEWRs are expressed in terms of 2019 dollars. The data indicates an average AEWR of $11.83 (standard deviation = 1.02) for the years 2005-2019.

4.4 Other Control Variables

Continuing to use the ACS data source, I include a broad set of PUMA-level demographic and socioeconomic covariates. It aims to control the effects of other factors that may influence agricultural employment and AEWRs. To address labor market conditions, I include the log of the number of employed persons and the log of the population at the PUMA level in a given year. In addition, to control for demographics and socioeconomic composition, I include population shares by age, gender, race, educational attainment, and family income groups.

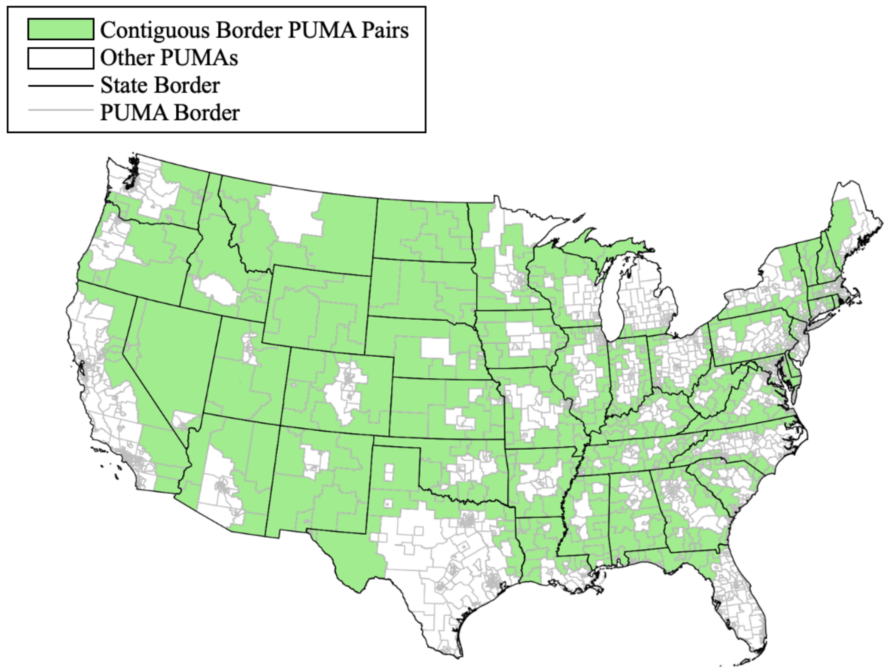
I also incorporate the immigration policy variable into my analysis. Given that undocumented workers constitute a significant portion of farm laborers, stringent immigration policies can impact the demand and supply of agricultural labor (Charlton and Kostandini, 2021; Kostandini et al., 2014). Previous studies have highlighted the influence of the E-Verify immigration policy, which mandates private employers to verify their workers' eligibility to work in the US. This policy has been shown to exacerbate local farm labor shortages (Lim and Paik, 2023). Consequently, I include a dummy variable which is one if a state implemented the E-Verify policy for private employers in a given year. The implementation dates of E-Verify mandates are obtained from the National Conference of State Legislatures.[5] As of 2019, two states (AZ and MS) implemented E-Verify since 2008, one state (UT) since 2010, and six states (GA, TN, SC, LA, AL, NC) since 2012.

4.5 Sample Construction

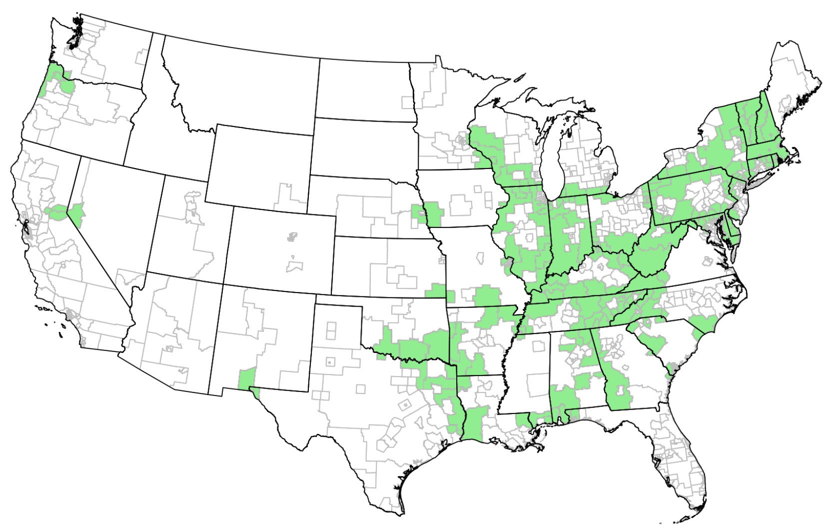
The sample comprises all contiguous PUMA-pairs that straddle a state border and have continuous data available for the years 2005-2019. Among the 2,334 PUMAs in the contiguous United States, 357 are located along a state boundary. Figure 5 (A) displays the locations of the 357 PUMAs that lie along a state border, resulting in 451 distinct PUMA-pairs.

One potential issue with using all PUMAs lying on the state border is that a contiguous PUMA may not represent a suitable control group for its cross-state counterpart when substantial differences exist within the PUMA-pair due to the large distance between them. As shown in Figure 5 (A), some of the border PUMAs

[5] The data is available from https://www.ncsl.org/documents/immig/StateActions_Everify.pdf.



(A) All PUMA-pairs along the state border



(B) PUMA pairs with PUMA centroids no greater than 80 miles apart

FIGURE 5: Contiguous border PUMA-pairs in the United States, 2005-2019
Notes: Alaska and Hawaii are excluded from both the analysis and the map because these states do not share borders with other states. Figure (B) drops nine states (Arizona, Colorado, Idaho, Maine, Montana, North Dakota, South Dakota, Utah, Wyoming).

in the Western and Midwestern parts of the country are much larger in size and cover large geographic areas. For example, PUMAs in Wyoming, North Dakota, and South Dakota states are all indicated to be along the state border.

The issue of having a large PUMA size arises from two main reasons. First, the determination of PUMA boundaries is contingent upon population distribution. In states with sparse populations, the number of PUMAs is reduced, potentially resulting in the absence of PUMAs encompassed by others. Consequently, all PUMAs in such states are considered to be along the state border. Second, PUMA codes provided by IPUMS (CPUMA0010) have a slightly larger geographical unit due to the harmonization process between PUMA codes before and after 2012. The Census Bureau periodically redraws PUMA boundaries every 10 years based on updated population data from the decennial census (US Census Bureau, 2021). The 2012 ACS data files were the first to include PUMAs defined using the 2010 Census data. Owing to discrepancies between PUMA codes across sample years, IPUMS created CPUMA0010 by aggregating one or more 2010 Census PUMAs.

The question may arise as to whether estimates derived from such contiguous PUMAs genuinely reflect a local context. To address this concern and avoid instances where the geographic centroids of PUMAs in such pairs are situated several hundred miles apart, I exclude PUMAs whose centroids have a distance of more than 80 miles (see Figure 5 (B)). This criterion preserves approximately 48 percent of the sample dropping nine states (Arizona, Colorado, Idaho, Maine, Montana, North Dakota, South Dakota, Utah, Wyoming). The selection of the distance cutoff involves a trade-off between similarity and error variance. A lower distance cutoff selects PUMA-pairs in close proximity with greater similarity, but this choice results in fewer pairs and higher error variance. To demonstrate the robustness of my results against the choice of distance cutoff, Appendix Tables A4 to A6 present key findings with cutoffs ranging between 50 and 100 miles, as well as all PUMA-pairs along the state border without restricting cutoffs. Tests for the representativeness of the main sample are also conducted and explained in Section 6.1.

4.6 Summary Statistics

The main sample consists of all contiguous PUMA-pairs along a state boundary where the centroid distance between the pair is 80 miles or below. It includes 215 PUMA-pairs with unique 246 PUMAs in 39 states. Using these PUMA-pairs, I create a balanced panel for 15 years (2005-2019), providing 6,450 observations.

Table 1 presents descriptive statistics for dependent and treatment variables using the main sample over 15 years. It presents the estimated average numbers of workers, total annual hours of work, and hourly wages in the agriculture sector, including subgroups by citizenship status and race/ethnicity, as well as AEWRs. The average PUMA-pair-year reports 1,750 workers in the agricultural sector, with 1,168 workers being less-educated (67 percent). Among the less-educated workers, an average of 1,014 workers (87 percent) are citizen workers. Among them, 927 workers are non-Hispanic Whites (91 percent), 27 workers are non-Hispanic Blacks (3 percent), 15 workers are from non-Hispanic other race groups (1 percent), and 45 workers are Hispanic (4 percent). On average, each PUMA-pair has a total of 111 guest workers per year. Maps illustrating the variation of employment levels by PUMA in 2019 are available in Appendix D.

TABLE 1: **Descriptive Statistics for dependent and treatment variables using PUMA-pairs with an 80-mile distance cutoff, 2005-2019**

Dependent Variables	Mean	Std. Dev.	Min	Max
Employment				
Total agricultural workers	1,750	2,177	0	16,312
Less-educated	1,168	1,441	0	11,072
Non-citizen	154	366	0	5,053
Citizen	1,014	1,289	0	9,718
White	927	1,225	0	9,486
Black	27	120	0	2,744
Other	15	59	0	1,021
Hispanic	45	125	0	1,956
Guest workers	111	275	0	4,751
Total annual hours of work				
Total agricultural workers	3,780,658	4,774,319	0	36,100,000
Less-educated	2,500,979	3,195,901	0	24,400,000
Non-citizen	303,668	761,290	0	12,100,000
Citizen	2,197,311	2,892,541	0	21,100,000
White	2,026,894	2,780,902	0	20,900,000
Black	49,845	244,011	0	5,677,244
Other	31,367	137,535	0	2,320,245
Hispanic	89,205	264,396	0	4,748,100
Hourly wage				
Total agricultural workers	19(21)	26	0	794
Less-educated	16(18)	23	0	1,364
Non-citizen	5(13)	13	0	351
Citizen	16(18)	24	0	1,364
White	16(19)	25	0	1,364
Black	2(16)	8	0	204
Other	2(19)	15	0	1,012
Hispanic	3(15)	8	0	125
Treatment Variable				
AEWR	11.798	0.867	9.611	15.042
Observations	6,450			

Notes: Summary statistics are provided for 215 PUMA-pairs in the 39 states. The numbers in parentheses for the hourly wage dependent variable represent the mean, excluding PUMAs in which there are no corresponding workers available. For the 'Guest workers' variable, there are 6,020 observations for the years 2006-2019, sourced from the Department of Labor (DOL). The remaining variables are from the American Community Survey (ACS).

In line with the employment trend, the total annual hours of work exhibit a similar relative magnitude among subgroups of agricultural workers. Among less-educated agricultural workers, the total supply of labor is predominantly contributed by citizen non-Hispanic Whites.

Notably, the average hourly wages differ across each group of agricultural workers. The hourly wage, enclosed in parentheses, represents the mean hourly wage, excluding PUMAs that did not report having a specific group of agricultural workers. As expected, less-educated agricultural workers were paid lower wages compared to all agricultural workers. Among less-educated agricultural workers, non-citizen workers earned $13 per hour, significantly less than the $18 earned by citizen workers. Among citizen workers, Hispanics received the lowest average hourly wage at $15.

Figure 6 illustrates a consistent upward trend in the average number of less-educated agricultural workers over time. This pattern is similarly reflected in the overall employment of hired farmworkers, as evidenced by data from QCEW, CPS, and ACS (USDA, 2023). The growth in less-educated agricultural workers can be primarily attributed to the increasing numbers of Hispanic citizen workers and guest workers invited to the US, as depicted in Figure 4. In contrast, there has been a decline in both non-citizen workers and non-Hispanic White citizens. Appendix Table A3 provides detailed summary statistics for all control variables.

5 Results and Discussion

The outcome and treatment variables are represented at the level without any logarithmic transformation (e.g., the number of agricultural workers, real AEWR in 2019 dollar terms). In contrast to the traditional approach of transforming outcome variables (such as log(employment)) and treatment variables (log(minimum

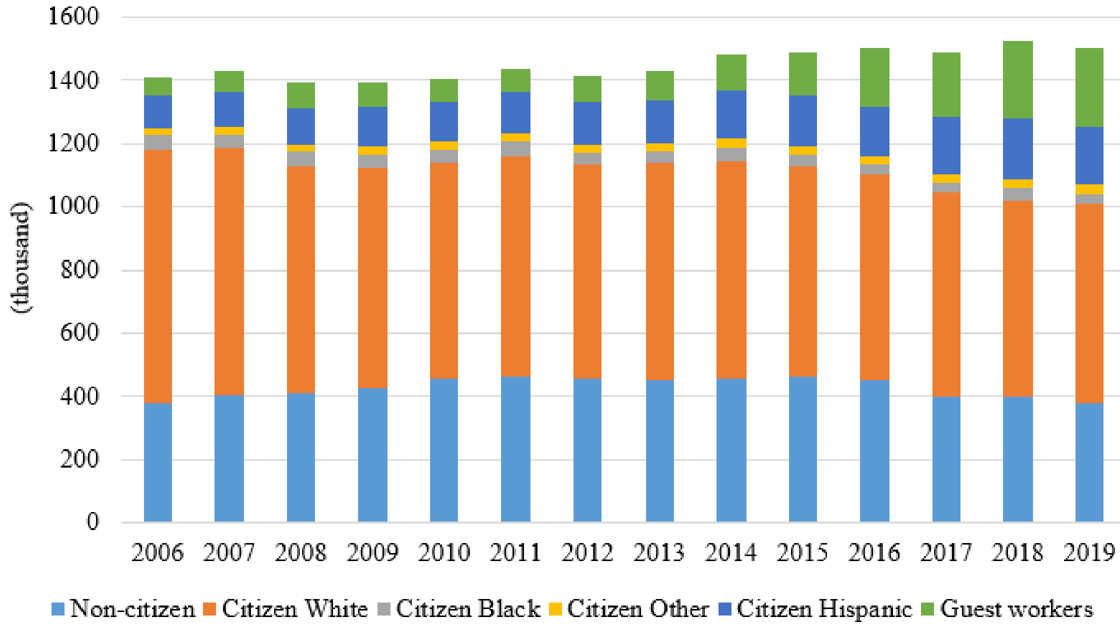


FIGURE 6: Number of less-educated agricultural workers (in thousands), 2006-2019

wages)) in the minimum wage literature (Allegretto et al., 2011; Dube et al., 2010; Neumark et al., 2014) and reporting the results as elasticities, I employ the level primarily due to the presence of zero values in the outcome variable. It is not feasible to transform zero into a logarithmic form as it results in negative infinity. The occurrence of zero values in the outcome variable is due to certain groups of agricultural workers not residing in all PUMAs along the state border, or they were not included in the sampling for the ACS.

I report estimated coefficients obtained from Equation 1 as well as estimated elasticities at means, which are equal to $\frac{\partial y}{\partial AEWR} * \frac{AEWR}{y} = \beta * \frac{AEWR}{y}$. These can be computed by taking the product of β and the mean of the real AEWR and dividing it by the mean of the relevant dependent variable. This approach facilitates easier interpretation by quantifying the economic significance of my results.

The following sections report results and are organized as follows: Section 5.1 presents regression results for employment, working hours, and hourly wages of all agricultural workers and those with less-educated workers. Section 5.2 reports regression estimates of three groups: less-educated citizen workers, less-educated non-citizen workers, and guest workers. Section 5.3 shows estimated results for four groups of less-educated citizen workers: 1) non-Hispanic White, 2) non-Hispanic Black, 3) non-Hispanic other races, and 4) Hispanic.

5.1 Total Agricultural Workers and Those with Less Education

Table 2 shows that the real AEWR is positively associated with the employment, working hours, and hourly wages of all agricultural workers, but this relationship is not statistically significant. The category of total agricultural workers encompasses all individuals involved in the agricultural sector, including managers, equipment operators, and truck drivers, whose hourly wages are typically higher than those of farmworkers. As evident in Table 1, the mean hourly wages for total agricultural workers amount to \$21, significantly exceeding the mean AEWR of \$11.8. Consequently, the AEWR demonstrates no causal effect on the employment, working hours, and hourly wages for overall agricultural workers.

Within the agricultural sector, an increase in the real AEWR is positively correlated with both the employment and working hours of less-educated workers, and this correlation is statistically significant at the 10 percent level. Specifically, a one-dollar increase in real AEWR corresponds to an average increase of 105 less-educated workers. In other words, a 1-percent rise in real AEWR is associated with a 1.065 percent increase in the employment of less-educated workers. Similarly, a one-dollar increase in real AEWR results in a total annual working hours increase of 251,039 for less-educated workers, with an AEWR elasticity of 1.184 that is statistically significant. This outcome suggests that a higher AEWR attracts less-

TABLE 2: **Impact of AEWRs on the employment, working hours, and hourly wages of total agricultural workers and those with less education**

	Employment		Working hours		Hourly wages	
	(1)	(2)	(3)	(4)	(5)	(6)
	β	elasticity	β	elasticity	β	elasticity
Total agricultural workers						
AEWR	131.344	0.886	287,108	0.896	0.676	0.412
	(91.737)	(0.619)	(210,632)	(0.657)	(2.504)	(1.528)
R^2	0.970		0.960		0.540	
Less-educated agricultural workers						
AEWR	105.376*	1.065*	251,039*	1.184*	-2.897	-2.168
	(54.683)	(0.552)	(140,045)	(0.661)	(2.627)	(1.966)
R^2	0.950		0.940		0.550	
PUMA FE	Y	Y	Y	Y	Y	Y
Pair-year FE	Y	Y	Y	Y	Y	Y
N			6,450			

Notes: Estimation results are provided for 430 PUMA-pairs in the 39 states for the years 2005-2019. The odd columns display the estimated coefficients, while the even columns show the estimated elasticities at means. Relevant control variables are included in all regressions which consist of the population by age group (0-14, 15-24, 25-34, 35-44, 45-54, 55-64), by gender (female), by race (White, Black), by educational attainment (less than high school, high school graduate), by family income group (less than 25k, 25k-35k, 35k-50k, 50k-75k, 75k-100k, 100k-150k,150k-200k), and E-Verify immigration policy implementation in both public and private sectors, log(employment) and log(population). Standard errors are clustered at both the state and border segment levels in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

educated workers, whose wages are more affected by the AEWR increase, to enter the agricultural labor market and increase their working hours, while employers bear higher labor costs.

As robustness checks, Appendix Table A4 presents the estimated results, including all PUMA-pairs along the state border and restricting PUMA-pairs whose centroids have a distance of less than 100, 90, 80, 70, 60, or 50 miles. Although the statistically significant positive employment and working hours effects for less-educated agricultural workers are observed when the distance cutoff is set at 80 and 70 miles, the consistent positive sign holds across all distance cutoffs.

5.2 Less-Educated Citizen, Non-citizen, and Guest Workers

Table 3 presents estimation results for three groups of less-educated agricultural workers: citizens, non-citizens, and guest workers. The findings reveal that a higher AEWR positively influences the employment of less-educated citizen workers. Specifically, a one-dollar increase in real AEWR results in a rise of 96 less-educated citizen workers, displaying an elasticity of 1.114. If an increase in AEWR has a spillover effect on wages for a specific subgroup of less-educated citizens, it may incentivize them to enter the agricultural labor market. To further discern the specific impact among less-educated citizen workers based on their race/ethnicity, the analysis is detailed in the next Section 5.3.

An increase in real AEWR has a positive impact on the working hours of less-educated citizen workers, but it is only statistically significant at the 10 percent level. Also, this result lacks significance across samples that use different cutoffs between PUMA-pairs. In addition, the AEWR has no impact on hourly wages for this group.

TABLE 3: **Impact of AEWRs on the employment, working hours, and hourly wages of less-educated citizen, non-citizen, and guest workers**

	Employment		Working hours		Hourly wages	
	(1)	(2)	(3)	(4)	(5)	(6)
	β	elasticity	β	elasticity	β	elasticity
Less-educated citizen workers						
AEWR	95.767**	1.114**	230,450*	1.237*	-2.757	-2.027
	(45.767)	(0.532)	(117,137)	(0.629)	(2.642)	(1.943)
R2	0.950		0.940		0.550	
Less-educated non-citizen workers						
AEWR	9.609	0.738	20,590	0.800	-0.688	-1.664
	(32.039)	(2.461)	(65,085)	(2.529)	(1.160)	(2.807)
R2	0.810		0.800		0.600	
Guest workers						
AEWR	-20.019	-2.138				
	(35.182)	(3.758)				
R2	0.940					
PUMA FE	Y	Y	Y	Y	Y	Y
Pair-year FE	Y	Y	Y	Y	Y	Y
N			6,450			

Notes: The estimation results are reported for 430 PUMA-pairs in the 39 states, spanning the years 2005-2019. However, the results for guest workers only cover the years 2006-2019 due to the unavailability of data for the year 2005. The odd columns display the estimated coefficients, while the even columns show the estimated elasticities at means. Relevant control variables are included in all regressions which consist of the population by age group (0-14, 15-24, 25-34, 35-44, 45-54, 55-64), by gender (female), by race (White, Black), by educational attainment (less than high school, high school graduate), by family income group (less than 25k, 25k-35k, 35k-50k, 50k-75k, 75k-100k, 100k-150k,150k-200k), and E-Verify immigration policy implementation in both public and private sectors, log(employment) and log(population). Standard errors are clustered at both the state and border segment levels in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

The AEWR shows no significant impact on less-educated non-citizen workers. Despite positive coefficient signs for their employment and working hours, statistical significance is lacking. An argument might arise that employers hire more non-citizen workers to avoid employing guest workers and, consequently, evade paying at or above the AEWR. A counterargument is that employers may seek to avoid hiring non-citizen workers, despite being paid lower wages, due to stringent immigration policies. Approximately 93 percent of non-citizen workers are likely undocumented, according to the proxy used by Amuedo-Dorantes and Bansak (2012), Bohn et al. (2014), and Good (2013), estimating unauthorized workers who are non-citizen, Hispanic, aged 15–65, and possess high school education or less.

As demonstrated in previous studies, immigration enforcement policies tend to reduce labor supply and have negative impacts on labor shortages (Charlton and Kostandini, 2021; Devadoss and Luckstead, 2018; Kostandini et al., 2014; Lim and Paik, 2023). Employers may also choose to avoid hiring undocumented workers by offering higher wages to authorized workers, especially if there's a risk of detection. As shown in Table 1, the mean hourly wages for less-educated non-citizen workers stand at \$13, whereas it is \$15 for less-educated Hispanic citizen workers and \$12 for guest workers. Employers might opt for authorized workers by offering slightly higher wages, ranging from \$1 to \$2 per hour, ensuring compliance with immigration and labor laws.

Results for guest workers indicate that an increase in AEWR reduces the number of guest workers, but the effect is statistically insignificant. The anticipated negative sign aligns with employers' inclination to avoid hiring guest workers to evade higher wage payments. However, the lack of statistical significance suggests that employers cannot substantially reduce the number of guest workers due to a lack of viable alternative ways to substitute them.

Appendix Table A5 presents the robustness checks for the results obtained in Table 3 by using different distance cutoffs for PUMA-pairs included in the samples. The evidence from the sample for PUMA-pairs with a distance of less than 80 miles is consistent with the findings from the samples for all PUMA-pairs along the state border, as well as those for PUMA-pairs with distances less than 100, 90, 70, 60, and 50 miles.

5.3 Less-Educated Cititzen Workers by Race/Ethnicity

In Section 5.2, I find a positive impact of AEWR on the employment of less-educated citizen workers. Do the AEWRs increase the employment of these workers differently by their race and ethnicity? Table 4 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.

The AEWR shows no significant impact on less-educated White, Black, and other citizen workers. While it positively affects employment and working hours for White citizen workers, these effects are only statistically significant at the 10 percent level and only significant for the sample of PUMA-pairs whose distance is below 80 miles (see Appendix Table A6).

On the other hand, the employment and working hours effects for less-educated Hispanic citizen workers are both positive and significant at the 5 and 1 percent levels, respectively. A one percent increase in AEWR corresponds to a 5.989 percent increase in employment and an 8.140 percent increase in working hours for this group. This trend remains consistent across various samples with different settings for PUMA-pairs distances, as indicated in Appendix Table A6.

The increased hourly wages resulting from the higher AEWR play a role in attracting less-educated Hispanic citizen workers. These workers can serve as an alternative option for employers as they are paid lower wages compared to other groups of citizen workers. As shown in Table 1, the mean hourly wage for less-educated Hispanic citizen workers is $15, while non-Hispanic White, non-Hispanic

Black, and non-Hispanic other race group workers earn \$19, \$16, and \$19, respectively. Opting to hire Hispanic citizen workers also enables employers to avoid paying at least the AEWR, particularly if they choose not to hire guest workers.

TABLE 4: **Impact of AEWRs on the employment, working hours, and hourly wages of less-educated citizen workers by their race/ethnicity**

	Employment		Working hours		Hourly wages	
	(1)	(2)	(3)	(4)	(5)	(6)
	β	elasticity	β	elasticity	β	elasticity
White citizen workers						
AEWR	79.807*	1.016*	183,938*	1.071*	-2.763	-2.084
	(41.683)	(0.531)	(108,584)	(0.632)	(2.658)	(2.005)
R^2	0.950		0.950		0.550	
Black citizen workers						
AEWR	-3.799	-1.671	-9,988	-2.364	0.583	3.543
	(8.362)	(3.678)	(17,207)	(4.073)	(0.683)	(4.155)
R^2	0.850		0.840		0.630	
Other citizen workers						
AEWR	-3.083	-2.357	-5,048	-1.899	-1.074	-6.762
	(5.057)	(3.867)	(10,304)	(3.875)	(1.571)	(9.893)
R^2	0.670		0.650		0.550	
Hispanic citizen workers						
AEWR	22.842**	5.989**	61,549***	8.140***	1.705*	6.150*
	(8.718)	(2.286)	(18,709)	(2.474)	(0.875)	(3.156)
R^2	0.670		0.650		0.620	
PUMA FE	Y	Y	Y	Y	Y	Y
Pair-year FE	Y	Y	Y	Y	Y	Y
N			6,450			

Notes: The estimation results are reported for 430 PUMA-pairs in the 39 states, spanning the years 2005-2019. The odd columns display the estimated coefficients, while the even columns show the estimated elasticities at means. Relevant control variables are included in all regressions which consist of the population by age group (0-14, 15-24, 25-34, 35-44, 45-54, 55-64), by gender (female), by race (White, Black), by educational attainment (less than high school, high school graduate), by family income group (less than 25k, 25k-35k, 35k-50k, 50k-75k, 75k-100k, 100k-150k,150k-200k), and E-Verify immigration policy implementation in both public and private sectors, *log*(employment) and *log*(population). Standard errors are clustered at both the state and border segment levels in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

6 Robustness Tests

6.1 Sample Robustness

To confirm the representativeness of the sample, I conduct four different tests. First, I check whether the ACS data including all PUMAs in 48 states are comparable to the Census of Agriculture report. Appendix Table A10 displays the number of workers hired in the agricultural sector for each group in 2017 for all PUMAs in 48 states. The sum of total agricultural workers and guest workers obtained from the ACS and DOL-OFLC is 2,117,282. According to the 2017 Census of Agriculture report (USDA, 2019), the number of hired farm laborers in 48 states was 2,409,045. Although this figure is slightly higher than the hired farm laborers obtained from the ACS and DOL-OFLC, the ACS data still proves to be a good representation of agricultural workers. The discrepancy may be attributed to the Census of Agriculture including paid family members, while some of those were not counted in the ACS.

Second, one could raise concerns that the main sample (PUMA-pairs with an 80-mile distance cutoff) may exhibit systematic differences from all PUMAs in the 48 states. To assess the representativeness of the main sample in comparison to the total 2,334 PUMAs in the contiguous United States, I conduct a comparison of demographic and socioeconomic characteristics using control variables. Appendix Table A11 displays the population share for each variable. The contiguous border PUMA-pair sample exhibits a higher population than the overall PUMA sample. Nevertheless, both samples demonstrate similarities in the distribution of persons by age, gender, race, education attainment, family income, and employment.

Third, I employ two approaches to count guest workers at the PUMA level. The guest worker data does not provide PUMA information corresponding to the locations where employers operate their farms but includes the employer's address with a postal code. To address this limitation, I use two approaches for converting zip codes to CPUMA0010 codes: 1) using crosswalk files obtained from the Missouri Census Data Center and IPUMS, and 2) employing ArcGIS to map the zip codes for conversion to CPUMA0010. The detailed steps for counting guest workers using these two approaches and regression results are available in Appendix E. The regression analysis for guest workers, conducted with data obtained from both approaches, does not alter my results.

Fourth, I restrict the main sample to PUMA-pairs that have different AEWRs within the pair in any year between 2005 and 2019. As some states share the same AEWRs, certain PUMA-pairs have no AEWR differences. To assess the potential impact of excluding those PUMA-pairs on my results, I estimate Equation 1 using two samples. The odd columns 1, 3, and 5 in Appendix Table A12 use the main sample, including PUMA-pairs with distances of 80 miles and below, while the even columns 2, 4, and 6 use its subsample, consisting of PUMA-pairs with AEWR differences at any point in time between 2005 and 2019. The former includes 215 PUMA-pairs, while the latter includes 114 PUMA pairs, dropping 47 percent of the main sample.

The statistically significant results observed in the main sample remain consistent when using the subsample. However, the estimated elasticities at means are larger for the subsample, suggesting that the subsample experiences a more pronounced treatment effect compared to the average treatment effect for the main sample. Thus, the results from the main sample are considered more conservative.

6.2 Cross-Border Spillovers

While I find positive effects on employment, working hours, and hourly wages for less-educated Hispanic citizen workers, spillovers between the treatment and control PUMAs could be influencing my results. Such spillovers may arise when either the labor or agriculture market within a PUMA-pair is interconnected.

In one scenario, the amplification effect may exist (Dube et al., 2010). Let's consider a PUMA-pair along a state border consisting of PUMA i in state s and PUMA j in state n. An increase in AEWR in state s results in a positive employment effect in all PUMAs in state s. Individuals working in PUMA j in state n may seek higher wages in PUMA i and migrate to it, potentially leading to a disemployment effect on PUMA j. Comparing the border PUMA-pair i and j may overestimate the true effect. This suggests that the positive employment effects will likely be stronger in PUMA i along the state border than in the interior PUMAs of the state s that experiences the AEWR increase.

In another scenario, the efficiency wage model comes into play, and the attenuation effect may exist (Dube et al., 2010). The positive employment effect in PUMA i along the state border with a higher AEWR exerts pressure on employers in PUMA j across the border to partly match the wage increase to retain workers. In this case, the hourly wage in PUMA j can also increase, leading to an increase in employment in both PUMA i and j. If this is the case, comparing border PUMAs may underestimate the true effect, and the observed employment effect in PUMA i in state s could be lower than in the interior PUMAs in the same state, which is called the attenuation effect.

To evaluate the potential impact of border spillovers, I analyze the effects on PUMAs located at the border and compare them to those in the state's interior, which are less influenced by such spillovers. I then estimate the spatial differences specification as follows:

$$\left(y_{ipt} - \overline{y_{st}}\right) = \alpha + \beta AEWR_{it} + \delta\left(X_{ipt} - \overline{X_{st}}\right) + \delta_i + \tau_{pt} + \epsilon_{it} \tag{2}$$

Here, $\overline{y_{st}}$ represents the average employment (working hours, hourly wage) of interior PUMAs in state s in year t. Given that interior PUMAs are relatively farther from PUMA j in state n, workers in PUMA j may not migrate to those interior PUMAs, or they may not consider labor market conditions in those PUMAs as a reference point. Thus, interior PUMAs serve as a control group for PUMA i in state s.

To test for any spillover effects, I compare the employment in the PUMA along the border with the average employment in interior PUMAs by subtracting the latter from the former. The same subtraction is conducted for each control variable and included in the equation. The coefficient β measures the effect of a change in AEWR on a PUMA along the border relative to the interior PUMAs, in relation to the other side of the border.

I test the null hypothesis that $H_0 : \beta = 0$ versus the alternative hypothesis that $H_0 : \beta \neq 0$. Rejecting the null hypothesis confirms the existence of spillover effects: $\beta > 0$ implies the existence of the implication effect while $\beta < 0$ implies the attenuation effect.

Appendix Tables A7, A8, and A9 present spillover estimates for employment, working hours, and hourly wages, respectively. As some border PUMAs do not have interior PUMAs to compared to, the sample composition changes when examining interior PUMAs. To address this, I provide estimation results for my main sample using an 80-mile distance cutoff (column 1) and a subsample (column 2) where border PUMAs can be matched with state interiors; this subsample excludes Delaware and Vermont border segments. The results are reported in estimated elasticities at means, and both columns 1 and 2 present results estimated from Equation 1. In addition, using the subsample, the estimated results from Equation 2 are reported in column 3.

When I restrict the main sample to PUMAs in states that have interior PUMAs, the employment effect is slightly smaller for less-education agricultural workers, less-educated citizen workers, and White citizen workers and slightly bigger for Hispanic citizen workers. The spillover measures (column 3) are not statistically significant. Likewise, there are marginal differences in the effects on working hours and hourly wages between the main sample (column 1) and the spillover sample (column 2), but the spillover effects are not statistically significant. In summary, I do not find any evidence that employment, working hours, and hourly wages are contaminating my local estimates.

The conclusion that farmworkers are reluctant to migrate is consistent with findings from previous studies. For instance, Fan et al. (2015) reported a 30 percentage point drop in the migration rate of hired agricultural workers within the US, from 53% in 1998 to 23% in 2009. Green et al. (2003) and Luo and Guan (2022) also found that welfare benefits, such as unemployment insurance and Medicaid, have contributed to a decrease in migration across states.

6.3 Falsification Tests Using Another Sector

To evaluate the validity of the model, I conduct falsification tests using a sector expected to be not affected by AEWRs. Specifically, I examine professional, scientific, and technical service sector (NAICS code = 54, hereinafter referred to as professional service sector), which is less likely to experience workers switching their jobs to the agricultural sector.[6]

As illustrated in Appendix Table A13, the mean hourly wages for all workers in the professional service sector are \$37. This is significantly higher than the mean hourly wages observed in the agricultural sector (\$21) and notably exceed the mean AEWR (\$12). Furthermore, the mean hourly wages for various worker subgroups within the professional service sector surpass those in the agricultural sector. This suggests that employees in professional service sectors are unlikely to be influenced by changes in AEWR.

I regress employment, working hours, and hourly wages for workers in professional service sectors, and results are presented in Appendix Table A14. The consistent lack of statistical significance across different types of workers in the professional service sector supports the credibility of my core results.

7 Summary and Concluding Remarks

Over the past 30 years, employers seeking to hire guest workers under the H-2A program have been required to pay them as well as citizen workers at the Adverse Effect Wage Rates or more. I analyze the impact of AEWRs on agricultural workers and their subgroups based on their education, citizenship status, and race/ethnicity. Using a border discontinuity approach, I find a positive employment effect on less-educated agricultural workers. This is mainly driven by the increased employment of Hispanic citizen workers, the group more likely affected by AEWRs due to their lower wages. This positive employment effect is also re-

[6]Manufacturing and construction sectors are not considered, as the mean hourly wages in the manufacturing sector are not significantly higher than those in the agricultural sector, and the possibility of workers switching between these sectors is ruled out.

ported in previous studies, especially for low-wage industries (Card and Krueger, 1994; Dube et al., 2010; Wang et al., 2019).

The positive impact of AEWR on less-educated Hispanic citizen workers also appears in working hours and hourly wages. The higher AEWR increases total annual working hours and hourly wages for them. This result implies that higher AEWR raises the wages for this group and attracts them to enter the industry as well as work more hours. However, no impact is observed for other groups of agricultural workers such as less-educated citizen workers or guest workers. Overall, AEWRs have no adverse effects on citizen workers as intended.

My findings remain robust when using various samples for PUMA-pairs with different distance cutoffs and for PUMA-pairs restricted to those with different AEWRs within the pair, and my results are not affected by any border spillover effects. In addition, falsification tests, where I replace agricultural workers with workers in the professional service sector, indicate that AEWR has no impact on the sector that is unlikely to be affected by AEWRs.

My work is limited in terms of external validity. The selection of PUMA-pairs along state borders excludes interior PUMAs within states. Moreover, my primary sample, which confines PUMA-pairs to those with a distance of 80 miles and below, omits nine states and a substantial portion of PUMAs in the Western and Midwestern regions of the country. Thus, my findings cannot be be extrapoliated to predict the impact of AEWRs on agricultural workers across all local areas in the United States. Second, the study cannot explore the effects of the AEWRs on seasonal agricultural employment but year-round agricultural employment. Given that many agricultural workers are employed during growing and harvesting seasons, an analysis of monthly or quarterly employment data would offer a more comprehensive understanding, elucidating seasonal hiring fluctuations 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.

The AEWR policy is designed to prevent any negative impact on the wages, job opportunities, and working conditions of citizen workers employed in roles similar to guest workers. In line with this policy objective, my findings reveal no adverse effects of AEWR increases on citizen workers. There is also no negative impact on guest workers or non-citizen workers. However, higher AEWRs appear to impose a financial burden on farmers and ranchers, leading to increased labor costs. In future research, it would be valuable to investigate whether farm employers respond to these elevated labor costs by substituting labor with capital and to explore whether small farms and labor-intensive industries are disproportionately affected by the challenges posed by high labor costs.

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Appendix

A Tables

TABLE A1: **Nominal 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	8.07	8.37	8.51	8.53	8.77	9.11	9.12	9.39	9.78	10	10	10.59	10.62	10.95	11.13
Arizona	7.63	8	8.27	8.7	9.82	9.71	9.6	9.94	9.73	9.97	10.54	11.2	10.95	10.46	12
Arkansas	7.8	7.58	8.01	8.41	8.92	9.1	8.97	9.3	9.5	9.87	10.18	10.69	10.38	10.73	11.33
California	8.56	9	9.2	9.72	10.16	10.25	10.31	10.24	10.74	11.01	11.33	11.89	12.57	13.18	13.92
Colorado	8.93	8.37	8.64	9.42	9.88	10.06	10.48	10.43	10.08	10.89	11.37	11.27	11	10.69	13.13
Connecticut	9.05	9.16	9.5	9.7	10.2	10.16	10.25	10.56	10.91	11.22	11.26	11.74	12.38	12.83	13.25
Delaware	8.48	8.95	9.29	9.7	9.5	9.94	10.6	10.34	10.87	11.06	11.29	11.66	12.19	12.05	13.15
Florida	8.07	8.56	8.56	8.82	9.08	9.2	9.5	9.54	9.97	10.26	10.19	10.7	11.12	11.29	11.24
Georgia	8.07	8.37	8.51	8.53	8.77	9.11	9.12	9.39	9.78	10	10	10.59	10.62	10.95	11.13
Hawaii	9.75	9.99	10.32	10.86	11.06	11.45	12.01	12.26	12.72	12.91	12.98	12.64	13.14	14.37	14.73
Idaho	8.2	8.47	8.76	8.74	9.64	9.9	9.9	10.19	9.99	10.69	11.14	11.75	11.66	11.63	13.48
Illinois	9.2	9.21	9.88	9.9	10.45	10.51	10.84	11.1	11.74	11.63	11.61	12.07	13.01	12.93	13.26
Indiana	9.2	9.21	9.88	9.9	10.45	10.51	10.84	11.1	11.74	11.63	11.61	12.07	13.01	12.93	13.26
Iowa	8.95	9.49	9.95	10.44	10.77	10.86	11.03	11.5	11.41	12.22	12.62	12.17	13.12	13.42	13.34
Kansas	9	9.23	9.55	9.9	10.39	10.66	11.52	11.61	12.33	13.41	13.59	13.8	13.79	13.64	14.38
Kentucky	8.17	8.24	8.65	9.13	9.41	9.71	9.48	9.38	9.8	10.1	10.28	10.85	10.92	11.19	11.63
Louisiana	7.8	7.58	8.01	8.41	8.92	9.1	8.97	9.3	9.5	9.87	10.18	10.69	10.38	10.73	11.33
Maine	9.05	9.16	9.5	9.7	10.2	10.16	10.25	10.56	10.91	11.22	11.26	11.74	12.38	12.83	13.25
Maryland	8.48	8.95	9.29	9.7	9.5	9.94	10.6	10.34	10.87	11.06	11.29	11.66	12.19	12.05	13.15
Massachusetts	9.05	9.16	9.5	9.7	10.2	10.16	10.25	10.56	10.91	11.22	11.26	11.74	12.38	12.83	13.25
Michigan	9.18	9.43	9.65	10.01	10.63	10.57	10.62	10.78	11.3	11.49	11.56	12.02	12.75	13.06	13.54
Minnesota	9.18	9.43	9.65	10.01	10.63	10.57	10.62	10.78	11.3	11.49	11.56	12.02	12.75	13.06	13.54
Mississippi	7.8	7.58	8.01	8.41	8.92	9.1	8.97	9.3	9.5	9.87	10.18	10.69	10.38	10.73	11.33
Missouri	8.95	9.49	9.95	10.44	10.77	10.86	11.03	11.5	11.41	12.22	12.62	12.17	13.12	13.42	13.34
Montana	8.2	8.47	8.76	8.74	9.64	9.9	9.9	10.19	9.99	10.69	11.14	11.75	11.66	11.63	13.48
Nebraska	9	9.23	9.55	9.9	10.39	10.66	11.52	11.61	12.33	13.41	13.59	13.8	13.79	13.64	14.38
Nevada	8.93	8.37	8.64	9.42	9.88	10.06	10.48	10.43	10.08	10.89	11.37	11.27	11	10.69	13.13
New Hampshire	9.05	9.16	9.5	9.7	10.2	10.16	10.25	10.56	10.91	11.22	11.26	11.74	12.38	12.83	13.25

TableA1 – continued from previous page

State	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
New Jersey	8.48	8.95	9.29	9.7	9.5	9.94	10.6	10.34	10.87	11.06	11.29	11.66	12.19	12.05	13.15
New Mexico	7.63	8	8.27	8.7	9.82	9.71	9.6	9.94	9.73	9.97	10.54	11.2	10.95	10.46	12
New York	9.05	9.16	9.5	9.7	10.2	10.16	10.25	10.56	10.91	11.22	11.26	11.74	12.38	12.83	13.25
North Carolina	8.24	8.51	9.02	8.85	9.34	9.59	9.3	9.7	9.68	9.87	10.32	10.72	11.27	11.46	12.25
North Dakota	9	9.23	9.55	9.9	10.39	10.66	11.52	11.61	12.33	13.41	13.59	13.8	13.79	13.64	14.38
Ohio	9.2	9.21	9.88	9.9	10.45	10.51	10.84	11.1	11.74	11.63	11.61	12.07	13.01	12.93	13.26
Oklahoma	7.89	8.32	8.66	9.02	9.27	9.78	9.65	9.88	10.18	10.86	10.35	11.15	11.59	11.87	12.23
Oregon	9.03	9.01	9.77	9.94	10.12	10.85	10.6	10.92	12	11.87	12.42	12.69	13.38	14.12	15.03
Pennsylvania	8.48	8.95	9.29	9.7	9.5	9.94	10.6	10.34	10.87	11.06	11.29	11.66	12.19	12.05	13.15
Rhode Island	9.05	9.16	9.5	9.7	10.2	10.16	10.25	10.56	10.91	11.22	11.26	11.74	12.38	12.83	13.25
South Carolina	8.07	8.37	8.51	8.53	8.77	9.11	9.12	9.39	9.78	10	10	10.59	10.62	10.95	11.13
South Dakota	9	9.23	9.55	9.9	10.39	10.66	11.52	11.61	12.33	13.41	13.59	13.8	13.79	13.64	14.38
Tennessee	8.17	8.24	8.65	9.13	9.41	9.71	9.48	9.38	9.8	10.1	10.28	10.85	10.92	11.19	11.63
Texas	7.89	8.32	8.66	9.02	9.27	9.78	9.65	9.88	10.18	10.86	10.35	11.15	11.59	11.87	12.23
Utah	8.93	8.37	8.64	9.42	9.88	10.06	10.48	10.43	10.08	10.89	11.37	11.27	11	10.69	13.13
Vermont	9.05	9.16	9.5	9.7	10.2	10.16	10.25	10.56	10.91	11.22	11.26	11.74	12.38	12.83	13.25
Virginia	8.24	8.51	9.02	8.85	9.34	9.59	9.3	9.7	9.68	9.87	10.32	10.72	11.27	11.46	12.25
Washington	9.03	9.01	9.77	9.94	10.12	10.85	10.6	10.92	12	11.87	12.42	12.69	13.38	14.12	15.03
West Virginia	8.17	8.24	8.65	9.13	9.41	9.71	9.48	9.38	9.8	10.1	10.28	10.85	10.92	11.19	11.63
Wisconsin	9.18	9.43	9.65	10.01	10.63	10.57	10.62	10.78	11.3	11.49	11.56	12.02	12.75	13.06	13.54
Wyoming	8.2	8.47	8.76	8.74	9.64	9.9	9.9	10.19	9.99	10.69	11.14	11.75	11.66	11.63	13.48

Source: 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)

TABLE A2: **Real Adverse Effect Wage Rates by State in 2019 dollars, 2005-2019**

State	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Alabama	10.57	10.61	10.49	10.13	10.46	10.68	10.37	10.46	10.73	10.81	10.79	11.28	11.07	11.14	11.14
Arizona	9.99	10.14	10.19	10.34	11.71	11.39	10.92	11.08	10.68	10.77	11.37	11.93	11.41	10.65	12.01
Arkansas	10.21	9.61	9.87	9.99	10.64	10.67	10.20	10.36	10.43	10.67	10.99	11.39	10.82	10.92	11.34
California	11.21	11.41	11.34	11.55	12.12	12.02	11.73	11.41	11.79	11.90	12.23	12.67	13.10	13.41	13.93
Colorado	11.69	10.61	10.65	11.19	11.78	11.80	11.92	11.62	11.06	11.77	12.27	12.01	11.46	10.88	13.14
Connecticut	11.85	11.61	11.71	11.52	12.17	11.92	11.66	11.77	11.97	12.12	12.15	12.51	12.90	13.06	13.26
Delaware	11.10	11.35	11.45	11.52	11.33	11.66	12.06	11.52	11.93	11.95	12.18	12.42	12.71	12.26	13.16
Florida	10.57	10.85	10.55	10.48	10.83	10.79	10.81	10.63	10.94	11.09	11.00	11.40	11.59	11.49	11.25
Georgia	10.57	10.61	10.49	10.13	10.46	10.68	10.37	10.46	10.73	10.81	10.79	11.28	11.07	11.14	11.14
Idaho	10.74	10.74	10.80	10.38	11.50	11.61	11.26	11.36	10.96	11.55	12.02	12.52	12.15	11.84	13.49
Illinois	12.05	11.68	12.18	11.76	12.46	12.33	12.33	12.37	12.88	12.57	12.53	12.86	13.56	13.16	13.27
Indiana	12.05	11.68	12.18	11.76	12.46	12.33	12.33	12.37	12.88	12.57	12.53	12.86	13.56	13.16	13.27
Iowa	11.72	12.03	12.26	12.40	12.85	12.74	12.55	12.82	12.52	13.21	13.62	12.96	13.67	13.66	13.35
Kansas	11.78	11.70	11.77	11.76	12.39	12.50	13.10	12.94	13.53	14.49	14.67	14.70	14.37	13.88	14.39
Kentucky	10.70	10.45	10.66	10.85	11.22	11.39	10.78	10.45	10.76	10.91	11.09	11.56	11.38	11.39	11.64
Louisiana	10.21	9.61	9.87	9.99	10.64	10.67	10.20	10.36	10.43	10.67	10.99	11.39	10.82	10.92	11.34
Maine	11.85	11.61	11.71	11.52	12.17	11.92	11.66	11.77	11.97	12.12	12.15	12.51	12.90	13.06	13.26
Maryland	11.10	11.35	11.45	11.52	11.33	11.66	12.06	11.52	11.93	11.95	12.18	12.42	12.71	12.26	13.16
Massachusetts	11.85	11.61	11.71	11.52	12.17	11.92	11.66	11.77	11.97	12.12	12.15	12.51	12.90	13.06	13.26
Michigan	12.02	11.96	11.89	11.89	12.68	12.40	12.08	12.01	12.40	12.42	12.47	12.80	13.29	13.29	13.55
Minnesota	12.02	11.96	11.89	11.89	12.68	12.40	12.08	12.01	12.40	12.42	12.47	12.80	13.29	13.29	13.55
Mississippi	10.21	9.61	9.87	9.99	10.64	10.67	10.20	10.36	10.43	10.67	10.99	11.39	10.82	10.92	11.34
Missouri	11.72	12.03	12.26	12.40	12.85	12.74	12.55	12.82	12.52	13.21	13.62	12.96	13.67	13.66	13.35
Montana	10.74	10.74	10.80	10.38	11.50	11.61	11.26	11.36	10.96	11.55	12.02	12.52	12.15	11.84	13.49
Nebraska	11.78	11.70	11.77	11.76	12.39	12.50	13.10	12.94	13.53	14.49	14.67	14.70	14.37	13.88	14.39
Nevada	11.69	10.61	10.65	11.19	11.78	11.80	11.92	11.62	11.06	11.77	12.27	12.01	11.46	10.88	13.14
New Hampshire	11.85	11.61	11.71	11.52	12.17	11.92	11.66	11.77	11.97	12.12	12.15	12.51	12.90	13.06	13.26
New Jersey	11.10	11.35	11.45	11.52	11.33	11.66	12.06	11.52	11.93	11.95	12.18	12.42	12.71	12.26	13.16

TableA2 – continued from previous page

State	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
New Mexico	9.99	10.14	10.19	10.34	11.71	11.39	10.92	11.08	10.68	10.77	11.37	11.93	11.41	10.65	12.01
New York	11.85	11.61	11.71	11.52	12.17	11.92	11.66	11.77	11.97	12.12	12.15	12.51	12.90	13.06	13.26
North Carolina	10.79	10.79	11.12	10.51	11.14	11.25	10.58	10.81	10.62	10.67	11.14	11.42	11.75	11.66	12.26
North Dakota	11.78	11.70	11.77	11.76	12.39	12.50	13.10	12.94	13.53	14.49	14.67	14.70	14.37	13.88	14.39
Ohio	12.05	11.68	12.18	11.76	12.46	12.33	12.33	12.37	12.88	12.57	12.53	12.86	13.56	13.16	13.27
Oklahoma	10.33	10.55	10.67	10.72	11.06	11.47	10.98	11.01	11.17	11.74	11.17	11.88	12.08	12.08	12.24
Oregon	11.82	11.42	12.04	11.81	12.07	12.72	12.06	12.17	13.17	12.83	13.40	13.52	13.95	14.37	15.04
Pennsylvania	11.10	11.35	11.45	11.52	11.33	11.66	12.06	11.52	11.93	11.95	12.18	12.42	12.71	12.26	13.16
Rhode Island	11.85	11.61	11.71	11.52	12.17	11.92	11.66	11.77	11.97	12.12	12.15	12.51	12.90	13.06	13.26
South Carolina	10.57	10.61	10.49	10.13	10.46	10.68	10.37	10.46	10.73	10.81	10.79	11.28	11.07	11.14	11.14
South Dakota	11.78	11.70	11.77	11.76	12.39	12.50	13.10	12.94	13.53	14.49	14.67	14.70	14.37	13.88	14.39
Tennessee	10.70	10.45	10.66	10.85	11.22	11.39	10.78	10.45	10.76	10.91	11.09	11.56	11.38	11.39	11.64
Texas	10.33	10.55	10.67	10.72	11.06	11.47	10.98	11.01	11.17	11.74	11.17	11.88	12.08	12.08	12.24
Utah	11.69	10.61	10.65	11.19	11.78	11.80	11.92	11.62	11.06	11.77	12.27	12.01	11.46	10.88	13.14
Vermont	11.85	11.61	11.71	11.52	12.17	11.92	11.66	11.77	11.97	12.12	12.15	12.51	12.90	13.06	13.26
Virginia	10.79	10.79	11.12	10.51	11.14	11.25	10.58	10.81	10.62	10.67	11.14	11.42	11.75	11.66	12.26
Washington	11.82	11.42	12.04	11.81	12.07	12.72	12.06	12.17	13.17	12.83	13.40	13.52	13.95	14.37	15.04
West Virginia	10.70	10.45	10.66	10.85	11.22	11.39	10.78	10.45	10.76	10.91	11.09	11.56	11.38	11.39	11.64
Wisconsin	12.02	11.96	11.89	11.89	12.68	12.40	12.08	12.01	12.40	12.42	12.47	12.80	13.29	13.29	13.55
Wyoming	10.74	10.74	10.80	10.38	11.50	11.61	11.26	11.36	10.96	11.55	12.02	12.52	12.15	11.84	13.49

Notes: I adjust hourly wages to 2019 dollars by multiplying the mean of nominal hourly wages by both the price deflator (CPI99) and a factor of 1.535, as recommended by IPUMS.

TABLE A3: **Descriptive Statistics for control variables using 430 PUMA-pairs, 2005-2019**

Control Variables	Mean	Std. Dev.	Min	Max
Age 0-14	67,789	120,324	8,168	886,224
Age 15-24	48,198	86,072	8,566	622,360
Age 25-34	43,794	75,410	6,792	576,861
Age 35-44	47,704	89,603	9,004	726,601
Age 45-54	53,269	103,073	9,275	767,432
Age 55-64	46,927	87,511	8,256	698,309
Female	184,968	338,247	46,771	2,445,696
White	300,568	567,981	15,834	4,023,067
Black	32,933	55,411	0	622,819
Less than high school	111,905	189,106	16,218	1,391,712
High school graduate	110,927	177,242	10,908	1,283,409
Income below 25K	69,034	95,057	3,013	704,306
Income 25k-35k	33,253	46,513	1,028	348,402
Income 35k-50k	46,123	67,803	4,323	540,091
Income 50k-75k	63,808	104,304	9,924	846,955
Income 75k-100k	48,105	90,853	4,184	701,016
Income 100k-150k	55,017	128,706	1,969	930,022
Income 150k-200k	23,042	66,630	0	595,593
E-Verify implementation	0.1	0.3	0.0	1.0
log(employment)	11.6	0.8	10.4	14.7
log(population)	12.4	0.8	11.5	15.4
Observations	6,450			

Notes: Summary statistics are provided for 430 PUMA-pairs in the 49 states, excluding Alaska. The variables are from the American Community Survey (ACS).

TABLE A4: Robustness checks: Impact of AEWRs on the employment, working hours, and hourly wages of total agricultural workers and those with less education, 2005-2019

	Employment (elasticity)							Working hours (elasticity)							Hourly wages (elasticity)						
	All	100 miles	90 miles	80 miles	70 miles	60 miles	50 miles	All	100 miles	90 miles	80 miles	70 miles	60 miles	50 miles	All	100 miles	90 miles	80 miles	70 miles	60 miles	50 miles
Total agricultural workers																					
AEWR	0.314	0.337	0.527	0.886	0.954	0.760	0.868	0.351	0.231	0.473	0.896	1.038	0.784	0.626	-0.867	-0.596	-0.179	0.412	0.066	1.083	0.269
	(0.192)	(0.480)	(0.557)	(0.619)	(0.675)	(0.637)	(0.675)	(0.210)	(0.491)	(0.574)	(0.657)	(0.702)	(0.685)	(0.772)	(0.790)	(1.484)	(1.445)	(1.528)	(1.727)	(1.977)	(2.669)
R2	0.990	0.980	0.970	0.970	0.970	0.970	0.970	0.990	0.970	0.970	0.960	0.960	0.960	0.960	0.540	0.540	0.540	0.540	0.540	0.550	0.550
Less-educated agricultural workers																					
AEWR	0.255	0.437	0.537	1.065*	1.194**	0.861	1.201*	0.311	0.370	0.596	1.184*	1.388**	1.052	1.103	-0.521	-1.050	-1.683	-2.168	-2.795	-2.046	-2.452
	(0.233)	(0.516)	(0.558)	(0.552)	(0.565)	(0.586)	(0.626)	(0.256)	(0.588)	(0.643)	(0.661)	(0.676)	(0.712)	(0.843)	(0.612)	(1.429)	(1.622)	(1.966)	(2.245)	(2.238)	(2.807)
R2	0.990	0.970	0.960	0.950	0.950	0.950	0.940	0.990	0.960	0.950	0.940	0.940	0.930	0.930	0.550	0.550	0.540	0.550	0.550	0.570	0.580
PUMA FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Pair-year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	13,530	7,950	7,260	6,450	5,730	4,620	3,750	13,530	7,950	7,260	6,450	5,730	4,620	3,750	13,530	7,950	7,260	6,450	5,730	4,620	3,750

TABLE A5: Robustness checks: Impact of AEWRs on the employment, working hours, and hourly wages of less-educated citizen, non-citizen, and guest workers, 2005-2019

	Employment (elasticity)							Working hours (elasticity)							Hourly wages (elasticity)						
	All	100 miles	90 miles	80 miles	70 miles	60 miles	50 miles	All	100 miles	90 miles	80 miles	70 miles	60 miles	50 miles	All	100 miles	90 miles	80 miles	70 miles	60 miles	50 miles
Less-educated citizen workers																					
AEWR	0.398	0.545	0.776	1.114**	1.080*	0.735	1.020	0.469	0.496	0.812	1.237*	1.294*	0.986	0.975	-0.247	-0.837	-1.594	-2.027	-2.645	-2.185	-2.843
	(0.257)	(0.496)	(0.522)	(0.532)	(0.583)	(0.663)	(0.793)	(0.297)	(0.580)	(0.614)	(0.629)	(0.666)	(0.667)	(0.778)	(0.639)	(1.475)	(1.630)	(1.943)	(2.188)	(2.176)	(2.870)
R2	0.990	0.970	0.960	0.950	0.950	0.950	0.950	0.990	0.960	0.950	0.940	0.940	0.940	0.930	0.550	0.550	0.550	0.550	0.550	0.580	0.590
Less-educated non-citizen workers																					
AEWR	-0.617	-0.258	-0.942	0.738	1.936	1.557	2.100	-0.726	-0.515	-0.870	0.800	2.064	1.453	1.801	-0.409	-2.110	-1.953	-1.664	-2.397	-1.180	0.613
	(0.572)	(1.550)	(1.971)	(2.461)	(2.551)	(3.080)	(3.913)	(0.593)	(1.577)	(2.070)	(2.529)	(2.646)	(3.230)	(4.137)	(0.879)	(2.121)	(2.509)	(2.807)	(3.259)	(3.724)	(3.260)
R2	0.960	0.850	0.850	0.810	0.780	0.800	0.810	0.960	0.840	0.840	0.800	0.770	0.790	0.800	0.620	0.610	0.610	0.600	0.600	0.600	0.610
Guest workers																					
AEWR	0.940	-1.974	-1.971	-2.138	-0.076	4.057	6.178														
	(1.282)	(1.790)	(2.606)	(3.758)	(3.103)	(3.194)	(4.170)														
R2	0.910	0.900	0.920	0.940	0.940	0.920	0.920														
PUMA FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Pair-year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	13,530	7,950	7,260	6,450	5,730	4,620	3,750	13,530	7,950	7,260	6,450	5,730	4,620	3,750	13,530	7,950	7,260	6,450	5,730	4,620	3,750

Note: The observations for guest workers are smaller than those indicated above due to the unavailability of data for the year 2005.

TABLE A6: Robustness checks: Impact of AEWRs on the employment, working hours, and hourly wages of less-educated citizen workers by their race/ethnicity, 2005-2019

	Employment (elasticity)							Working hours (elasticity)							Hourly wages (elasticity)						
	All	100 miles	90 miles	80 miles	70 miles	60 miles	50 miles	All	100 miles	90 miles	80 miles	70 miles	60 miles	50 miles	All	100 miles	90 miles	80 miles	70 miles	60 miles	50 miles
White citizen workers																					
AEWR	0.302	0.220	0.659	1.016	0.940	0.478	0.581	0.353	0.176	0.643	1.071*	1.101	0.733	0.652	-0.348	-0.809	-1.572	-2.084	-2.544	-2.193	-2.545
	(0.294)	(0.514)	(0.535)	(0.531)	(0.590)	(0.653)	(0.763)	(0.337)	(0.622)	(0.635)	(0.632)	(0.680)	(0.678)	(0.813)	(0.852)	(1.552)	(1.656)	(2.005)	(2.273)	(2.325)	(2.988)
R2	0.990	0.960	0.960	0.950	0.950	0.950	0.950	0.990	0.950	0.950	0.950	0.940	0.940	0.930	0.550	0.550	0.550	0.550	0.550	0.590	0.600
Black citizen workers																					
AEWR	-1.152	0.659	-1.957	-1.671	0.473	6.928	11.993	-2.154	-0.351	-2.348	-2.364	-0.245	5.638	10.561	1.639	3.050	3.087	3.543	4.778	9.466	7.126
	(1.298)	(2.913)	(2.168)	(3.678)	(5.342)	(4.662)	(6.124)	(1.420)	(2.476)	(2.420)	(4.073)	(5.803)	(5.279)	(6.720)	(1.647)	(3.431)	(3.340)	(4.155)	(5.403)	(6.957)	(5.963)
R2	0.960	0.930	0.910	0.850	0.690	0.700	0.720	0.950	0.920	0.900	0.840	0.650	0.660	0.670	0.670	0.650	0.640	0.630	0.630	0.630	0.630
Other citizen workers																					
AEWR	0.955	4.251	2.344	-2.357	-2.235	-2.835	-6.083	2.850	6.486*	4.395	-1.899	-2.131	-2.807	-7.770	-1.935	-6.194	-6.122	-6.762	-11.203	-3.840	-8.314
	(1.695)	(3.294)	(3.873)	(3.867)	(4.291)	(5.825)	(7.310)	(2.116)	(3.785)	(4.490)	(3.875)	(4.217)	(5.993)	(7.690)	(5.756)	(7.518)	(7.525)	(9.893)	(11.202)	(5.961)	(6.997)
R2	0.830	0.840	0.800	0.670	0.670	0.680	0.690	0.800	0.820	0.780	0.650	0.660	0.660	0.680	0.580	0.560	0.560	0.550	0.550	0.580	0.580
Hispanic citizen workers																					
AEWR	3.037**	4.774**	4.471**	5.989**	5.205**	3.719	5.350	3.776**	5.123***	5.164***	8.140***	7.315***	5.146*	5.302	1.005	3.970	4.657*	6.150*	5.719**	3.687	1.190
	(1.321)	(1.901)	(1.686)	(2.286)	(2.225)	(2.653)	(3.492)	(1.703)	(1.782)	(1.518)	(2.474)	(2.345)	(2.547)	(3.463)	(1.400)	(2.361)	(2.675)	(3.156)	(2.570)	(2.820)	(3.970)
R2	0.910	0.800	0.810	0.670	0.660	0.670	0.660	0.910	0.770	0.780	0.650	0.650	0.660	0.650	0.660	0.630	0.630	0.620	0.620	0.630	0.650
PUMA FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Pair-year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	13,530	7,950	7,260	6,450	5,730	4,620	3,750	13,530	7,950	7,260	6,450	5,730	4,620	3,750	13,530	7,950	7,260	6,450	5,730	4,620	3,750

TABLE A7: **Tests of cross-border spillover effects on employment**

	Main sample	Spillover sample	
	(1)	(2)	(3)
	Border PUMAs	Border PUMAs	Border and interior PUMAs
Total agricultural workers			
AEWR	0.886	0.879	0.851
	(0.619)	(0.623)	(1.361)
Less-educated agricultural workers			
AEWR	1.065*	1.057*	0.899
	(0.552)	(0.559)	(1.327)
Less-educated citizen workers			
AEWR	1.114**	1.099**	1.356
	(0.532)	(0.530)	(1.071)
Less-educated non-citizen workers			
AEWR	0.738	0.757	-18.801
	(2.461)	(2.683)	(30.931)
Guest workers			
AEWR	-2.138	-2.202	-5.834
	(3.758)	(3.868)	(7.296)
White citizen workers			
AEWR	1.016*	1.005*	1.406
	(0.531)	(0.530)	(1.030)
Black citizen workers			
AEWR	-1.671	-1.806	3.419
	(3.678)	(3.684)	(14.313)
Other citizen workers			
AEWR	-2.357	-2.466	-3.858
	(3.867)	(3.767)	(24.680)
Hispanic citizen workers			
AEWR	5.989**	6.069**	-11.353
	(2.286)	(2.290)	(57.089)
PUMA FE	Y	Y	Y
Pair-year FE	Y	Y	Y
N	6,450	6,000	6,000

Notes: This table displays the estimated elasticities at means. The main sample includes 430 PUMA-pairs in the 39 states for the years 2005-2019. The spillover sample (columns 2 and 3) restricts states with interior PUMAs. Delaware and Vermont are dropped from the main sample. (Note: Delaware, Idaho, Montana, North Dakota, South Dakota, Vermont, and Wyoming do not have interior PUMAs.) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

TABLE A8: **Tests of cross-border spillover effects on working hours**

	Main sample	Spillover sample	
	(1)	(2)	(3)
	Border PUMAs	Border PUMAs	Border and interior PUMAs
Total agricultural workers			
AEWR	0.896	0.894	1.064
	(0.657)	(0.664)	(1.440)
Less-educated agricultural workers			
AEWR	1.184*	1.190*	1.229
	(0.661)	(0.672)	(1.566)
Less-educated citizen workers			
AEWR	1.237*	1.226*	1.747
	(0.629)	(0.631)	(1.330)
Less-educated non-citizen workers			
AEWR	0.800	0.911	-26.335
	(2.529)	(2.783)	(30.611)
White citizen workers			
AEWR	1.071*	1.060	1.594
	(0.632)	(0.636)	(1.272)
Black citizen workers			
AEWR	-2.364	-2.478	0.392
	(4.073)	(4.081)	(14.971)
Other citizen workers			
AEWR	-1.899	-2.087	7.528
	(3.875)	(3.790)	(19.276)
Hispanic citizen workers			
AEWR	8.140***	8.324***	31.770
	(2.474)	(2.486)	(49.941)
PUMA FE	Y	Y	Y
Pair-year FE	Y	Y	Y
N	6,450	6,000	6,000

Notes: This table displays the estimated elasticities at means. The main sample includes 430 PUMA-pairs in the 39 states for the years 2005-2019. The spillover sample (columns 2 and 3) restricts states with interior PUMAs. Delaware and Vermont are dropped from the main sample. (Note: Delaware, Idaho, Montana, North Dakota, South Dakota, Vermont, and Wyoming do not have interior PUMAs.) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

TABLE A9: **Tests of cross-border spillover effects on hourly wages**

	Main sample	Spillover sample	
	(1)	(2)	(3)
	Border PUMAs	Border PUMAs	Border and interior PUMAs
Total agricultural workers			
AEWR	0.412	0.433	7.233
	(1.528)	(1.532)	(13.420)
Less-educated agricultural workers			
AEWR	-2.168	-2.156	-7.043
	(1.966)	(1.971)	(9.480)
Less-educated citizen workers			
AEWR	-2.027	-2.023	-8.127
	(1.943)	(1.952)	(7.994)
Less-educated non-citizen workers			
AEWR	-1.664	-1.762	-8.456
	(2.807)	(2.862)	(10.804)
White citizen workers			
AEWR	-2.084	-2.085	-5.183
	(2.005)	(2.001)	(6.324)
Black citizen workers			
AEWR	3.543	3.881	1.343
	(4.155)	(4.480)	(2.774)
Other citizen workers			
AEWR	-6.762	-6.722	-60.478
	(9.893)	(9.730)	(46.775)
Hispanic citizen workers			
AEWR	6.150*	6.316*	11.177
	(3.156)	(3.202)	(10.670)
PUMA FE	Y	Y	Y
Pair-year FE	Y	Y	Y
N	6,450	6,000	6,000

Notes: This table displays the estimated elasticities at means. The main sample includes 430 PUMA-pairs in the 39 states for the years 2005-2019. The spillover sample (columns 2 and 3) restricts states with interior PUMAs. Delaware and Vermont are dropped from the main sample. (Note: Delaware, Idaho, Montana, North Dakota, South Dakota, Vermont, and Wyoming do not have interior PUMAs.) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

TABLE A10: **The number of workers hired in the agricultural sector, aggregated across all PUMAs for the year 2017**

Employment	
Total agricultural workers	1,912,445
Less-educated	1,283,707
Non-citizen	400,700
Citizen	883,007
White	646,338
Black	27,802
Other	27,056
Hispanic	181,811
Guest workers	204,837
Total hired workers	155,340,656
Population	324,285,408

TABLE A11: **Comparison between all PUMAs sample and contiguous border PUMA-pair sample, 2005-2019**

	(1) All PUMA sample		(2) Contiguous border PUMA-pair sample		
Control Variables	Mean	Std. Dev.	Mean	Std. Dev.	Diff
Age 0-14	0.189	0.031	0.185	0.023	0.005
Age 15-24	0.137	0.031	0.134	0.021	0.002
Age 25-34	0.135	0.033	0.122	0.022	0.001
Age 35-44	0.133	0.019	0.129	0.015	-0.002
Age 45-54	0.139	0.018	0.144	0.016	-0.004
Age 55-64	0.122	0.020	0.130	0.017	-0.002
Female	0.509	0.015	0.508	0.011	-0.003
White	0.738	0.200	0.829	0.148	-0.004
Black	0.124	0.151	0.101	0.126	-0.004
Less than high school	0.318	0.067	0.315	0.049	0.009
High school graduate	0.292	0.067	0.329	0.058	-0.001
Income below 25K	0.210	0.085	0.213	0.076	0.011
Income 25k-35k	0.099	0.031	0.102	0.029	0.005
Income 35k-50k	0.136	0.032	0.139	0.032	0.005
Income 50k-75k	0.179	0.034	0.184	0.031	0.003
Income 75k-100k	0.129	0.030	0.131	0.027	-0.002
Income 100k-150k	0.138	0.053	0.133	0.052	-0.009
Income 150k-200k	0.055	0.038	0.049	0.035	-0.007
Employment	0.472	0.056	0.462	0.049	-0.006
Population	291,054	397,365	362,569	65,859	-71,514
Observations	16,065		6,450		

Notes: Except population, the mean is represented as a share by dividing the corresponding numbers by the population.

TABLE A12: **Robustness checks: Impact of AEWRs on employment, working hours, and hourly wages, 2005-2019**

	Employment		Working hours		Hourly wages	
	(1)	(2)	(3)	(4)	(5)	(6)
	80 miles	AEWR difference	80 miles	AEWR difference	80 miles	AEWR difference
Total agricultural workers						
AEWR	0.886	1.169	0.896	1.172	0.412	0.781
	(0.619)	(0.699)	(0.657)	(0.728)	(1.528)	(1.432)
Less-educated agricultural workers						
AEWR	1.065*	1.446**	1.184*	1.575**	-2.168	-1.396
	(0.552)	(0.626)	(0.661)	(0.769)	(1.966)	(1.913)
Less-educated citizen workers						
AEWR	1.114**	1.575**	1.237*	1.677**	-2.027	-1.184
	(0.532)	(0.598)	(0.629)	(0.732)	(1.943)	(1.932)
Less-educated non-citizen workers						
AEWR	0.738	0.489	0.800	0.724	-1.664	-2.070
	(2.461)	(3.024)	(2.529)	(3.193)	(2.807)	(3.159)
Guest workers						
AEWR	-2.138	-2.214				
	(3.758)	(4.036)				
White citizen workers						
AEWR	1.016*	1.458**	1.071*	1.497*	-2.084	-1.171
	(0.531)	(0.607)	(0.632)	(0.748)	(2.005)	(2.023)
Black citizen workers						
AEWR	-1.671	-1.763	-2.364	-3.296	3.543	4.407
	(3.678)	(4.205)	(4.073)	(4.872)	(4.155)	(4.650)
Other citizen workers						
AEWR	-2.357	-2.174	-1.899	-1.225	-6.762	-9.707
	(3.867)	(3.793)	(3.875)	(3.666)	(9.893)	(11.912)
Hispanic citizen workers						
AEWR	5.989**	7.971**	8.140***	10.761***	6.150*	8.149**
	(2.286)	(3.002)	(2.474)	(3.253)	(3.156)	(3.488)
PUMA FE	Y	Y	Y	Y	Y	Y
Pair-year FE	Y	Y	Y	Y	Y	Y
N	6,450	3,420	6,450	3,420	6,450	3,420

Notes: This table presents the estimated elasticities at means using the main sample for PUMA-pairs with an 80-mile distance cutoff and its subsample, which restricts PUMA-pairs with AEWR differences in any year between 2005 and 2019. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

TABLE A13: **Mean hourly wages of workers employed in agricultural and professional service sectors using PUMA-pairs with an 80-mile distance cutoff, 2005-2019**

	Agriculture	Professional
Dependent Variables	Mean	Mean
Hourly wage		
Total workers	19 (21)	37 (37)
Less-educated	16 (18)	24 (24)
Non-citizen	5 (13)	24 (24)
Citizen	16 (18)	5 (28)
White	16 (19)	24 (25)
Black	2 (16)	7 (26)
Other	2 (19)	6 (27)
Hispanic	3 (15)	7 (24)
Treatment Variable		
AEWR	11.798	
Observations	6,450	

Notes: Summary statistics are provided for 215 PUMA-pairs in the 39 states. The numbers in parentheses for the hourly wage dependent variable represent the mean, excluding PUMAs in which there are no corresponding workers available.

TABLE A14: **Falsification tests: Impact of AEWRs on employment, working hours, and hourly wages in construction sector, 2005-2019**

	Employment	Working hours	Hourly wages
Total workers			
AEWR	-0.266	-0.293	0.697
	(0.225)	(0.239)	(0.599)
Less-educated workers			
AEWR	-0.113	-0.251	0.821
	(0.414)	(0.400)	(0.605)
Less-educated citizen workers			
AEWR	-0.191	-0.301	0.770
	(0.411)	(0.388)	(0.619)
Less-educated non-citizen workers			
AEWR	2.438	1.360	3.038
	(2.606)	(2.532)	(2.605)
White citizen workers			
AEWR	-0.049	-0.148	0.672
	(0.471)	(0.400)	(0.635)
Black citizen workers			
AEWR	0.554	0.835	2.722
	(2.347)	(2.317)	(2.906)
Other citizen workers			
AEWR	-3.304*	-3.107	1.345
	(1.949)	(2.140)	(2.988)
Hispanic citizen workers			
AEWR	-1.862	-2.833	0.746
	(2.897)	(3.433)	(2.308)
PUMA FE	Y	Y	Y
Pair-year FE	Y	Y	Y
N		6,450	

Notes: This table presents the estimated elasticities at means using the sample for PUMA-pairs with an 80-mile distance cutoff. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

B Figures

C Individual variables definition and description

The outcome variables of interest are constructed for nine different groups of workers:

1. Agricultural workers
    2. Agricultural workers, Less-educated
        3. Agricultural workers, Less-educated, Non-citizen
        4. Agricultural workers, Less-educated, Citizen
            5. Agricultural workers, Less-educated, Citizens, White
            6. Agricultural workers, Less-educated, Citizens, Black
            7. Agricultural workers, Less-educated, Citizens, Other
            8. Agricultural workers, Less-educated, Citizens, Hispanic
9. Guest workers

To define the first group, comprising agricultural workers, I narrow down the criteria to individuals who are employed (EMPSTAT = code 1) and are 16 years or older, focusing on employment within the agriculture, forestry, fishing, or hunting sector (identified by the first two digits of INDNAICS = 11, where INDNAICS reflects the type of establishment following the North American Industrial Classification System - NAICS).

In contrast to previous studies that excluded individuals residing in group quarters (Edo and Rapoport (2019); Ottaviano and Peri (2008)), I retain such individuals in my study. This decision is based on the recognition that some agricultural workers may reside in shared housing, and I intend to include them in this study. Although I include persons in group quarters, only a minimal fraction—3,983 out of a total of 229,643 agricultural workers in the sample (1.73%)—is considered as residing in group quarters. This percentage is relatively small. Furthermore, none of the agricultural workers in group quarters were found to be living in institutional settings, such as correctional and mental institutions. Instead, they were residing in non-institutional housing units, such as rooming houses or work sites.

The second group is defined as less-educated agricultural workers, specifically those individuals who have completed high school or less (EDUC <= 6).

The third and fourth groups further categorize less-educated agricultural workers based on their US citizenship status. Individuals born in the US, born abroad to American parents, or naturalized citizens (CITIZEN = 0, 1, or 2) are considered US citizens, while those who don't meet these criteria are classified as non-US citizens (CITIZEN = 3).

The fifth to eighth groups distinguish less-educated citizen agricultural workers by their race/Hispanic origin. Those identified as White (RACE=1) and non-Hispanic (HISPAN=0) fall into the category of 'Agricultural workers, Less-educated, Citizen, White.' Similarly, those identified as Black (RACE=2) and non-Hispanic (HISPAN=0) are classified as 'Agricultural workers, Less-educated, Citizen, Black.' The seventh group, 'Agricultural workers, Less-educated, Citizen, Other,' includes individuals whose race is neither White nor Black (RACE $\geq$ 3 and RACE $\leq$ 9) and are non-Hispanic (HISPAN=0). The eighth group, 'Agricultural workers, Less-educated, Citizen, Hispanic,' comprises individuals who are Hispanic (HISPAN $\geq$ 1 and HISPAN $\leq$ 4).

The ninth group comprises guest workers, and their employment is derived from the Department of Labor's Office of Foreign Labor Certification (OFLC). A detailed explanation of the data and the process for constructing this variable is provided in Appendix E.

The main three outcome variables are the number of workers employed, the total amount of hours worked in a year, and the hourly wage at the PUMA level in a given year for each group of workers. Each outcome variable is constructed as follows:

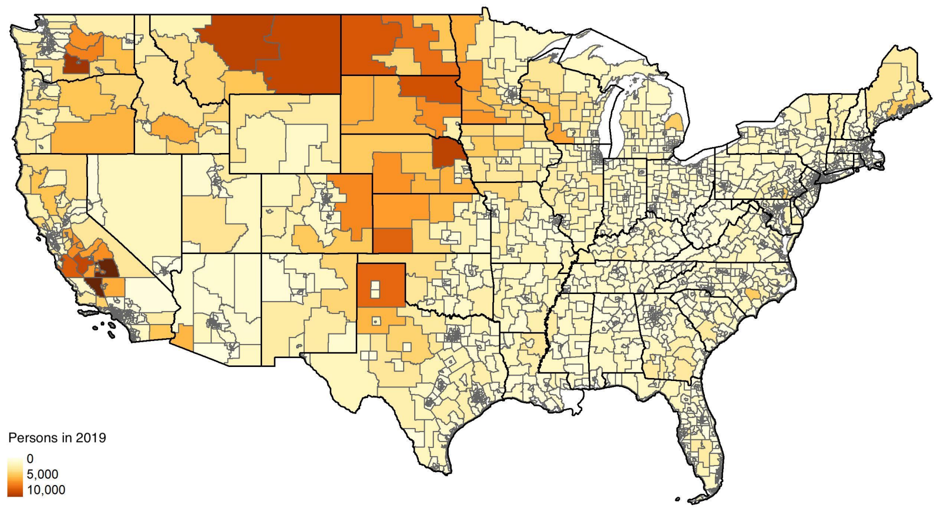
Employment: The total employment for each group of workers is obtained by summing the personal weight (PERWT) for each individual within a specific citizenship-race group in each PUMA and for a given year.

Hours worked in a year: The total number of hours worked by each group of workers in a PUMA for a given year is calculated as follows. To obtain individual working hours, I multiply the usual hours worked (UHRSWORK) by the median value for the interval of weeks worked in a year (WKSWORK2). Since the ACS provides intervals rather than exact weeks worked, I opt for the median value for each interval, following Ottaviano and Peri (2008). I impute the weeks worked in the past 12 months based on the following criteria: 6.5 weeks for 1-13 weeks (WKSWORK2=1); 20 weeks for 14-26 weeks (WKSWORK2=2); 33 weeks for 27-39 weeks (WKSWORK2=3); 43.5 weeks for 40-47 weeks (WKSWORK2=4); 48.5 weeks for 48-49 weeks (WKSWORK2=5); 51 weeks for 48-49 weeks (WKSWORK2=6). Next, I multiply individual working hours by her personal weight (PERWT). Finally, I aggregate these hours for each group within each PUMA and for a given year.

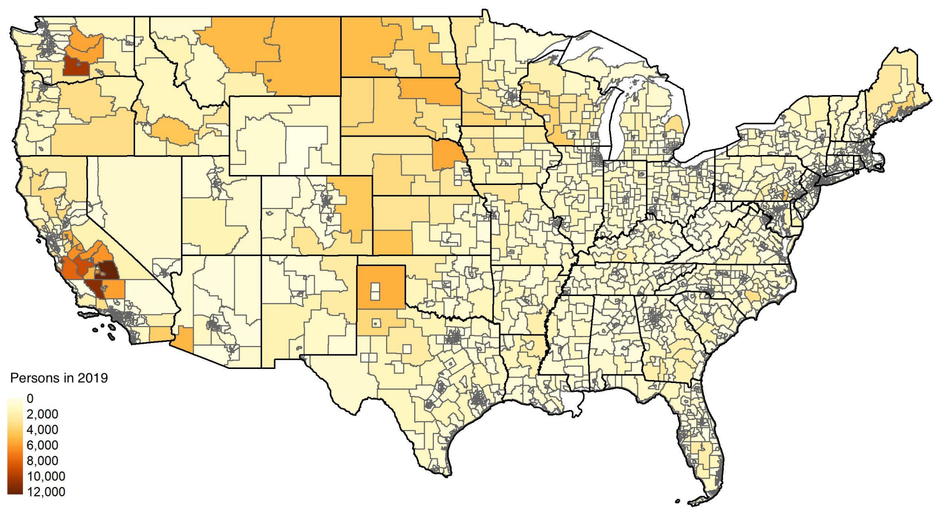
Hourly wages: Hourly wages are computed by dividing annual wage and salary incomes by individual working hours in a year (=INCWAGE/(UHRSWORK*median value of WKSWORK2). To determine the average hourly wages for each group of workers, I calculate the mean of hourly wages within a PUMA and for a given year using weight equal to individual working hours times PERWT. To adjust hourly wages to 2019 dollars, I multiply the average hourly wages by both the price deflator (CPI99) and a factor of 1.535, as recommended by IPUMS.

D Employment of agricultural workers by PUMA, 2019

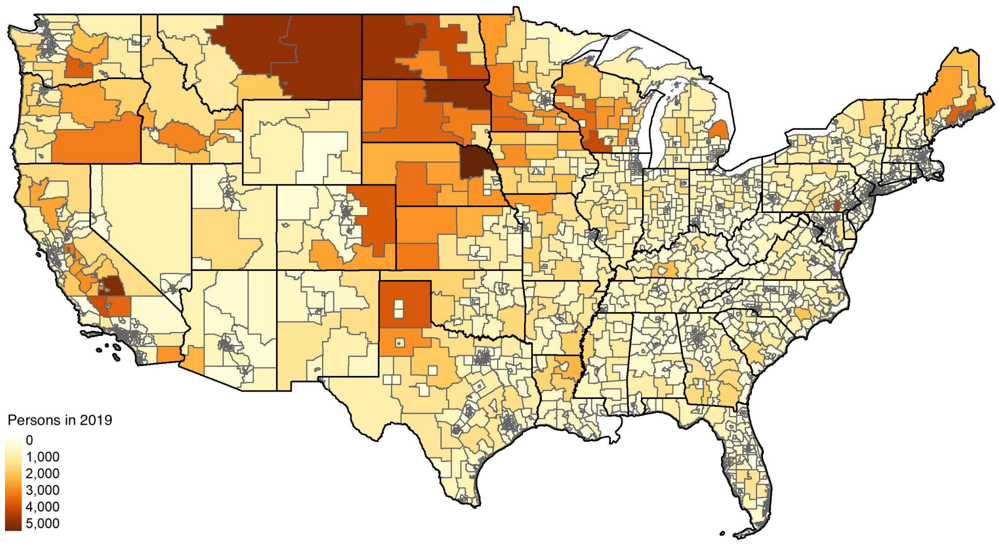
A. Estimated number of agricultural workers



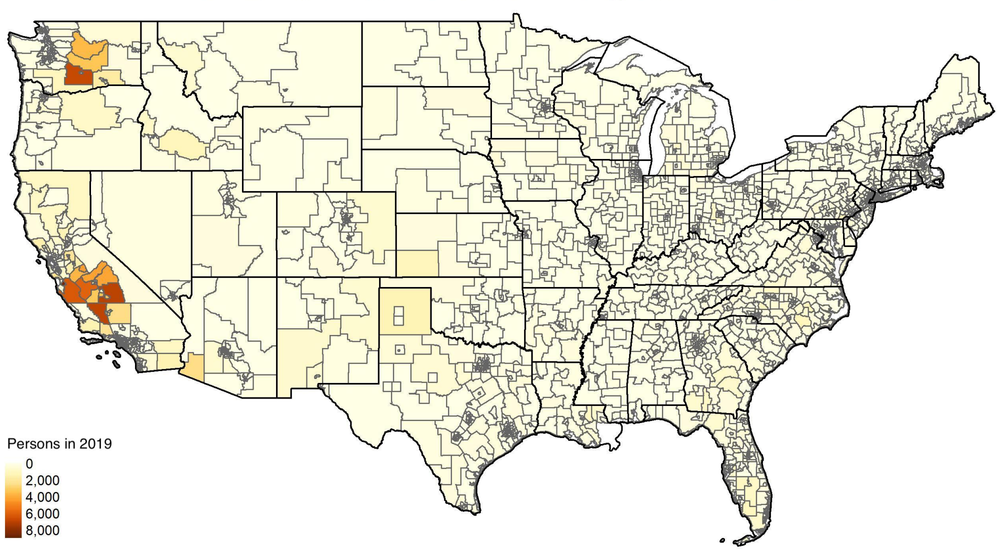
B. Estimated number of agricultural workers with a high school education or less

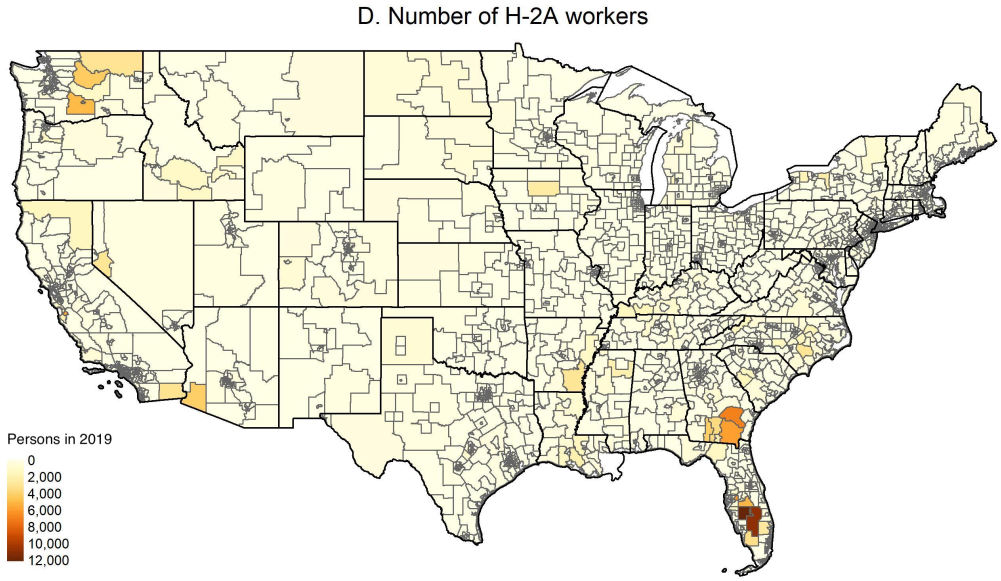


D. Estimated number of domestic agricultural workers with a high school education or less



C. Estimated number of unauthorized agricultural workers





E Description of H-2A data and cleaning procedure

The guest worker data comes from the DOL, Office of Foreign Labor Certification (OFLC). This administrative data contains 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. On average, employers file an H-2A application in May. Given that the AEWRs are released around February every year, most employers are aware of new AEWRs when they submit an H-2A application.

The data files contain both master and sub-records, and I removed the master records to avoid double-counting. If two or more employers jointly employ workers, they are recorded under the same case number called master records. However, 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 have removed the master records from my data.

The guest worker data does not include PUMA information corresponding to the locations where employers operate their farms but provides the employer's address with a postal code. To overcome this limitation, I employed two distinct approaches for converting zip codes to CPUMA0010 codes: using the crosswalk file and utilizing ArcGIS to map the zip codes for conversion.

The first approach is that I convert zip codes to 2010-based PUMA codes using the crosswalk file obtained from the Missouri Census Data Center.[7] The 2010-based PUMA codes represent the updated version used since the 2012 ACS. As explained in Section 4.5, the Census Bureau updates the PUMA codes after the Census results based on population changes. Since there is no available method to convert zip codes to CPUMA0010 codes, which harmonize the 2000-based and 2010-based PUMA codes provided by IPUMS, I first convert zip codes to 2010-based PUMA codes.

The crosswalk file includes allocation factors, facilitating the distribution of the number of guest workers in one zip code to one or multiple 2010-based PUMA codes based on the 2010 Census population. Subsequently, I convert the 2010-based PUMA codes to CPUMA0010 codes using IPUMS's file, which provides a comprehensive listing of the 2010-based PUMA codes that constitute each CPUMA0010 code.[8] Given that each CPUMA0010 is merely an aggregation of one or more 2010-based PUMAs, the conversion process involves simply retaining or adding the number of workers included in each CPUMA0010.

The second approach is that I convert zip codes to CPUMA0010 codes using the

[7]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'

[8]The IPUMS's file is available from `https://usa.ipums.org/usa/volii/cpuma0010.shtml`, and the file name is 'CPUMA0010 2010 PUMA Components.'

shapefile provided by IPUMS.[9] The shapefile provides the CPUMA0010 boundary, and it allows me to identify where the zipcodes belong to which CPUMA0010 area using ArcGIS. However, the zipcode geometry object is a polygon which can belong to multiple CPUMA0010 areas. In this case, I distribute the number of guest workers in one zip code to multiple CPUMA0010 codes, accounting for the proportional land area covered by each respective CPUMA0010 region.

The first approach involves distributing the count of guest workers within a zip code proportionally across multiple CPUMA0010 codes, based on population size. In contrast, the second approach entails distributing the count of guest workers within a zip code proportionally across multiple CPUMA0010 codes, considering the land size of each respective CPUMA0010 area. In the main analysis, I use the number of guest workers obtained through the first approach, with the second approach serving as a robustness check.

Table A compares estimated elasticities at means using both the first and second approaches. The coefficients are not statistically different from zero and consistent across different distance cutoffs. Thus, the interpretation that AEWRs have no impacts on the employment of guest workers does not change.

[9] The shapefile is available from `https://usa.ipums.org/usa/volii/cpuma0010.shtml`, and the file name is '0010 ConsPUMAs.'

TABLE A15: **Robustness checks: Impact of AEWRs on employment of guest workers**, 2006-2019

	Employment (elassticity))						
	All	100 miles	90 miles	80 miles	70 miles	60 miles	50 miles
Guest workers (2010 Census population)							
AEWR	0.940	-1.974	-1.971	-2.138	-0.076	4.057	6.178
	(1.282)	(1.790)	(2.606)	(3.758)	(3.103)	(3.194)	(4.170)
R2	0.910	0.900	0.920	0.940	0.940	0.920	0.920
Guest workers (ArcGIS)							
AEWR	0.855	0.902	1.466	0.850	1.524	2.749	4.098
	(1.219)	(1.389)	(1.665)	(1.711)	(1.824)	(2.489)	(2.808)
R2	0.910	0.921	0.931	0.942	0.948	0.935	0.932
PUMA FE	Y	Y	Y	Y	Y	Y	Y
Pair-year FE	Y	Y	Y	Y	Y	Y	Y
N	12,628	7,420	6,776	6,020	5,348	4,312	3,500

Notes: This table presents the estimated elasticities at means using two samples for guest workers. The first approach involves distributing the number of guest workers in one zip code to one or multiple PUMAs based on the 2010 Census population. The second approach distributes them based on proportional land area covered by PUMAs using ArcGIS. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$