Adverse Effect Wage Rates and US Farm Wages

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Abstract

Adverse Effect Wage Rates (AEWRs) are regional minimum wages paid to foreign employees working in the United States under the H-2A visa non-immigrant agricultural guest worker program. AEWRs were established as a mechanism to prevent US farmworkers from adverse effects due to the employment of foreign guest workers. However, AEWRs may have unintended consequences. We develop a simple theoretical framework to gain insights into how the AEWRs may influence the wages of non-H-2A farm employees. Our model predicts that higher AEWRs cause the wages of non-H-2A farm employees to rise through two channels: (i) a substitution effect and (ii) a market signalling effect, or "lighthouse effect," where non-H-2A employees use the AEWR as a benchmark to demand higher wages from employers. We test these hypotheses using a regression framework with data from the National Agricultural Workers Survey. Our estimates suggest that a 10% increase in the AEWR causes a three percent wage increase of non-H-2A farm employees across the nation and a five percent increase in the top five H-2A employment states where more than half the H-2A jobs are certified. We find that one-year AEWR freeze would reduce the growth of wages paid to US-based farm employees by about $500 million.

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Introduction

Adverse Effect Wage Rates (AEWR) are minimum wages guaranteed to foreign employees working under the H-2A visa agricultural guest worker program and any US worker in similar employment.[1] AEWRs were originally designed to prevent American farm employees from having their wages depressed by the presence of H-2A workers (UFW v. DOL, 2020; Congressional Research Service, 2008). However, unlike other minimum wages, AEWRs are based on a survey that was not designed to serve as the basis of the minimum wage for the H-2A visa program (Critterden, 2020; Lewison, 2021; Rutledge and Mérel, 2023; Castillo and Rutledge, 2023). According to former United States Secretary of Agriculture, Sonny Purdue, "The Farm Labor Survey ... was not designed to be used as a source of wage rates for a guest worker program ... " (Purdue, 2023).[2] In this paper, we provide empirical estimates that quantify the extent to which changes in the AEWR affect the wages of US-based farm employees. We conclude by quantifying the economic impacts of using the AEWR as a policy tool.

Growers who pay wages lower than their state's AEWR have reason to be concerned about flaws in the AEWR's data source and methodology even if the AEWR is not legally binding for their employees. To the extent that AEWRs cause employers to raise wages above local market values because they fail to reflect local economic conditions and distort local labor markets, domestic producers will suffer losses. While such a scenario is beneficial for farm employees and enables the DOL to meet its mandate to prevent adverse effects among American farm employees, the FLS data and methodological flaws are reshaping domestic production activities (Rutledge and Taylor, 2019; Rutledge and Mérel, 2023). While imports serve a key role in the American consumer's basket, lost domestic production creates risk

[1] Throughout this article, we use the term "US-based" employees when referencing farm employees who are working on US farms but not through the H-2A visa program and not for employers who have H-2A employees working for them. These individuals may be present in the United States without legal authorization.

[2] The FLS produces an estimate of the average hourly gross earnings, which is calculated by taking an estimate of the total gross earnings and dividing by an estimate of the total number of hours worked (see Appendix A **?**)USDA, 2023.

exposure to international supply chain disruptions and threatens the security of the domestic food supply. As the United States continues to navigate global peace and security challenges and recovers from the COVID pandemic, securing a stable source of labor for fruit and vegetable production at actual market rates would likely reduce this risk exposure.

AEWRs act as wage floors for foreign workers, and some argue they serve as wage ceilings for US-based workers because employers who advertise employment opportunities to US-based employees at the AEWR can request H-2A employees if US-based employees are unwilling to perform farm work at that wage rate (Congressional Research Service, 2008). Farm employer advocates claim the AEWR operates as a *de facto* minimum wage for all agricultural workers and that changes to the AEWR methodology are needed to keep farming viable in the US (Critterden, 2020; Lewison, 2021).

In a typical setting, minimum wages are exogenously determined by policymakers such that variation in the minimum wage variable can be directly used to identify minimum wage effects on labor market outcomes. Seminal work by Card and Krueger (1994) found that rising minimum wages did not reduce employment in the fast-food industry, suggesting that low-skilled labor markets may be imperfectly competitive and employers can absorb higher labor costs. Manning (2003) also makes a case for imperfectly competitive labor markets, although he also discusses the role of the neoclassic model in serving as an approximation to the truth in some cases. Neumark and Wascher (2000) argue that labor markets are likely competitive and that employers offset higher labor costs by reducing employment. These studies highlight the controversial nature of minimum wage policies and the need for context specific studies that investigate the impacts on a case-by-case basis.

Another branch of minimum wage literature focuses on employees who are exposed to non-binding minimum wages. For example, employees working in "informal" labor markets, such as undocumented immigrants working under the table, may ask for higher wages when the minimum wage increases. Thus, the minimum wages serve as a signal and imbue a "lighthouse effect" that provides them with increased bargaining power (Jones, 1997; Lemos, 2004; Fajnzylber, 2001; Gindling and Terrell, 2007). AEWRs are legally-binding only for H-2A employees and the US-based employees in similar employment, but they are not binding for the remaining 80% of the workforce.

AEWRs are not exogenously determined by single policy event. In our case, AEWRs are functions of market conditions, so unobserved labor market shocks that influence the market wage structure present identification challenges. To the extent that such shocks have persistent effects and are correlated with US-based farm employee wages that span a period of time lasting more than one year, they may confound our parameter estimates. As as result, our empirical analysis requires additional steps to achieve identification.

We start by developing a simple theoretical model that provides insights into the mechanisms through which the AEWR may impact the wages of US-based farm employees. From our model, we derive an equation for the equilibrium wage of US-based farm employees as a function of the AEWR and use it to derive an equation for our parameter of interest. Our model suggests that the AEWR causes US-based farm wages to rise through two mechanisms: a substitution effect that reduces the demand for H-2A employees and increases the demand for US-based employees, and a lighthouse effect through which US-based employees gain bargaining power to obtain higher wages, reflecting an upward shift in the supply of US-based farm labor.

Our empirical strategy relies upon a regression framework where the outcome variable is the natural logarithm of US-based farm employee wages, and the main regressor of interest is the natural logarithm of the AEWR. To mitigate bias resulting from unobserved labor demand shocks, we develop a labor demand proxy variable and include it as a control variable. To mitigate bias resulting from unobserved labor supply shocks, we construct instrumental variables and use a two-stage least squares regression approach. The first instrument we use is a Hausman et al. (1994) instrument that is constructed from the average AEWR in all other FLS regions. The second instrument is a lagged AEWR variable. Our wage data come from the National Agricultural Workers Survey, our AEWR data come from the FLS, and labor demand proxy variable is generated with earnings and employment data from the Quarterly Census of Employment and Wages.

Our preliminary results indicate that a 10% increase in the AEWR causes a 2.4% increase in real US-based farm wages nationwide and a 4.5% increase in the top 5 H-2A employment states. These results are consistent with those in Buccola et al. (2012) and produce results that are qualitatively similar to the hourly wage results of Moretti and Perloff (2000).

We make several contributions to the literature. First, we isolate the causal effects of the AEWR on US-based farm employee labor market outcomes. In the extant literature, minimum wages are exogenously-imposed policy variables with readily estimable impacts on labor market outcomes. In our case, however, the AEWR is endogenous because it is based on a measure of lagged wages, so if labor shocks tend to affect wages in the subsequent period, OLS estimates will suffer from bias. Only a few studies have analyzed the impacts of minimum wages in the US agricultural sector and none have produced estimates of the causal effects of the AEWR on wages or employment (Ifft, 2021; Buccola et al., 2012; Kandilov and Kandilov, 2020; Meer and West, 2016; Moretti and Perloff, 2000).

Second, we develop a theoretical model that provides important insights into how the AEWRs may cause spillover effects in the US-based farm labor market. In doing so, we demonstrate that higher AEWRs may cause substitution effects and labor supply shocks that affect US-based farm employees.

Last, we contribute to the policy discussion regarding the AEWR calculation method by providing insights into the unintended consequences of changes to the AEWR calculation method. We contribute to this discussion by providing a quantitative measure of potential externalities using an example from a recently proposed policy change that would have frozen the AEWR for a year. Our findings suggest that the AEWR likely influences domestic farm employee wages, so it is not the neutral benchmark it is intended to be. As a result, any changes made to the AEWR data source or methodology will likely have significant impacts on domestic agricultural producers and the US-based employees that work for them.

The following section provides some background details related to the H-2A visa program and the AEWR. Section 2 provides a simple theoretical framework to investigate whether the AEWR effects are expected to be positive or negative on domestic labor market outcomes, Section 3 describes our empirical strategy and data, and Section 4 describes the results. We provide some concluding remarks in Section 5.

1 Background

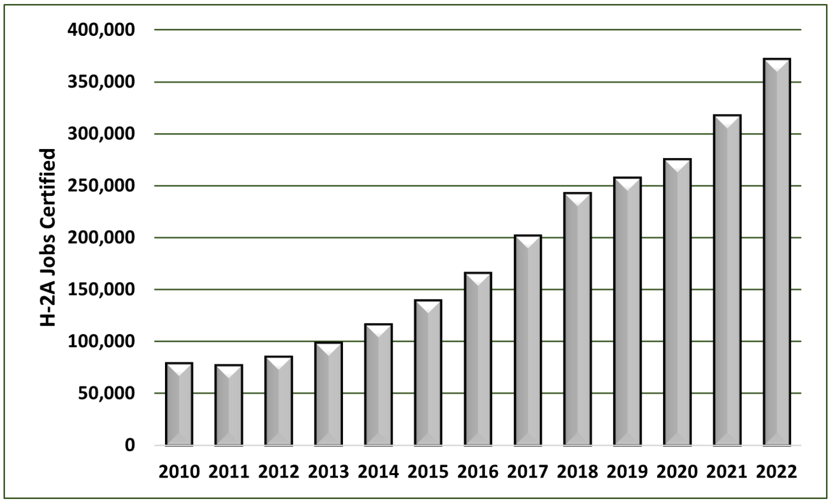
In 1952, the H-2 program was created with the passage of the Immigration and Nationality Act, permitting foreign employees to enter the country on a temporary basis to perform "low-skilled labor." When the the Immigration Reform and Control Act passed in 1986, the H-2 program was split into H-2A for agricultural workers and H-2B for non-agricultural workers. There is no cap on the number of H-2A visas that can be issued, but DOL must certify that US workers are not available and H-2A workers will not have adverse effects on US workers before farm employers can recruit and employ H-2A workers.

Over the past decade, the farm labor supply has become tighter due to a number of political, economic, and demographic factors, and the H-2A program has expanded to fill the void. Between FY2012 and FY2022, the number of H-2A jobs certified to agricultural employers increased by more than 300% from about 85,000 to over 370,000 (see Figure 1; USDOS, 2021).[3] In 2022, the DOL certified agricultural employers to fill between 15% to 20% of the full-time equivalent (FTE) jobs on US crop farms with H-2A guest workers, accruing an estimated H-2A wage bill of about $5.3 billion (Castillo et al., 2022).

Low-skilled foreign-born employees tend to have low reservation wages and have been viewed as an economic threat to the US-based farm workforce (Congressional Research Service, 2008). To mitigate adverse effects from the employment of temporary foreign workers in the agricultural sector, H-2A workers and the US-based workers who work for H-2A em-

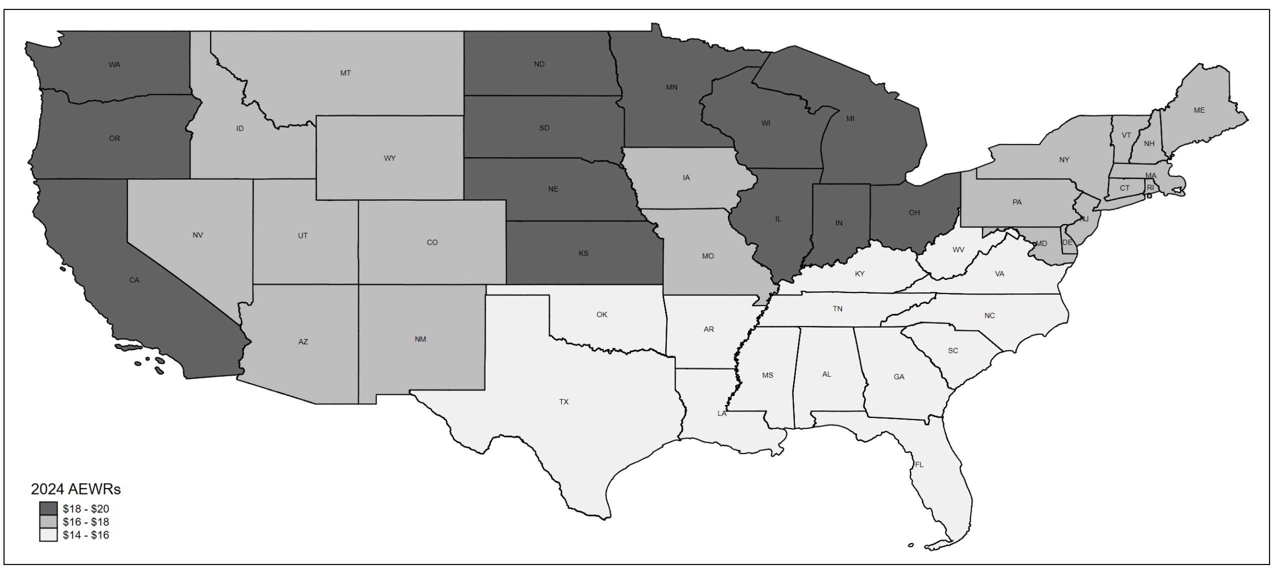
[3]Historically between 70 and 80 percent of the jobs certified by the DOL have actually been issued a visa by the DOS.

Figure 1: Number of H-2A Jobs Certified, FY2005 – FY2022



ployers must be paid an amount no less than the AEWR. They must also be paid the highest of the state or federal minimum wage, the prevailing wage as determined by a state workforce agency, the negotiated collective bargaining agreement wage, or the relevant state AEWR.

Figure 2: Adverse Effect Wage Rates in 2024



Source: https://www.dol.gov/sites/dolgov/files/ETA/oflc/pdfs/AEWR-Map-2023.pdf.

The state-level AEWRs are currently based on two data sources: the USDA's Farm Labor Survey (FLS) and the US Bureau of Labor Statistics' Occupational and Employment and Wage Statistics survey. In 2024, the AEWRs ranged from a low of $14.53 in the southeastern part of the country to a high of \$19.75 in California. The AEWRs are adjusted on an annual basis (typically upward) and are supposed to reflect the average wage in the region from the previous year.

According to DOL estimates, which use data from FY 2020, an AEWR freeze would save employers of H-2A workers an estimated \$140 million a year (DOL, 2020). Castillo et al. (2022) estimate that an AEWR freeze could also save employers an additional \$29 million per year for the corresponding US workers who are employed by the H-2A employers.[4] In addition to the economic impacts associated with the direct employment of H-2A workers, any proposed changes to the AEWR could potentially save farm employers hundreds of millions of dollars if they also slow the wage growth of US-based farm employees, who make up about 85% of average farmworker employment.

2 Theory

To gain insight into the theoretical underpinnings of the relationship between the AEWR and US-based farm employee wages, we develop a simple cost minimization framework. We assume markets are perfectly competitive and that an aggregate farmer produces a homogeneous labor-intensive crop output using three inputs, US-based farm labor (U), H-2A labor (H), and capital (K). We assume the farmer seeks to minimize her total production costs subject to a fixed amount of contracted production during the growing season, which is generated by a constant returns to scale Cobb-Douglas production technology.[5]

To make ideas clear, we define US-based wages as w^U where the capital superscript U

[4] This figure was calculated by first identifying the number of jobs that were requested in each partially approved H-2A application that were not granted. The number of jobs in each contract was multiplied by the value of the contract specified in the application. The total value was calculated by summing up the value over all jobs.

[5] Many fruit and vegetable producers sign production contracts with buyers prior to the growing season and are contractually obligated to produce a certain amount of the crop. Therefore, the assumption of fixed production is consistent with industry practices for many labor-intensive crop producers (see https://www.ers.usda.gov/webdocs/publications/40764/18614_aer747a_1_.pdf).

denotes US-based. We explicitly define the domestic labor supply function as follows:

$$D = e^{[\tau+\rho \ln w^D]} \iff \ln D = \tau + \rho \ln w^D, \tag{1}$$

where the elasticity of US-based farm labor supply is defined as $\rho \geq 0$, and $\tau \equiv -\mu \ln(w^H + C)$ defines the intercept in the $D - w^D$ space.[6] The AEWR-driven shock to the US-based supply of farm labor is defined as $\frac{\partial \ln D}{\partial \ln w^H} = -\mu\eta$, which defines the elasticity of the US-based farm labor supply shock with respect to the AEWR (a leftward horizontal shift in the domestic labor supply curve relative to the initial equilibrium).[7] The primary mechanism through which the AEWR-driven labor supply shocks occur is through a "lighthouse effect," which occurs when domestic farm workers view the AEWR as a market signal and demand higher wages to supply their labor to the market (Fan and Pena, 2019; Boeri et al., 2011).[8] The parameter $\mu > 0$ characterizes the magnitude of the elasticity of the labor supply shock with respect to the total cost of H-2A labor, and $\eta \equiv \frac{w^H}{w^H+C} \in (0, 1)$ is the AEWR's share of total H-2A labor costs at the initial equilibrium. We assume the supply of H-2A labor is perfectly elastic at the level of the AEWR, which is set by the US Department of Labor prior to the growing season.[9] As such, we drop the subscripts s and d on the AEWR variable and simply define it as w^H where the capital superscript H refers to "H-2A." H-2A employers are required to provide housing and pay for employees' transportation to and from their home country, and they also incur various administrative costs associated with filing applications and recruiting. We define these non-wage H-2A costs as C, which are expressed on a per-hour basis. The variable r denotes the rental rate of capital. We assume that all markets

[6]In the standard textbook model where the domestic wage is on the vertical axis and domestic employment is on the horizontal axis, the vertical intercept is defined as $\frac{\mu}{\rho} \ln(w^H + C)$.

[7]While we express the AEWR-driven US-based farm labor supply shock in the direction of the US-based employment axis, an equivalent interpretation is that a one percent increase in the AEWR causes a $\frac{\mu\eta}{\rho}$ percent increase in US-based farm wages at the initial level of employment.

[8]Industry sources claim that when H-2A labor is employed in a local labor market, employers of US-based workers must raise their wages to match or exceed the AEWR so that their employees do not quit and seek work in corresponding employment at the H-2A employer's place of work where all employees are guaranteed the AEWR. Such a scenario is consistent with a lighthouse effect.

[9]The AEWR is set by the US Department of Labor using data from the USDA's Agricultural Labor Survey (commonly referred to as the Farm Labor Survey or FLS).

clear. We characterize the farmer's optimal input decision making process in the current growing season as follows:

$$\min_{D,H,K} \; w^D D + (w^H + C)H + rK$$

subject to

$$Q = AD^{\alpha}H^{\beta}K^{\gamma}. \tag{2}$$

Our empirical analysis is conducted at the state-year level of aggregation, and every state in the US uses capital and domestic and H-2A labor, so we assume that the input cost shares are positive (i.e., $\{\alpha, \beta, \gamma\} \in (0, 1)$). We assume constant returns to scale in production such that $\alpha + \beta + \gamma = 1$. Using this framework, the aggregate farmer's optimal (log) demand for US-based labor can be expressed as follows:[10]

$$\ln D_d = \left[\frac{-(\beta+\gamma)}{\alpha+\beta+\gamma}\right] \ln w_d^D + \left[\frac{\beta}{\alpha+\beta+\gamma}\right] \ln(w^H + C) + Z \tag{3}$$

where

$$Z = \ln\left(\frac{Q}{A}\right) + \beta \ln\left(\frac{\alpha}{\beta}\right) + \gamma \ln\left(\frac{\alpha r}{\gamma}\right).$$

2.1 The Effect of the AEWR on US-Based Farm Employee Wages

Since markets clear, we use equations (1) and (3) to set the (log) US-based farm labor supply equal to the (log) US-based farm labor demand and solve for the equilibrium (log) US-based farm wage, which is defined as:

$$\ln w^{D*} = \Gamma + \overbrace{\left[\frac{\beta+\mu}{\rho+\beta+\gamma}\right]}^{\Sigma>0} \ln(w^H + C) + \overbrace{\left[\frac{1}{\rho+\beta+\gamma}\right]}^{\Omega>0} \ln Q + \overbrace{\left[\frac{\gamma}{\rho+\beta+\gamma}\right]}^{\Pi>0} \ln r, \tag{4}$$

where

$$\Gamma = \left[\frac{1}{\rho+\beta+\gamma}\right] \left[\beta \ln\left(\frac{\alpha}{\beta}\right) + \gamma \ln\left(\frac{\alpha}{\gamma}\right) - \ln A\right].$$

[10]See Appendix B for proof.

To simplify the notation, we denote the coefficients on the variables $\ln(w^H + C)$, $\ln Q$, and $\ln r$, as Σ, Ω, and Π, respectively. We derive the elasticity of the equilibrium US-based farm wage with respect to the AEWR, denoted Λ, by taking the partial derivative of (4) with respect to $\ln w^H$ as follows:

$$\Lambda \equiv \frac{\partial \ln w^{D*}}{\partial \ln w^H} = \Sigma\eta = \frac{(\beta+\mu)\eta}{\rho+\beta+\gamma} = \underbrace{\frac{\beta\eta}{\rho+\beta+\gamma}}_{\theta} + \underbrace{\frac{\mu\eta}{\rho+\beta+\gamma}}_{\chi} > 0, \tag{5}$$

where θ represents an AEWR-driven substitution effect, and χ represents characterizes a US-based labor supply driven lighthouse effect. The following two sections provide insights into the underlying structural mechanisms driving these effects and an explanation about why $\theta > 0$ and $\chi > 0$ such that the total effect of the AEWR results in higher US-based farm wages (i.e., $\Lambda > 0$).

2.1.1 AEWR-Driven Substitution Effect

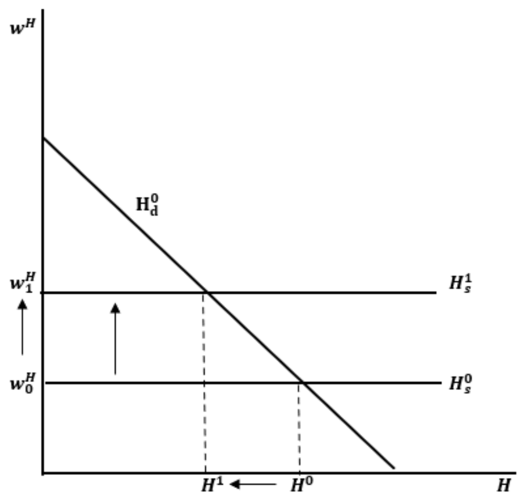
AEWR-driven US-based labor demand shocks induce a substitution effect, denoted $\theta \in (0, 1)$ in equation (5), that shifts the US-based farm labor demand curve outward. This substitution effect results from the fact that, for a given production technology, rental rate, and output level, an increase in the AEWR causes the quantity of H-2A labor demanded to fall, requiring an increase in US-based farm employment to maintain the contracted level of production. In Figure 3(a), the H-2A labor market equilibrium prior to an increase in the AEWR is characterized by the initial AEWR, w_0^H, and H-2A employment level, H^0. If a given level of production is to be maintatined, when the quantity of H-2A labor demanded falls, the demand for US-based farm labor must increases, causing the equilibrium wage in the US-based farm labor market to rise.

Figure 3 depicts the farm labor market equilibrium at a fixed level of capital in the D - H space.[11] Similarly, the initial equilibrium in the US-based farm labor market is characterized

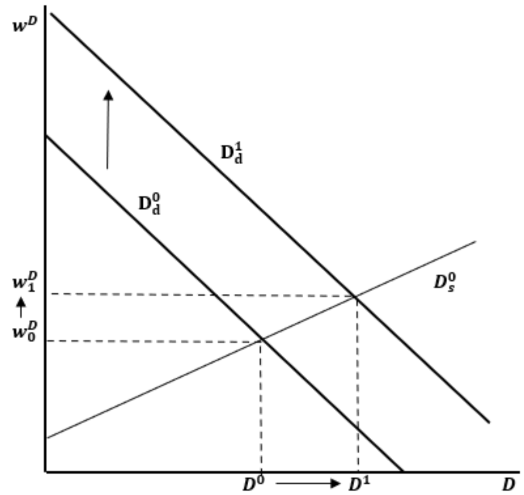
[11]While we acknowledge that capital-labor substitution occurs, existing technologies are generally unable

by w_0^D and D^0 in Figure 3(b). Figure 3(c) depicts the initial equilibrium in the $D-H$ space with the isoquant Q implied by equation (2).

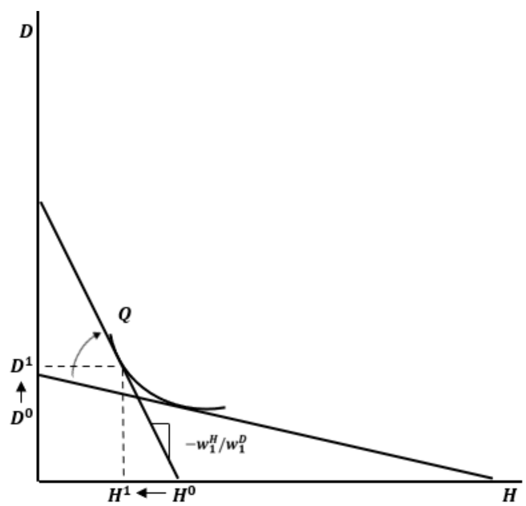
Figure 3: AEWR-Driven Substitution Effect



(a) H-2A Labor Market



(b) US-Based Labor Market



(c) Substitution Effect

Note: The initial wages, changes in wages, and slopes of the the lines depicted in this figure are not necessarily drawn to scale and do not necessarily depict specific values.

As shown in Figure 3(a), when the AEWR increases from w_0^H to w_1^H, the quantity of H-2A labor demanded decreases from H^0 to H^1 (a movement along the initial H-2A demand

to replace labor for most labor-intensive crop production tasks such that the first-order adjustments likely occur in the labor markets. Therefore, our discussion focuses on substitution between the US-based and H-2A labor inputs.

curve H_d^0). Figure 3(c) reveals that this AEWR increase changes the relative wage ratio from (-w_0^H/w_0^D) to (-w_1^H/w_1^D), which causes the slope of the isocost line in the $D-H$ space to decrease (become steeper). Thus, the farmer must increase the amount of US-based labor she employs to meet her contracted production level, so her demand for US-based farm labor rises.[12]

Figure 3(b) displays an increase in US-based farm labor demand and a corresponding increase in domestic farm employment from D^0 to D^1. The equilibrium wage in the domestic farm labor market increases from w_0^D to w_1^D.[13] While an increase in the US-based farm wage will also induce substitution back into H-2A labor, there is net substitution out of H-2A labor into domestic farm labor because $\theta < 1 \iff (-w_1^H/w_1^D) < (-w_0^H/w_0^D)$, so the slope of isocost line ultimately decreases (becomes steeper).

If the US-based farm labor supply is fixed, and is thus perfectly inelastic (i.e., $\rho = 0$), the AEWR-driven increase in US-based farm labor supply will push up the wage without a corresponding increase in domestic employment. In such a case, the US-based farm wage must rise to a level that returns the slope of the isocost line to its initial value. In other words, when $\rho = 0$, the following condition must hold:[14]

$$\frac{w_1^H}{w_1^D} = \frac{w_0^H}{w_0^D} \iff \theta = 1.$$

However, such a case is implausible because $\gamma > 0$ implies that capital is a productive input, so a higher AEWR will also induce substitution into capital, which attenuates the magnitude of θ, so it must be the case that $\theta < 1$.[15] The magnitude of θ is also influenced by the domestic farm labor supply elasticity, ρ, the H-2A labor cost share, β, and the AEWR's

[12] In many cases, farmers who employ only US-based workers will have to match or exceed the AEWR so they can retain their US-based employees and refrain from having to rely on the H-2A visa program, which is typically more expensive due to the AEWR and the non-wage costs of using the program. Such a scenario may also explain increased demand for US-based labor (i.e., increase wages at the initial level of employment).

[13] Note that the cost minimizing solution in Figure 3(c) is characterized by increases in the AEWR and the US-based farm wage.

[14] See Appendix C for proof.

[15] The attenuation of θ by γ can also be seen by looking at the denominator of θ in equation (5).

initial share of H-2A labor costs, η. In the limiting case where the supply of US-based farm labor is perfectly inelastic (i.e., $\rho = 0$), one can infer an upper bound for θ by substituting in values for the cost shares $\beta \approx .08$ and $\gamma \approx 0.60$ and $\eta \approx 0.75$ such that the AEWR-driven substitution effect is likely at most $\frac{0.08 \times 0.75}{0.08+0.60} \approx 0.09$.[16]

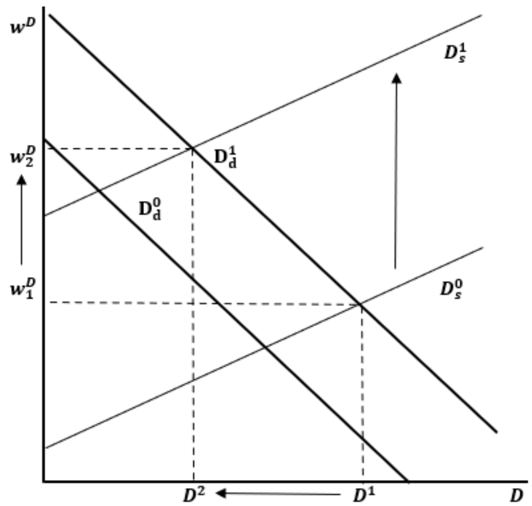
2.1.2 AEWR-Driven Lighthouse Effect

Section 2.1.1 reveals that higher AEWRs put upward pressure on the demand for US-based farm labor, which will lead to higher US-based employment. However, such a scenario is inconsistent with the current state of affairs. In fact, H-2A expansion is driven by a decline in the supply of US-based farm labor. It is well documented that the decline in the supply of farm labor has resulted from a confluence of factors (e.g., Taylor et al., 2012; Fan et al., 2015; Zahniser et al., 2012; Charlton and Taylor, 2016), but the literature has yet to investigate the extent to which the AEWR is one of them. Equation (5) reveals that the AEWR induces a "lighthouse effect" because it causes US-based farm employees to demand higher wages to supply their labor to the market. The lighthouse effect is denoted $\chi > 0$ in equation (5).

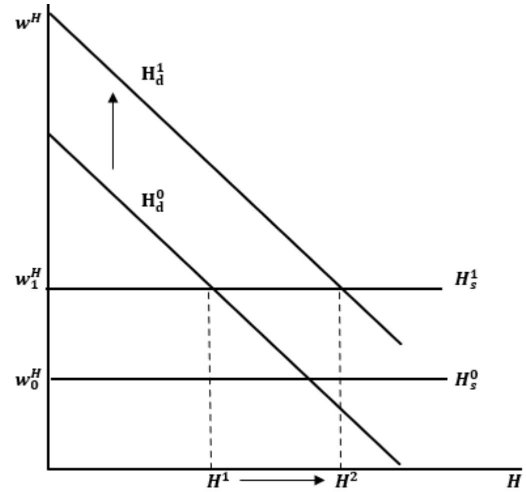
A graphical depiction of the lighthouse effect can be found in Figure 4. As can be seen in Figure 4(a), when the AEWR increases, US-based workers view it as a market signal and demand higher wages, causing the US-based farm labor supply curve to shift from D_s^0 to D_s^1. This shift causes the US-based farm wage to increase from w_1^D to w_2^D and the US-based employment level to drop from D^1 to D^2. As shown in Figure 4(c), the increase in the US-based farm wage is accompanied by an increase in the slope of the isocost line (it becomes flatter) from $(-w_1^H/w_1^D)$ to $(-w_1^H/w_2^D)$. As shown in Figure 4(b), the farmer's demand for H-2A labor must increase from H_d^0 to H_d^1 to maintian the contracted level of production so that H^2 units of H-2A labor are employed.

[16]Estimates suggest that the non-wage per-hour costs of employing H-2A labor is about \$5.00 per hour. The average state AEWR in 2023 was \$16.13 so that $\eta \approx 0.75 \approx \frac{\$16.13}{\$16.13+\$5.00}$. Our estimate of 0.08 for β comes from the fact that total labor costs comprise about 40% of the cost of specialty crop production (i.e., $\alpha+\beta \approx 0.40$), and the H-2A wage bill in the US is about 20% of all labor costs so that $\beta \approx 0.08 \approx 0.20 \times 0.40$. Similarly, labor costs account for roughly 40% of production costs, so the cost share of capital is about 0.60 (i.e., $\gamma \approx 0.60 \approx 1 - 0.40 \approx 1 - \alpha - \beta$).

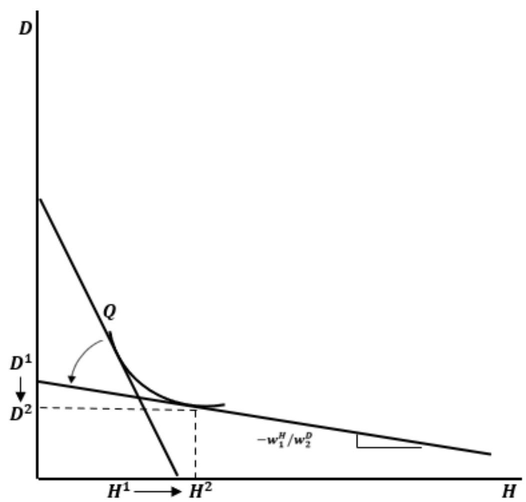
Figure 4: AEWR-Driven Lighthouse Effect



(a) US-Based Labor Market



(b) H-2A Labor Market



(c) Lighthouse Effect

Note: The initial wages, changes in wages, and slopes of the the lines depicted in this figure are not necessarily drawn to scale and do not necessarily depict specific values.

Moreover, the AEWR's effect on the domestic farm wage is self-perpetuating because $\Lambda > 0$ implies that the AEWR causes the US-based farm wage to increase in year t, which causes the AEWR to increase in year $t+1$. As such, an AEWR increase in year t will induce an inter-temporal spillover, causing the AEWR to increase again the following year. This cyclical effect is exacerbated by other non-AEWR factors that may cause the supply of US-based farm labor to decline, so the AEWR in the next growing season will be even higher than it otherwise would have been because the AEWR induces shocks to the US-based farm labor market.

Given our empirical setting, it is not feasible to identify the AEWR-driven substitution and lighthouse effects separately because our outcome variable of interest is an equilibrium value that reflects changes in the supply of and demand for US-based farm labor. The substitution effect arises from AEWR-driven shocks to the demand for US-based farm labor, and the lighthouse effect is a result of AEWR-driven labor supply shocks. Therefore, our empirical estimates reflect the total effect, i.e., the sum of the substitution and lighthouse effects.

2.1.3 Non-AEWR H-2A Labor Cost Spillover Effects

Interestingly, a similar result emerges when the non-wage cost (e.g., housing, transportation, etc.) of employing H-2A workers increases. By taking the partial derivative of equation (4) with respect to $\ln C$, we derive the following formula for the elasticity of US-baed farm wages with respect to the non-wage H-2A costs, denoted Υ:

$$\Upsilon \equiv \frac{\partial \ln w^{D*}}{\partial \ln C} = \Sigma\kappa = \frac{\beta\kappa}{\rho+\beta+\gamma} + \frac{\mu\kappa}{\rho+\beta+\gamma} > 0, \tag{6}$$

where $\kappa \equiv 1-\eta = \frac{C}{w^H+C} \in (0,1)$ is the non-wage cost share of employing H-2A workers at the initial equilibrium. Equation (6) reveals that, ceteris paribus, an increase in C will also increase the equilibrium wage in the US-based farm labor market. This result occurs because any increase in the cost of employing H-2A workers, whether through the AEWR or through non-wage channels, induces US-based farm labor supply and demand shocks that mimic the effects of the AEWR. In fact, the magnitude of Υ only differs from Λ to the extent that the non-wage H-2A labor costs differs from the AEWR. We describe our empirical strategy to estimate Λ in the following section.

3 Empirical methodology and data

3.1 Reduced-Form Regression Model

Our primary research objective is to test the null hypothesis that the AEWR has no effect on the wages of domestic farm employees against the alternative hypothesis that there is an effect. From an empirical perspective, the main identification challenge is overcoming omitted variables bias from unobserved labor market shocks in year $t-1$. To make ideas clear, suppose we want to estimate the following model:

$$\ln w_{ist}^{D} = \Lambda \ln w_{st}^{H} + \phi_s + \phi_t + \theta \mathbf{X} + \epsilon_{ist},$$

where $\ln w_{st}^{D}$ identifies the average log real wage (in \$2020) of US-based farm employees in state s in survey year t (net of individual-level observables), $\ln w_{st}^{H}$ identifies the natural logarithm of the real AEWR (in \$2020), ϕ_s are state fixed effects, ϕ_t are year fixed effects, and ϵ_{st} is the error term. The AEWR is based on farm labor market data from the previous period (i.e., period $t-1$), so it is likely influenced by labor supply and demand shocks in taht period. If labor market shocks from the previous period are correlated with labor market outcomes in the current period, then OLS estimates may suffer from bias if the model does not control for these shocks.

Suppose the researcher is able to adequately control for labor demand shocks in period $t-1$ such that the error term only contains an omitted lagged labor supply shock variable and an idiosyncratic error term such that the true model is

$$\ln w_{ist}^{D} = \Lambda \ln w_{st}^{H} + \phi_s + \phi_t + \theta \mathbf{X} + \alpha LD_{st-1} + \underbrace{\beta LS_{st-1} + \nu_{ist}}_{\epsilon_{ist}}, \tag{7}$$

where LD_{t-1} (respectively LS_{t-1}) denotes a labor demand (respectively supply) shock variable in period $t-1$, and ν_{st} is the error term that satisfies the condition $\mathbb{E}[\nu \mid \phi_t, \phi_s, \mathbf{X}, LS, LD] =$

0. If labor market shocks are serially correlated with US-based farm wages, then it would follow that $\alpha \geq 0$ and $\beta \leq 0$.[17] Since the AEWR in period t is determined by market conditions in year $t-1$, it is a function of lagged labor supply and demand shocks in period $t-1$, so it can be modelled as follows:

$$\ln w_{st}^{H} = \gamma LD_{st-1} + \delta LS_{st-1} + \phi_s + \phi_t + \theta \mathbf{X} + \xi_{st}, \tag{8}$$

where $\mathbb{E}[\xi_{st} \mid \phi_s, \phi_t, \mathbf{X}, LS_{t-1}, LD_{t-1}] = 0$. Because labor demand (respectively supply) shocks in period $t-1$ will tend to increase (respectively decrease) regional wages in period $t-1$ (and thus the AEWR in period t), it is natural to assume that $\gamma \geq 0$ and $\delta \leq 0$. Under the assumption that labor demand shocks are uncorrelated with labor supply shocks (i.e., $\text{cov}(LS_t, LD_{t-k}) = 0$), where $k \in (0, ..., T-1)$, the probability limit of the OLS estimate of Λ in Equation (7) can be expressed as follows:[18]

$$\text{plim}\, \Lambda^{OLS} = \Lambda + \overbrace{\beta \delta \text{var}(LS_{st-1})}^{\text{Bias } \geq 0}.$$

To help mitigate the potential for upward bias resulting from omitted labor demand shocks, we develop a proxy for agricultural sector labor demand shocks using a Bartik instrument and include it as a control variable (Basso and Peri, 2015; Notowidigdo, 2020; Bartik, 1991). Our Bartik control variable is defined as follows:

$$LD_{st-1} = \sum_{j} \left(\frac{emp_{js,1990}}{emp_{j1990}} \right) I_{jt-1} \tag{9}$$

[17] If labor supply and demand shocks are not serially correlated with wages (i.e., $\alpha = \beta = 0$), there would be no omitted variables bias. In that case, the OLS estimate would identify the causal effect of interest. As a result, controlling for labor demand shocks should reduce the magnitude of the positive regression coefficients.

[18] Note that the omitted variables bias from unobserved lagged labor demand shocks can be expressed as $\alpha \gamma \text{var}(LD_{st-1}) \geq 0$ such that both sources of omitted variables bias are positive.

where

$$I_{jt-1} = \left(\frac{e_{jt-1}}{e_{j1990}}\right),$$

and $j \in \{111, 112, 113, 114, 115\}$ denotes one of the five agricultural NAICS codes, emp_{js1990} denotes the employment in sector j in state s in 1990, emp_{s1990} denotes total agricultural employment in the state in 1990 such that the term in parentheses in equation (9) represents the share of sector j's agricultural employment in the state in 1990, e_{jt-1} (resp. e_{j1990} denotes the average earnings in sector j across the entire country in year $t-1$ (resp., 1990). Thus, I_{st-1} is an earnings growth index between the base year 1990 and the year $t-1$. Despite controlling for lagged labor demand shocks by including LD_{st-1} as a control variable, an OLS estimate of Λ could still suffer from bias if the model does not sufficiently control for lagged labor supply shocks.

To address this remaining issue, we deploy two instrumental variables in separate specifications. The first instrument, defined below, is inspired by Hausman et al. (1994) and identifies the log of the average AEWR across all other states excluding the FLS region that the state belongs to:

$$\overline{\ln w^H}_{st} = \ln\left(\frac{1}{K}\sum_{k \notin \{R\} t} w^H_{kt}\right) \tag{10}$$

where K denotes the number of states that belong to all the other FLS regions that the state does not belong to, and R denotes the FLS region that the state belongs to. The second instrument is a lagged log AEWR variable (i.e., $\ln w^H_{st-1}$). In order for the first instrument to satisfy the exclusion restriction, assuming that labor supply and demand shocks are not correlated and that the labor demand proxy variable sufficiently controls for labor demand shocks, it must be the case that labor market shocks outside of the local labor market are not correlated with the labor supply shocks in the local market. We argue such a condition is plausible because (a) our model includes year fixed effects, which control for labor supply shocks that are common to all states within a given year such that macroeconomic labor supply shocks that impact regional labor markets across time are effectively controlled for and (b) to the extent that some states are more susceptible to labor supply shocks, such that a state that experiences a shock in one year would tend to experience a similar shock in the following year, the state fixed effects adequately control for that. Thus, we believe our set of year and state fixed effects, the Bartik labor demand proxy control, and the robust set of demographic controls is sufficient to identify the causal effect of interest.[19]

3.2 Data

We bring together data from five sources to conduct our analyses. Our US-based farm employee wage data consists of individual-level data from the 1990-2020 samples of the restricted-access National Agricultural Workers Survey (NAWS). We restrict our sample to include only those individuals who were between the ages of 18 and 64 at the time of the survey, which retains about 95% of the sample. We adjust the nominal wage data to real 2020 dollar values using a consumer price index. The NAWS also contains a host of individual-level variables that we use as controls, including age, years of education, marital status, gender, English language ability, and legal status.

Our Bartik control variable is constructed from average annual employment and weekly wage data from the Quarterly Census of Employment and Wages (QCEW). To create a proxy for labor demand shocks in the agricultural sector, we utilize data for each of the three-digit industries within the agricultural sector. Specifically, we use NAICS codes 111 (crop production), 112 (animal production), 113 (forestry and logging), 114 (fishing, hunting, and trapping), and 115 (crop support services). The employment data is aggregated at the state-industry level using 1990 as the base year, and the earnings data are aggregated at the

[19]The requirement for the exclusion restriction to hold for the latter instrument are as follows: $\text{cov}(w^H_{st-1}, \epsilon_{ist}) = 0 \iff \text{cov}(\ln w^H_{st-1}, \beta LS_{t-1}) = 0 \iff \text{cov}(\delta LS_{st-2}, \beta LS_{st-1}) = 0 \iff \delta\beta\text{cov}(LS_{st-2}, LS_{st-1}) = 0$. In this case, either (i) labor supply shocks do not have a contemporaneous effect on the AEWR (i.e., $\delta = 0$), (ii) labor supply shocks from the previous period do not have an impact on US-based farm wages in the current period (i.e., $\beta = 0$) such that there are no omitted variables, (iii) there is no serial correlation between labor supply shocks (i.e., $\text{cov}(LS_{st-2}, LS_{st-1}) = 0$), or (iv) serial correlation between labor supply shocks is adequately controlled for in the model.

industry-year level.

Finally, the AEWR data were obtained from the USDA's Farm Labor Survey (FLS) through the NASS Quickstats website. Specifically, the AEWR represents the average regional wage for hired crop and animal workers from the previous year, which we assign to the states that belong to each FLS region. A selection of summary statistics can be found in Table 1.

Table 1: Summary Statistics

	Mean	St. Err. of Mean	Observations
Real AEWR ($2020)	11.451	1.274	684
Real wage ($2020)	10.961	0.026	61,432
Age (years)	34.893	0.095	61,432
Male	0.752	0.004	61,432
Married	0.586	0.004	61,432
Undocumented	0.450	0.004	61,432
Speaks good English	0.251	0.004	61,432
Number of years of education	7.641	0.032	61,432

4 Empirical Results

4.1 Main Analysis

Our main results from the wage analysis are presented in Table 2. The table has two sets of results, one that focuses on the top five H-2A employment states and the other that focuses on the entire nation.[20] The results from our preferred specification, which use the Hausman et al. (1994)-inspired instrument are displayed in column (5), while the IV estimates with the lagged AEWR variable are displayed in column (6).

First, it is worth noting that relative to the model with no controls, the inclusion of the Bartik control variable reduces the magnitudes of the empirical estimates in most cases when comparing the estimates in column (2) to (1), suggesting that the labor demand proxy

[20]The top 5 H-2A employment states include Florida, California, Georgia, Washington, and North Carolina.

variable does mitigate upward bias in most cases. For example, a comparison of the OLS coefficient in column (2) to the one in column (4) of the top panel reveals a reduction in the elasticity estimate from 1.15 to 1.01.

Table 2: US-Based Farm Employee Wage-AEWR Elasticity Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
	Top 5 H-2A States					
	OLS					
$\ln w^H$	1.149***	1.009***	0.959***	0.599***	0.572***	0.572***
	(0.051)	(0.076)	(0.106)	(0.200)	(0.186)	(0.186)
	IV					
$\ln w^H$	1.203***	2.653**	0.956***	0.502***	0.518***	0.449*
	(0.069)	(1.122)	(0.113)	(0.190)	(0.175)	(0.261)
N	36,001	36,001	36,001	36,001	36,001	36,001
First Stage F-Statistic	3,040	1	2,813	1,273	1,303	2,983
	All H-2A States					
	OLS					
$\ln w^H$	0.939***	0.724***	0.687***	0.429***	0.355***	0.355***
	(0.036)	(0.056)	(0.060)	(0.112)	(0.102)	(0.102)
	IV					
$\ln w^H$	1.070***	0.722	0.657***	0.367***	0.324***	0.243*
	(0.045)	(3.150)	(0.067)	(0.140)	(0.124)	(0.135)
N	59,604	59,604	59,604	59,604	59,604	59,604
First Stage F-Statistic	3,040	1,946	16	13,009	2,403	2,439
Bartik Control	–	X	X	X	X	X
Year Fixed Effects	–	–	X	X	X	X
State Fixed Effects	–	–	–	X	X	X
Demographic Controls	–	–	–	–	X	X
IV Specification						
Leave-One-Out AEWR	X	X	X	X	X	–
Lagged AEWR	–	–	–	–	–	X

Standard errors are survey-design corrected according to DOL guidelines. * $p < .1$, ** $p < .05$, *** $p < .01$. The top 5 H-2A states include Florida, California, Georgia, Washington, and North Carolina.

Within each set of results are a subset of OLS estimates and a subset of IV estimates. We also note that in all cases, the IV estimates for our preferred specification are smaller than the OLS estimates, suggesting that our instrument does resolve upward bias from the unobserved labor supply shocks. Consider, for example, the coefficient in column (5) of the top panel. The IV estimate of 0.52 is smaller than the OLS estimate of 0.57, which is consistent with the theoretical expectation that the instrument is serving its purpose to mitigate upward bias. In cases where the IV coefficients are not statistically significant and the OLS coefficients are, the OLS coefficients can be interpreted as upper bounds for the effects of interest due to the inherent upward bias from the unobserved labor market shocks. Our preferred specification in column (5) reveals that a 10% increase in the AEWR causes a 3.2% increase in US-based farm wages when considering the whole nation and 5.2% in the top five H-2A employment states. To put this in context, the average AEWR in the US increased by 5.6% between 2019 and 2020 (from \$13.25 and \$13.99), and the average wage of US-based farm employees during FY2019-FY2020 was \$15.56. A 5.6% increase in the AEWR would have caused the average wage of US-based farm employees to rise to \$15.84 (or an additional \$0.28 per hour).[21] With a total wage bill of approximately \$30 billion, such an increase would have caused farmers to pay an additional \$54 million in wages to US-based farm employees during 2021.

4.2 Robustness Tests

In this section, we present the results from a set of heterogeneity analyses that use the NAWS to investigate the extent to which the AEWR effects differ across various subsets of US-based farm employees and a set of robustness tests that use data from the American Community Survey.

4.2.1 Heterogeneity Analysis

Next, we turn our attention to various sub-populations of the US-based farm workforce to investigate whether there is evidence of heterogeneity in the AEWR effects between different groups of workers. We select a set of key observable farm employee characteristics that identify important differences between groups of employees. For example, a number of studies have found evidence that labor markets are segmented with respect to documented

[21] $x = \$15.84 \iff x - \$15.56 = \$0.28 = (0.032 \times 0.056 \times \$15.56) + \$15.56 \iff \frac{x-\$15.56}{\$15.56} = 0.032 \times 0.056.$

and undocumented status and that undocumented workers tend to experience significant wage disparities even after controlling for differences in human capital accumulation, so we investigate differences among individuals who are documented and those who are not (Borjas and Cassidy, 2019; Durand et al., 2016; Massey and Gentsch, 2014; Rivera-Batiz, 1999). We also investigate heterogeneity between those who are hired directly and those who work for farm labor contractors, those with and without good English skills, and those with lower and higher formal educational attainment.

Table 3 displays the results for documented and undocumented workers in the top and second panels and for those with documented and undocumented statuses and those who work for different types of employers. Our instruments fail to pass the weak instrument test (i.e., $F > 10$) when we perform the subsample analyses, so we rely upon the OLS estimates in column (4) for this analysis and interpret them as upper bounds. The upper bound estimates from our preferred model reveal the AEWR likely has a larger effect on the wages of documented US-based farm employees. The elasticity for documented workers is 0.42 while it is only 0.36 for undocumented workers. With respect to workers who are directly hired, the elasticity is about 0.46 while the coefficient for the employees who work for farm labor contractors is not statistically significant.

The results in Table 4 compare heterogeneity across English ability (good versus not good) and education (at least twelve years of school and less than twelve years). The upper bound estimate for workers with good English ability shows an elasticity of 0.45 and 0.38 for those who do not speak good English. With respect to education, a similar story emerges. In this case, employees with at least a high school education show an upper bound of 0.48 while those without show an upper bound of 0.41. These results suggest that employees who are less vulnerable are better positioned to leverage the AEWR to their advantage to negotiate higher wages with their employers.

Table 3: US-Based Farm Employee Wage-AEWR Elasticity Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
	Documented					
$\ln w^H$	0.755***	0.699***	0.418***	0.418***	0.312**	0.215
	(0.063)	(0.064)	(0.119)	(0.119)	(0.146)	(0.152)
N	32,368	32,368	32,368	32,368	32,368	32,368
First Stage F-Statistic	–	–	–	–	4	2
	Undocumented					
$\ln w^H$	0.649***	0.657***	0.362**	0.362**	0.422**	0.303
	(0.074)	(0.083)	(0.170)	(0.170)	(0.174)	(0.214)
N	27,358	27,358	27,358	27,358	27,358	27,358
First Stage F-Statistic	–	–	–	–	6	2
	Direct Hire					
$\ln w^H$	0.737***	0.707***	0.464***	0.464***	0.321**	0.298**
	(0.059)	(0.062)	(0.114)	(0.114)	(0.130)	(0.138)
N	50,214	50,214	50,214	50,214	50,214	50,214
First Stage F-Statistic	–	–	–	–	6	5
	Works for Farm Labor Contractor					
$\ln w^H$	0.565***	0.442***	-0.088	-0.088	-0.226	-0.515*
	(0.080)	(0.081)	(0.196)	(0.196)	(0.181)	(0.293)
N	9,465	9,465	9,465	9,465	9,465	9,465
First Stage F-Statistic	–	–	–	–	2	3
Bartik Control	X	X	X	X	X	X
Year Fixed Effects	–	X	X	X	X	X
State Fixed Effects	–	–	X	X	X	X
Demographic Controls	–	–	–	X	X	X
Specification						
OLS	X	X	X	X	–	–
Leave-One-Out AEWR IV	–	–	–	–	X	–
Lagged AEWR IV	–	–	–	–	–	X

Standard errors are survey-design corrected according to DOL guidelines. * $p < .1$, ** $p < .05$, *** $p < .01$. The top 5 H-2A states include Florida, California, Georgia, Washington, and North Carolina.

Table 4: US-Based Farm Employee Wage-AEWR Elasticity Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
			Good English			
$\ln w^H$	0.790***	0.713***	0.450***	0.450***	0.192	0.185
	(0.079)	(0.079)	(0.169)	(0.169)	(0.228)	(0.206)
N	12,839	12,839	12,839	12,839	12,839	12,839
First Stage F-Statistic	–	–	–	–	1	1
			Not Good English			
$\ln w^H$	0.714***	0.695***	0.375***	0.375***	0.397***	0.247
	(0.063)	(0.068)	(0.133)	(0.133)	(0.147)	(0.171)
N	46,887	46,887	46,887	46,887	46,887	46,887
First Stage F-Statistic	–	–	–	–	7	2
			High School or More			
$\ln w^H$	0.728***	0.634***	0.478***	0.478***	0.286	0.184
	(0.077)	(0.081)	(0.165)	(0.165)	(0.238)	(0.214)
N	12,214	12,214	12,214	12,214	12,214	12,214
First Stage F-Statistic	–	–	–	–	4	3
			Less Than High School			
$\ln w^H$	0.709***	0.694***	0.414***	0.414***	0.365***	0.273*
	(0.062)	(0.066)	(0.121)	(0.121)	(0.121)	(0.154)
N	47,512	47,512	47,512	47,512	47,512	47,512
First Stage F-Statistic	–	–	–	–	7	3
Bartik Control	X	X	X	X	X	X
Year Fixed Effects	–	X	X	X	X	X
State Fixed Effects	–	–	X	X	X	X
Demographic Controls	–	–	–	X	X	X
Specification						
OLS	X	X	X	X	–	–
Leave-One-Out AEWR IV	–	–	–	–	X	–
Lagged AEWR IV	–	–	–	–	–	X

Standard errors are survey-design corrected according to DOL guidelines. * $p < .1$, ** $p < .05$, *** $p < .01$.
The top 5 H-2A states include Florida, California, Georgia, Washington, and North Carolina.

4.2.2 American Community Survey Results

The results from the American Community Survey (ACS) data are qualitatively similar to those found with the NAWS data with a few discrepancies. The model specifications we use with the ACS are nearly identical to those we use with the NAWS except we do not observe undocumented status in the ACS and we do not control for English language ability. We use a proxy for documented status by creating a binary variable that identifies farm employees who are US citizens. All the regressions are weighted with the sample probability weights, and the standard errors are clustered at the state level. Our sample covers the period 2000 - 2019 to avoid issues with exploratory sample weights that were developed for the ACS during the COVID-19 pandemic due to unreliable sample methodology.

Our preferred estimates can be found in column (5) of Table 5, which contain the coefficients from the specification that includes the most robust set of controls and relies upon the Hausman et al. (1994) instrument. When focusing on the entire US, the estimate using our preferred instrument reveals an elasticity of 0.37. This estimate is similar to the NAWS estimate of 0.32. The ACS data also produce a larger coefficient among individuals in the top 5 H-2A employment states, with an elasticity around 0.86. This estimate is larger than the one we find for the entire US, which is qualitatively consistent with our NAWS estimates and is in line with our theoretical expectations. However, our instrument does not appear to mitigate upward bias as we would expect in the top 5 states when we use the ACS data, so it is plausible that the instrument fails to satisfy the exclusion restriction in this case. As such, we can interpret the OLS coefficient for the top 5 states (0.75) as an upper bound, which is consistent with the estimate produced by the NAWS (0.52).

Taking this evidence into consideration, we believe the NAWS data are likely more reflective of actual market conditions because the ACS may suffer from significant sample selection bias resulting from issues reaching a representative sample of farm employees. This sample selection bias has been noted in the previous literature and explains that the household-based survey format of the ACS may fail to accurately reflect the farm workforce as some farm employees are migrants and may not be present during the time the survey is implemented and many others do not live in traditional housing. Therefore, we put more credence in the estimates generated by the NAWS when focusing on the top 5 H-2A states.

Table 5: US-Based Farm Employee Wage-AEWR Elasticity Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
	Top 5 H-2A States					
	OLS					
$\ln w^H$	0.707***	0.835***	0.766***	0.748**	0.754**	0.754**
	(0.128)	(0.174)	(0.080)	(0.187)	(0.192)	(0.192)
	IV					
$\ln w^H$	0.696***	-18.376	0.738***	0.868***	0.863***	0.873**
	(0.066)	(178.575)	(0.106)	(0.197)	(0.204)	(0.343)
N	43,439	43,439	43,439	43,439	43,439	43,439
First Stage F-Statistic	96	1	194	91	91	109
	All H-2A States					
	OLS					
$\ln w^H$	0.664***	0.749***	0.674***	0.466***	0.444***	0.444***
	(0.071)	(0.089)	(0.098)	(0.103)	(0.102)	(0.102)
	IV					
$\ln w^H$	0.642***	3.025	0.665***	0.380***	0.368***	0.811***
	(0.069)	(2.505)	(0.097)	(0.138)	(0.138)	(0.182)
N	105,637	105,637	105,637	105,637	105,637	105,637
First Stage F-Statistic	51	0	32	19	19	15
Bartik Control	–	X	X	X	X	X
Year Fixed Effects	–	–	X	X	X	X
State Fixed Effects	–	–	–	X	X	X
Demographic Controls	–	–	–	–	X	X
IV Specification						
Leave-One-Out AEWR	X	X	X	X	X	–
Lagged AEWR	–	–	–	–	–	X

Standard errors are survey-design corrected according to DOL guidelines. * $p < .1$, ** $p < .05$, *** $p < .01$. The top 5 H-2A states include Florida, California, Georgia, Washington, and North Carolina.

5 Conclusion

The H-2A visa program is expanding rapidly, sparking new interest in the rules and regulations that govern the program. In fiscal year 2022, more than 370,000 H-2A jobs were certified to work in the US, and that number will likely continue to rise. Recent legislation has been proposed that would make a number of changes to the H-2A program, including provisions that would freeze the AEWR and place a limit on its year-to-year growth. To date, these proposals have not received full bi-partisan support in the US Congress. The US Department of Labor has implemented regulatory rule changes that have faced legal challenges by both employee and employer groups (Columbia Legal Services, 2023; Florida Growers Association, et al., 2023).

Industry groups continue to grapple with labor scarcity and express concern about the impacts of the AEWR on their farming operations. The USDA's Farm Labor Survey has suffered from low response rates in recent years, and it fails to incorporate a significant share of employers, notably employees of farm labor contractors who tend to pay lower wages. Moreover, the FLS does not produce an estimate of the average hourly wage but rather a measure of average gross hourly earnings, which include some forms of non-wage compensation and includes compensation from salaried employees whose hours may not be accurately recorded in employer records. In this paper, we investigate the extent to which the AEWR is creating spillovers into the US-based farm labor market to determine whether there are unintended consequences that may arise from faulty methodological aspects of the AEWR determination process. We develop a theoretical model to provide insights into the mechanisms through which the AEWR may create unintended secondary consequences, and we provide empirical estimates of these spillover effects.

Our simple theoretical model suggests that, for a given production technology and level of output, an increase in the AEWR will lower the demand for H-2A labor and create a substitution effect that increases the demand for US-based farm employees. This increase in US-based farm labor demand causes US-based farm wages to rise. Our model also suggests that higher AEWRs may serve as a bargaining chip for US-based farm employees through a "lighthouse effect," which increases their bargaining power and forces non-H-2A farm employers to raise their wages.

Our reduced-form empirical analysis provides evidence that is consistent with our theoretical model, substantiating the notion that changes in the AEWR have a direct effect on the labor market outcomes of US-based farm employees. The estimates from our preferred models indicate that a 10% increase in the AEWR causes the average wage of domestic farm employees to increase by 3.2% nationwide and by 5.2% in the top five H-2A employment states. A closer look at subsamples of the data indicate that workers who tend to be less vulnerable are more likely to benefit from increases in the AEWR, suggesting that human capital accumulation and legal status are associated with higher bargaining power. Robustness tests using data from the American Community Survey produce elasticity estimates that are similar to those produced by the NAWS when we focus on the entire nation but are somewhat higher than those produced by the NAWS when we focus on the leading H-2A employment states.

Nationally, the AEWR has grown at a rate of 4.7% per year over the past decade. Our results suggest that an AEWR freeze could potentially slow the wage growth of US-based farm employees by about 1.5% ($4.7\% \times 0.324 \approx 1.5\%$). The recently proposed Farm Workforce Modernization Act would cap the AEWR growth at 3.25%. US-based farm wages account for roughly \$36 billion per year, so an AEWR freeze would reduce the growth of US-based farm employees worker wages by \$550 million (\$36B × 1.5%) per year while the 3.25% AEWR growth cap would reduce the total wage growth of all US-based farm employees by about \$170 million ($\$36B \times (4.7\% - 3.25\%) \times 0.324 \approx \$180$ million) per year. These reductions in wage growth would be added to the estimated \$140 million in reduced wage growth for H-2A workers and the \$29 million for corresponding US-based workers who work for H-2A employers (Castillo et al., 2022). In sum, our findings reveal that changes to the AEWR data source or methodology would likely impact the amount of compensation that US-based employees receive. Moreover, we find that the AEWR does create unintended secondary consequences that are likely beneficial for US-based farm employees but harmful to domestic producers.

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Online Appendices

A AEWR Methodology

Figure A.1: USDA Farm Labor Survey Instructions

Section 1 - Paid Workers for April (continued)

4. In the table below, report all agricultural workers on the payroll during the week of April 9th through April 15th.

- Report workers under the worker code (provided on page 5) in which they are working, not under the worker code for which they have been trained.
- Report workers who fall under the same worker code on a single line.
- Report the total hours and wages paid to the group of workers during the week of April 9th through April 15th.
- Record each worker only once.
- If the worker performs work in two or more worker codes, report them under the worker code that requires the highest level of skill. If there is no measurable difference in skill requirements, report workers under the worker code in which they spend the most time.
- For workers on paid leave, report the number of hours normally worked during the week of April 9th through April 15th.
- Gross wages are the total amount paid to workers before taxes and other deductions. INCLUDE the worker's share of social security and unemployment insurance, but EXCLUDE the employer's share.INCLUDE in-kind payments (e.g., agricultural product like a side of beef, bushels of grain, etc.) provided in lieu of wages for work done. In-kind payments do NOT INCLUDE benefits such as housing, meals or insurance.

Enter the Worker Code from Page 5	Number of Paid Workers that week	Total Hours Worked that week	Total Gross Wages Paid that week (Dollars)
611	612	613	614
611	612	613	614
611	612	613	614
611	612	613	614
611	612	613	614
611	612	613	614
611	612	613	614
611	612	613	614
611	612	613	614
611	612	613	614

Office Use Only – Completion Code Usability	1 – Incomplete, Has Labor 2 – Incomplete, Unknown 3 – No Labor	698
		599 **1**

B Optimal US-Based Farm Labor Demand Derivations

The farmer's optimal input decision making process in the current growing season is characterized by the following cost minimization problem:

$$\min_{D,H,K} \; w^D D + (w^H + C)H + rK$$

subject to

$$Q = AD^{\alpha}H^{\beta}K^{\gamma}. \tag{B.1}$$

The Lagrangean function can be expressed as follows:

$$\mathscr{L} = w^D D + (w^H + C)H + rK + \lambda(Q - AD^{\alpha}H^{\beta}K^{\gamma}).$$

The first order conditions imply that

$$H = \frac{\beta w^D}{\alpha(w^H + C)} D \tag{B.2}$$

and

$$K = \frac{\gamma w^D}{\alpha r} D. \tag{B.3}$$

Substituting (B.2) and (B.3) into (B.1), taking logs, and solving for $\ln D_d$ allows us to derive the optimal (log) demand for US-based labor:

$$\ln D_d = \left[\frac{-(\beta+\gamma)}{\alpha+\beta+\gamma}\right] \ln w_d^D + \left[\frac{\beta}{\alpha+\beta+\gamma}\right] \ln(w^H + C) + \underbrace{\ln\left(\frac{Q}{A}\right) + \beta \ln\left(\frac{\alpha}{\beta}\right) + \gamma \ln\left(\frac{\alpha r}{\gamma}\right)}_{Z}.$$

C Proof that $\frac{w_1^H}{w_1^D} = \frac{w_0^H}{w_0^D} \iff \Lambda = 1$

Assume the following condition holds:

$$\frac{w_1^H}{w_1^D} = \frac{w_0^H}{w_0^D} \tag{C.4}$$

By using the following algebraic process, one can see that equation (C.4) is equivalent to $\Lambda = 1$:

$$\frac{w_1^H}{w_1^D} = \frac{w_0^H}{w_0^D} \iff \frac{w_1^H}{w_0^H} = \frac{w_1^D}{w_0^D} \iff \frac{w_1^H}{w_0^H} - 1 = \frac{w_1^D}{w_0^D} - 1 \iff$$
$$\frac{(w_1^H - w_0^H)/w_0^H}{(w_1^D - w_0^D)/w_0^D} = \frac{1}{\Lambda} = 1 \iff \Lambda = 1.$$