# Labor Shortages and Farmer Adaptation Strategies

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## Abstract

An increasing body of empirical evidence indicates that labor shortages are becoming a major challenge for agricultural producers in the United States. However, little is known about how farmers are adapting to this challenge. In this study, we quantify the extent to which labor shortages are impacting farming practices for labor-intensive crop producers and determine which mitigation strategies are the most prevalent. Our results indicate that wage increases are the most common adaptation strategy, followed by changes in cultivation practices, and adoption of labor-saving technologies. Our estimates reveal that labor shortages increase the probability of raising wages by at most 29 percentage points. We also find that labor shortages increase the probability of changing cultivation practices by at most 11 percentage points and the probability of adopting new labor-saving technology by at most 10 percentage points. Additionally, we find small, significant effects of labor shortages on the use of farm labor contractors in the top 10 labor-intensive counties. We do not uncover meaningful effects on the use of the H-2A program during our sample period. Generally, the effects of labor shortages on these adaptation strategies are very similar when comparing farmers throughout the state to those in the top 10 labor-intensive counties.

**Keywords**

Agricultural Technology; Labor Substitution; Labor Shortages, Adaptation Strategies, Farm Wages; Cultivation Practices; Farm Labor Contractors; Labor-intensive Crops

**JEL Classification**

J01, J08, J21, J43, Q18

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# 1 Introduction

On February 23, 2023, the United States (US) Secretary of Agriculture, Tom Vilsack, moderated the plenary session of the USDA Agricultural Outlook Forum, which focused on "Workers and the Workforce: Essential Contributors to American Agriculture" (Ohlemeir, 2023). The Secretary asked panel members about the extent to which farm labor shortages are prevalent in the US and the potential consequences of not solving this problem. Experts on the panel explained that the issue of farm workforce shortages is a national security concern and that if we do not figure out a way to resolve it, the US will become increasingly reliant upon foreign producers to provide the foods that would have otherwise been produced by American farmers. Such a shift would put the US at increased food security risk, particularly in the event that future supply chain disruptions occur, such as those that could arise from a new global pandemic or a major global or regional armed conflict.

The production of fruits, vegetables, and horticultural commodities (FVH) is highly labor-intensive, with labor costs accounting for 40% of the total production costs (USDA, 2022). The US agricultural sector relies extensively on immigrant workers from Mexico, most of whom have settled in the US. However, the number of US-based Mexican employees willing and able to perform hired farm labor has been declining (Charlton & Taylor, 2016; Richards, 2018; Taylor, Charlton, & Yúnez-Naude, 2012; Rutledge & Mérel, 2023; Zahniser et al., 2018), and labor shortages are becoming a major challenge for agricultural producers (CFBF and UC Davis, 2019; Hertz & Zahniser, 2013; Martin, 2007; Rutledge & Taylor, 2019a, 2019b,).[1] Economic theory suggests that a decline in the supply of labor should cause wages to rise, which would

[1] This trend is a result of a multiple factors, including structural changes in the Mexican economy, increased education among the rural Mexican population, lower birth rates in Mexico, and increased non-farm job opportunities for low-skilled workers both in Mexico and the US.

shift the optimal input mix and cause some producers to adopt new production technologies. As such, a decline in the supply of labor will inevitably impact the production decisions of farmers who have historically relied upon an abundant supply of hired laborers to work on their farms. However, the extent to which labor shortages impact specific farming practices generally remains unclear. In this study, we provide empirical estimates of the effects of farm labor shortages on a set of key production and labor management practices, and we determine which adaptation strategies are the most prevalent.

The recent US farm labor literature focuses on several distinct research objectives. One set of studies attempts to identify whether labor shortages are prevalent in US agriculture (Hertz & Zahniser, 2013; Martin, 2007; Richards, 2018; Taylor, Charlton, & Yúnez-Naude, 2012). A second set of studies identifies key drivers of labor supply shocks (Boucher et al., 2007; Charlton & Taylor, 2016; Fan et al., 2015; Richards & Patterson, 1998). Another set attempts to identify policy options and mitigation strategies that could potentially allay the labor shortage issue (Charlton et al., 2019; Charlton & Kostandini, 2021; Hamilton et al., 2022; Richards, 2018; Zahniser et al., 2018). Other studies focus on the impact of labor supply shocks on agricultural production (Brady et al., 2016; Cassey et al., 2018; Rutledge & Mérel, 2023; Zahniser et al., 2012).

Martin (2017) identifies several adaptation strategies that farmers are likely to use to address reduced labor availability. These strategies include satisfying workers by providing higher wages and better services, stretching the current workforce with mechanical aids to increase productivity and make farm work easier, substituting or replacing workers with machinery, and supplementing the current workforce with guest workers via the H-2A visa program. However, to the best of our knowledge, only one study quantifies the extent to which farmers are changing farming and labor management practices. Santos, Park, & Escalante (2009) find that adjusting wages and nonwage benefits are the most effective adaptation strategies for farmers in the Southeastern US, which is consistent with our research findings. Moreover, Santos, Park, & Escalante (2009) argue that, in addition to offering better compensation for employees, changing certain farming practices is likely a more effective long-run strategy. We also find evidence consistent with this long run strategy in our empirical setting. These findings are important because they provide empirical evidence that can be used to inform the farm labor policy discussion by shining light on the types of interventions that could help ensure that a stable source of fresh fruits and vegetables is produced domestically.

Our analysis uses a retrospective panel of data obtained from a 2019 survey of California farmers. California is the largest FVH producer and agricultural employer in the US with labor expenses accounting for nearly one-third of the nation's total (NASS, 2021). While our full dataset contains complete survey information on 720 crop and dairy farmers over the period 2014 to 2018 (N ≈ 3,500), we restrict our sample to the set of farmers who report producing a labor-intensive crop as their main revenue generating commodity.[2] As such, our final data set contains approximately 1,320 observations.

Our primary research objective is to gain insight into how labor supply-driven workforce shortages impact the adoption of specific farming and labor management practices. Our outcomes of interest include the following adaptation strategies: wage increases, changes in

[2] Our definition of labor-intensive crops follows the convention used in in Rutledge and Mérel (2023), which relies upon the set of California crops that did not have a mechanical harvest option available during the survey period. These hand-harvest-only crops were determined by using "a combination of common knowledge (e.g., tree fruits intended for the fresh market are generally not mechanically harvested due to unacceptable damage that occurs from the use of mechanical shake and catch systems), conversations with UC Davis Professor Emeritus and farm labor expert Philip Martin, and an examination of University of California Agriculture and Natural Resources commercial fruit and vegetable production publications, which contain information about harvesting practices for California's FV crops (see e.g., https://anrcatalog.ucanr.edu/pdf/7234.pdf, p. 4, par. 6)." (as quoted in Rutledge and Mérel, 2023).

cultivation practices, adoption of labor-saving technologies, use of farm labor contractors, and use of the H-2A temporary agricultural guest worker visa program. Our empirical strategy deploys fixed-effects panel regression models at the individual-year level of aggregation. Our outcome variables and the main explanatory variable of interest are binary indicator variables that identify farmers' experiences with labor shortages and adaptation strategies. To help mitigate omitted variables bias (OVB) that could result from unobserved labor demand shocks, our preferred specification includes individual and year fixed effects, county-specific time trends, a set of weather variables, and a proxy for local agricultural labor demand shocks. While we expect these controls to mitigate the lion's share of the OVB, we derive formal expressions for the bias for each of our outcome variables and determine that they are likely positive in all cases (see Section 3 for more details). As such, we err on the side of caution and interpret our estimates as upper bounds for the population parameters of interest.

Another valid concern has to do with the potential for reverse causality because the adoption of a certain farming practice in year $t$ could reduce the likelihood of experiencing a labor shortage in that year. We argue that labor demand shocks are the primary channel through which reverse causality is of concern such that adequate labor demand controls should address that concern. To test this hypothesis, we conduct robustness tests that use a lagged labor shortage variable in place of the contemporaneous labor shortage variable. Such a modeling approach should alleviate any concern for reverse causality because the adoption of a farming practice in year $t$ cannot cause a labor shortage in year $t-1$ due to the implicit chronological nature of causality. Our results from this robustness test are qualitatively similar, but the coefficients are slightly smaller in magnitude than those produced with the contemporaneous labor shortage variable. Based on these findings, we rely upon the contemporaneous labor shortage variable for our main analysis and interpret the coefficients as upper bounds.

Our empirical results provide strong evidence that farmers are changing production and labor management practices to cope with labor shortages. The most prevalent adaptation strategies include raising wages, changing cultivation practices, and adopting labor-saving technologies. Our results indicate that, throughout the state, labor shortages increase the probability of raising wages by as much as 29 percentage points, changing cultivation practices by as much as 11 percentage points, and use of labor-saving technologies by up to 10 percentage points. Our estimates are similar when we focus on farmers who report their main revenue generating activities in the top 10 labor-intensive counties. We also find a small statistically significant effect of labor shortages on the use of farm labor contractors in those counties (an increase of up to 4 percentage points). We do not find any meaningful effects on the use of the H-2A program during our sample period.

Our study makes three main contributions. First, we contribute to an emerging branch of farm labor research that investigates the impacts of reduced labor availability, adding to a handful of studies that investigate the implication of employment or labor supply shocks on production. For example, Zahniser et al. (2012) examine the impact of a hypothetical shock to the immigrant population on the production of various crops, Brady et al. (2016) perform a simulation exercise to investigate the potential impacts of reduced labor supply on tree fruit production, and Cassey et al. (2018) investigate how a labor shortage in the pre-harvest labor market affects the post-harvest labor market and downstream commodity markets. However, our study adds new context to this area of research by focusing on how labor shortages affect the underlying production and labor management practices that are ultimately responsible for these types of production changes.

Second, to the best of our knowledge, we are the first to provide empirical estimates of the effects of farm labor shortages on specific farming practices in the US. While Santos, Park, & Escalante (2009) estimate models that analyze the impact of fluctuations in labor inputs on a single variable that identifies whether farmers changed at least one production practice (i.e., downsizing, changing commodities, and adjusting machinery), their empirical estimates do not quantify the effects of labor shortages, but rather fluctuations in farm employment. Moreover, the sample in their study is very small (N=72), while ours is much larger. Furthermore, we are able to identify changes in individual farming practices and document whether each farmer is unable to hire all the employees she wanted to in a given production season.

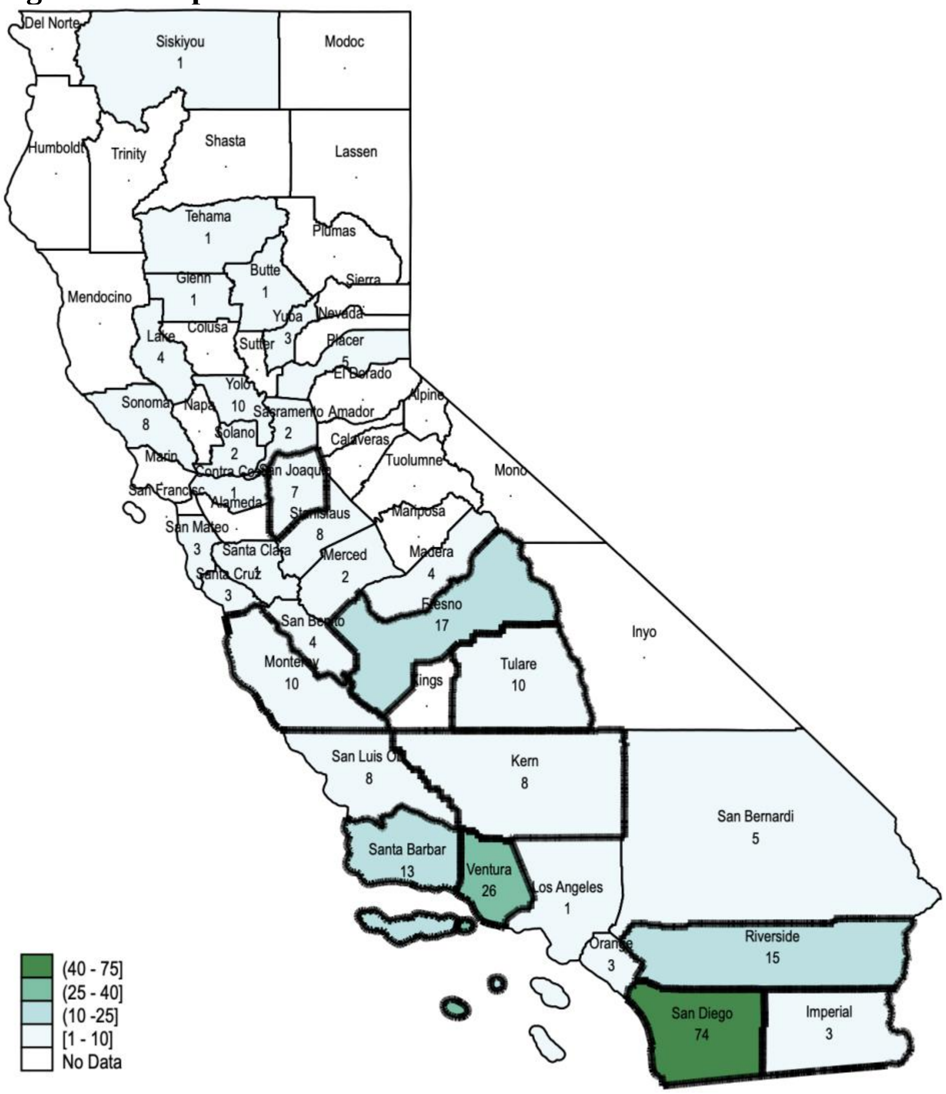
Third, our findings contribute to the ongoing policy discussion related to food stability in the US. Specifically, our study provides insights into the types of adaptation strategies that are most prevalent among labor-intensive crop producers in the leading FVH state, which can inform decision-makers about the types of policy options that are best suited to strengthen our food supply chain by securing adequate supplies of domestically produced fresh, nutritious food.

In the next section, we present the data, followed by the empirical method in section 3. Section 4 discusses the results. In section 5, we conclude.

# 2 Data

In this study, we use proprietary, individual-level panel data from a California Farm Bureau Federation (CFBF)—University of California, Davis survey of California farmers collected in 2019. This survey collected information on farmers' experiences with labor shortages and their production and labor management practices between the period 2014 and 2018. 720 crop and dairy farmers completed the entire survey. However, this study focuses on the set of farmers that report a labor-intensive crop as being the main crop in their main crop-producing county. In addition to our main analysis, which includes data from farmers from any county in the state, we also provide separate estimates for a sample that focuses on the top 10 labor-intensive crop-producing counties to test the hypothesis that farmers in the major labor-intensive crop producing counties are impacted by labor shortages more than the average farmer in the state (see the list of the top 10 counties in Figure 1).[3]

**Figure 1: Sample distribution across California counties**




**Note:** The top 10 labor-intensive producing counties are outlined with a thick black border.

[3] We use the same top 10 counties as Rutledge and Mérel (2023).

We also test the robustness of our results to alternative definitions of "labor-intensive" crops, each of which is progressively less restrictive. Our preferred definition is the most restrictive set of crops, which removes all crops that had a mechanical harvest option available during our survey period. Our preferred sample includes 264 farmers located across 33 of California's (CA) 58 counties (See Figure 1). Using this sample, we construct a retrospective balanced panel, which contains approximately 1,320 observations spanning the period 2014 to 2018.

We complement this survey data with two other publicly available datasets. First, we obtain weather data from the National Oceanic and Atmospheric Administration Climate Data Online website (NOAA, 2022), which captures the average temperature and cumulative precipitation each month at the county level. Second, we use annual employment and weekly wage data from the Quarterly Census of Employment and Wages to construct a Bartik instrument as a proxy for agricultural sector labor demand shocks (Bartik, 1994; Basso & Peri, 2015; BLS, 2022). To calculate the Bartik control variable, we use data from crop production workers (NAICS 111) and those in agricultural and forestry support activities (NAICS 115), which capture the bulk of employment in the agricultural sector.

Table 1 displays summary statistics of the variables used in our analysis. Farmers in our sample cultivated an average of 855 acres with 453 acres being dedicated to their main revenue generating crop (See Panel A, Table 1). Panel B reveals that the most common crops grown in our sample were citrus fruits (22%), ornamental, floral, or nursery products (22%), avocados (17%), and vegetables (17%), and deciduous tree fruits (13%). The 5-year averages of labor shortages and farming practices can be found in Panel C. On average, 32% of sampled farmers experienced labor shortages over the 5-year period. The most common production and labor management practices include wage increases (56%), use of farm labor contractors (52%), adoption of labor-saving technology (31%), and changes in cultivation practices (22%). Only a small percentage of farmers (4%) hired workers through the H-2A temporary agricultural guest worker visa program.

In Figure 2, we illustrate the pattern of labor shortages between 2014 and 2018. The percentage of farmers experiencing a labor shortage increased significantly over our sample period. In 2014, only 14% of farmers reported a labor shortage, but the share of farmers experiencing a labor shortage reached 46% in 2018. Consistent with the pattern of labor shortages, the shares of farmers increasing wages, adopting labor-saving technology, and changing cultivation practices also increased over our sample period. In 2014, about 29% of farmers reported increasing wages, and it reached 81% in 2018.

**Table 1: Summary Statistics**

| | N | Mean | SD |
|---|---|---|---|
| **Panel A: Farm Characteristics (2018)** | | | |
| Acres cultivated for all crops | 264 | 854.78 | 2448.66 |
| Acres cultivated for a major crop | 248 | 453.62 | 1601.29 |
| **Panel B: Main Revenue Generating Crop (2018)** | | | |
| Avocados | 264 | 0.17 | 0.38 |
| Berries | 264 | 0.05 | 0.22 |
| Citrus Fruits | 264 | 0.22 | 0.42 |
| Deciduous tree fruits | 264 | 0.13 | 0.33 |
| Ornamental, floral, or nursery products | 264 | 0.22 | 0.42 |
| Other fruits | 264 | 0.01 | 0.12 |
| Table grapes | 264 | 0.03 | 0.16 |
| Vegetables (excluding leafy greens) | 264 | 0.17 | 0.38 |
| **Panel C: Key Variables (5-year average from 2014 to 2018)** | | | |
| Experienced labor shortage | 1,320 | 0.32 | 0.46 |
| Increased wages | 1,245 | 0.56 | 0.49 |
| Adopted labor-saving technology | 1,155 | 0.31 | 0.46 |
| Changed cultivation practices | 1,175 | 0.22 | 0.42 |
| Used farm labor contractors (FLC) | 1,265 | 0.52 | 0.49 |
| Used H-2A | 1,275 | 0.04 | 0.20 |

Similarly, the percentages of farmers who adopted labor-saving technology and changed cultivation practices were only 16% and 10% in 2014. But in 2018, 48% of farmers used a labor-saving technology, and 32% implemented at least one change to their usual cultivation practices. We do not see as much variation in the use of farm labor contractors over the 5-year period, but a large share of farmers (46%) already used a farm labor contractor in 2014 and the percentage grew to 58% in 2018. Hiring labor through the H-2A visa program was not that common among farmers in our sample period. Only 2% of farmers in 2014 and 9% in 2018 used the H-2A program. While these statistics provide some summary evidence that farmers may be changing production and labor management practices in response to labor shortages, they do not reflect evidence of causality. In the next section, we explain our empirical model that is used to generate estimates of the upper bounds of the causal effects of interest.

**Figure 2: Share of farmers reporting a labor shortage between 2014 and 2018**

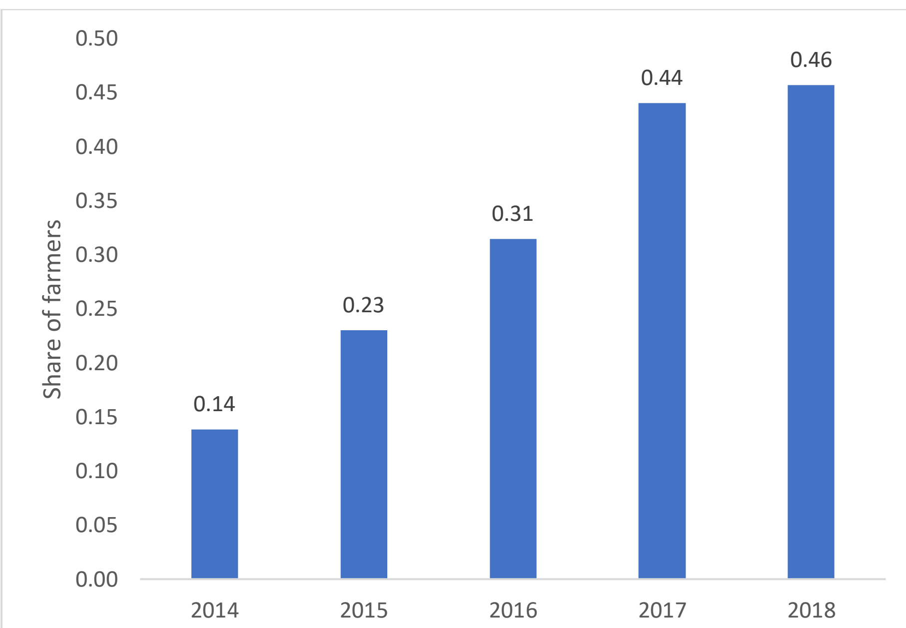
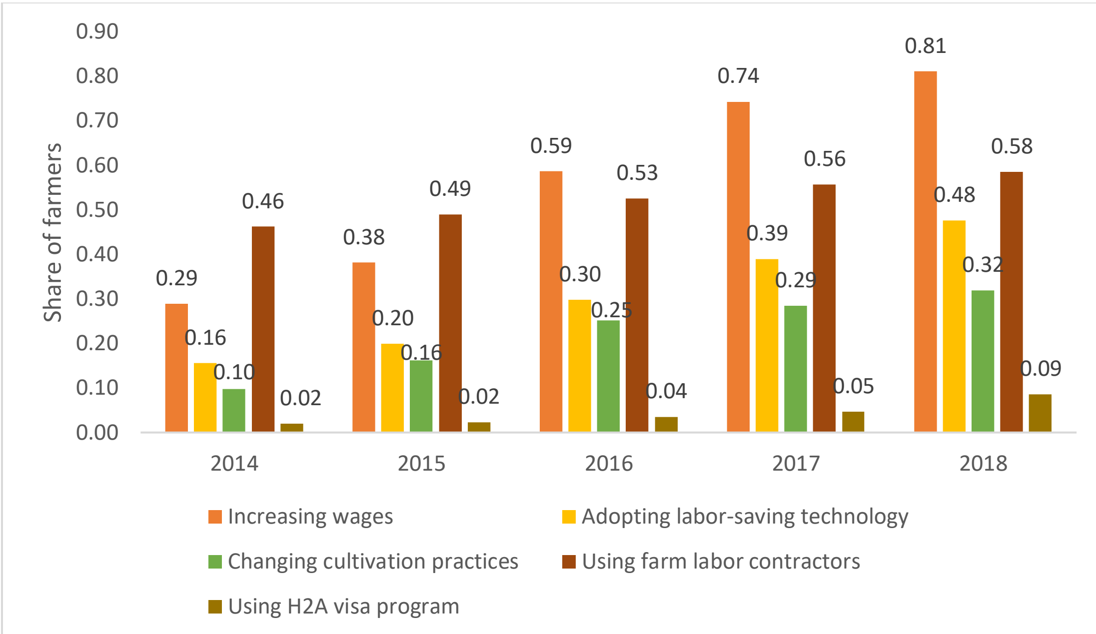


**Figure 3: Share of farmers using specific production and labor management practices between 2014 and 2018**




# 3 Empirical Method

## 3.1 Identification Strategy

In this study, we are interested in estimating the effects of labor-supply induced labor shortages on farmer behavior. We use the following fixed-effects panel regression model to estimate the impact of labor shortages on each of the adaptation strategies:

$$y_{ijt} = \beta_0 + \beta_1 LS_{ijt} + \phi_i + \phi_t + \phi_j t + \sum_m^{12} (\gamma_m Temp_{jt}^m + \omega_m Precip_{jt}^m) + \beta_2 Bartik_{jt} + \varepsilon_{ijt}, \quad (1)$$

where $i$ denotes the farmer, $j$ denotes the county, and $t$ denotes the year. The outcome variables $y_{ijt} \in \{W_{ijt}, C_{ijt}, T_{ijt}, FLC_{ijt}, H2A_{ijt}\}$ are a set of binary variables that take on the value of one if a farmer increased wages, changed cultivation practices, used a labor-saving technology, used a farm labor contractor (FLC), or hired workers through the H-2A visa program in year $t$, respectively, and zero otherwise. The cultivation practice variable identifies whether a farmer made a change to one of their usual cultivation practices in a given year.[4] The main explanatory variable is $LS_{ijt}$, a binary indicator variable that takes on the value of one if farmer $i$ experienced a labor shortage in county $j$ in year $t$ and zero otherwise.[5]

To control for local agricultural labor demand shocks, we construct a Bartik (1994) instrument using QCEW data from the crop production (NAICS 111) and agricultural and forestry support activities (NAICS 115) as follows:

$$Bartik_{jt} = \sum_j \frac{EMP_{kj,2010}}{Emp_{j,2010}} \times \Delta \ln wage_{kt},$$

where $Emp_{kj,2010}$ denotes the employment level in industry $k \in \{111, 115\}$ in county $j$ in the base year 2010, $Emp_{j,2010}$ denotes the total employment in NAICS 111 and 115 in county $j$ in 2010, and $\Delta \ln wage_{kt}$ identifies the state-level growth of the log of real weekly wages for each industry $k$ in year $t$ relative to 2010.

## 3.2 Omitted Variables and Identification of Causality

Our empirical setting has two main identification challenges. The first challenge is omitted variable bias due to unobserved local labor demand shocks. Labor shortages result from market disequilibrium, so they may be caused by labor supply or demand shocks. For example, Fisher & Knutson (2013) explain that regional weather conditions may affect the timing of peak

[4] The most prevalent changes in cultivation practices include reduced pruning or weeding (43%), delayed pruning or weeding (27%), delaying harvest (16%), and reduced harvest (14%).

[5] Labor shortages are based on a farmer's response to the question "During which of the years listed below were you unable to obtain all the workers you needed to produce [your main crop] in [your main] county? (please check all that apply or click "I don't know")." Respondents were allowed to select from a list of years spanning 2014 to 2018.

harvest labor demand, which may create local labor shortages at a time when an insufficient number of qualified harvest workers are not present in the local labor market.[6] Since our main interest is labor-supply induced labor shortages, identification requires that we sufficiently control for labor demand shocks that could confound our estimates.

Rutledge & Mérel (2023) note that three types of shocks can influence the demand for farm labor. First, nonlabor input supply shocks, such as urbanization that may reduce the available land available for crop production, can cause the local farm labor demand curve to shift inward. The second shock involves changes in demand for the crop output that may arise from shifting consumer preferences or consumption patterns that influence the crop mix and ultimately the acreage devoted to labor-intensive crop production. Third, productivity shocks that influence the marginal products of the inputs can cause the optimal demand for labor to change. This last type of shock may arise from weather events, such as extreme heat exposure during the growing season or precipitation during the pollination period.

**Table 2: Potential sources of omitted variables bias and corresponding control variables**

| Source of bias | Example | Mitigating variables |
|---|---|---|
| Nonlabor input supply shocks | Land and capital availability | $\phi_t$, $\phi_j$t, $Bartik_{it}$ |
| Crop output demand shocks | Changes in consumer preferences or consumption patterns | $\phi_t$, $Bartik_{it}$ |
| Productivity shocks | Weather | $Temp_{jt}^m$, $Precip_{jt}^m$, |
| Minimum wage changes | Minimum wage law | $\phi_t$ |
| Farmer/farm heterogeneity | Crops, education, assets, land ownership | $\phi_i$ |

[6] A highly publicized instance of this occurred in Lake County, California during 2006 (see Preston, 2006).

To help mitigate bias resulting from these shocks, we include a robust set of control variables. First, we include a set of individual fixed effects $\phi_i$ to control for unobserved farm/farmer heterogeneity such as education level, farming knowledge, or farm characteristics such as soil quality. Next, we include a set of year fixed effects $\phi_t$ to control for state-wide shocks common to all counties in a given year, such as changes in minimum wages.[7] To help control for nonlabor input supply shocks, we also include a set of county-specific time trends $\phi_j t$, where $\phi_j$ is a set of county fixed effects and $t$ is a continuous time variable. To help control for weather-driven productivity shocks, we include sets of 12 county-month-year-level average temperature $Temp_{jt}^m$ variables and 12 cumulative precipitation $Precip_{jt}^m$ variables, where $m \in \{1, 2, \ldots, 12\}$ denotes the month. Finally, to help control for local farm labor demand shocks, we include the local farm labor demand proxy variable $Bartik_{jt}$. We summarize the relevant sources of omitted variables bias and the corresponding variables that are expected to mitigate them in Table 2. To the extent that our covariates do not fully control for unobserved labor demand shocks, one may be concerned that our OLS estimates are still biased. To address this concern, we conduct an exercise to formally investigate the likely direction of the bias of our OLS estimates for each of our outcome variables. For simplicity, assume that the omitted labor demand shock variable is defined as $LD$ so that the equations of interest are:

$$y = \beta_1 LS + \theta LD + e,$$

where $E[e|LS, LD] = 0$. The probability limit of the OLS estimate of $\beta_1$ is:

[7] California had several mandated minimum wage increases over our sample period.

$$\beta_1^{OLS} = \beta_1 + \theta \frac{\text{cov}(LS,\ LD)}{\text{var}(LS)}.$$

As Fisher & Knutson (2013) point out, increases in labor demand will typically lead to more labor shortages, so it is natural to assume that $\text{cov}(LS, LD) \geq 0$. Moreover, it is plausible that that $\theta \geq 0$ for all of our outcome variables (see Appendix A for more details).[8] Thus, the omitted variables bias for each of our outcomes is likely positive. This exercise indicates that if our models fail to fully control for unobserved labor demand shocks, our OLS estimates can be interpreted as upper bounds for the population parameters of interest. While we note that such a concern is likely unwarranted due to robust set of controls, we err on the side of caution and interpret our results as upper bounds.

## 3.3 Reverse Causality

Another valid concern has to do with the potential for reverse causality because the adoption of a certain farming practice in year $t$ could reduce the likelihood of experiencing a labor shortage in that year. However, unobserved labor demand shocks remain the first-order concern for reverse causality, too. As such, sufficiently controlling for the farmer's labor demand shocks should resolve this issue. For example, suppose a Fresno County peach farmer, who typically hires employees from the local farm labor market, decides that she is only going to prune half of her orchard this year. Naturally, this decision will reduce her demand for labor in the current year as she will require fewer employees on her farm (i.e., $\text{cov}(LS, LD) \geq 0$). As

[8] Ex ante, it seems unclear whether $\theta \geq 0$ for the labor-saving technology model. However, the estimates of $\beta_1$ in Table 5 are attenuated as additional control variables are included in the model. This attenuation is consistent with the theoretical expectation that unobserved labor demand shocks create upward bias in the labor-saving technology use model. Thus, it is plausible that $\theta \geq 0$ for all of our outcome variables.

such, she is less likely to experience a labor shortage simply because she demands fewer workers from the fixed pool of local farm employees. To investigate whether reverse causality is a major concern in our empirical setting, we estimate a set of regressions that use a lagged labor shortage variable in place of the contemporaneous labor shortage variable. We argue that such a test should alleviate any concern for reverse causality because the adoption of a farming practice in year $t$ cannot cause a labor shortage in year $t - 1$ due to the implicit chronological nature of causality. Our results from this analysis are qualitatively similar but slightly smaller in magnitude relative to the specification that uses the contemporaneous labor shortage variable (See Appendix D). In light of this finding, we present our upper bound estimates using the contemporaneous labor shortage variable as our main set of results in Section 4.

### 3.4 Cross-sectional Dependence

In many empirical settings with spatially differentiated panel data, it is common to use standard errors clustered at the region level (Roger, 1993). However, clustered standard errors are only valid for inference if the errors are not correlated across clusters. Since California counties are geographically close to each other, the potential for the inter-cluster error independence is a concern. As such, we conduct Pesaran tests for cross-sectional dependence, which show strong evidence of cross-sectional dependence. To address this issue, we rely upon Driscoll-Kraay standard errors (Driscoll & Kraay, 1998; Hoechle, 2007) for inference, which are robust to spatial and temporal error dependence up to a specified number of lags. We determine the number of lags by using the heteroskedastic-robust Cumby-Huizinga general test for serial correlation (Cumby & Huizinga, 1992). We run this test separately for each model, and we determine the most conservative degree of serial correlation across the entire panel of models within a table (e.g., Panel A of Table 3).[9] We correct for the same level of serial correlation across all of the model specifications within each panel so that all of the results within a panel can be directly compared to each other.

# 4 Regression Results

The regression results from equation (1) are shown in Tables 3- 7. Each table contains two panels (A and B) of results that are estimated with different samples. Panel A displays the results from the sample that includes data from the full set of counties while Panel B shows the results from the sample that is restricted to the top 10 labor-intensive counties. Moving from left to right (from column 1 to column 6), each estimate is produced from a model that has progressively more fixed effects and controls. For instance, the model used in column 1 does not contain any fixed effects or controls, and the model used in column 6, which is our preferred specification, includes individual and year fixed effects, county trends, weather controls, and the Bartik proxy.

## 4.1 Increased Wages

We start out by presenting the results from the wage increase regression in Table 3. The coefficients in this table represent upper bounds for the effects of labor shortages on the probability of increasing wages. We find statistically significant effects among farmers who produced labor-intensive crops in both the full set of counties (Panel A) and when we focus on the top 10 counties (Panel B).

[9] When the Cumby-Huizinga tests suggests that we should correct for different levels of serial correlation for different models within a panel of results (e.g., Panel A of Table 3), we instead correct for the most conservative degree of serial correlation across the entire set of models within a panel. Specifically, we correct for the degree of serial correlation that produces the largest standard errors across the entire set of models within a panel so that that all models can be directly compared to each other and that the significance levels are conservative in nature.

**Table 3: Estimated effects of labor shortage on increasing wage**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Increased Wage | | | | | |
| Panel A: Full Sample | | | | | | |
| Labor shortage | 0.390*** | 0.295*** | 0.308*** | 0.287*** | 0.286*** | 0.288*** |
| | (0.031) | (0.011) | (0.014) | (0.009) | (0.010) | (0.010) |
| Observations | 1,245 | 1,245 | 1,245 | 1,245 | 1,245 | 1,245 |
| Number of farmers | 249 | 249 | 249 | 249 | 249 | 249 |
| Panel B: Top 10 Counties | | | | | | |
| Labor shortage | 0.388*** | 0.293*** | 0.297*** | 0.281*** | 0.278*** | 0.280*** |
| | (0.029) | (0.010) | (0.010) | (0.011) | (0.012) | (0.012) |
| Observations | 865 | 865 | 865 | 865 | 865 | 865 |
| Number of farmers | 173 | 173 | 173 | 173 | 173 | 173 |
| Year fixed effects | No | Yes | Yes | Yes | Yes | Yes |
| County trends | No | No | Yes | Yes | Yes | Yes |
| Individual fixed effects | No | No | No | Yes | Yes | Yes |
| Weather controls | No | No | No | No | Yes | Yes |
| Ag Bartik | No | No | No | No | No | Yes |

Source: Authors' calculations
Note: Significance levels are based on Driscoll-Kraay standard errors, which are reported in parentheses. Driscoll-Kraay standard errors correct for serial correlation up to four lags for both Panel A and Panel B. *** p<0.01, ** p<0.05, * p<0.1.

The estimates across the different models are relatively stable for both panels. Our preferred estimate in column 6 indicates that labor shortages cause at most a 29 (resp. 28) percentage point increase in the probability of raising wages when including farmers from all the counties (resp. the top 10 counties) in our sample. Our preferred model controls for year fixed effects, which effectively control for any minimum wage increases over our sample period, so our estimates reflect changes in wages above and beyond what would have been required due to mandated wage increases. As additional covariates are included in the model, the estimates tend to get smaller in magnitude, consistent with the hypothesis that our choice of controls is mitigating upward bias from the unobserved labor demand shocks.

## 4.2 Change in Cultivation Practices

Table 4 presents our estimates of the effects of labor shortages on the probability of changing cultivation practices. The effects are statistically significant for both the full set of counties and also when we focus on the top 10 counties. The results show that our estimates are significantly attenuated after controlling for year fixed effects, county trends, and individual fixed effects. However, the estimates are relatively stable once the weather controls and labor demand proxy are included. Our preferred specification indicates that labor shortages increase the probability of changing cultivation practices by at most 11 percentage points for farmers in the full sample of counties and at most 12 percentage points for farmers in the top 10 labor-intensive counties.

**Table 4: Estimated effects of labor shortage on the change in cultivation practices**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Change in Cultivation Practices | | | | | |
| | Panel A: Full Sample | | | | | |
| Labor shortage | 0.212*** | 0.179*** | 0.164*** | 0.111*** | 0.108*** | 0.109*** |
| | (0.007) | (0.008) | (0.008) | (0.005) | (0.005) | (0.005) |
| Observations | 1,175 | 1,175 | 1,175 | 1,175 | 1,175 | 1,175 |
| Number of groups | 235 | 235 | 235 | 235 | 235 | 235 |
| | Panel B: Top 10 Counties | | | | | |
| Labor shortage | 0.205*** | 0.176*** | 0.171*** | 0.116*** | 0.114*** | 0.116*** |
| | (0.011) | (0.005) | (0.006) | (0.009) | (0.008) | (0.008) |
| Observations | 825 | 825 | 825 | 825 | 825 | 825 |
| Number of groups | 165 | 165 | 165 | 165 | 165 | 165 |
| Year fixed effects | No | Yes | Yes | Yes | Yes | Yes |
| County trends | No | No | Yes | Yes | Yes | Yes |
| Individual fixed effects | No | No | No | Yes | Yes | Yes |
| Weather controls | No | No | No | No | Yes | Yes |
| Ag Bartik | No | No | No | No | No | Yes |

Source: Authors' calculations
Note: Significance levels are based on Driscoll-Kraay standard errors, which are reported in parentheses. Driscoll-Kraay standard errors correct for serial correlation up to four lags for both Panel A and Panel B. *** p<0.01, ** p<0.05, * p<0.1.

## 4.3 Use of Labor-Saving Technology

Table 5 reports our estimates for the effects of labor shortages on the use of labor-saving technology. Relative to the results in Tables 3 and 4, the range of the estimated effects of labor shortages on adopting labor-saving technology is more variable in both panels of the table.

Moving from columns 1 to 6, the magnitudes of the estimates decline when we add more control variables, consistent with the notion that unobserved labor demand shocks create upward bias in the technology use models. In other words, the attenuation of the estimates in Table 5 are consistent with $\theta \geq 0$ (see Section 3.2). Our preferred estimates indicate that labor shortages cause at most a 10 percentage points for farmers in all counties, as well as those in the top 10 counties.

**Table 5: Estimated effects of labor shortage on the adoption of labor-saving technology**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Technology Adoption | | | | | |
| | Panel A: Full Sample | | | | | |
| Labor shortage | 0.179*** | 0.122*** | 0.111*** | 0.100*** | 0.097*** | 0.098*** |
| | (0.012) | (0.015) | (0.012) | (0.013) | (0.013) | (0.013) |
| Observations | 1,155 | 1,155 | 1,155 | 1,155 | 1,155 | 1,155 |
| Number of farmers | 231 | 231 | 231 | 231 | 231 | 231 |
| | Panel B: Top 10 Counties | | | | | |
| Labor shortage | 0.206*** | 0.156*** | 0.144*** | 0.100*** | 0.099*** | 0.098*** |
| | (0.009) | (0.010) | (0.008) | (0.012) | (0.013) | (0.014) |
| Observations | 800 | 800 | 800 | 800 | 800 | 800 |
| Number of farmers | 160 | 160 | 160 | 160 | 160 | 160 |
| Year fixed effects | No | Yes | Yes | Yes | Yes | Yes |
| County trends | No | No | Yes | Yes | Yes | Yes |
| Individual fixed effects | No | No | No | Yes | Yes | Yes |
| Weather controls | No | No | No | No | Yes | Yes |
| Ag Bartik | No | No | No | No | No | Yes |

Source: Authors' calculations
Note: Significance levels are based on Driscoll-Kraay standard errors, which are reported in parentheses. Driscoll-Kraay standard errors correct for serial correlation up to four lags for both Panel A and Panel B. *** p<0.01, ** p<0.05, * p<0.1.

## 4.4 Use of Farm Labor Contractors

Table 6 displays our estimates of the effects of labor shortage on the use of farm labor contractors. Our estimates do not reveal any statistically significant effects of labor shortages on the use of farm labor contractors for farmers in the full set of sample (Panel A). However, we find a small, statistically significant effect for farmers in the top 10 counties in Panel B. Our estimate reveals that labor shortages increase the likelihood of using farm labor contractors by as much as 4 percentage points for farmers in those counties.

**Table 6: Estimated effects of labor shortage on the use of farm labor contractors**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Use of Farm Labor Contractors | | | | | |
| | Panel A: Full Sample | | | | | |
| Labor shortage | 0.077*** | 0.056*** | 0.090 | 0.018 | 0.017 | 0.017 |
| | (0.004) | (0.004) | (0.000) | (0.012) | (0.012) | (0.012) |
| Observations | 1,265 | 1,265 | 1,265 | 1,265 | 1,265 | 1,265 |
| Number of farmers | 253 | 253 | 253 | 253 | 253 | 253 |
| | Panel B: Top 10 Counties | | | | | |
| Labor shortage | 0.045* | 0.026 | 0.072** | 0.038*** | 0.041*** | 0.040*** |
| | (0.017) | (0.022) | (0.023) | (0.007) | (0.007) | (0.007) |
| Observations | 875 | 875 | 875 | 875 | 875 | 875 |
| Number of farmers | 175 | 175 | 175 | 175 | 175 | 175 |
| Year fixed effects | No | Yes | Yes | Yes | Yes | Yes |
| County trends | No | No | Yes | Yes | Yes | Yes |
| Individual fixed effects | No | No | No | Yes | Yes | Yes |
| Weather controls | No | No | No | No | Yes | Yes |
| Ag Bartik | No | No | No | No | No | Yes |

Source: Authors' calculations
Note: Significance levels are based on Driscoll-Kraay standard errors, which are reported in parentheses. Driscoll-Kraay standard errors correct for serial correlation up to four lags for both Panel A and Panel B. *** p<0.01, ** p<0.05, * p<0.1.

## 4.5 Use of H-2A Visa

Table 7 displays our estimates of the effects of labor shortages on the use of the H-2A visa program. Similar to the findings in Tables 3 - 6, the magnitudes of the estimates decrease as we include additional control variables. This pattern holds true for both panels. However, the signs of coefficients turn negative once we include the individual fixed effects in both panels. These negative coefficients are contrary to our hypothesis, but the coefficients are very close to zero and do not appear to be economically meaningful. During our sample period, hiring labor through the H-2A visa program was not that common. As shown in Table 1, only a small fraction of our surveyed farmers (4%) used the H-2A visa program between 2014 and 2018.

**Table 7: Estimated effects of labor shortage on the use of the H2A visa program**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Use of H2A visa program | | | | | |
| Panel A: Full Sample | | | | | | |
| Labor shortage | 0.057*** | 0.049*** | 0.036*** | -0.022** | -0.022** | -0.022** |
| | (0.002) | (0.005) | (0.005) | (0.006) | (0.006) | (0.006) |
| Observations | 1,275 | 1,275 | 1,275 | 1,275 | 1,275 | 1,275 |
| Number of farmers | 255 | 255 | 255 | 255 | 255 | 255 |
| Panel B: Top 10 Counties | | | | | | |
| Labor shortage | 0.086*** | 0.080*** | 0.059*** | -0.017** | -0.017** | -0.017** |
| | (0.002) | (0.003) | (0.003) | (0.005) | (0.005) | (0.005) |
| Observations | 885 | 885 | 885 | 885 | 885 | 885 |
| Number of farmers | 177 | 177 | 177 | 177 | 177 | 177 |
| Year fixed effects | No | Yes | Yes | Yes | Yes | Yes |
| County trends | No | No | Yes | Yes | Yes | Yes |
| Individual fixed effects | No | No | No | Yes | Yes | Yes |
| Weather controls | No | No | No | No | Yes | Yes |
| Ag Bartik | No | No | No | No | No | Yes |

Source: Authors' calculations
Note: Significance levels are based on Driscoll-Kraay standard errors, which are reported in parentheses. Driscoll-Kraay standard errors correct for serial correlation up to four lags for both Panel A and Panel B. *** p<0.01, ** p<0.05, * p<0.1.

## 4.6 Robustness tests

In this section, we highlight our findings from regressions that rely upon alternative definitions of labor-intensive crops (see Table 8 for definitions).[10] For each alternative

[10] The estimates can be found in Appendices B and C.

specification, we include an additional set of crops that are both hand harvested and mechanically harvested, where definition 1 includes the most comprehensive set of crops.

**Table 8: Alternative Definitions of Labor-Intensive Crops**

| Definition | Crops |
|---|---|
| 1 | Fruits, Leafy greens, Ornamental, floral, or nursery products, Table grapes, Vegetables, Olives, Raisins, Wine grapes |
| 2 | Fruits, Leafy greens, Ornamental, floral, or nursery products, Table grapes, Vegetables, Olives |
| 3 | Fruits, Leafy greens, Ornamental, floral, or nursery products, Table grapes, Vegetables |

For the sake of parsimony, we only discuss the results from the full set of counties under definition 1 here.[11] Our estimates indicate that labor shortages lead to at most a 27 percentage point increase in the probability of raising wages for the full sample. We also find that labor shortages increase the probability of changing cultivation practices by as much as 11 percentage points. These estimates are very similar to those produced by our preferred definition. The upper bounds for technology adoption, on the other hand, become slightly smaller when the set of labor-intensive crops is less restricted. Under definition 1, labor shortages lead to at most a 7 percentage point increase in adopting of labor-saving technology while the estimates show at most a 10 percentage point increase under our preferred definition. We also uncover significant upper bounds for the use of farm labor contractors across the entire set of counties under definition 1, where we only uncovered significant bounds in the top 10 counties using the more restrictive definition. Specifically, we find that labor shortages increase the use of farm labor contractors by at most 4 percentage points for farmers in the full set of counties. We do not uncover meaningful effects of labor shortages on the use of the H-2A visa program under our alternative definitions. While the magnitudes of our estimates vary somewhat across the different

[11] The results from definition 2 are qualitatively and quantitatively similar to those under definition 1 (see Appendix C).

labor-intensive crop definitions we use, the entire body of empirical evidence produced by this analysis indicates that labor shortages are causing farmers to change their production and labor management practices in a manner that is generally consistent with our core set of hypotheses.

# 5 Conclusion

An abundance of evidence indicates that labor shortages are becoming increasingly problematic for labor-intensive crop producers in the US. To the best of our knowledge, there are no existing studies that quantify the extent to which farmers are changing production and labor management practices in response to this issue. In this study, we help fill this gap by quantifying the extent to which labor shortages are impacting a key set of farming practices using novel survey data from a retrospective panel collected from California farmers in 2019.

Our results indicate that raising wages, changing cultivation practices (such as the timing and intensity of pruning, weeding, and harvesting), and use of labor-saving technologies are the most prevalent strategies. We find that labor shortages cause at most a 29 (resp. 11, resp. 10) percentage point increase in the probability of increasing wages (resp. changing cultivation practices, resp. using labor-saving technologies) across the state. In the top 10 labor-intensive counties, we find that labor shortages cause as much as a 4 percentage point increase in the use of farm labor contractors. We do not find meaningful effects on the use of the H-2A program during our sample period.

Our analysis indicates that farm labor shortages are highly prevalent and are causing domestic farmers to change their production and labor management practices. Industry sources claim that if these trends continue, domestic labor-intensive crop production will have to be scaled back, and production will likely be shifted to Mexico where farm wages are between \$2.00 and \$3.00 per hour. While the H-2A program seems like it could be a viable alternative to domestic labor, recent empirical evidence indicates that employment through the program is not fully replenishing the reduction in domestic employees (Kim, Castillo, & Rutledge, 2023). As such, it is likely that American farmers will have to figure out new ways to enhance the productivity of the existing workforce, search for alternatives to labor inputs, or reduce the amount of labor-intensive crops they produce.

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# Online Appendices

## A. Estimation Bias

For simplification, suppose we estimate the effects of labor shortages $X_1$ on each adaptation strategy $Y$as follows:

$$\hat{Y} = X_1\widehat{\beta_1} + \hat{U}$$

Assume the true model is:

$$Y = X_1\beta_1 + X_2\beta_2 + U$$

Where $X_2$ is the omitted variables which is correlated $X_1$ and a determinant of each adaptation strategy $Y$. Using our regression equation, we can estimate $\beta_1$ as follows:

$$\hat{\beta}_1 = ({X_1}^T X_1)^{-1} X_1^T\ Y$$

Replacing the true model $Y$, we have :

$$\hat{\beta}_1 = ({X_1}^T X_1)^{-1} X_1^T\ (X_1\beta_1 + X_2\beta_2 + U)$$

$$\hat{\beta}_1 = ({X_1}^T X_1)^{-1} X_1^T\ X_1\beta_1 + ({X_1}^T X_1)^{-1} X_1^T\ X_2\beta_2 + ({X_1}^T X_1)^{-1} X_1^T\ U$$

$$\hat{\beta}_1 = \beta_1 + ({X_1}^T X_1)^{-1} X_1^T\ X_2\beta_2 + ({X_1}^T X_1)^{-1} X_1^T\ U$$

Taking conditional expectation, we have:

$$E(\hat{\beta}_1|X) = \beta_1 + \left({X_1}^T X_1\right)^{-1} X_1^T\ X_2\beta_2 + \left({X_1}^T X_1\right)^{-1} X_1^T\ E(U|X)$$

Assuming OLS assumption $E(U|X) = 0$ holds,

$$E(\hat{\beta}_1|X) = \beta_1 + \left({X_1}^T X_1\right)^{-1} X_1^T\ X_2\beta_2$$

This can be rewritten as

$$E(\hat{\beta}_1|X) = \beta_1 + \beta_2 \frac{Cov\ (X_1, X_2)}{Var\ (X_1)}$$

Thus, the direction of bias for $\hat{\beta}_1$ will be determined by the sign of $\beta_2$ and $Cov(X_1, X_2)$.

Suppose one of the omitted variables is labor demand shock. Thus, the higher labor demand shock will lead to a higher labor shortage. Thus, we assume that $Cov(X_1, X_2) > 0$. Depending on the sign of $\beta_2$ (i.e., how labor demand shocks affect each adaptation strategy), the overall direction of bias will vary. In the following, we consider case by case using each adaptation strategy as a dependent variable and summarize the direction of bias in Table A1.

**Case 1: Increasing wages**— $\beta_2$ is expected to be positive as higher labor demand shocks will lead to a higher likelihood of increasing wages. Thus, overall, $\beta_2 \frac{Cov\,(X_1,X_2)}{Var\,(X_1)} > 0$ and the estimate of labor shortage on increased wage is upward biased.

**Case 2: Technology adoption**—The sign of $\beta_2$ is ambiguous as higher labor demand shocks will increase the use of technology which is complementary to labor and decrease if labor and technology are substitutes. Thus, we cannot determine the overall direction of bias. However, evidence from our data suggests that the bias is possibly upward. The estimated effects of labor shortages on technology adoption are progressively smaller when we add more controls in each of the six models. This pattern also holds true under any definition of labor-intensive crops we use (See Table 4, B2, and C2). This suggests that labor demand shocks possibly increase the use of labor-saving technology that is complementary to labor than substitute. Therefore, we also assume that the estimated effect of labor shortage on the adoption of technology is also an upper-bound estimate.

**Case 3: Change in cultivation practices--** $\beta_2$ is expected to be positive as the higher labor demand shock will lead to a higher likelihood of changing cultivation practices. Thus, our estimate of labor shortage on the change in cultivation practices is upward biased.

**Case 4: Use of FLC—** The sign of $\beta_2$ is expected to be positive. The higher labor shortage leads to a higher likelihood of using FLC as farmers can ensure that they have enough labor in time.

Thus, we assume that our estimate of labor shortage on using FLC is upward biased.

**Case 5: Use of H2A**—We assume that $\beta_2$ is positive as the higher labor shortage will increase the likelihood of the farmer employing labor through the H2A visa program. Thus, our estimate of the labor shortage on the use of H2A is also biased upward.

**Table A1: Direction of bias**

| Omitted Variable | Adaptation Strategy | Covariance of labor shortage and omitted variable $Cov(X_1, X_2)$ | Sign of the coefficient of omitted variable on labor shortage ($\beta_2$) | Direction of bias |
|---|---|---|---|---|
| Labor demand shock | Increasing wages | Positive | Positive | Positive |
| | Technology adoption | Positive | Possibly positive | Possibly positive |
| | Change in cultivation practices | Positive | Positive | Positive |
| | Use of FLC | Positive | Positive | Positive |
| | Use of H2A | Positive | Positive | Positive |

## B: Estimated effects of labor shortages on different adaptation strategies using labor-intensive crop definition one.

**Table B1: Estimated effects of labor shortage on increasing wage**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Increased Wage | | | | | |
| Panel A: Full Sample | | | | | | |
| Labor shortage | 0.334*** | 0.254*** | 0.256*** | 0.273*** | 0.273*** | 0.274*** |
| | (0.040) | (0.023) | (0.022) | (0.011) | (0.010) | (0.010) |
| Observations | 2,280 | 2,280 | 2,280 | 2,280 | 2,280 | 2,280 |
| Number of farmers | 456 | 456 | 456 | 456 | 456 | 456 |
| Panel B: Top 10 Counties | | | | | | |
| Labor shortage | 0.356*** | 0.268*** | 0.271*** | 0.290*** | 0.287*** | 0.289*** |
| | (0.030) | (0.014) | (0.007) | (0.015) | (0.016) | (0.016) |
| Observations | 1,200 | 1,200 | 1,200 | 1,200 | 1,200 | 1,200 |
| Number of farmers | 240 | 240 | 240 | 240 | 240 | 240 |
| Year fixed effects | No | Yes | Yes | Yes | Yes | Yes |
| County trends | No | No | Yes | Yes | Yes | Yes |
| Individual fixed effects | No | No | No | Yes | Yes | Yes |
| Weather controls | No | No | No | No | Yes | Yes |
| Ag Bartik | No | No | No | No | No | Yes |

Note: Significance levels are based on Driscoll-Kraay standard errors, which are reported in parentheses. Driscoll-Kraay standard errors correct for serial correlation up to four lags for both Panel A and Panel B. *** p<0.01, ** p<0.05, * p<0.1.

**Table B2: Estimated effects of labor shortage on the change in cultivation practices**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Change in Cultivation Practices | | | | | |
| Panel A: Full Sample | | | | | | |
| Labor shortage | 0.180*** | 0.141*** | 0.137*** | 0.107*** | 0.106*** | 0.107*** |
| | (0.004) | (0.012) | (0.011) | (0.005) | (0.005) | (0.005) |
| Observations | 2,140 | 2,140 | 2,140 | 2,140 | 2,140 | 2,140 |
| Number of farmers | 428 | 428 | 428 | 428 | 428 | 428 |
| Panel B: Top 10 Counties | | | | | | |
| Labor shortage | 0.191*** | 0.158*** | 0.157*** | 0.097*** | 0.092*** | 0.093*** |
| | (0.017) | (0.011) | (0.008) | (0.007) | (0.006) | (0.006) |
| Observations | 1,135 | 1,135 | 1,135 | 1,135 | 1,135 | 1,135 |
| Number of farmers | 227 | 227 | 227 | 227 | 227 | 227 |
| Year fixed effects | No | Yes | Yes | Yes | Yes | Yes |
| County trends | No | No | Yes | Yes | Yes | Yes |
| Individual fixed effects | No | No | No | Yes | Yes | Yes |
| Weather controls | No | No | No | No | Yes | Yes |
| Ag Bartik | No | No | No | No | No | Yes |

Note: Significance levels are based on Driscoll-Kraay standard errors, which are reported in parentheses. Driscoll-Kraay standard errors correct for serial correlation up to four lags for both Panel A and Panel B. *** p<0.01, ** p<0.05, * p<0.1.

**Table B3: Estimated effects of labor shortage on the adoption of labor-saving technology**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Technology Adoption | | | | | |
| Panel A: Full Sample | | | | | | |
| Labor shortage | 0.162*** | 0.117*** | 0.117*** | 0.071*** | 0.074*** | 0.074*** |
| | (0.013) | (0.009) | (0.008) | (0.012) | (0.012) | (0.012) |
| Observations | 2,105 | 2,105 | 2,105 | 2,105 | 2,105 | 2,105 |
| Number of farmers | 421 | 421 | 421 | 421 | 421 | 421 |
| Panel B: Top 10 Counties | | | | | | |
| Labor shortage | 0.170*** | 0.122*** | 0.118*** | 0.097*** | 0.100*** | 0.099*** |
| | (0.011) | (0.014) | (0.014) | (0.015) | (0.015) | (0.015) |
| Observations | 1,115 | 1,115 | 1,115 | 1,115 | 1,115 | 1,115 |
| Number of farmers | 223 | 223 | 223 | 223 | 223 | 223 |
| Year fixed effects | No | Yes | Yes | Yes | Yes | Yes |
| County trends | No | No | Yes | Yes | Yes | Yes |
| Individual fixed effects | No | No | No | Yes | Yes | Yes |
| Weather controls | No | No | No | No | Yes | Yes |
| Ag Bartik | No | No | No | No | No | Yes |

Note: Significance levels are based on Driscoll-Kraay standard errors, which are reported in parentheses. Driscoll-Kraay standard errors correct for serial correlation up to four lags for both Panel A and Panel B. *** p<0.01, ** p<0.05, * p<0.1.

**Table B4: Estimated effects of labor shortage on the use of farm labor contractors**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Use of Farm Labor Contractors | | | | | |
| | Panel A: Full Sample | | | | | |
| Labor shortage | 0.070** | 0.050* | 0.071** | 0.039** | 0.041** | 0.041** |
| | (0.021) | (0.019) | (0.018) | (0.009) | (0.009) | (0.009) |
| Observations | 2,235 | 2,235 | 2,235 | 2,235 | 2,235 | 2,235 |
| Number of farmers | 447 | 447 | 447 | 447 | 447 | 447 |
| | Panel B: Top 10 Counties | | | | | |
| Labor shortage | 0.050*** | 0.033** | 0.073*** | 0.052*** | 0.056*** | 0.055*** |
| | (0.008) | (0.011) | (0.010) | (0.005) | (0.005) | (0.005) |
| Observations | 1,200 | 1,200 | 1,200 | 1,200 | 1,200 | 1,200 |
| Number of farmers | 240 | 240 | 240 | 240 | 240 | 240 |
| Year fixed effects | No | Yes | Yes | Yes | Yes | Yes |
| County trends | No | No | Yes | Yes | Yes | Yes |
| Individual fixed effects | No | No | No | Yes | Yes | Yes |
| Weather controls | No | No | No | No | Yes | Yes |
| Ag Bartik | No | No | No | No | No | Yes |

Note: Significance levels are based on Driscoll-Kraay standard errors, which are reported in parentheses. Driscoll-Kraay standard errors correct for serial correlation up to four lags for both Panel A and Panel B. *** p<0.01, ** p<0.05, * p<0.1.

**Table B5: Estimated effects of labor shortage on the use of the H2A visa program**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Use of H2A visa program | | | | | |
| | Panel A: Full Sample | | | | | |
| Labor shortage | 0.061*** | 0.054*** | 0.055*** | -0.008 | -0.008 | -0.009 |
| | (0.005) | (0.006) | (0.010) | (0.007) | (0.007) | (0.007) |
| Observations | 2,265 | 2,265 | 2,265 | 2,265 | 2,265 | 2,265 |
| Number of farmers | 453 | 453 | 453 | 453 | 453 | 453 |
| | Panel B: Top 10 Counties | | | | | |
| Labor shortage | 0.076*** | 0.071*** | 0.063*** | -0.000 | -0.000 | -0.001 |
| | (0.002) | (0.004) | (0.004) | (0.010) | (0.011) | (0.011) |
| Observations | 1,210 | 1,210 | 1,210 | 1,210 | 1,210 | 1,210 |
| Number of farmers | 242 | 242 | 242 | 242 | 242 | 242 |
| Year fixed effects | No | Yes | Yes | Yes | Yes | Yes |
| County trends | No | No | Yes | Yes | Yes | Yes |
| Individual fixed effects | No | No | No | Yes | Yes | Yes |
| Weather controls | No | No | No | No | Yes | Yes |
| Ag Bartik | No | No | No | No | No | Yes |

Source: Authors' calculations
Note: Significance levels are based on Driscoll-Kraay standard errors, which are reported in parentheses. Driscoll-Kraay standard errors correct for serial correlation up to four lags for both Panel A and Panel B. *** p<0.01, ** p<0.05, * p<0.1.

## C: Estimated effects of labor shortages using labor-intensive crop definition two

**Table C1: Estimated effects of labor shortage on increasing wage**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Increased Wage | | | | | |
| | Panel A: Full Sample | | | | | |
| Labor shortage | 0.397*** | 0.307*** | 0.311*** | 0.286*** | 0.286*** | 0.288*** |
| | (0.031) | (0.015) | (0.014) | (0.013) | (0.014) | (0.013) |
| Observations | 1,345 | 1,345 | 1,345 | 1,345 | 1,345 | 1,345 |
| Number of farmers | 269 | 269 | 269 | 269 | 269 | 269 |
| | Panel B: Top 10 Counties | | | | | |
| Labor shortage | 0.387*** | 0.293*** | 0.288*** | 0.282*** | 0.279*** | 0.281*** |
| | (0.029) | (0.011) | (0.007) | (0.014) | (0.015) | (0.014) |
| Observations | 935 | 935 | 935 | 935 | 935 | 935 |
| Number of farmers | 187 | 187 | 187 | 187 | 187 | 187 |
| Year fixed effects | No | Yes | Yes | Yes | Yes | Yes |
| County trends | No | No | Yes | Yes | Yes | Yes |
| Individual fixed effects | No | No | No | Yes | Yes | Yes |
| Weather controls | No | No | No | No | Yes | Yes |
| Ag Bartik | No | No | No | No | No | Yes |

Source: Authors' calculations

Note: Significance levels are based on Driscoll-Kraay standard errors, which are reported in parentheses. Driscoll-Kraay standard errors correct for serial correlation up to four lags for both Panel A and Panel B. *** p<0.01, ** p<0.05, * p<0.1.

**Table C2: Estimated effects of labor shortage on the change in cultivation practices**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Change in Cultivation Practices | | | | | |
| Panel A: Full Sample | | | | | | |
| Labor shortage | 0.204*** | 0.170*** | 0.159*** | 0.109*** | 0.107*** | 0.108*** |
| | (0.009) | (0.008) | (0.008) | (0.006) | (0.007) | (0.007) |
| Observations | 1,260 | 1,260 | 1,260 | 1,260 | 1,260 | 1,260 |
| Number of farmers | 252 | 252 | 252 | 252 | 252 | 252 |
| Panel B: Top 10 Counties | | | | | | |
| Labor shortage | 0.203*** | 0.174*** | 0.168*** | 0.118*** | 0.119*** | 0.121*** |
| | (0.016) | (0.009) | (0.010) | (0.007) | (0.005) | (0.005) |
| Observations | 885 | 885 | 885 | 885 | 885 | 885 |
| Number of farmers | 177 | 177 | 177 | 177 | 177 | 177 |
| Year fixed effects | No | Yes | Yes | Yes | Yes | Yes |
| County trends | No | No | Yes | Yes | Yes | Yes |
| Individual fixed effects | No | No | No | Yes | Yes | Yes |
| Weather controls | No | No | No | No | Yes | Yes |
| Ag Bartik | No | No | No | No | No | Yes |

Source: Authors' calculations

Note: Significance levels are based on Driscoll-Kraay standard errors, which are reported in parentheses. Driscoll-Kraay standard errors correct for serial correlation up to four lags for both Panel A and Panel B. *** p<0.01, ** p<0.05, * p<0.1.

**Table C3: Estimated effects of labor shortage on the adoption of labor-saving technology**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Technology Adoption | | | | | |
| Panel A: Full Sample | | | | | | |
| Labor shortage | 0.164*** | 0.103*** | 0.097*** | 0.085*** | 0.081*** | 0.082*** |
| | (0.014) | (0.016) | (0.018) | (0.015) | (0.014) | (0.014) |
| Observations | 1,250 | 1,250 | 1,250 | 1,250 | 1,250 | 1,250 |
| Number of farmers | 250 | 250 | 250 | 250 | 250 | 250 |
| Panel B: Top 10 Counties | | | | | | |
| Labor shortage | 0.183*** | 0.128*** | 0.118*** | 0.084*** | 0.086*** | 0.084*** |
| | (0.011) | (0.013) | (0.010) | (0.014) | (0.015) | (0.015) |
| Observations | 865 | 865 | 865 | 865 | 865 | 865 |
| Number of farmers | 173 | 173 | 173 | 173 | 173 | 173 |
| Year fixed effects | No | Yes | Yes | Yes | Yes | Yes |
| County trends | No | No | Yes | Yes | Yes | Yes |
| Individual fixed effects | No | No | No | Yes | Yes | Yes |
| Weather controls | No | No | No | No | Yes | Yes |
| Ag Bartik | No | No | No | No | No | Yes |

Source: Authors' calculations

Note: Significance levels are based on Driscoll-Kraay standard errors, which are reported in parentheses. Driscoll-Kraay standard errors correct for serial correlation up to four lags for both Panel A and Panel B. *** p<0.01, ** p<0.05, * p<0.1.

**Table C4: Estimated effects of labor shortage on the use of farm labor contractors**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Use of Farm Labor Contractors | | | | | |
| | Panel A: Full Sample | | | | | |
| Labor shortage | 0.086*** | 0.066*** | 0.094*** | 0.013 | 0.013 | 0.013 |
| | (0.007) | (0.007) | (0.005) | (0.012) | (0.012) | (0.012) |
| Observations | 1,355 | 1,355 | 1,355 | 1,355 | 1,355 | 1,355 |
| Number of farmers | 271 | 271 | 271 | 271 | 271 | 271 |
| | Panel B: Top 10 Counties | | | | | |
| Labor Shortage | 0.046** | 0.027 | 0.066** | 0.034** | 0.036*** | 0.036*** |
| | (0.015) | (0.020) | (0.019) | (0.008) | (0.007) | (0.007) |
| Observations | 935 | 935 | 935 | 935 | 935 | 935 |
| Number of farmers | 187 | 187 | 187 | 187 | 187 | 187 |
| Year fixed effects | No | Yes | Yes | Yes | Yes | Yes |
| County trends | No | No | Yes | Yes | Yes | Yes |
| Individual fixed effects | No | No | No | Yes | Yes | Yes |
| Weather controls | No | No | No | No | Yes | Yes |
| Ag Bartik | No | No | No | No | No | Yes |

Source: Authors' calculations
Note: Significance levels are based on Driscoll-Kraay standard errors, which are reported in parentheses. Driscoll-Kraay standard errors correct for serial correlation up to four lags for both Panel A and Panel B. *** p<0.01, ** p<0.05, * p<0.1.

**Table C5: Estimated effects of labor shortage on the use of the H2A visa program**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Use of H2A visa program | | | | | |
| Panel A: Full Sample | | | | | | |
| Labor shortage | 0.078*** | 0.068*** | 0.062*** | -0.014 | -0.014 | -0.014 |
| | (0.004) | (0.007) | (0.007) | (0.009) | (0.010) | (0.010) |
| Observations | 1,370 | 1,370 | 1,370 | 1,370 | 1,370 | 1,370 |
| Number of farmers | 274 | 274 | 274 | 274 | 274 | 274 |
| Panel B: Top 10 Counties | | | | | | |
| Labor shortage | 0.096*** | 0.089*** | 0.078*** | -0.004 | -0.005 | -0.006 |
| | (0.003) | (0.005) | (0.002) | (0.012) | (0.013) | (0.013) |
| Observations | 950 | 950 | 950 | 950 | 950 | 950 |
| Number of farmers | 190 | 190 | 190 | 190 | 190 | 190 |
| Year fixed effects | No | Yes | Yes | Yes | Yes | Yes |
| County trends | No | No | Yes | Yes | Yes | Yes |
| Individual fixed effects | No | No | No | Yes | Yes | Yes |
| Weather controls | No | No | No | No | Yes | Yes |
| Ag Bartik | No | No | No | No | No | Yes |

Source: Authors' calculations

Note: Significance levels are based on Driscoll-Kraay standard errors, which are reported in parentheses. Driscoll-Kraay standard errors correct for serial correlation up to four lags for both Panel A and Panel B. *** p<0.01, ** p<0.05, * p<0.1.

## D: Estimated effects of *previous-year* labor shortages on different adaptation strategies using labor-intensive crop definition three

**Table D1: Estimated effects of *previous-year* labor shortage on increasing wage**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Increased Wage | | | | | |
| Panel A: Full Sample | | | | | | |
| Previous year labor shortage | 0.353*** | 0.282*** | 0.286*** | 0.155** | 0.161** | 0.160** |
| | (0.036) | (0.017) | (0.021) | (0.032) | (0.031) | (0.031) |
| Observations | 996 | 996 | 996 | 996 | 996 | 996 |
| Number of farmers | 249 | 249 | 249 | 249 | 249 | 249 |
| Panel B: Top 10 Counties | | | | | | |
| Previous year labor shortage | 0.357*** | 0.286*** | 0.286*** | 0.168** | 0.168** | 0.168** |
| | (0.033) | (0.014) | (0.016) | (0.035) | (0.035) | (0.035) |
| Observations | 692 | 692 | 692 | 692 | 692 | 692 |
| Number of farmers | 173 | 173 | 173 | 173 | 173 | 173 |
| Year fixed effects | No | Yes | Yes | Yes | Yes | Yes |
| County trends | No | No | Yes | Yes | Yes | Yes |
| Individual fixed effects | No | No | No | Yes | Yes | Yes |
| Weather controls | No | No | No | No | Yes | Yes |
| Ag Bartik | No | No | No | No | No | Yes |

Note: Significance levels are based on Driscoll-Kraay standard errors, which are reported in parentheses. Driscoll-Kraay standard errors correct for serial correlation up to three lags for both Panel A and Panel B. *** p<0.01, ** p<0.05, * p<0.1.

**Table D2: Estimated effects of *previous-year* labor shortage on the change in cultivation practices**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Change in Cultivation Practices | | | | | |
| | Panel A: Full Sample | | | | | |
| Previous year labor shortage | 0.194*** | 0.174*** | 0.155*** | 0.082 | 0.084* | 0.084* |
| | (0.015) | (0.012) | (0.017) | (0.000) | (0.029) | (0.029) |
| Observations | 940 | 940 | 940 | 940 | 940 | 940 |
| Number of farmers | 235 | 235 | 235 | 235 | 235 | 235 |
| | Panel B: Top 10 Counties | | | | | |
| Previous year labor shortage | 0.165*** | 0.143*** | 0.135*** | 0.019 | 0.023 | 0.023 |
| | (0.020) | (0.016) | (0.020) | (0.023) | (0.025) | (0.025) |
| Observations | 660 | 660 | 660 | 660 | 660 | 660 |
| Number of farmers | 165 | 165 | 165 | 165 | 165 | 165 |
| Year fixed effects | No | Yes | Yes | Yes | Yes | Yes |
| County trends | No | No | Yes | Yes | Yes | Yes |
| Individual fixed effects | No | No | No | Yes | Yes | Yes |
| Weather controls | No | No | No | No | Yes | Yes |
| Ag Bartik | No | No | No | No | No | Yes |

Note: Significance levels are based on Driscoll-Kraay standard errors, which are reported in parentheses. Driscoll-Kraay standard errors correct for serial correlation up to three lags for both Panel A and Panel B. *** p<0.01, ** p<0.05, * p<0.1.

**Table D3: Estimated effects of *previous-year* labor shortage on the adoption of labor-saving technology**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Technology Adoption | | | | | |
| Panel A: Full Sample | | | | | | |
| Previous year labor shortage | 0.158*** | 0.109** | 0.101** | 0.055** | 0.055** | 0.055** |
| | (0.021) | (0.025) | (0.021) | (0.016) | (0.017) | (0.017) |
| Observations | 924 | 924 | 924 | 924 | 924 | 924 |
| Number of farmers | 231 | 231 | 231 | 231 | 231 | 231 |
| Panel B: Top 10 Counties | | | | | | |
| Previous year labor shortage | 0.213*** | 0.174** | 0.164** | 0.076*** | 0.076** | 0.076** |
| | (0.029) | (0.035) | (0.031) | (0.013) | (0.013) | (0.013) |
| Observations | 640 | 640 | 640 | 640 | 640 | 640 |
| Number of farmers | 160 | 160 | 160 | 160 | 160 | 160 |
| Year fixed effects | No | Yes | Yes | Yes | Yes | Yes |
| County trends | No | No | Yes | Yes | Yes | Yes |
| Individual fixed effects | No | No | No | Yes | Yes | Yes |
| Weather controls | No | No | No | No | Yes | Yes |
| Ag Bartik | No | No | No | No | No | Yes |

Note: Significance levels are based on Driscoll-Kraay standard errors, which are reported in parentheses. Driscoll-Kraay standard errors correct for serial correlation up to three lags for both Panel A and Panel B. *** p<0.01, ** p<0.05, * p<0.1.

**Table D4: Estimated effects of *previous-year* labor shortage on the use of farm labor contractors**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Use of Farm Labor Contractors | | | | | |
| | Panel A: Full Sample | | | | | |
| Previous year labor shortage | 0.087*** | 0.072*** | 0.093*** | 0.024* | 0.028* | 0.028* |
| | (0.005) | (0.004) | (0.012) | (0.009) | (0.009) | (0.009) |
| Observations | 1,012 | 1,012 | 1,012 | 1,012 | 1,012 | 1,012 |
| Number of farmers | 253 | 253 | 253 | 253 | 253 | 253 |
| | Panel B: Top 10 Counties | | | | | |
| Previous year labor shortage | 0.043 | 0.029 | 0.065** | 0.041* | 0.041 | 0.041 |
| | (0.022) | (0.025) | (0.015) | (0.017) | (0.018) | (0.018) |
| Observations | 700 | 700 | 700 | 700 | 700 | 700 |
| Number of farmers | 175 | 175 | 175 | 175 | 175 | 175 |
| Year fixed effects | No | Yes | Yes | Yes | Yes | Yes |
| County trends | No | No | Yes | Yes | Yes | Yes |
| Individual fixed effects | No | No | No | Yes | Yes | Yes |
| Weather controls | No | No | No | No | Yes | Yes |
| Ag Bartik | No | No | No | No | No | Yes |

Note: Significance levels are based on Driscoll-Kraay standard errors, which are reported in parentheses. Driscoll-Kraay standard errors correct for serial correlation up to three lags for both Panel A and Panel B. *** p<0.01, ** p<0.05, * p<0.1.

**Table D5: Estimated effects of *previous-year* labor shortage on the use of the H2A visa program**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Use of H2A visa program | | | | | |
| | Panel A: Full Sample | | | | | |
| Previous year labor shortage | 0.088*** | 0.080*** | 0.057*** | -0.013* | -0.011* | -0.011* |
| | (0.001) | (0.003) | (0.003) | (0.005) | (0.004) | (0.004) |
| Observations | 1,020 | 1,020 | 1,020 | 1,020 | 1,020 | 1,020 |
| Number of farmers | 255 | 255 | 255 | 255 | 255 | 255 |
| | Panel B: Top 10 Counties | | | | | |
| Previous year labor shortage | 0.118*** | 0.113*** | 0.082*** | 0.002 | 0.003 | 0.003 |
| | (0.002) | (0.004) | (0.005) | (0.008) | (0.008) | (0.008) |
| Observations | 708 | 708 | 708 | 708 | 708 | 708 |
| Number of farmers | 177 | 177 | 177 | 177 | 177 | 177 |
| Year fixed effects | No | Yes | Yes | Yes | Yes | Yes |
| County trends | No | No | Yes | Yes | Yes | Yes |
| Individual fixed effects | No | No | No | Yes | Yes | Yes |
| Weather controls | No | No | No | No | Yes | Yes |
| Ag Bartik | No | No | No | No | No | Yes |

Note: Significance levels are based on Driscoll-Kraay standard errors, which are reported in parentheses. Driscoll-Kraay standard errors correct for serial correlation up to three lags for both Panel A and Panel B. *** p<0.01, ** p<0.05, * p<0.1.