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No Farm Workers, No Food?
Evidence From Specialty Crop Production†

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Abstract

This study provides empirical estimates of the effects of changes in the farm labor supply on fruit and vegetable production. The results are based on fixed-effects panel regressions at the crop-county-year level of aggregation using crop production and employment data in California. I use an equilibrium displacement model to derive formulas for the estimation bias under different market scenarios, which reveal that my empirical estimates should be interpreted as upper bounds. These bounds indicate that a 10% decrease in the farm labor supply (in terms of the number of workers) causes *at most* a 3.8% reduction in production in the top 10 producing counties, which together produce 86% of the total value of hand-harvested crops in the state. Production effects are channeled primarily through a reduction in harvested acreage, although there are some effects on yield (the quantity harvested per acre). In the top 10 counties, a 10% decrease in the farm labor supply causes *at most* a 2.4% reduction in harvested acreage and *at most* a 1.4% reduction in the average yield per acre.

1 Introduction

Farm labor is an essential input in the production of many fruit and vegetable crops because these crops typically need to be harvested manually. Recent studies document what many view as a worrying decline in the farm labor supply. For instance, Richards (2018) finds that there has been an "insufficient supply [of harvest workers] to meet the demand from firms, even in the steady state equilibrium" and that this issue is "chronic and not merely a feature of our current policy environment." Farmer surveys further suggest that this situation has been exacerbated by recent changes in immigration policy, including tighter border security and stronger internal enforcement (CFBF and UC Davis, 2019; Rutledge and Taylor, 2019). Reductions in the farm labor supply could have far-reaching consequences, such as reducing the nation's access to safe and healthy produce, putting upward pressure on food prices, or causing farmers to suffer significant economic losses.

But how much do changes in the farm labor supply really affect the production of fruits and vegetables, and what impacts do they have on farm revenue? To answer these key empirical questions, I estimate elasticities of hand-harvested fruit and vegetable production with respect to the harvest labor supply using data from California spanning the period 1990 to 2017. My empirical strategy deploys fixed-effects panel regression models at the crop-county-year level of aggregation where the explanatory variable of interest is a measure of county-level crop employment during the peak harvest season. The identifying variation is generated from differences across counties in the evolution of employment about the crop-county average.[1] Because the main explanatory variable measures actual employment, which is an equilibrium value and not a measure of the labor supply (the variable of interest), I pay special attention to addressing potential threats to identification. To gain insight into these threats, I use an equilibrium displacement model to illustrate likely sources of bias and show why, in many respects, my empirical estimates should be interpreted as upper bounds. In doing so, I am able to relate structural parameters descriptive of the fruit and vegetable market to each potential source of bias in a transparent fashion. For example, the model allows me to decipher how factor-neutral changes in productivity or shifts in the supply of farm inputs, such as land or water, affect the empricially estimated elasticity of output with respect to labor. Therefore, although my regression analysis is reduced-form, it is directly linked to a structural model of fruit and vegetable supply.

[1]In some cases the crop-county average differs from the county average because some crops are not produced in all years. Two thirds of the crops produced within a county are produced in all years.

My empirical results indicate that a 10 percent decrease in the farm labor supply (in terms of the number of workers) causes *at most* a 3.8% decrease in hand-harvested fruit and vegetable production in the top 10 labor-intensive crop producing counties, which together produce 86% of the value of all labor-intensive crops in the state.[2] My findings further suggest that reduced production is primarily channeled through fewer acres harvested, although there are some yield effects. In the top 10 counties, a 10% decrease in the farm labor supply causes *at most* a 2.4% reduction in harvested acreage and *at most* a 1.4% reduction in average yield. These results suggest that moderate decreases in the farm labor supply could have meaningful impacts, but they would not likely devastate California's aggregate fruit and vegetable production. Falsification tests run on mechanically-harvested field and nut crops deliver estimates that are much smaller than those in labor-intensive crops and are never positive and statistically significant, consistent with the hypothesis that labor supply shocks should have a smaller impact on crops that do not rely heavily on labor inputs.

Over the past century, two major policy events have motivated economists to investigate the effects of farm labor supply shocks on U.S. agriculture. The first was the termination of the Bracero Program in 1964, which ended an era of legal temporary migration from Mexico. The second was the passage of the Immigration Reform and Control Act (IRCA) in 1986, which, among other things, legalized the unauthorized farm workforce. In each case, major shocks to the farm labor supply failed to materialize, and aggregate crop production was not seriously affected (Shultz, 1965; Martin, 1966; Duffield, 1990; Gunter et al., 1992). Labor supply shocks were short lived in the post-Bracero years due to a sustained inflow of unauthorized Mexican workers who could earn wages as much as eight times higher in the U.S. (Martin, 2006). During the post-IRCA years, the number of legalized farm workers who left for other sectors of the economy, the main concern from a policy standpoint, was met by an equal (or greater) inflow of new farm workers as a result of family reunification policies that granted visas to the spouses and dependents of those legalized under the law (Boucher et al., 2007).

However, mounting evidence suggests that this historically abundant supply of Mexican farm workers is shrinking as demographic and structural changes take place in Mexico and border security becomes more stringent (Passel et al., 2012; Charlton and Taylor, 2016; Zahniser et al., 2018). Increased border security has been accompanied by higher coyote (smuggler) fees, which increases the financial cost of entering the U.S. (Orrenius, 2004; Dickerson and Medina, 2017). And those who do attempt to cross the

[2]Throughout this study, a "labor-intensive" crop is defined as a fruit or vegetable crop that did not have a viable automated harvest technology available during the period of study.

border have been driven further into the desert to avoid apprehension, leading to an increase in the number of fatalities (Jones, 2020). In some regions of the U.S., local immigration enforcement policies have caused farm workers to leave local labor markets, providing evidence that the threat of deportation may lead to a smaller farm workforce (Ifft and Jodlowski, 2016; Kostanini et al., 2013).

Other labor market frictions result from the fact that domestic workers are unwilling to perform farm work because of its physical nature and the fact that it does not pay well (Taylor et al., 2012). To highlight this fact, during the great recession, when unemployment rates were close to 10%, the United Farm Workers (UFW) launched the nationwide "Take Our Jobs" campaign, which offered farm employment to any domestic worker who wanted a job.[3] Although the UFW received thousands of responses, the union's president, Arturo Rodriguez, said that only a few dozen domestic workers followed through on the offer after realizing that the work involved "back-breaking jobs in triple-digit temperatures that pay minimum wage, usually without benefits" (Smith, 2010). Consistent with economic theory, the shrinking farm labor supply is also putting upward pressure on wages. According to the USDA's Farm Labor Survey (NASS, 2020), real farm wages have increased by 10% over the last decade, and estimates indicate that they will need to increase by an another 10% over the next decade just to keep the labor supply constant (Charlton et al., 2019). Taken together, this body of evidence points to a farm labor supply that is shifting inward and becoming more inelastic.

To the best of my knowledge, only one recent study examines the effects of changes in farm employment on labor-intensive crop production in the U.S. Zahniser et al. (2011) use a computable general equilibrium (CGE) model to simulate how changes in immigration policy could affect agricultural production, among other things.[4] They find that a policy aimed at increasing immigration enforcement would lead to a 3.4% reduction in farm employment and a 2.0% (resp. 2.9%) reduction in fruit (resp. vegetable) production. Since the reduction in farm employment is an equilibrium measure and not a measure of the farm labor supply, this implies an upper bound for the nationwide elasticity of fruit (resp. vegetable) production with respect to the farm labor supply of 0.58 (resp. 0.85). However, their approach relies upon on a strong set of assumptions, whereas my approach only requires weak positive correlation between a single variable and the error term in a reduced-form regression. Admittedly my strategy does not provide a point estimate of the true effect. Nonetheless, it provides an upper bound, which estimates the "worst case

[3]The UFW is a farm worker union formerly led by Cesar Chavez.

[4]The first policy they consider simulates increased use of the H-2A visa program, and the second policy simulates increased immigration enforcement across the entire U.S. economy.

scenario," a measure that is still policy relevant. In addition, my bounds improve upon the existing literature by narrowing down the range of potential effects compared to the most recent estimates provided by Zahniser et al. (2011).

This paper contributes to the literature in three ways. First, I extend in a useful direction the existing farm labor literature, which has found evidence of farm labor shortages among harvest workers, by quantifying the impacts of such reduced harvest worker availability on production and revenue (Richards, 2018; Hertz and Zahniser, 2012). Second, I provide new upper bounds for a recent period of time, improving upon those found in the literature, the most recent of which were generated nearly a decade ago. As Duffield (1990) points out, if the structure of the farm labor market changes over time, it is important to develop new estimates that reflect current conditions because optimal policy strategies rely on the current structure of the farm labor market. Third, I add to the larger labor literature a useful extension of the equilibrium displacement framework of Muth (1964), which delivers new insights about the bias that may result from using an equilibrium employment measure in place of a labor supply variable, a common problem in labor economics (Card, 1990; Borjas, 2003; Jaeger et al., 2018; Mérel and Rutledge, 2020).

The rest of the paper is organized as follows: section 2 provides some background on California crop production and labor, section 3 provides a theoretical framework to better understand how the farm labor supply is related to crop production and what types of bias may arise in the empirical analysis, section 4 describes the data and methodology used in the analysis, section 5 discusses the main results, and section 6 provides some concluding remarks.

2 Background

In terms of the value of production, California is the leading agricultural state in the U.S., generating one third of all domestic vegetables and two thirds of the fruits and nuts (CDFA, 2018). In 2017, California's farms and ranches produced more than 400 commodities worth nearly $60 billion (NASS, 2018).[5] Fruit, vegetable, and horticulture (FVH) crop production accounted for 52% ($31.2 billion) of the value of all agricultural production in the state and 68% of the non-animal production. Of the total FVH crop value, 56% ($17.4 billion) was generated by fruits, 32% ($10.0 billion) by vegetables, and 12% ($3.8 billion) by horticulture (see Figure 1). California also employs the most farm

[5]This figure differs from the $50 billion in cash receipts due to the fact that some production, such as cattle feed, is used on the farm where it is produced. However, the value of fruit and vegetable crops should reflect cash receipts because these crops are not directly consumed by the farms that produce them.

workers, with labor expenses accounting for nearly one third of the nation's total (NASS, 2019). The state is also unique because each county has an agricultural commissioner who compiles an annual report of the gross production and value of each commodity produced. Each year, the California Department of Food and Agriculture collaborates with the U.S. Department of Agriculture to consolidate all of the county-level data, providing a rich set of quantitative crop production data that can be utilized by researchers. Together, these factors make California an ideal setting to study how changes in the farm labor supply affect fruit and vegetable crop production.

[Figure 1 about here.]

The statewide production of hand-harvested vegetables steadily increased from about eight million to 10 million tons between 1990 and 2010 and then started to decline (see Figure 2A). The upward trend in vegetable production prior to 2010 was driven by higher yields rather than through an expansion in acreage, which may have resulted from the the adoption of new cultivars or through changes in the types of vegetables being grown (or both) (see Figure 2B). Other than a significant drop in production in 1991, which was driven by a winter freeze that devastated orange crops (Brooks, 1991), hand-harvested fruit production remained relatively stable at about eight million tons until 2010, after which a noticeable expansion occurred.[6] The contraction of hand-harvested vegetable production after 2010 coincided with a considerable decrease in harvested acreage while the increase in fruit production was driven mainly by higher yields instead of a large expansion in acreage.[7]

[Figure 2 about here.]

In order to produce these labor-intensive crops, California farmers employ an army of workers, who can be classified into three broad categories: (i) those who are recruited and hired directly by farmers (direct hires), (ii) those who are hired by farm labor contractors (FLCs) and are brought to farms to perform certain tasks (e.g., pruning, weeding, or harvesting), and (iii) non-FLC crop-support workers who are contracted to perform certain tasks, such as tilling the soil or providing mechanical harvesting services. The non-FLC crop-support workers generally do not hand-harvest fruit and vegetable crops and, as a result, are removed from the analysis. The direct hires and FLC workers *do*, however, perform hand harvest labor and are the focus of this study.

[6] This number only accounts for crops that are hand harvested. Crops such as wine grapes, which are both hand picked and mechanically harvested, have been removed from this calculation.

[7] Production data for horticulture crops is not available in the CDFA Ag Commissioners' Reports.

In 2017, California crop farmers employed an average of 386,000 workers each month (BLS, 2018). However, due to the seasonal nature of agriculture, the number of workers employed at any given time fluctuates throughout the year. Figure 3A shows the average crop employment for each month during 2017, broken down by type of worker, revealing that statewide employment peaks during the summer months when the bulk of the harvest activities take place.

[Figure 3 about here.]

Figure 3B shows the evolution of the statewide average annual employment for each type of worker between 1990 and 2017. The number of direct hires has been declining since the early 1990s, while the number of employees hired through FLCs has increased. However, these statewide averages mask significant heterogeneity among local labor markets, as can be seen in Figure 4. Importantly, my empirical strategy nets out any common statewide effects (e.g., droughts) through year fixed effects and exploits variation in the evolution of employment across counties about the crop-county average.

[Figure 4 about here.]

3 Theoretical Framework

3.1 The Model

To provide a theoretical framework that can be used to express the relationship between changes in the farm labor supply and labor-intensive crop production, I adopt the equilibrium displacement model of Muth (1964) and relate it to my setting. I develop an extension to this model by deriving formulas for the bias of my empirical estimates under three scenarios. These derivations reveal that the empirical estimates can be interpreted as upper bounds for the parameters of interest in each case.

The model assumes that there is a group of producers who produce a single homogeneous good and that each firm has an identical production function that uses two inputs: labor and a composite non-labor input. The production function is homogeneous of degree one (i.e., it exhibits constant returns to scale), and firms are assumed to be price takers in both the input and output markets. Adopting the notation of Muth (1964), I define Q as California's labor-intensive crop output (a composite fruit and vegetable good), A as the labor input, and B as the non-labor input.

The model describes an industry equilibrium that is characterized by six equations in six unknown variables (Q, p, A, B, p_A, p_B) that define the industry demand (1) and production (2) functions, two equations that equate the marginal value product of each input to their respective prices (3) and (4), and two input supply functions (5) and (6) as follows:

$$Q = f(p) \tag{1}$$
$$Q = Q(A, B) \tag{2}$$
$$p_A = pQ_A \tag{3}$$
$$p_B = pQ_B \tag{4}$$
$$A = g(p_A) \tag{5}$$
$$B = h(p_B), \tag{6}$$

where p represents the output price, p_A (resp. p_B) denotes the price of input A (resp. B), and Q_A (resp. Q_B) denotes the partial derivative of the industry production function with respect to input A (resp. B). By taking the total derivative of (1), (5), and (6) and dividing each equation by its respective left-hand-side variable, one can derive equations (1′), (5′), and (6′). Using the homogeneity assumption defined above, additional manipulation of (2) - (4) outlined in Muth (1964) leads to the derivation of equations (2′) - (4′). Together (1′) - (6′) define a system of six equations in the six unknowns, where dX^* denotes the percentage change in some variable X, and the following variables are taken to be exogenous: η is the elasticity of demand for the final output, k_A (resp. k_B) is the share of industry revenue paid to (i.e., the production cost share of) factor A (resp. B), e_A (resp. e_B) is the elasticity of supply of input A (resp. B), and σ is the elasticity of substitution between inputs A and B. Setting up this system of equations in matrix form and using Cramer's rule allows for the derivation of a solution to any of the unnkown variables (in terms of percentage changes).

$$-\frac{1}{\eta}dQ^* + dp^* = 0 \tag{1'}$$

$$dQ^* - k_A dA^* - k_B dB^* = 0 \tag{2'}$$

$$-dp^* + \frac{k_B}{\sigma}dA^* - \frac{k_B}{\sigma}dB^* + dp_B^* = 0 \tag{3'}$$

$$-dp^* - \frac{k_A}{\sigma}dA^* + \frac{k_A}{\sigma}dB^* + dp_B^* = 0 \tag{4'}$$

$$\frac{-1}{e_A}dA^* + dp_A^* = 0 \tag{5'}$$

$$\frac{-1}{e_B}dB^* + dp_B^* = 0 \tag{6'}$$

The elasticity of the industry's labor-intensive crop output with respect to the labor input A, defined as ψ, can be expressed as a function of the exogenous parameters η, k_A, k_B, e_A, e_B, and σ

$$\psi \equiv \frac{\partial Q^*}{\partial A^*} = \frac{k_A\eta(\sigma + e_B)}{\eta\sigma + e_B(k_A\eta - k_B\sigma)}. \tag{7}$$

Under the following commonly accepted assumptions: $\eta < 0$, $k_A, k_B > 0$, $e_A, e_B > 0$, and $\sigma > 0$, ψ is strictly positive. All else equal, a decrease in the amount of farm labor used in production will necessarily lead to a decrease in the production of labor-intensive fruits and vegetables.

The model also provides guidance about the range of values that ψ may fall into. Assuming the industry is considered small enough to lack market power in the global market, it can be considered a price taker.[8] Under the price-taking scenario, industry demand is considered perfectly elastic (i.e., $lim\ \eta \rightarrow -\infty$), and if inputs A and B are not perfect substitutes (i.e., $\sigma < \infty$), then $-\eta \geq \sigma$. Under these assumptions, the model suggests that the lower bound for ψ should be determined by the cost share of the labor input k_A

$$-\eta \geq \sigma \iff \psi \geq k_A. \tag{8}$$

When inputs A and B are perfect complements (i.e., $lim\ \sigma \rightarrow 0$), industry output is unit elastic with respect to the labor input

[8] In the empirical setting, the data are aggregated at the crop-county-year level, so each county is considered its own industry.

$$\lim_{\sigma \to 0} \psi = \frac{k_A \eta e_B}{k_A \eta e_B} = 1. \tag{9}$$

If empirical estimates reveal an elasticity of output with respect to the labor input that is smaller than one, this provides evidence that, to some extent, labor can be substituted for non-labor inputs. Furthermore, if the industry demand elasticity is non-positive and the supply elasticity of the non-labor input is non-negative, then ψ is bounded above by the value 1

$$\eta - e_B \leq 0 \iff \psi \leq 1. \tag{10}$$

Under these conditions, ψ should be bounded by the interval $[k_A, 1]$. Martin et al. (2016) estimate that $k_A \in [.2, .4]$, which implies that ψ should be bounded by the interval $[.2, 1]$.[9]

Although one can estimate ψ with the available data, it is not the parameter of interest because it only identifies how production responds to changes in the amount of labor used, which is an equilibrium value. The true parameter of interest is the elasticity of labor-intensive crop production with respect to the farm labor supply, although measures of the farm labor supply are not available for use. A shift in the supply of input A (in percentage terms) in the direction of the price axis at any given quantity on the supply curve β can be defined as

$$\beta = -\frac{1}{e_A} dA^* + dp_A^*, \tag{11}$$

which can be transformed into a shift in the direction of the quantity axis at any given price on the supply curve (denoted $\bar{\beta}$) by multiplying β by the negative of the supply elasticity of input A. Because $\bar{\beta}$ is a percentage change, it can be expressed in logarithmic differential form as $dln(\beta')$, where $ln(\beta')$ represents the unavailable (log) farm labor supply variable.

$$\bar{\beta} = dln(\beta') = -e_A \beta. \tag{12}$$

The true parameter of interest, ξ_1, is defined as[10]

$$\xi_1 \equiv \frac{\partial Q^*}{\partial \bar{\beta}} = \frac{\partial ln(Q)}{\partial ln(\beta')}. \tag{13}$$

[9]Additional special cases of ψ can be found in Appendix A.

[10]It is important to note that an increase in the supply of labor corresponds to a decrease in the price such that $\beta < 0 \iff dA^* > 0$. Therefore, the transformation in (12) implies that $\bar{\beta} < 0 \iff dA^* < 0$.

3.2 Bias of ψ

Understanding if ψ is an upward or downward biased estimate of ξ_1 is important for inference. If ψ is biased upwards, it can be interpreted as an upper bound for ξ_1. Fortunately, the model provides a framework from which one can derive a formula for the bias of ψ under a variety of scenarios. To extend the model in a useful direction while keeping it tractable, I assume that the industry is a price taker (i.e., $lim\ \eta \to -\infty$). I define the limiting case of ψ as $\eta \to -\infty$ as $\bar{\psi}$ and start out with a derivation of the bias of $\bar{\psi}$ under the assumption that there are no omitted variables and then consider cases where there are (i) unobserved factor neutral productivity shocks and (ii) unobserved factor neutral productivity and non-labor input supply shocks. In the latter case, the reduced-form equations for dQ^* and dA^*, can be expressed as

$$dQ^* = \overbrace{\left[\frac{k_A(\sigma + e_B)}{D'}\right]}^{\xi_1}\bar{\beta} + \overbrace{\left[\frac{k_B(\sigma + e_A)}{D'}\right]}^{\xi_2}\bar{\gamma} + \\ + \underbrace{\left[\frac{\sigma(1 + k_A e_A + k_B e_B) + k_B e_A + k_A e_B + e_A e_B}{D'}\right]}_{\xi_3}\delta \tag{14}$$

and

$$dA^* = \underbrace{\left[\frac{\sigma + k_A e_B}{D'}\right]}_{\rho_1}\bar{\beta} + \underbrace{\left[\frac{k_B e_A}{D'}\right]}_{\rho_2}\bar{\gamma} + \underbrace{\left[\frac{(\sigma + e_B)e_A}{D'}\right]}_{\rho_3}\delta, \tag{15}$$

where

$$D^{'} = \sigma + k_B e_A + k_A e_B > 0. \tag{16}$$

The variable $\bar{\gamma}$, which represents a shift in the supply of the composite non-labor input (in percentage terms) along the quantity axis at a given price, can be expressed as the logarithmic differential of the non-labor input supply variable $\gamma^{'}$ as follows:

$$\bar{\gamma} = dln(\gamma^{'}) = -e_B\gamma, \tag{17}$$

where γ represents a shift in the supply of the non-labor input along the price axis at a given quantity

$$\gamma = -\frac{1}{e_B}dB^* + p_B^*. \tag{18}$$

The model also allows for factor neutral productivity shocks δ, which increase the marginal product of both inputs by the same proportion and can be expressed in logarithmic differential form as $dln(\delta')$

$$\delta = dln(\delta') = dQ_A^* = dQ_B^*, \tag{19}$$

where Q_j represents the marginal product of input j. To simplify the notation, the coefficients on $\bar{\beta}$, $\bar{\gamma}$, and δ in equations (14) and (15) are denoted by ξ_1, ξ_2, ξ_3, ρ_1, ρ_2, and ρ_3, and the transformations thereof, $\bar{\psi}$, Λ, and Υ, are defined as[11]

$$\bar{\psi} \equiv \frac{\xi_1}{\rho_1} = \left[\frac{k_A(\sigma + e_B)}{\sigma + k_A e_B}\right] > 0 \tag{20}$$

$$\Lambda \equiv \left[\frac{\xi_3\rho_1 - \xi_1\rho_3}{\rho_1}\right] = \left[\frac{(\sigma + k_A e_B + k_B e_A)[\sigma + e_B(k_A + \sigma k_B)]}{D'(\sigma + k_A e_B)}\right] > 0 \tag{21}$$

$$\Upsilon \equiv \left[\frac{\xi_2\rho_1 - \xi_1\rho_2}{\rho_1}\right] = \left[\frac{k_B(\sigma + e_A)(\sigma + k_A e_B) - k_A k_B e_A(\sigma + e_B)}{D'(\sigma + k_A e_B)}\right] > 0. \tag{22}$$

3.2.1 Case I: Labor Supply Shock Only

First, I consider the case where there are no omitted variables. In this case $\bar{\beta} \neq 0$, but $\bar{\gamma} = \delta = 0$. By using equation (15) to solve for $\bar{\beta}$ and substituting the formula for $\bar{\beta}$ into (14), one can express the relationship between production and the labor input as

$$dQ^* = \bar{\psi} dA^*. \tag{23}$$

By transforming (23) into its logarithmic differential form and integrating, the production-labor relationship can be expressed as

$$ln(Q) = a + \bar{\psi} ln(A), \tag{24}$$

where a is the constant of integration. The production-labor relationship be estimated empirically by using the following model via ordinary least squares (OLS) regression

$$ln(Q) = a + \bar{\psi} ln(A) + \epsilon, \tag{25}$$

[11] I make use of the identity $k_B = 1 - k_A$ in (21) and prove that $\Upsilon > 0$ in Appendix B.

where ϵ is an *iid* error term. The OLS coefficient on the (log) equilibrium employment variable has a probability limit equal to

$$\bar{\psi}_{OLS} = \left[\frac{k_A(\sigma + e_B)}{\sigma + k_A e_B}\right] = \xi_1 + \underbrace{\left[\frac{k_A k_B e_A(\sigma + e_B)}{(\sigma + k_A e_B)(\sigma + k_B e_A + k_A e_B)}\right]}_{\theta_1}, \tag{26}$$

where $\theta_1 > 0$ represents the bias from using an equilibrium employment measure to estimate the effect of a change in the labor supply. Therefore, if there are no omitted variables, $\bar{\psi}_{OLS}$ can be interpreted as an upper bound for ξ_1. The formula for the magnitude of the relative bias is

$$\frac{\theta_1}{\xi_1} = \frac{k_B e_A}{\sigma + k_A e_B}, \tag{27}$$

which should be small if one or more of the following conditions is met: (i) the supply of labor is highly inelastic, (ii) the cost share of input B is small, (iii) labor and non-labor inputs are highly substitutable, or (iv) the supply of the non-labor input is highly elastic. In the case where the supply of labor is perfectly inelastic, there is no bias because a horizontal shift in a vertical labor supply curve causes an equivalent change in equilibrium employment (i.e., $e_A = 0 \implies \bar{\psi} = \xi_1$). Similarly, there is no bias if the supply of input A is not perfectly elastic (i.e., $lim\ e_A \nrightarrow \infty$) and either (i) the two inputs are perfect substitutes (i.e., $lim\ \sigma \rightarrow \infty$) or (ii) the supply of input B is perfectly elastic (i.e., $lim\ e_B \rightarrow \infty$).

3.2.2 Case II: Unobserved Factor Neutral Productivity Shocks

Now I consider the case where there are unobserved neutral productivity shocks δ. In this case, $\bar{\beta} \neq 0$ and $\delta \neq 0$, but $\bar{\gamma} = 0$. One can use equation (15) to solve for $\bar{\beta}$ and substitute the formula for $\bar{\beta}$ into (14) to derive the following formula for dQ^*:

$$dQ^* = \bar{\psi} dA^* + \Lambda\delta. \tag{28}$$

By transforming (28) into its logarithmic differential form and integrating, one can derive the following equation:

$$ln(Q) = b + \bar{\psi} ln(A) + \Lambda ln(\delta'), \tag{29}$$

where b is the constant of integration. The elasticity of labor-intensive crop production with respect to the labor supply can be estimated empirically using (25), but in this case, the error term ϵ contains the unobserved term $\Lambda ln(\delta')$ and is not *iid*. Under this scenario, the coefficient on the (log) equilibrium employment variable has a probability limit equal to

$$\bar{\psi}_{OLS} = \xi_1 + \theta_1 + \underbrace{\left[\frac{\text{cov}(ln(A), \Lambda ln(\delta'))}{\text{var}(ln(A))}\right]}_{\theta_2}, \tag{30}$$

where cov(X, Y) (resp. var(X)) denotes the covariance between two variables X and Y (resp. variance of the variable X), and θ_2 represents the bias that results from unobserved factor neutral productivity shocks. By transforming (15) into its logarithmic differential form and integrating, one can obtain formulas for $ln(A)$ and var$(ln(A))$ and substitute them into θ_2. Under the assumption that labor supply shocks are not correlated with productivity shocks (i.e., cov$(ln(\beta'), ln(\delta')) = 0$), θ_2 condenses to

$$\theta_2 = \left[\frac{\Lambda \rho_3 \text{var}(ln(\delta'))}{\rho_1^2 \text{var}(ln(\beta')) + \rho_3^2 \text{var}(ln(\delta'))}\right] > 0. \tag{31}$$

Therefore, $\bar{\psi}$ will be subject to two sources of upward bias: one from the use of an equilibrium employment variable in place of a labor supply variable (θ_1) and one from unobserved factor neutral productivity shocks (θ_2). The magnitude of the relative bias from latter source can be expressed as

$$\frac{\theta_2}{\xi_1} = \left[\frac{\Lambda}{\xi_1}\right]\left[\frac{\rho_3 \text{var}(ln(\delta'))}{\rho_1^2 \text{var}(ln(\beta')) + \rho_3^2 \text{var}(ln(\delta'))}\right]. \tag{32}$$

All else equal, (32) will tend to be small if the elasticity of equilibrium employment with respect to the productivity shocks is larger than one (i.e., $\rho_3 >> 1$), if the labor supply shocks (β') are highly variable, or if the elasticity of equilibrium employment with respect to the labor supply, which is bounded between 0 and 1, is closer to 1 (i.e., $\rho_1 \approx 1$). The latter is likely to occur if the supply of labor is inelastic. If the supply of labor is perfectly inelastic (i.e., if $e_A = 0$), then $\rho_1 = 1$. The relative bias will also tend to be small if the elasticity of production with respect to factor neutral productivity shocks is small relative to the elasticity of production with respect to the labor supply (i.e., if $\Lambda << \xi_1$).

3.2.3 Case III: Unobserved Non-Labor Input Supply and Factor Neutral Productivity Shocks

Now I consider the case where there are unobserved non-labor input supply shocks $\bar{\gamma}$ and factor neutral productivity shocks δ. In this case, $\bar{\beta} \neq 0, \bar{\gamma} \neq 0$, and $\delta \neq 0$. One can use equation (15) to solve for $\bar{\beta}$ and substitute the formula for $\bar{\beta}$ into (14) to derive the following formula:

$$dQ^{*} = \bar{\psi} dA^{*} + \Upsilon \bar{\gamma} + \Lambda \delta. \tag{33}$$

By transforming (33) into its logarithmic differential form and integrating, one can derive the following equation:

$$ln(Q) = c + \bar{\psi} ln(A) + \Upsilon ln(\gamma') + \Lambda ln(\delta'), \tag{34}$$

where c is the constant of integration. The elasticity of labor-intensive crop production with respect to the labor supply can be estimated empirically using (25), but under this scenario, the error term ϵ contains the two unobserved terms $\Upsilon ln(\gamma')$ and $\Lambda ln(\delta')$ and is not iid. In this case, the coefficient on the (log) equilibrium employment variable has a probability limit equal to

$$\bar{\psi} = \xi_1 + \theta_1 + \underbrace{\left[\frac{\text{cov}(ln(A), \Upsilon ln(\gamma') + \Lambda ln(\delta'))}{\text{var}(ln(A))} \right]}_{\theta_3}, \tag{35}$$

where θ_3 represents the two sources of omitted variables bias. By transforming (15) into its logarithmic differential form and integrating, one can obtain formulas for $ln(A)$ and $\text{var}(ln(A))$ and substitute them into θ_3. Under the assumption that factor neutral productivity shocks are not correlated with input supply shocks and that labor supply shocks are not correlated with non-labor input supply shocks (i.e., $\text{cov}(ln(\beta'), ln(\gamma')) = \text{cov}(ln(\beta'), ln(\delta')) = \text{cov}(ln(\gamma'), ln(\delta')) = 0$) the formula for θ_3 condenses to

$$\theta_3 = \frac{\Upsilon \rho_2 \text{var}(ln(\gamma')) + \Lambda \rho_3 \text{var}(ln(\delta'))}{\rho_1^2 \text{var}(ln(\beta')) + \rho_2^2 \text{var}(ln(\gamma')) + \rho_3^2 \text{var}(ln(\delta'))} > 0. \tag{36}$$

In this case, $\bar{\psi}$ will be subject to three sources of upward bias: one from the use of an equilibrium employment variable in place of a labor supply variable (θ_1) and two from the unobserved non-labor input supply and factor neutral productivity shocks (θ_3). The formula for the relative bias can be expressed as follows:

$$\frac{\theta_3}{\xi_1} = \left[\frac{1}{\xi_1} \right] \left[\frac{\Lambda \rho_3 \text{var}(ln(\delta')) + \Upsilon \rho_2 \text{var}(ln(\gamma'))}{\rho_1^2 \text{var}(ln(\beta')) + \rho_2^2 \text{var}(ln(\gamma')) + \rho_3^2 \text{var}(ln(\delta'))} \right]. \tag{37}$$

As one might expect, the magnitude of the relative bias from the factor unobserved neutral productivity shocks in this case depends on the same factors as those described in Case II, although a higher variance of the non-labor input supply shocks (γ') and a larger elasticity of equilibrium employment with respect to the non-labor input (ρ_2) will also tend to reduce this source of bias. The bias from the unobserved non-labor input supply shocks will tend to be relatively small if the elasticity of equilibrium employment with respect to the non-labor input suppply shocks, which is bounded by the interval [0, 1], is close to one (i.e., $\rho_2 \approx 1$), if the labor supply shocks (β') or factor neutral productivity shocks (δ') are highly variable, or if either the elasticity of equilibrium employment with respect to the farm labor supply (ρ_1) or factor neutral productivity shocks (ρ_3) is large. Furthermore, if the elasticity of production with respect to the non-labor input supply is small relative to the elasticity of production with respect to the labor supply (i.e., if $\Upsilon << \xi_1$), then this source of bias will tend to be small.

4 Data and Methodology

4.1 Data

The data used for this analysis span the period 1990 to 2017 and cover 10 of the 44 fruit and vegetable crop producing California counties. These 10 counties produce 86% of the farm gate value of all labor-intensive crops in the state.[12] The crop production data were obtained from the California County Agricultural Commissioners' reports, which are available in .pdf and .csv format on the website of the USDA's National Agricultural Statistics Service (NASS, 2018). These data include the value (in U.S. dollars) and quantity (in U.S. tons) of production, the number of acres harvested, and the average yield per acre for each crop in each California county in each year. In a handful of cases, the source .csv data files contained apparent data entry errors, which were detected by conducting a visual examination of statewide production graphs for each commodity and investigating outliers. When possible, these errors were corrected by entering the values from the .pdf text reports.[13] Observations were dropped in cases where errors were unable to be reconciled with values from the text reports.[14] Data on the value of production (in dollars)

[12]There are a total of 91 labor-intensive crops used in the analysis. For a list of all the commodities used in this analysis, see Appendix C.

[13]A report containing time series graphs for the statewide production of each of the crop used in the analysis can be found at: https://www.zachrutledge.com/uploads/1/2/5/6/125679559/california_crop_production_graphs_v3.pdf.

[14]In a few cases, there were outliers that appeared consistent in the .csv and .pdf files but were an order of magnitude different from adjacent observations in the data set. I dropped those observations out of an

is available for all crops in all counties in all year, however in some cases one or more of the production measures is missing for some crops in some years. In order to maintain a consistent set of observations throughout the study, observations are also dropped if at least one of the three production measures is missing. In order to determine the extent to which missing observations might affect the empirical results, I calculate the share of the total value that the missing production observations account for. The missing production observations account for less than 1% of the total value of the labor-intensive crops in any given year, so it is unlikely that the dropped observations significantly influence the estimates.

The county-level crop employment data were obtained from the public use Quarterly Census of Employment and Wages (QCEW) data files (BLS, 2018). These data include the average quarterly employment measures for each county based on the North American Industry Classification System (NAICS). To provide a measure of the hand harvest workforce, I include all crop workers directly hired by farmers (NAICS code 111) and those hired by farm labor contractors (NAICS code 115115). In certain counties, employment measures for one of the NAICS codes have been suppressed for some years in order to prevent the identification of individual employers. In these cases, observations corresponding to that county-year are dropped from the analysis. However, I also estimate a set of results using imputed data for the suppressed observations. The results from both methods are qualitatively similar, although the analysis with imputed values delivers upper bounds that are larger in magnitude.[15] The employment measure used in the analysis corresponds to the average employment during each county's peak employment quarter, assumed to be the period of time when the majority of the harvest activities take place. This "peak quarter" is identified separately for each county by determining the quarter during which each county had its highest average employment over the time period 1990 to 2017. Once the peak quarter is defined for each county, the employment measures that correspond to that quarter are assigned to each county for the entire sample period. For example, in Imperial county, where winter lettuce is grown, the peak harvest activities occur during the first quarter of the calendar year, and in San Joaquin county, they occur in the second quarter. Assigning each county the employment measure during their peak harvest season ensures that the analysis captures fluctuations in the local labor supply

abundance of caution as they appear to be data entry errors that carried over into both the .pdf text reports and the .csv data files. Five data entry errors were updated with values from the .pdf files, and 14 were dropped from the analysis.

[15]Values are imputed by estimating a quadratic trend with the non-suppressed observations (separately for each county and NAICS code that has suppressed data) and assigning the predicted values to the missing data. The results with imputed values are available upon request.

during the period of time when farmers are particularly susceptible to labor availability problems.

Weather data were obtained from the National Oceanic and Atmospheric Administration Climate Data Online website (NOAA, 2019). These data include information about temperature and precipitation provided by weather stations located in each county throughout the state. From these data, I generate 12 monthly county-level average temperature variables and 12 monthly county-level cumulative precipitation variables. There are no temperature data for Sutter county, and a few precipitation data points are missing in Sutter county (which is only relevant for the falsification tests).

Table 1 shows the summary statistics for the variables used in the analysis. Note that the production, harvested acres, and yield statistics are aggregated at the crop-county-year level, and the employment and weather measures are aggregated at the county-year level such that employment and weather values are repeated in the analysis when there is more than one crop grown in a county in a given year.

[Table 1 about here.]

4.2 Methodology

As discussed in section 3, the main threats to identification when estimating the effect of a change in the farm labor supply on labor-intensive crop production are the use of an equilibrium employment measure in place of a labor supply variable and omitted variables bias. In an ideal setting, one could deal with both of these threats by using an instrumental variable that induces labor-supply driven variation in the equilibrium employment variable but is uncorrelated with the omitted variables. Of course, instruments that satisfy these conditions are rarely found in practice, therefore I rely upon the following fixed-effects panel regression model:[16]

$$ln(O_{ict}) = \bar{\psi} ln(A_{ct}) + \phi_{ic} + \phi_t + \alpha_1^c t_c + \alpha_2^c t_c^2 + \sum_{m=1}^{12} (\delta^m Temp_{ct}^m + \gamma^m Precip_{ct}^m) + \epsilon_{ict}, \quad (38)$$

where ln denotes the natural logarithm, i denotes crop, c denotes county, and t denotes year. The outcomes of interest $O_{ict} \in (Q_{ict}, H_{ict}, Y_{ict})$ are three measures of crop production, where Q_{ict} is the amount of production of each labor-intensive fruit and vegetable

[16]I explored the use of several instrumental variables including some that were "imperfect" (i.e., instruments that violate the exclusion restriction but are less correlated with the error term than the endogenous regressor of interest) based on the methodology of Nevo and Rosen (2012). However, each instrument failed to provide an improvement over the strategy presented below.

crop in each county in each year, H_{ict} is the number of acres harvested, and Y_{ict} is the average yield (quantity harvested per acre). The main variable of interest $ln(A_{ct})$ is the (log) number of crop workers employed at the county level during the county's peak harvest time. In order to mitigate the bias that arises from unobserved productivity shocks (as defined in section 3.2), the model contains a set of year fixed effects and a set of 24 weather control variables. The year fixed effects help control for productivity shocks that are common to all counties, such as droughts, and the weather variables help control for productivity shocks that arise from local weather events, such as regional freezes that may destroy crops or spring rains that may inhibit pollination. The weather variables may also help control for unobserved labor demand shocks because local weather conditions are closely tied to the timing of the demand for labor (Fisher and Knutson, 2012). Each set of weather control variables $Temp_{ct}^{m}$ and $Precip_{ct}^{m}$ consists of 12 ($m = 1, ..., 12$) monthly county average temperature and cumulative precipitation variables. The quadratic county trends $t_c + t_c^2$ are included to help control for smooth, yet potentially nonlinear, temporal changes that are specific to each county, such as urban expansion, which might affect the amount of land that is available to produce crops on. Because land is one of the main non-labor inputs, the inclusion of quadratic county trends should help mitigate the bias that results from non-labor input supply shocks. The crop-by-county fixed effects ϕ_{ic} are included to control for time-invariant unobserved factors that are differentiated by crop and county, such as soil quality or geography. And ϵ_{ict} is the error term. Although this set of fixed effects and control variables likely controls for a significant amount of the omitted variables bias, they may not fully address the bias that results from using an equilibrium employment variable in place of a labor supply variable (defined as θ_1 in section 3.2.1). As a result, the point estimates may still suffer from upward bias, so I interpret the coefficient on the equilibrium employment variable $\bar{\psi}$ in this regression as an upper bound for ξ_1.

In panel settings that have a natural regional clustering of observations (such as the crop-county level data used in this analysis), it is common to use standard errors that are clustered at the region level (Rogers, 1993). Clustering standard errors at the region level corrects for heteroskedasticity and auto-correlation within geographic regions, which, if present, renders inference based on White (1980)'s heteroskedastic-robust standard errors invalid due to the violation of the error independence assumption. In order to conduct valid inference with clustered standard errors, the errors must not be correlated across clusters. However, the inter-cluster independence assumption may be difficult to justify in certain settings, especially when the geographic regions under consideration are located within close proximity to each other, such as the counties used in this study (see Figure 5).

[Figure 5 about here.]

If there is cross-sectional or spatial correlation in the error term, the across-region error independence assumption is violated and clustered standard error estimates are biased, which leads to invalid inference. Using the Frees test, which is appropriate for use in my setting[17] (De Hoyos and Sarafidis, 2006; Frees, 1995), I test for cross-sectional dependence in the error term to determine if the use of clustered standard errors is appropriate.[18] The Frees tests provide strong evidence of cross-sectional dependence, which likely results from the close geographic proximity of the 10 labor-intensive crop producing counties considered in the analysis, leading to spatial correlation across counties. To conduct inference that is robust to this type of cross-sectional dependence, I use Driscoll-Kraay standard errors (see Driscoll and Kraay, 1998; Hoechle, 2007), which are robust to general forms of cross-sectional dependence, heteroskedasticity, and error auto-correlation up to a specified number of lags.[19] I determine the value of q in the $MA(q)$ process by using the heteroskedastic-robust Cumby-Huzinga general test for auto-correlation.[20]

5 Results

5.1 Labor-Intensive Crops

The results from equation (38) are shown in Table 2. The table consists of two sets of results: one for the top 5 producing counties, and the other for the top 10 counties. According to the data, the top 5 (resp. 10) counties produce 65% (resp. 86%) of the value of all labor-intensive fruit and vegetable crops produced in the state. Within each set of results is a subset of results for production, harvested acres, and average yield per acre. Each column in the table displays estimates that include a different set of control variables. When focusing on an individual row, columns (1) through (4) show estimates that are similar in magnitude and level of significance. However, the results in column (5)

[17]The Frees test is appropriate for use with static panel models when the number of years in the data is less than the number of observations in the cross sectional dimension and year fixed effects are included in the model, which is the setting that fits my study (De Hoyos and Sarafidis, 2006)

[18]Inference based on clustered standard errors is also not valid in this case because the number of clusters (G) must be large in order for the standard error estimates to be consistent. My analysis is based off of the largest 10 producing counties (i.e., $G = 10$), which is too small for clustered standard errors to be reliable. Cameron and Miller (2015) propose the use of the wild cluster bootstrap in cases where the number of clusters is small, however inference based on the wild cluster bootstrap also requires the absence of error correlation across clusters, which does not hold in my setting (see below).

[19]For reference, I also report clustered standard error estimates in the tables that follow.

[20]The number of degrees of error auto-correlation present in each regression can be found in Appendix D.

are mostly insignificant with coefficients that are substantially smaller than those in the other columns. These smaller and often insignificant coefficients likely result from the fact that this specification includes a full set of crop fixed effects interacted with each of the 24 monthly county-level weather variables, adding more than 2000 additional regressors into the model. The inclusion of such a large set of control variables likely soaks up the identifying variation in the main regressor of interest. In light of this, my preferred specification is the model outlined by column (4), which includes the 12 monthly county-level average temperature and 12 monthly county-level cumulative precipitation variables but appears to leave enough variation in the main regressor to identify meaningful upper bounds.

[Table 2 about here.]

When focusing on the production results for the top 5 counties, the results indicate that a 10 percent decrease in the farm labor supply causes *at most* a 5.3% decrease in labor-intensive fruit and vegetable production. Reduced production is primarily channeled through a decrease in the number of acres harvested, although there are some minor effects on average yields. One potential explanation for yield effects is that farmers may not be able to get workers to perform multiple rounds of harvesting on certain crops that do not ripen uniformly. In the top 5 counties, a 10% reduction in the farm labor supply in these counties causes *at most* a 3.5% reduction in harvested acres and *at most* a 1.8% decrease in the average yield per acre.

As the effects are estimated across a larger set of counties, the coefficients become smaller, although they generally remain significant. In the top 10 counties, a 10% reduction in the farm labor supply causes *at most* a 3.8% reduction in production, *at most* a 2.4% reduction in harvested acres, and *at most* a 1.4% reduction in yields.

5.2 Falsification Tests: Mechanically-Harvested Crops

Nut and field crops are harvested by machines and, therefore, do not require a substantial amount of labor to bring to market.[21] As a result, one should not expect to find effects of a declining farm labor supply on the production of these crops as large as those found on labor-intensive fruit and vegetable crops. In order to test this hypothesis, I estimate the effects of changes in the farm labor supply on the production of these crops. The results for nuts (resp. field crops) can be found in Table 3 (resp. Table 4). A review of these tables reveals two important facts. First, the magnitude of the coefficients, when

[21] See Figures 6 (resp. 7) for a map of the top 10 field crop (resp. nut) producing counties.

positive, are much smaller than those found in the fruit and vegetable crop analysis. Second, in some cases, the coefficients are statistically significant and negative, indicating that a smaller labor supply is associated with an increase in the production of these crops, which could result from a switch out of the production of labor-intensive crops into the production of those that are mechanically harvested. Although this is consistent with anecdotal evidence (e.g., Ryssdal, 2017; Martin, 2019), one should use caution when interpreting these negative coefficients as causal evidence because they are not statistically significant in the top five nut (resp. field crop) producing counties, which is where the main effects should be found, and in the set of counties where they are significant, they are not robust to different model specifications. Nevertheless, the evidence from this analysis is consistent with the hypothesis that effects of a declining farm labor supply are not large and statistically significant in mechanically-harvested crops but are, instead, concentrated in the sub-sector of agriculture that is particularly reliant upon labor inputs.

[Figure 6 about here.]

[Figure 7 about here.]

[Table 3 about here.]

[Table 4 about here.]

6 Conclusion

This study provides empirical evidence of the effects of changes in the farm labor supply on labor-intensive crop production using a rich set of panel data from California, the leading agricultural producer and employer in the U.S. The empirical results reveal economically meaningful and statistically significant upper bounds for the effects on hand-harvested fruit and vegetable production but not on mechanically-harvested field or nut crops. The equilibrium displacement model suggests that the elasticity of labor-intensive crop production with respect to the labor input should be bounded by the interval [.2, 1], and the point estimates are consistent with this theory. Additional derivations reveal that the empirical estimates are potentially biased upwards and can be interpreted as upper bounds. The effects are perhaps best exemplified by focusing on the top 5 producing counties. In those counties, the results indicate that a 10% decrease in the farm labor supply causes *at most* a 5.3% reduction in labor-intensive crop production, which is primarily channeled through a reduction in the number of acres harvested, and to some extent lower average yields, perhaps due to constraints on the ability to get enough workers to perform multiple rounds of harvesting on crops that do not ripen uniformly. These upper bounds improve upon the most recent estimates provided by Zahniser et al. (2011), who find an (implied) upper bound for the elasticity of fruit (resp. vegetable) production of 0.58 (resp. 0.85), indicating that the effects are perhaps smaller than previously thought.

Nevertheless, the bounds are economically significant. A 5.3% decrease in the production of labor-intensive crops in the top 5 counties corresponds to 750,000 tons of fruits and vegetables each year worth about $750,000,000. These results suggest that, although a moderate decrease in the farm labor supply would not devastate the aggregate production of fruits and vegetables in California, it could generate economically meaningful reductions in the amount of hand-harvested fruit and vegetable crops that are produced domestically and cause substantial revenue losses. Reduced production could potentially put upward pressure on fresh produce prices and may lead to increased reliance upon imports to meet consumer demand, although these results suggest that that the impacts would not likely be large.

The results from this study also suggest that there is not a one-to-one relationship between labor-intensive crop production and farm labor, which is an indication that, to some extent, labor inputs can be substituted for other inputs. There are at least three factors that likely contribute to this result.

First, the farm labor supply in this study only measures the number of workers and does not account for adjustments on the intensive margin, such as changes in the number of weeks worked per year or hours of work per week. Data from the NAWS indicate that farmers have been employing farm workers for more weeks per year and more hours per week. As a result, estimates based on the number of units of labor (e.g., hours of work) rather than the number of workers could potentially be larger than those that are uncovered by this analysis.

Second, farmers are becoming increasingly reliant upon farm labor contractors and the H-2A visa program to help reduce frictions in the farm labor market. The use of farm labor contractors helps reduce the burden associated with finding harvest workers (although the optimal number of workers may not always be available on short notice when the farmer requests them), while the H-2A program ensures that enough harvest workers will be available when the farmer needs them (although at a higher cost). The use of the H-2A program has historically lagged behind in California, although it is gaining momentum as the labor supply continues to tighten.

Third, farmers are making adjustments to their production practices to help mitigate issues stemming from reduced employee availability. Some farmers report delaying or reducing their pruning, weeding, or harvesting, while others report adopting labor-saving technologies, although mechanical harvesters are currently not available for the vast majority of fruit and vegetable crops, and those crops that can be mechanically harvested have been removed from this analysis (CFBF and UC Davis, 2019; Rutledge and Taylor, 2019). Nevertheless, the fact that California is so well suited to produce high-value specialty crops, coupled with the fact that farmers are actively making adjustments to mitigate issues stemming from labor-availability problems, means that farmers will likely continue producing fruits and vegetables into the foreseeable future even if fewer workers are available.

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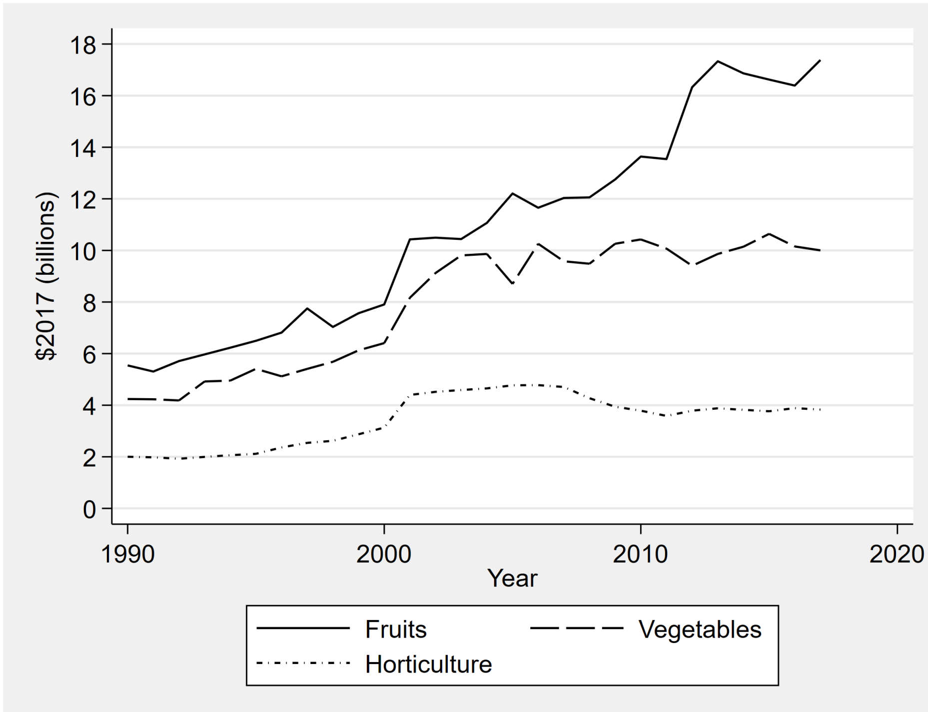
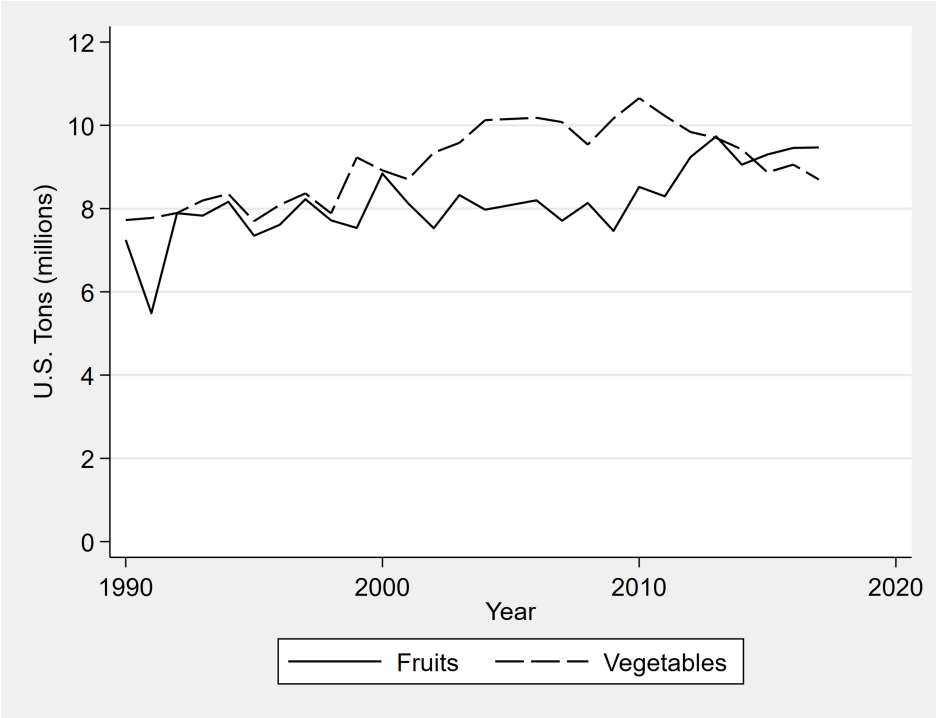
Figure 1: Value of FVH Crop Production in California, 1990-2017



Note: Values have been adjusted to real $2017 using the current CPI for the U.S. city average for all items found at: `https://www.bls.gov/cpi/data.htm`.

Figure 2: Labor-Intensive Fruit and Vegetable Production
and Harvested Acreage in California, 1990-2017

A: Production



B: Harvested Acres

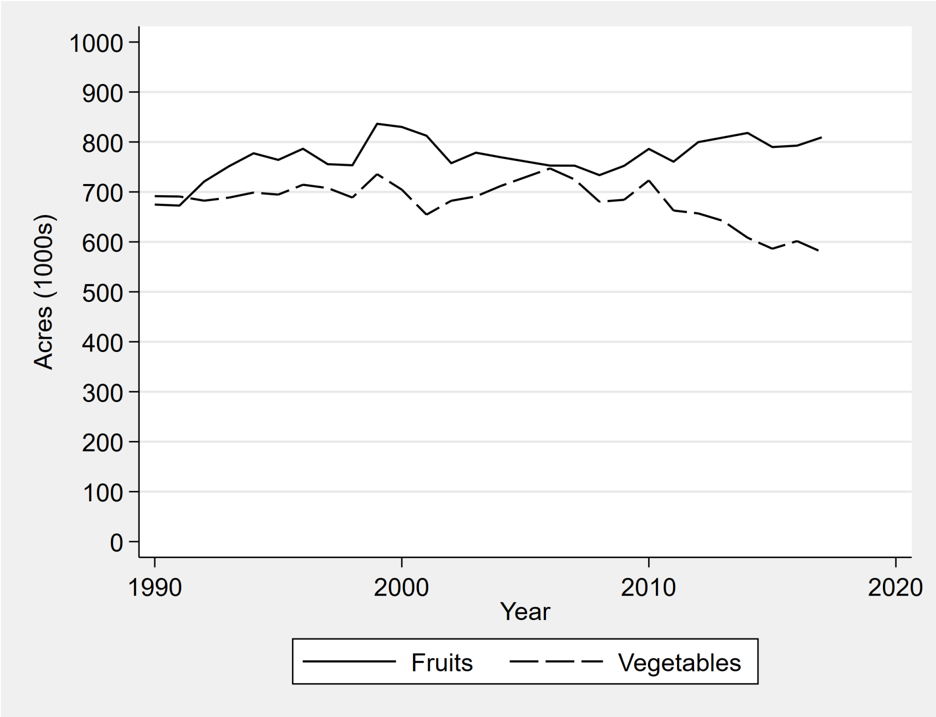
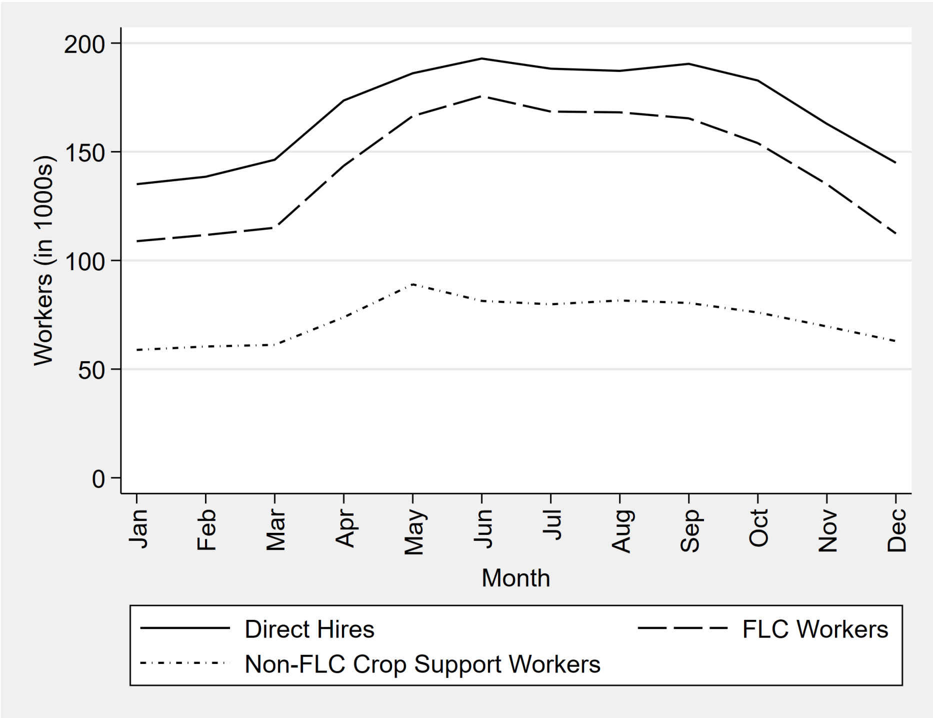


Figure 3: California Crop Employment by Worker Type

A: Average Monthly Employment, 2017



B: Average Annual Employment, 1990-2017

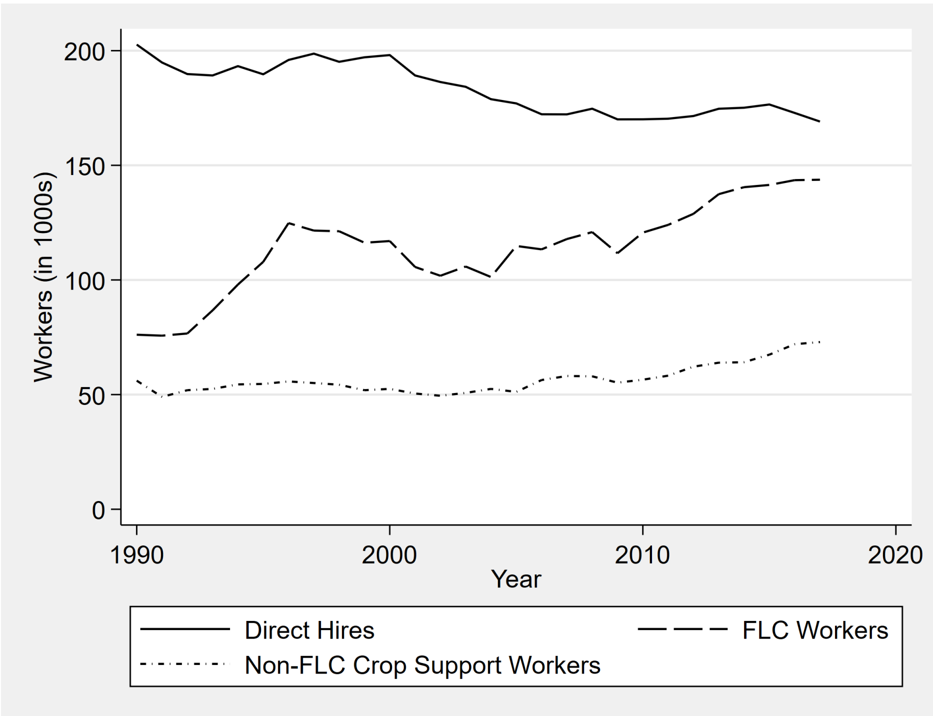
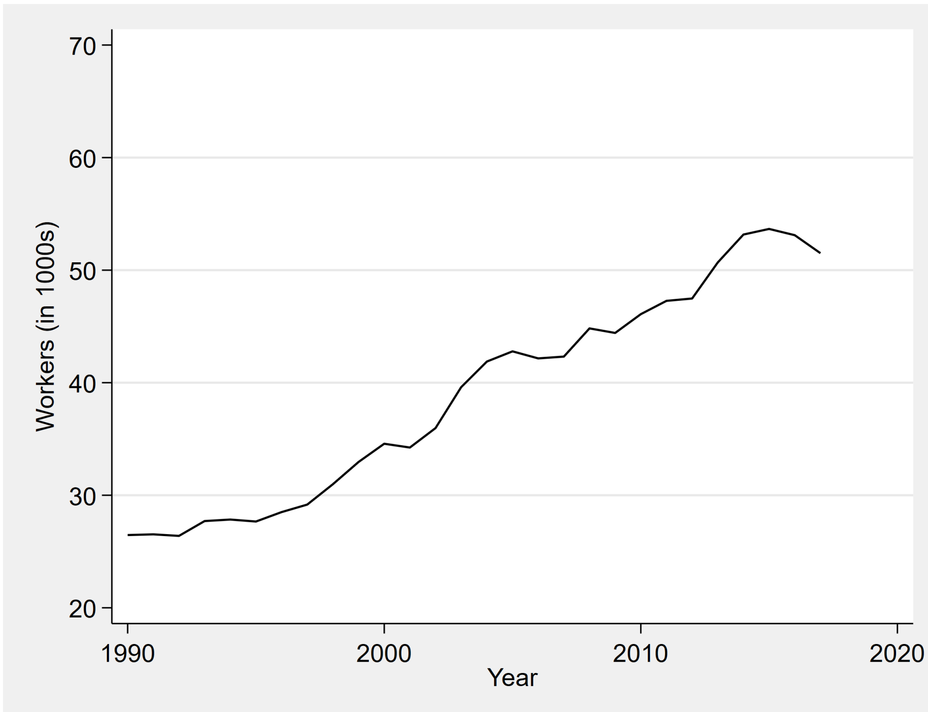


Figure 4: Average Quarterly Employment During Peak Harvest Season (Q3) for Monterey and Fresno Counties, 1990-2017

A: Monterey County



B: Fresno County

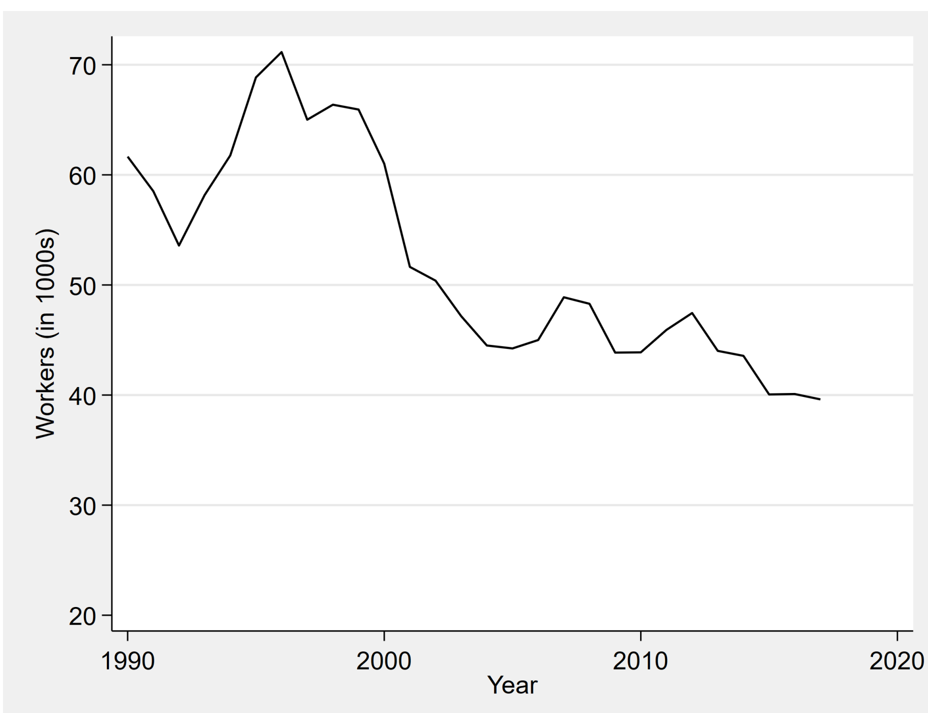


Figure 5: Geography of Top 10 Labor-Intensive
Fruit and Vegetable Producing Counties in California

Note: The calculations that determine the top 10 counties exclude all fruit and vegetable crops that have a viable option for mechanical harvest. After excluding those crops, these 10 counties produce about 86% of the value of all hand-harvested fruit and vegetable crops in the state.

Figure 6: Geography of the Top 10 Field Crop Producing Counties

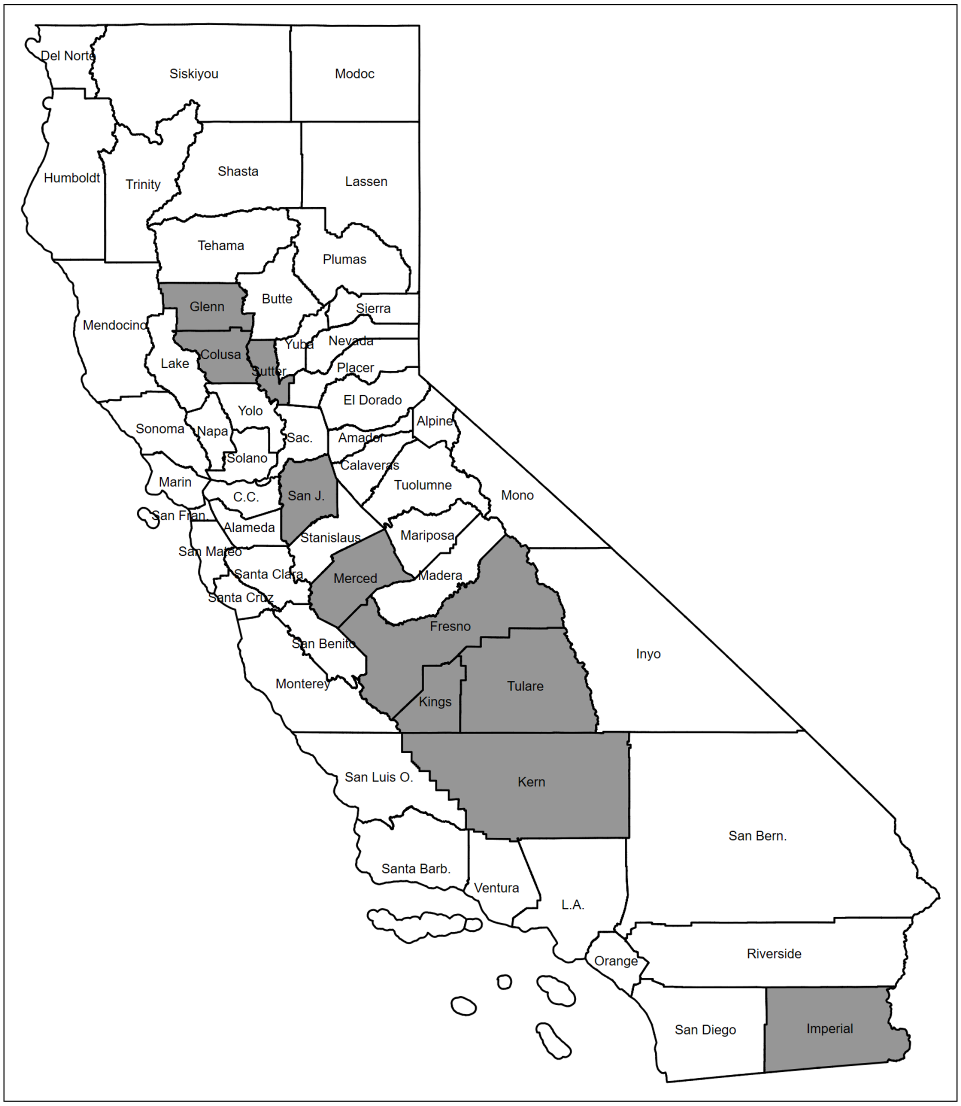


Figure 7: Geography of the Top 10 Nut Producing Counties

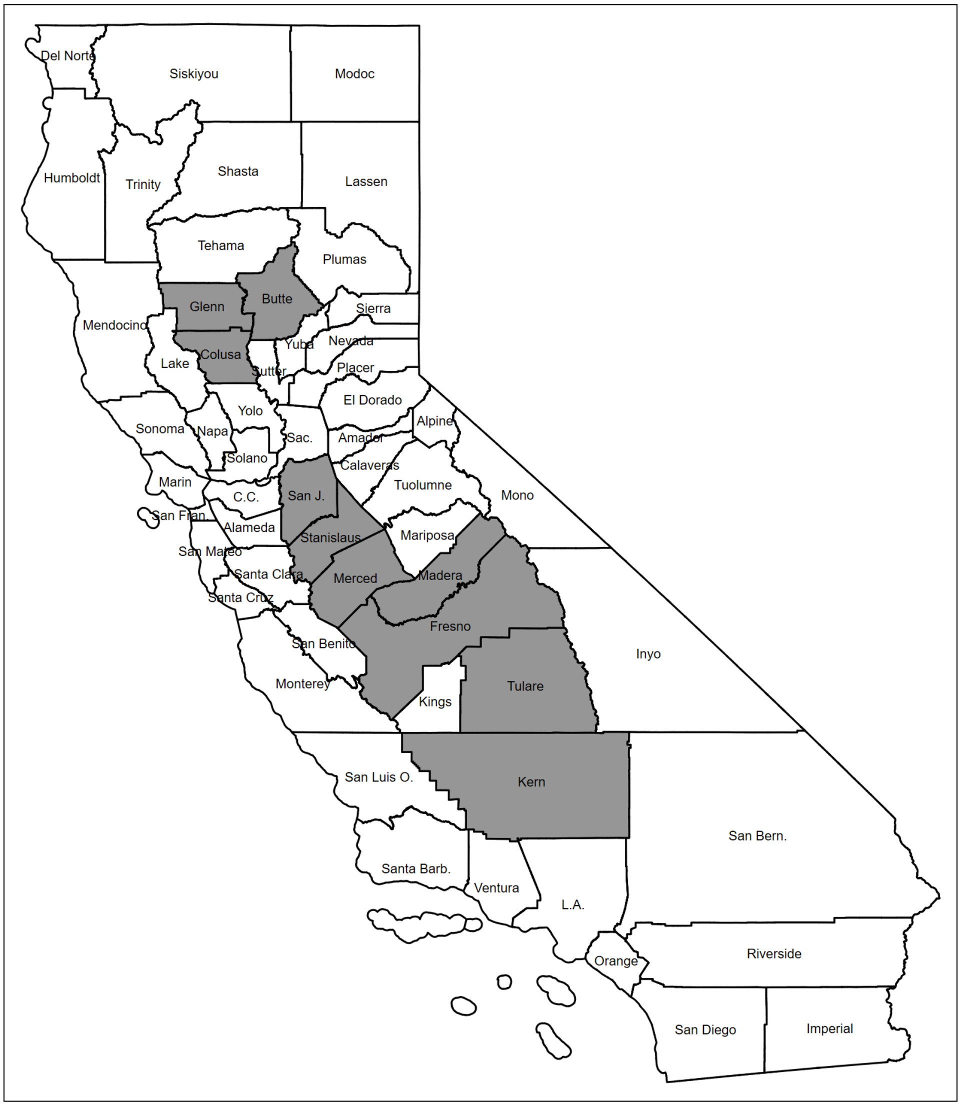


Table 1: Summary Statistics for Top 10
Labor-Intensive Fruit and Vegetable Crop Producing Counties

	Median	Mean	SD
Production (in U.S. tons)	15,546	60,780	133,616
Harvested Acres	1,480	5,066	9,486
Yield/Acre (in U.S. tons)	10.0	13.1	16.9
Obs.	6,364	6,364	6,364
Number of Workers	19,194	25,513	16,216
Ave. County Temperature (in Fahrenheit)	61.3°	62.4°	5.1°
Ave. Cumulative County Precipitation (inches annually)	13.6	14.4	8.3
Obs.	279	279	279

Note: One U.S. ton is equal to 2000 pounds (or 907.18 kilograms). The production, harvested acres, and yield statistics are aggregated at the crop-county-year level, while the employment and weather variables are aggregated at the county-year level. The average county temperature and precipitation statistics presented here are each constructed from 12 monthly variables.

Table 2: Effects of a Change in the Farm Labor Supply on Labor-Intensive Crop Production for the Top 5 and 10 Labor-Intensive Crop Producing California Counties

	(1)	(2)	(3)	(4)	(5)
			Top 5 Counties		
	0.476***	0.549***	0.478***	0.531***	0.121
Production	(0.106)	(0.071)	(0.087)	(0.079)	(0.208)
	[0.275]	[0.195]	[0.238]	[0.198]	[0.199]
	0.286***	0.340***	0.309***	0.352***	0.109
Harvested Acres	(0.053)	(0.057)	(0.047)	(0.061)	(0.121)
	[0.181]	[0.131]	[0.116]	[0.117]	[0.173]
	0.190***	0.210**	0.169**	0.179*	0.012
Yield	(0.066)	(0.087)	(0.067)	(0.090)	(0.180)
	[0.102]	[0.068]	[0.127]	[0.095]	[0.151]
N	3,485	3,485	3,485	3,485	3,485
			Top 10 Counties		
	0.388***	0.370***	0.409***	0.381***	0.216***
Production	(0.072)	(0.049)	(0.061)	(0.060)	(0.071)
	[0.157]	[0.147]	[0.147]	[0.138]	[0.087]
	0.263***	0.239***	0.266***	0.244***	0.183**
Harvested Acres	(0.028)	(0.034)	(0.040)	(0.046)	(0.070)
	[0.103]	[0.106]	[0.095]	[0.101]	[0.090]
	0.125*	0.131**	0.142**	0.137***	0.032
Yield	(0.063)	(0.058)	(0.056)	(0.034)	(0.058)
	[0.080]	[0.065]	[0.090]	[0.068]	[0.079]
N	6,364	6,364	6,364	6,364	6,364
Year FE	X	X	X	X	X
Crop-x-County FE	X	X	X	X	X
Quadratic County Trends	X	X	X	X	X
Monthly Temp. Controls	–	X	–	X	–
Monthly Precip. Controls	–	–	X	X	–
Crop-x-Temp. Controls	–	–	–	–	X
Crop-x-Precip. Controls	–	–	–	–	X

Significance levels are based on Driscoll-Kraay standard errors, which are reported in parentheses. Standard errors clustered at the county-level are reported in brackets. * $p < .1$, ** $p < .05$, *** $p < .01$.

Table 3: Effects of a Change in the Farm Labor Supply
on Nut Crop Production for the Top 5 and 10
Nut Crop Producing California Counties

	(1)	(2)	(3)	(4)	(5)
			Top 5 Counties		
Production	0.155	-0.010	0.085	-0.031	-0.187
	(0.218)	(0.088)	(0.223)	(0.103)	(0.175)
	[0.071]	[0.019]	[0.113]	[0.029]	[0.108]
Harvested Acres	0.142	0.072	0.106	0.105	0.025
	(0.103)	(0.057)	(0.105)	(0.119)	(0.088)
	[0.136]	[0.111]	[0.176]	[0.134]	[0.130]
Yield	0.013	-0.082	-0.021	-0.137	-0.212
	(0.204)	(0.159)	(0.196)	(0.170)	(0.183)
	[0.118]	[0.115]	[0.180]	[0.112]	[0.131]
N	368	368	368	368	368
			Top 10 Counties		
Production	0.098	0.075	0.057	0.057	-0.000
	(0.068)	(0.063)	(0.068)	(0.043)	(0.069)
	[0.063]	[0.078]	[0.070]	[0.058]	[0.067]
Harvested Acres	0.008	-0.012	0.031	0.022	-0.009
	(0.027)	(0.036)	(0.026)	(0.026)	(0.040)
	[0.041]	[0.047]	[0.036]	[0.048]	[0.058]
Yield	0.090	0.087	0.026	0.035	0.009
	(0.061)	(0.061)	(0.059)	(0.052)	(0.093)
	[0.074]	[0.088]	[0.059]	[0.054]	[0.069]
N	772	772	760	760	760
Year FE	X	X	X	X	X
Crop-x-County FE	X	X	X	X	X
Quadratic County Trends	X	X	X	X	X
Monthly Temp. Controls	–	X	–	X	–
Monthly Precip. Controls	–	–	X	X	–
Crop-x-Temp. Controls	–	–	–	–	X
Crop-x-Precip. Controls	–	–	–	–	X

Significance levels are based on Driscoll-Kraay standard errors, which are reported in parentheses. Standard errors clustered at the county-level are reported in brackets. * $p < .1$, ** $p < .05$, *** $p < .01$.

Table 4: Effects of a Change in the Farm Labor Supply
on Field Crop Production for the Top 5 and 10
Field Crop Producing California Counties

	(1)	(2)	(3)	(4)	(5)
			Top 5 Counties		
Production	0.063 (0.159) [0.210]	-0.027 (0.179) [0.170]	0.050 (0.152) [0.182]	-0.084 (0.138) [0.117]	0.017 (0.174) [0.163]
Harvested Acres	0.073 (0.134) [0.174]	-0.051 (0.139) [0.171]	0.089 (0.109) [0.143]	-0.078 (0.113) [0.137]	0.076 (0.150) [0.168]
Yield	-0.010 (0.056) [0.048]	0.025 (0.065) [0.049]	-0.039 (0.059) [0.052]	-0.006 (0.058) [0.059]	-0.059 (0.075) [0.090]
N	1,525	1,525	1,525	1,525	1,525
			Top 10 Counties		
Production	-0.168 (0.108) [0.110]	-0.131 (0.126) [0.111]	-0.237** (0.110) [0.126]	-0.210* (0.107) [0.126]	-0.073 (0.092) [0.162]
Harvested Acres	-0.110 (0.083) [0.075]	-0.079 (0.114) [0.079]	-0.132 (0.107) [0.083]	-0.126 (0.100) [0.088]	-0.015 (0.083) [0.121]
Yield	-0.058 (0.037) [0.050]	-0.051* (0.028) [0.047]	-0.105*** (0.029) [0.047]	-0.083*** (0.024) [0.044]	-0.058* (0.030) [0.054]
N	3,529	3,025	3,347	2,959	2,959
Year FE	X	X	X	X	X
Crop-x-County FE	X	X	X	X	X
Quadratic County Trends	X	X	X	X	X
Monthly Temp. Controls	–	X	–	X	–
Monthly Precip. Controls	–	–	X	X	–
Crop-x-Temp. Controls	–	–	–	–	X
Crop-x-Precip. Controls	–	–	–	–	X

Significance levels are based on Driscoll-Kraay standard errors, which are reported in parentheses. Standard errors clustered at the county-level are reported in brackets. * $p < .1$, ** $p < .05$, *** $p < .01$.

A Other Special Cases of ψ

If labor is the only input (i.e., $lim\ k_A \to 1$), then industry output is unit elastic with respect to labor:

$$\lim_{k_A \to 1} \psi = \frac{\eta(\sigma + e_B)}{\eta(\sigma + e_B)} = 1. \tag{A-1}$$

If input B is perfectly elastic (i.e., $lim\, e_B \to \infty$), then industry output is inelastic with respect to labor:

$$\lim_{e_B \to \infty} \psi = \frac{k_A \eta}{k_A \eta - k_B \sigma} < 1. \tag{A-2}$$

If the supply of the non-labor input B is perfectly inelastic (i.e., $lim\, e_B = 0$), the output elasticity with respect to the labor input is equal to k_A, the cost share of input A:

$$\lim_{e_B \to 0} \psi = \frac{k_A \eta \sigma}{\eta \sigma} = k_A. \tag{A-3}$$

B Proof that $\Upsilon > 0$

Let Υ be defined as

$$\Upsilon \equiv \left[\frac{\xi_2 \rho_1 - \xi_1 \rho_2}{\rho_1}\right] = \left[\frac{k_B(\sigma + e_A)(\sigma + k_A e_B) - k_A k_B e_A(\sigma + e_B)}{D'(\sigma + k_A e_B)}\right]. \tag{B-1}$$

In order to prove that $\Upsilon > 0$, it is sufficient to show that

$$k_B(\sigma + e_A)(\sigma + k_A e_B) > k_A k_B e_A(\sigma + e_B). \tag{B-2}$$

Dividing both sides of (B-2) by $k_B e_A$ delivers the following inequality:

$$\underbrace{\left[\frac{(\sigma + e_A)}{e_A}\right]}_{G}(\sigma + k_A e_B) > k_A \sigma + k_A e_B, \tag{B-3}$$

which holds because $G > 1 > k_A$ and thus $G\sigma > k_A \sigma$ and $G k_A e_B > k_A e_B$. Therefore, $\Upsilon > 0$.

C List of Labor-Intensive Commodities Used in Analysis

[Table C.1 about here.]

D Lag Length Used in Driscoll-Kraay Standard Errors

[Table D.1 about here.]

[Table D.2 about here.]

[Table D.3 about here.]

Table C.1: List of Commodities

ANISE (FENNEL)	LETTUCE BULK SALAD PRODUCTS
APPLES ALL	LETTUCE HEAD
APRICOTS ALL	LETTUCE LEAF
ARTICHOKES	LETTUCE ROMAINE
ASPARAGUS FRESH MARKET	LETTUCE UNSPECIFIED
AVOCADOS ALL	LIMES ALL
BEANS FRESH UNSPECIFIED	MELONS CANTALOUPE
BEANS LIMA GREEN	MELONS CASABA
BEANS SNAP FRESH MARKET	MELONS CRENSHAW
BERRIES BLACKBERRIES	MELONS HONEYDEW
BERRIES BLUEBERRIES	MELONS UNSPECIFIED
BERRIES BOYSENBERRIES	MELONS WATERMELON
BERRIES BUSHBERRIES UNSPECIFIED	MUSHROOMS
BERRIES LOGANBERRIES	NECTARINES
BERRIES RASPBERRIES	OKRA
BERRIES STRAWBERRIES FRESH MARKET	OLIVES
BERRIES STRAWBERRIES PROCESSING	ONIONS GREEN & SHALLOT
BROCCOLI FOOD SERVICE	ORANGES NAVEL
BROCCOLI FRESH MARKET	ORANGES UNSPECIFIED
BROCCOLI PROCESSING	ORANGES VALENCIA
BRUSSELS SPROUTS	PARSLEY
CABBAGE CHINESE & SPECIALTY	PEACHES CLINGSTONE
CABBAGE HEAD	PEACHES FREESTONE
CABBAGE RED	PEACHES UNSPECIFIED
CAULIFLOWER FOOD SERVICE	PEARS ASIAN
CAULIFLOWER FRESH MARKET	PEARS UNSPECIFIED
CAULIFLOWER PROCESSING	PEAS EDIBLE POD (SNOW)
CELERY FOOD SERVICE	PEPPERS BELL
CELERY FRESH MARKET	PEPPERS CHILI HOT
CELERY PROCESSING	PERSIMMONS
CHERRIES SWEET	PLUMCOTS
CITRUS UNSPECIFIED	PLUMS
CORN SWEET ALL	POMEGRANATES
CUCUMBERS	PUMPKINS
CUCUMBERS GREENHOUSE	QUINCE
DATES	RADICCHIO
EGGPLANT ALL	RAPPINI
ENDIVE ALL	SALAD GREENS MISC.
ESCAROLE ALL	SQUASH
GRAPEFRUIT ALL	SWISS CHARD
GRAPES TABLE	TANGELOS
GREENS TURNIP & MUSTARD	TANGERINES & MANDARINS
KALE	TOMATILLO
KIWIFRUIT	TOMATOES CHERRY
KUMQUATS	TOMATOES FRESH MARKET
LEMONS ALL	

Table D.1: Degree of Serial Correlation in the Error Term for Table 2

	(1)	(2)	(3)	(4)	(5)
	Top 5 Counties				
Production	6	6	6	6	2
Harvested Acres	6	6	6	6	3
Yield	3	3	3	3	2
	Top 10 Counties				
Production	6	6	6	6	3
Harvested Acres	6	6	6	6	0
Yield	4	0	4	4	1
Year FE	X	X	X	X	X
Crop-x-County FE	X	X	X	X	X
Quadratic County Trends	X	X	X	X	X
Monthly Temp. Controls	–	X	–	X	–
Monthly Precip. Controls	–	–	X	X	–
Crop-x-Temp. Controls	–	–	–	–	X
Crop-x-Precip. Controls	–	–	–	–	X

Table D.2: Degree of Serial Correlation in the Error Term for Table 3

	(1)	(2)	(3)	(4)	(5)
	Top 5 Counties				
Production	6	6	6	6	4
Harvested Acres	7	7	7	7	6
Yield	0	0	0	0	0
	Top 10 Counties				
Production	7	7	7	7	6
Harvested Acres	8	7	7	8	4
Yield	2	4	2	2	0
Year FE	X	X	X	X	X
Crop-x-County FE	X	X	X	X	X
Quadratic County Trends	X	X	X	X	X
Monthly Temp. Controls	–	X	–	X	–
Monthly Precip. Controls	–	–	X	X	–
Crop-x-Temp. Controls	–	–	–	–	X
Crop-x-Precip. Controls	–	–	–	–	X

Table D.3: Degree of Serial Correlation in the Error Term for Table 4

	(1)	(2)	(3)	(4)	(5)
	Top 5 Counties				
Production	5	5	4	5	1
Harvested Acres	6	6	6	2	1
Yield	1	1	1	1	1
	Top 10 Counties				
Production	5	5	5	5	2
Harvested Acres	0	6	6	6	1
Yield	0	3	3	3	1
Year FE	X	X	X	X	X
Crop-x-County FE	X	X	X	X	X
Quadratic County Trends	X	X	X	X	X
Monthly Temp. Controls	–	X	–	X	–
Monthly Precip. Controls	–	–	X	X	–
Crop-x-Temp. Controls	–	–	–	–	X
Crop-x-Precip. Controls	–	–	–	–	X