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ARTICLE

Farm labor supply and fruit and vegetable production

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Abstract
This study provides econometric estimates of the effects of reductions in farm labor supply on the production of hand-harvested fruits and vegetables. Using crop production and employment data from California counties, we estimate panel regressions linking farm employment to crop production outcomes. Because we exploit variation in equilibrium employment, as opposed to exogenous variation in the labor supply curve, we use an equilibrium displacement model to identify the most likely sources of estimation bias and conclude that our regression estimates should be interpreted as upper bounds for the effect of interest. Our results indicate that a 10% decrease in the farm labor supply (in terms of the number of workers) causes at most a 4.2% reduction in production in the top 10 fruit and vegetable producing counties. Production effects are channeled primarily through a reduction in harvested acreage, although we also uncover some effects on yield.

KEYWORDS
agriculture, equilibrium displacement model, farm labor, fruit, harvest, immigration, labor supply, production, specialty crop, vegetable

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1 | INTRODUCTION

American farmers have reported recurrent farm labor shortages and lamented their effects for more than a decade (CFBF & UC Davis, 2019; della Cava & Lopez, 2019; Estrabrook, 2021; Glaister, 2006; Plummer, 2013). In the meantime, a rich economic literature has assessed their empirical prevalence (Hertz & Zahniser, 2012; Martin, 2007; Richards, 2018), identified some of their causes (Boucher et al., 2007; Charlton & Taylor, 2016; Fan et al., 2015; Kostandini et al., 2013; Richards & Patterson, 1998; Taylor et al., 2012), and discussed mitigating strategies (Charlton et al., 2019; Hamilton et al., 2021; Richards, 2018, 2020; Taylor et al., 2012; Zahniser et al., 2018). Although a consensus seems to have emerged that agricultural labor is indeed becoming scarcer (Charlton & Taylor, 2016; Richards, 2018; Taylor et al., 2012),[1] the extent to which labor shortages actually impact the supply of agricultural goods, particularly labor-intensive and perishable crops such as fruits and vegetables (FV), remains unclear. The question is important, notably because its answer partially determines whether consumers can be expected to bear some of the burden associated with reduced farm labor availability. The goal of the present article is to address this question empirically.

To be sure, there are good reasons to expect FV production to be sensitive to labor availability. First, even if the mechanization of certain field operations has reduced the need for human labor, many FV crops still need to be picked manually.[2] Second, because these crops are highly perishable, the timing of labor availability at harvest is key. Hence, labor market frictions have bigger consequences for FV production than for commodities that can stand in the field without immediate risk of spoilage (Ridley & Devadoss, 2021).

Of course, reduced domestic production could be compensated by imports, at least partially. If the supply of FV imports to the United States were perfectly elastic at current prices, the question of farm labor shortages would admittedly be moot from a long-run welfare perspective. Increased imports, however, likely come at higher marginal costs. First, although the United States is a net FV importer,[3] a large share of imports originates in countries with counterseasonal production and cannot be considered perfect substitutes for domestic products (Kenner, 2021). Second, one reason why farm labor is becoming scarcer in the United States is that countries where much of this labor originates, notably Mexico, are themselves undergoing an "agricultural transformation" with fewer people involved in agriculture and rising opportunity costs of farm work (Charlton & Taylor, 2016; Timmer, 1988). Thus, the prices of imports from these countries could be expected to rise with United States import demand. Such price increases could in turn stimulate procurement from more distant locations, but importing FV from faraway places implies a reduced shelf life once product reaches US markets, an increased risk of contamination due to limited reach of government oversight (Congressional Research Service, 2020), and higher transport costs and attendant external environmental effects. Hence, replacing domestic production by imports would, in all likelihood, come with additional consumer costs in terms of price, quality, and convenience, as well as higher social costs. In the short run, it would also cause American farmers, who have invested physical and human capital in FV operations, to suffer economic losses (Clemens et al., 2018).

But how much do changes in the farm labor supply really affect the production of labor-intensive crops in the United States? To answer this question, this article estimates elasticities of hand-harvested specialty crop production and value with respect to farm labor using data from California

[1]Although Quarterly Census of Employment and Wages data indicate that crop employment in California was lower in 2020 than in 2019, it is unclear whether COVID-19 contributed substantially to the decline. Hill (2020) suggests that it was mainly driven by demand-side factors. Martin (2021)'s analysis of California Employment Development Department survey data documents an increase in California's agricultural employment during the second half of 2020 (relative to 2019). Additionally, Martin (2020) notes that major workplace COVID-19 outbreaks were generally absent in California's agricultural sector during the first half of 2020, and that generous unemployment benefits, as opposed to COVID-19 related employee shortages, may explain the decline in crop employment.

[2]For crops, such as berries, that are harvested multiple times, it is not only the risk of produce damage that favors manual harvest but also the fact that the decision whether to pick individual fruit must be made according to caliber, ripeness, or the presence of visible defects.

[3]In net, the United States imported $11.4 billion of FV in 2015, excluding nuts; in 2013, the import share of U.S. demand was about 24% for fresh fruit and 22% for fresh vegetables in volume (Congressional Research Service, 2016, 2020).

counties spanning the 30-year period from 1990 to 2019. California is a natural setting for this analysis as it produces one-third of domestic vegetables and two-thirds of domestic fruits and nuts (CDFA, 2021); it is also the largest agricultural employer in the nation, with labor expenses accounting for nearly one-third of the US total (NASS, 2021). Notably, the agricultural workforce is mostly composed of Mexican laborers,[4] making the farm labor supply susceptible to changing economic opportunities in Mexico, competing labor demand from the US construction and services sectors, or changes in immigration rules and enforcement, all of which are arguably exogenous to local production outcomes.

Our study brings together three datasets pertaining respectively to crop production, farm employment, and weather. Our empirical strategy deploys fixed-effects panel regression models at the crop-county-year level of aggregation, where the regressor of interest measures county-year farm employment during the peak harvest season. The identifying variation comes from differences across counties in the evolution of employment about smooth county-level trends, net of weather effects. The fact that crop employment, an equilibrium value, is used as the explanatory variable in place of the underlying yet unobserved labor supply variable causes important identification challenges.

First, to the extent that the labor supply curve is upward sloping (as opposed to perfectly inelastic) and the labor demand curve is downward sloping (as opposed to perfectly elastic), a change in equilibrium employment understates the underlying shock to labor supply. Thus, the empirical employment-output elasticity overstates the elasticity of interest, which is with respect to the labor supply shift as measured along the labor quantity axis. Second, because farm employment is an equilibrium value, it may be influenced by other factors, such as weather-induced productivity shocks, that affect the outcome independently of labor supply shocks, raising concerns about omitted variables.

To develop a clear understanding of the bias resulting from these combined factors, we make novel use of the equilibrium displacement framework, a classical tool of agricultural policy analysis (e.g., Gardner, 1975; Gunter et al., 1992; Mérel, 2009; Okrent & Alston, 2012; Piggott et al., 1995; Wohlgenant, 1989). Specifically, we examine how labor supply shocks, shocks to the supply of other inputs, output demand shocks, and technology shocks jointly affect equilibrium quantities in the specialty crop and farm labor markets, and may thus contribute to the correlation between crop output and equilibrium employment present in the data. The equilibrium displacement model provides a set of reduced-form equations accounting for structural relationships across markets that are used to derive an expression for the estimation bias. This expression is a function of structural parameters, notably elasticities, with unknown magnitudes but known signs, allowing the sign of the bias to be discussed transparently. Thus, even if our regression analysis is reduced form, we explicitly link it to a structural model of FV supply for interpretation purposes.

This exercise reveals that the empirical employment-output elasticity should, in several respects, be interpreted as an upper bound to the effect of interest. Part of the upward bias may be reduced by appropriate controls, but the use of equilibrium employment instead of a direct yet unobservable measure of labor supply biases the elasticity estimate upward to an extent that cannot be eliminated, even with instrumental variables. Thus, our empirical strategy consists of mitigating, to the extent possible, the omitted variable bias through a host of control variables, while still interpreting the resulting elasticity estimate as an upper bound. Our preferred panel regression includes year fixed effects, quadratic county-level trends, and monthly temperature and precipitation controls, in addition to county fixed effects differentiated by crop. The identifying assumption for the upper bound is that, conditional on fixed effects and other control variables, there are no unobserved determinants of production outcomes that are correlated with labor supply.[5]

[4]According to the 2017–18 survey round of the National Agricultural Workers Survey, 86% of the state's crop labor force was born in Mexico (US Department of Labor, 2021).

[5]Importantly, for our upper bound interpretation to fail, it would have to be the case that unobserved determinants of production outcomes affect farm labor supply, not demand. Unobserved determinants of production outcomes that affect farm labor demand—and therefore farm employment through wage effects—would result in upward bias that is already accounted for by our upper bound interpretation.

Our empirical results indicate that a 10% decrease in the farm labor supply (in terms of the number of workers willing to supply labor at a given price) causes at most a 4.2% decrease in hand-harvested FV production in the top 10 producing counties, which together produce 86% of the value of all labor-intensive crops in the state.[6] Reduced production is primarily channeled through a decrease in the number of acres harvested (−2.8%), although we also uncover small yield effects (−1.4%). Impacts on the total value of production appear to be concentrated in the top five counties. There, a 10% decrease in the farm labor supply causes at most a 5.5% decrease in production value. If the labor supply declines at a rate of 1% per year, as suggested by Charlton and Taylor (2016), farmers in the leading FV producing counties could lose as much as $3.7 billion in revenue, or roughly 2.9% of the total revenue, over the course of a decade. Thus, moderate decreases in the farm labor supply could have meaningful economic impacts, but they would likely not devastate California's FV industry. Importantly, falsification tests run on mechanically harvested field and nut crops deliver elasticity estimates that are much smaller than those found for labor-intensive crops, sometimes negative, and generally not statistically significant, consistent with the hypothesis that labor supply shocks have a negligible impact on crops that do not rely heavily on manual labor.

To our knowledge, few recent studies have examined how changes in labor supply affect FV production in the United States. With the help of a computable general equilibrium model, Zahniser et al. (2011) calculate 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, implying an upper bound for the elasticity of production with respect to the farm labor supply of 0.58 (resp. 0.85). On balance, these bounds are larger than those produced by our analysis. Two other studies, Brady et al. (2016) and Cassey et al. (2018), use an equilibrium displacement model to examine how simultaneous shocks to output demand and labor supply affect the production of tree fruits. The implied elasticity of aggregate tree fruit production with respect to the labor supply in Brady et al. (2016) ranges from 0.21 to 0.54, in line with the upper bounds produced by our analysis. Cassey et al. (2018) estimate an elasticity of 0.42 for apples, which is consistent with our findings, but their estimate of 0.93 for peaches lies above our range of estimates.

Our article contributes to the literature in three ways. First, we extend the recent US farm labor literature, which points to a declining farm labor supply and identifies its plausible causes, by quantifying the consequences such changes may have on hand-harvested FV production.

Second, we provide a direct econometric bound on the elasticity of labor-intensive crop production with respect to the farm labor supply. In contrast, existing studies examining the impacts of farm labor supply shocks (e.g., Brady et al., 2016; Cassey et al., 2018; Gunter et al., 1992) have used the equilibrium displacement approach, which relies on structural parameter estimates taken from the literature. Although we also develop an equilibrium displacement model, we use it to determine the likely sign of the estimation bias and proceed to identify an upper bound for the effect of interest using detailed production, employment, and weather data without imposing structure in estimation.

Third, we demonstrate a novel use of the equilibrium displacement framework that could be adapted to a variety of empirical settings. Specifically, we show how an equilibrium displacement model can help formalize intuition about the estimation bias resulting from the use of an equilibrium employment variable in regression analysis, a common problem in labor economics. For example, in the immigration literature, researchers have often relied on instrumental variables to produce exogenous variation in the share of immigrant labor (e.g., Basso & Peri, 2015; Borjas, 2014; Mérel & Rutledge, 2021), but a commonly used class of instruments has been found to exacerbate bias in certain settings (Goldsmith-Pinkham et al., 2020; Jaeger et al., 2018). The approach developed here

[6]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 at any point during the period of study. That determination was made based on 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).

offers an alternative, or a complement, to the use of instrumental variables, allowing researchers to determine the extent to which their empirical estimates may be interpretable as bounds.

The article is organized as follows: Section 2 develops a structural framework to gain insight into the plausible estimation bias and presents our empirical strategy; Section 3 describes the data; Section 4 discusses the results; and Section 5 concludes.

2 | METHODOLOGY

2.1 | Model

Our empirical analysis regresses agricultural production outcomes on equilibrium farm employment. To evaluate the effects of unobserved market and technology shocks on equilibrium outcomes, we develop a simple equilibrium displacement model, building upon the seminal work of Muth (1964). We link the model to our regression framework to inform our choice of controls and analyze the expected direction of bias on the estimated labor supply-production relationship caused by the use of equilibrium employment in place of a labor supply variable and the omission of relevant variables affecting labor demand. This analysis reveals that, in several respects, our empirical estimates should be interpreted as upper bounds for the parameters of interest.

The conceptual model is meant to represent changes in equilibrium outcomes at the level of a California county, our empirical unit of analysis. Thus, shocks to labor supply and other primitives of the model are interpreted as occurring along the time dimension of our panel, as we include county fixed effects to capture permanent differences across counties in terms of crop mix, available farmland, or access to irrigation, that may explain both labor employment and production outcomes. In the spirit of parsimony, we also consider a composite crop output, as opposed to the individual crops used in our main regression analysis, because our regressor of interest, county farm employment, does not vary by crop.[7]

Our model assumes that farmers in a county produce a single homogeneous labor-intensive FV good (Q) using two factors: labor (A) and a composite non-labor input (B). The aggregate, county-level production function $Q(A, B)$ is assumed to be homogeneous of degree one, and markets are assumed to be perfectly competitive.[8] These considerations suffice to generate equilibrium conditions that implicitly define all quantities and prices in the input and output markets. Specifically, the industry equilibrium is characterized by six equations in six endogenous variables (Q, A, B, p, p_A, p_B), as follows:

$$Q = f(p) \tag{1}$$

$$Q = Q(A,B) \tag{2}$$

$$p_A = pQ_A(A,B) \tag{3}$$

[7]Our preferred empirical specification includes a set of crop-by-county fixed effects, which improves the explanatory power of the model. It should be noted, however, that once county fixed effects are included, the addition of crop-by-county fixed effects only impacts our regression estimates when the analysis is conducted on an unbalanced panel because the employment measure only varies at the county-year level.

[8]To the extent that labor market frictions impede the free movement of labor across employers, or that some producers claim a large market share for certain commodities, notably berries, the assumption of perfect competition may seem questionable. An in-depth investigation of imperfectly competitive labor markets by Manning (2003) suggests that the perfectly competitive model may provide a good approximation to reality when labor market frictions are low. Recent evidence from the NAWS suggests that the US farm labor market may be imperfectly competitive, but its deviation from the competitive equilibrium is modest (Rutledge et al., 2021). To help alleviate concerns about market power resulting from large producers, we show empirical results for a set of models that excludes berry crops in Appendix E.1, Appendix S1.

$$p_B = pQ_B(A,B) \tag{4}$$

$$A = g(p_A) \tag{5}$$

$$B = h(p_B), \tag{6}$$

where p is the output price, p_A (resp. p_B) is the price of input A (resp. input B), and Q_A and Q_B denote the marginal products. Equation (1) states that equilibrium in the output market occurs on the output demand schedule, denoted $f(p)$. Equation (2) imposes technical efficiency. Equations (3) and (4) state that input prices are equal to the value of their respective marginal product, conditions that are implied by profit-maximizing behavior. Finally, Equations (5) and (6) state that equilibrium in each input market occurs on the input supply schedules, denoted $g(p_A)$ and $h(p_B)$.

Following Muth (1964), we denote by $dQ^* \equiv d\ln Q \approx \frac{dQ}{Q}$ the logarithmic differential change in equilibrium output and, similarly for other equilibrium values, resulting from a series of exogenous shocks to the equilibrium to be defined below. The equilibrium in relative changes is described by the following set of equations[9]:

$$\begin{aligned}
&dQ^* - \eta dp^* = \alpha \\
&dQ^* - k_A dA^* - k_B dB^* = \delta \\
&-dp^* + \frac{k_B}{\sigma} dA^* - \frac{k_B}{\sigma} dB^* + dp_A^* = \delta \\
&-dp^* - \frac{k_A}{\sigma} dA^* + \frac{k_A}{\sigma} dB^* + dp_B^* = \delta \\
&dA^* - e_A dp_A^* = \beta \\
&dB^* - e_B dp_B^* = \gamma.
\end{aligned}$$

This system can be solved for the endogenous variables dQ^*, dA^*, dB^*, dp^*, dp_A^*, and dp_B^*, generating six reduced-form equations where the structural market parameters (η, e_A, e_B, σ, k_A, and k_B) and the shock variables (α, β, γ, and δ) appear on the right-hand side. The parameter $\eta \leq 0$ denotes the elasticity of derived demand for the crop aggregate, $\sigma \geq 0$ denotes the elasticity of substitution in production, $k_A > 0$ (resp. $k_B > 0$) is the cost share of input A (resp. B), with $k_A + k_B = 1$, and $e_A \geq 0$ and $e_B \geq 0$ are the supply elasticities of inputs A and B, respectively.

We consider four types of shocks to the equilibrium. The first shock, denoted β, represents a shift in the labor supply curve in percentage terms in the direction of the quantity axis, at the initial equilibrium price. This shock is critical to identification as we seek to relate fluctuations in labor supply to variation in crop output. In our empirical setting, shocks to local labor supply could plausibly arise from changes in local demand for construction or food service workers, changes in immigration enforcement, or changes in economic opportunities in foreign workers' countries of origin.

Other types of shocks to the equilibrium act as nuisance as they may confound our estimate of interest. The second shock, denoted γ, represents a shift in the nonlabor input supply (in percentage terms) in the direction of the quantity axis. Examples of nonlabor input supply shocks include decreases in the amount of agricultural land due to urban expansion and restrictions on surface water deliveries during periods of drought. The third shock, denoted α, represents a shift in crop output demand (in percentage terms) in the direction of the quantity axis. This shock could represent secular changes in demand driven by changes in domestic consumption patterns or access to new international markets. Thus, positive values of β, γ, and α represent increases in the supply of labor, the supply of nonlabor inputs, and the demand for output, respectively. The fourth shock,

[9]These equations are easily derived from the equilibrium in levels, as described in Muth (1964).

denoted δ, is a productivity shock representing the percentage change in the marginal products of the inputs at given level of input use. Productivity shocks may be caused by weather events such as spring freezes, extreme heat, and rain during the pollination period, or by the diffusion of productivity-enhancing technologies like smart irrigation.[10]

The reduced-form equations for $d\ln Q$ and $d\ln A$ can be expressed as

$$d\ln Q = \underbrace{\frac{k_A\eta(\sigma+e_B)}{D}}_{\xi_1}\beta + \underbrace{\frac{k_B\eta(\sigma+e_A)}{D}}_{\xi_2}\gamma \underbrace{-\frac{\sigma(k_Ae_A+k_Be_B)+e_Ae_B}{D}}_{\xi_3}\alpha + \underbrace{\frac{\eta[\sigma(1+k_Ae_A+k_Be_B)+k_Be_A+k_Ae_B+e_Ae_B]}{D}}_{\xi_4}\delta \tag{7}$$

and

$$d\ln A = \underbrace{\frac{\sigma\eta-(k_B\sigma-k_A\eta)e_B}{D}}_{\rho_1}\beta + \underbrace{\frac{k_B(\sigma+\eta)e_A}{D}}_{\rho_2}\gamma \underbrace{-\frac{e_A(\sigma+e_B)}{D}}_{\rho_3}\alpha + \underbrace{\frac{(\sigma+e_B)(1+\eta)e_A}{D}}_{\rho_4}\delta, \tag{8}$$

where

$$D \equiv \sigma\eta - \sigma(k_Ae_A+k_Be_B) + \eta(k_Be_A+k_Ae_B) - e_Ae_B \le 0. \tag{9}$$

To simplify notation, the coefficients on β, γ, α, and δ in Equation (7) (resp. Equation (8)) are denoted ξ_1, ξ_2, ξ_3, and ξ_4 (resp. ρ_1, ρ_2, ρ_3, and ρ_4). As β is a percentage change, it can be reparameterized as $d\ln\beta'$, where $\ln\beta'$ represents the unobserved log farm labor supply and β' is the underlying labor supply measured along the quantity axis. The same holds true for the other shocks, allowing us to define the corresponding variables γ', α', and δ'.

The relevant concern from a policy standpoint is with regard to how decreases in the supply of farm workers, which may result from increased border enforcement or an expanding Mexican economy, affect US crop production. As a result, we are not interested in how changes in equilibrium farm employment relate to changes in production because (i) variation in employment may be driven by fluctuations in labor demand and (ii) even if the demand for labor is stable, under commonly accepted assumptions, changes in employment will not accurately reflect changes in labor supply. In light of these considerations, the parameter of interest is the elasticity of labor-intensive crop production with respect to the underlying farm labor supply, namely:

$$\frac{\partial\ln Q}{\partial\ln\beta'} = \left.\frac{d\ln Q}{\beta}\right|_{\gamma=\alpha=\delta=0} = \frac{k_A\eta(\sigma+e_B)}{D} = \xi_1.$$

If the elasticity of substitution between labor and the composite nonlabor input (σ), the input supply elasticities (e_A and e_B), the output demand elasticity (η), and the cost shares (k_A and k_B) were known, a simple calculation could determine the value of ξ_1.[11] However, these parameter values are

[10]The shocks β, γ, and α differ from those used in Muth (1964). Here, we define output demand and input supply shocks as shifts in the direction of the quantity axis at a given price, whereas Muth (1964) defines them as shifts in the direction of the price axis at a given quantity, such that, for example, an increase in the supply of an input corresponds to a decrease in its price. The shock δ is defined as in Muth (1964), who refers to it as a neutral technological change.

[11]Such calculation would be most appropriate at an aggregate level, for example, California or the entire United States.

not known with certainty, and estimates tend to vary widely. For example, the farm labor supply elasticity estimates used in the most recent equilibrium displacement studies range from 0.71 to 3.37 (Brady et al., 2016; Cassey et al., 2018). An examination of Equation (7) reveals that without further parameter restrictions, ξ_1 is bounded between zero and one; this range is wide enough that an empirical estimate would arguably provide valuable information.

If β' were observed, direct estimates of ξ_1 could be obtained by using ordinary least squares (OLS) regression with a (log) production variable as the outcome variable and $\ln\beta'$ as the regressor of interest, possibly controlling for factors one may think could correlate with labor supply shocks. To the extent that the labor supply shocks are uncorrelated with other shocks (such as γ, α, and δ) or these shocks are controlled for in the regression, the resulting elasticity estimate would be unbiased. However, when ξ_1 is estimated using the employment variable (A) instead of the underlying labor supply variable (β'), the regression coefficients are typically biased. The equilibrium displacement model then provides a useful framework to identify the determinants, and assess the direction, of the estimation bias.

2.2 | Estimation bias

Using Equation (8) to solve for β and substituting the formula for β into Equation (7), one can express the employment-production relationship as

$$d\ln Q = \frac{\xi_1}{\rho_1} d\ln A + \Upsilon d\ln\gamma' + \Sigma d\ln\alpha' + \Lambda d\ln\delta', \tag{10}$$

where

$$\Upsilon \equiv \frac{\xi_2\rho_1 - \xi_1\rho_2}{\rho_1}, \quad \Sigma \equiv \frac{\xi_3\rho_1 - \xi_1\rho_3}{\rho_1}, \text{ and } \quad \Lambda \equiv \frac{\xi_4\rho_1 - \xi_1\rho_4}{\rho_1}.$$

By integrating Equation (10), the employment-production relationship can then be expressed as

$$\ln Q = C + \frac{\xi_1}{\rho_1}\ln A + \Upsilon\ln\gamma' + \Sigma\ln\alpha' + \Lambda\ln\delta',$$

where C is the constant of integration. This relationship can be estimated empirically using the following OLS regression model:

$$\ln Q = c + \Gamma\ln A + \underbrace{\Upsilon\ln\gamma' + \Sigma\ln\alpha' + \Lambda\ln\delta' + e}_{\nu}, \tag{11}$$

where ν is an error term with $\mathbb{E}[\nu|\ln A] \neq 0$ because the unobserved nonlabor input supply shocks, output demand shocks, and technology shocks are all correlated with equilibrium employment via Equation (8). Thus, even under the assumptions that labor supply shocks are not correlated with the other shocks and that these shocks are not correlated with each other,[12] there is omitted variables bias because the model is estimated with the equilibrium employment variable instead of the underlying labor supply variable. Under these assumptions, the OLS coefficient on the (log) equilibrium employment variable has a probability limit equal to

[12]These assumptions imply that $\text{cov}(\ln\beta', \ln\gamma') = \text{cov}(\ln\beta', \ln\alpha') = \text{cov}(\ln\beta', \ln\delta') = \text{cov}(\ln\gamma', \ln\alpha') = \text{cov}(\ln\gamma', \ln\delta') = \text{cov}(\ln\alpha', \ln\delta') = 0$.

$$\Gamma_{\text{OLS}} = \xi_1 + \theta_1 + \underbrace{\Upsilon \frac{\text{cov}(\ln A, \ln \gamma')}{\text{var}(\ln A)}}_{\theta_2} + \underbrace{\Sigma \frac{\text{cov}(\ln A, \ln \alpha')}{\text{var}(\ln A)}}_{\theta_3} + \underbrace{\Lambda \frac{\text{cov}(\ln A, \ln \delta')}{\text{var}(\ln A)}}_{\theta_4}, \tag{12}$$

where ξ_1 is the parameter of interest and the bias terms are defined as[13]

$$\theta_1 = \frac{\xi_1}{\rho_1} - \xi_1 = \frac{k_A \eta e_A (\sigma + e_B)(k_B \eta - k_A \sigma - e_B)}{[\sigma\eta - (k_B \sigma - k_A \eta) e_B] D} \tag{13}$$

$$\theta_2 = \frac{\Upsilon}{\rho_2} \left[\frac{\rho_2^2 \text{var}(\ln \gamma')}{F} \right] \tag{14}$$

$$\theta_3 = \frac{\Sigma}{\rho_3} \left[\frac{\rho_3^2 \text{var}(\ln \alpha')}{F} \right] \tag{15}$$

$$\theta_4 = \frac{\Lambda}{\rho_4} \left[\frac{\rho_4^2 \text{var}(\ln \delta')}{F} \right], \tag{16}$$

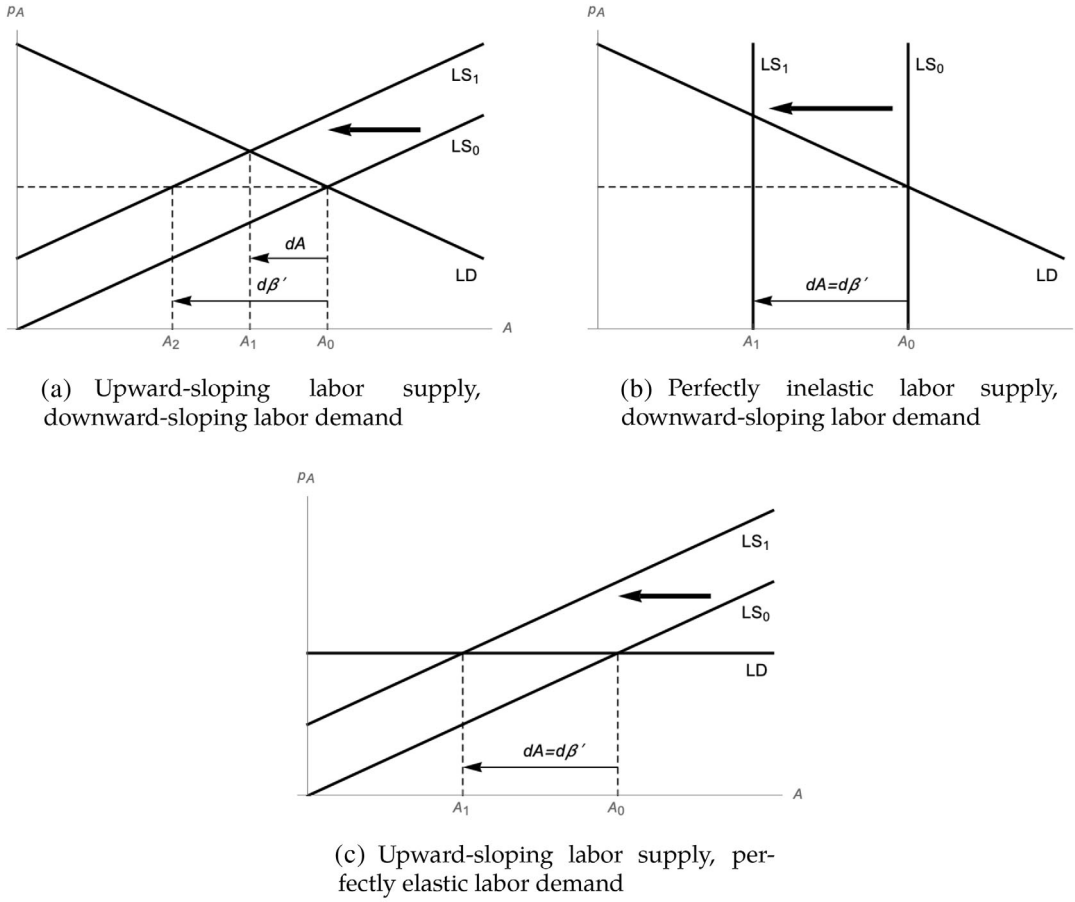
with

$$F \equiv \rho_1^2 \text{var}(\ln \beta') + \rho_2^2 \text{var}(\ln \gamma') + \rho_3^2 \text{var}(\ln \alpha') + \rho_4^2 \text{var}(\ln \delta'). \tag{17}$$

The term θ_1 captures the bias from using an equilibrium employment variable to estimate the effect of a change in the underlying labor supply. We refer to this source of bias as the "employment–labor supply mismatch bias." An examination of Equation (13) reveals that $\theta_1 \geq 0$. Thus, if there are no omitted variables, then Γ_{OLS} can be interpreted as an upper bound for ξ_1. Importantly, the employment–labor supply mismatch bias only exists (i.e., $\theta_1 > 0$) if the labor supply curve is not perfectly inelastic (i.e., $e_A > 0$) and the labor demand elasticity, defined as η_A, is finite (i.e., $\eta_A > -\infty$). Figure 1 provides a graphical depiction of the local farm labor market to demonstrate this result. As can be seen in Panel (a), when the demand for labor is downward sloping and the supply of labor is upward sloping, a horizontal shift in the labor supply from LS_0 to LS_1 corresponds to a shift that is larger in magnitude than the change in equilibrium employment (i.e., $|d\beta'| = |A_2 - A_0| > |A_1 - A_0| = |dA|$). As a result, the effect of the labor supply shock $d\beta'$ will be attributed to a smaller change in A, causing the empirical estimate to overstate the effect of the labor supply shock. When the labor supply is perfectly inelastic (i.e., $e_A = 0$), as shown in Panel (b), the shift from LS_0 to LS_1 causes an equivalent change in employment (i.e., $|dA| = |d\beta'| = |A_1 - A_0|$), so there is no bias. The same holds true when labor demand is perfectly elastic (i.e., $\eta_A \to -\infty$), as shown in Panel (c). If the county-level labor supply and demand elasticities were known with certainty, one could back out the population parameter of interest by dividing the OLS regression estimate by $1 + |e_A/\eta_A|$. To the extent that the supply of labor at the county level is much less elastic than the demand for labor, the required adjustment would be relatively small. These results are derived formally in Appendix A.1, Appendix S1.

We further show in Appendices A.2–A.4 that $\Upsilon \geq 0$, $\Sigma \geq 0$, and $\Lambda \geq 0$, which implies that the signs of θ_2, θ_3, and θ_4 are determined by the signs of ρ_2, ρ_3, and ρ_4, respectively. An examination of Equation (8) reveals that $\rho_3 \geq 0$, therefore $\theta_3 \geq 0$. Additional derivations reveal that $\rho_2 \geq 0 \Leftrightarrow \eta \leq -\sigma$ and $\rho_4 \geq 0 \Leftrightarrow \eta \leq -1$, so further discussion is warranted to determine the plausible signs of θ_2 and θ_4.

[13]To derive Equations (14), (15), and (16), we integrate Equation (8) and substitute the corresponding equation for $\ln A$ into the bias terms in Equation (12) while imposing the constraints outlined in footnote 12.



(a) Upward-sloping labor supply, downward-sloping labor demand

(b) Perfectly inelastic labor supply, downward-sloping labor demand

(c) Upward-sloping labor supply, perfectly elastic labor demand

FIGURE 1 The labor market under different supply and demand elasticities

Recall that our equilibrium displacement model is meant to describe equilibrium at the level of a county, our empirical unit of analysis. The derived demand for the crop aggregate at the county level is more elastic than aggregate demand, by an extent determined by the share of output produced by the county and the supply elasticity of the other regions. Thus, there are good reasons to believe that the demand for FV crops at the county level is highly elastic. For example, even if a county produces 5% of the total output, the elasticity of demand facing that county will be at least 20 times larger than the aggregate demand elasticity, and it may be much larger if the supply from other regions is not perfectly inelastic. Existing work suggests that the short-run aggregate demand elasticity for labor-intensive crops is about -1.2 (Gunter et al., 1992). Because the average county in our sample produces less than 5% of the national output, the relevant derived demand elasticity is likely at least -24.0 (20×-1.2) and could potentially be much larger. Regarding σ, estimates by Ejimakor, Quaicoe, and Asiseh (2017) for southeastern states suggest that the elasticity of substitution between labor and capital (resp. labor and land, resp. labor and chemicals) is 0.27 (resp. 0.28, resp. 0.48). Taken together, this evidence indicates that the conditions required to ensure an upper bound (i.e., $\eta < -\sigma$ and $\eta < -1$) are both likely to be met.[14]

[14]We found two estimates of σ relevant at the national level. The first one suggests that the short-run elasticity of substitution between all hired farm labor and capital is 0.32 (Brown & Christensen, 1980), whereas the second one suggests that the short-run elasticity of substitution between seasonal farm labor and capital is 0.63 (Gunter & Vasavada, 1988).

Intuitively, the bias from the unobserved nonlabor input supply shocks (θ_2) is expected to be positive because $\eta < -\sigma$ means that the two factors are gross complements. Thus, a positive shock to the supply of the nonlabor input, which tends to increase output, also increases the demand for labor. That the bias arising from unobserved technology shocks (θ_4) should be positive under the assumption of elastic output demand is also intuitive. When inputs are more productive, there is less need to employ them for given output, thus output price decreases, which boosts output demand and the derived demand for inputs. Whether the net effect is an increase in input use depends on the elasticity of output demand: When demand is elastic, the quantity effect is large and dominates the productivity effect, resulting in an increase in both output and input use. Finally, the bias resulting from unobserved output demand shocks (θ_3) is evidently positive as well: An increase in output demand results in a higher equilibrium quantity brought about by higher input use. As a result, all three sources of omitted variable bias considered here go in the same direction, and they also go in the same direction as the employment–labor supply mismatch bias.

In addition to identifying their likely signs, it may be interesting to compare the magnitudes of these biases. The results from a simulation exercise that compares the magnitudes of θ_1, θ_2, θ_3, and θ_4 under a range of structural parameter values can be found in Appendix B, Appendix S1. These simulations indicate that each source of bias can potentially be larger than any of the others, so additional information about the parameter values and the variances of the shocks to equilibrium would be required to determine which source of bias is of greatest concern in practice. This conclusion applies to an independent comparison of each source of omitted variable bias relative to the employment–labor supply mismatch bias, a comparison of the sum of all three sources of omitted variable bias relative to the employment–labor supply mismatch bias, and a comparison of each source of omitted variables bias relative to each of the other sources.

2.3 | Empirical strategy

As discussed above, 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 variable in place of a labor supply variable and, relatedly, the presence of omitted variables affecting labor demand. If an instrumental variable (Z) were available that generates labor supply-driven variation in the employment variable while being uncorrelated with the unobserved non-labor input supply, output demand, and productivity shocks (i.e., if $\mathbb{E}[\nu|Z]=0$), using two-stage least squares to estimate Γ would remedy the omitted variable bias. Still, the employment-labor supply mismatch bias would remain as employment is still used as the regressor in place of the underlying labor supply variable. Of course, instruments that are relevant and satisfy the exclusion restriction are rarely found in practice. Instead, we attempt to mitigate the primary sources of omitted variable bias through the use of fixed effects and appropriate control variables and interpret the empirical estimate as an upper bound for the effect of interest. Specifically, we estimate the following OLS regression:

$$\ln O_{ict} = \Omega \ln A_{ct} + \phi_{ic} + \phi_t + \alpha_1^c t_c + \alpha_2^c t_c^2 + \sum_{m=1}^{12} \left(\tau^m Temp_{ct}^m + \pi^m Precip_{ct}^m\right) + \mu_{ict}, \tag{18}$$

where i denotes a crop, c denotes a county, and t denotes a year. The outcomes of interest $O_{ict} \in \{Q_{ict}, H_{ict}, Y_{ict}\}$ are three measures of crop production: Q_{ict} is the production of labor-intensive crop i in county c in year t, H_{ict} is the number of acres harvested, and Y_{ict} is the average yield (quantity harvested per acre). The main explanatory variable of interest, $\ln A_{ct}$, is the (log) number of crop

TABLE 1 Sources of bias and mitigating variables

Source of bias	Example	Mitigating variables
Productivity shocks	Spring freezes, extreme heat	$Temp_{ct}^{m}$
	Rain during pollination	$Precip_{ct}^{m}$
	Technology diffusion	t_c, t_c^2
Nonlabor input supply shocks	Water restrictions during drought years	ϕ_t
	Local urban expansion	t_c, t_c^2
Output demand shocks	Changes in preferences, trade	ϕ_t

workers employed in county c during that county's peak employment quarter in year t.[15] The error term is μ_{ict}.

All of the models we estimate include a set of county fixed effects (ϕ_c) or crop-by-county fixed effects (ϕ_{ic}). The county fixed effects control for time-invariant factors that differ by county, such as seniority of water rights, geography, and soil quality, which could be correlated with production, harvested acreage, and labor demand for hand-harvested crops. Thus, in line with our county-level equilibrium displacement model, the identifying variation we exploit occurs along the time dimension.

Note that as long as the panel is balanced, once the county fixed effects are included in the regression, the addition of crop fixed effects (ϕ_i) or crop-by-county fixed effects (ϕ_{ic}) may improve the explanatory power of the model, but it will not mitigate any source of bias. This result emerges because the employment variable does not vary by crop, so once the county fixed effects are included, the crop fixed effects (or crop-by-county fixed effects) only explain variation in the outcome variable but not in the employment variable. Nonetheless, to the extent that some crops are not produced in a given county in every year of the sample, including crop fixed effects or crop-by-county fixed effects will influence the coefficient of interest. Our empirical results support these conclusions as they demonstrate that, whenever the panel is balanced, the coefficients are indeed identical.[16] Our preferred specification includes the crop-by-county fixed effects because they explain a significant amount of variation in the outcome variable, thus providing a better fit to the data, and their inclusion does not prevent the identification of meaningful upper bounds even when the panel of data is unbalanced.

Other fixed effects and control variables are included as part of our strategy to reduce omitted variable bias. Table 1 contains a list of potential sources of omitted variable bias and the included regressors that plausibly mitigate each one. First, we include year fixed effects (ϕ_t) to control for shocks common to all counties within a year, such as aggregate demand shocks, or statewide droughts, which may induce nonlabor input supply shocks in the form of restricted access to surface water.

The second set of control variables (t_c and t_c^2) are linear and quadratic trends differentiated by county, that is, $t_c = \phi_c \times t$ and $t_c^2 = \phi_c \times t^2$, where t is a continuous time variable. These trends control for smooth, yet potentially nonlinear, changes in productivity that could be caused by local technology diffusion, such as smart irrigation technologies, and factors that impact the nonlabor input supply, such as urban expansion, which affects the amount of land available for crop production at a local level.[17]

[15]A county's peak employment quarter is determined by its average quarterly employment over the entire sample of years and remains constant throughout the sample period (see Section 2). Appendix E.2 in Appendix S1 reports results from regressions that use average annual employment as the main explanatory variable. The bounds produced by that analysis are larger in magnitude and remain statistically significant.

[16]See Columns (4), (5), and (6) of Table 2, for instance.

[17]We provide results from a model that uses linear county trends instead of quadratic county trends in Appendix E.3 in Appendix S1.

The third set of variables includes 12 monthly county-level average temperature variables ($Temp_{ct}^{m}$) and 12 monthly county-level cumulative precipitation variables ($Precip_{ct}^{m}$), where m is a month index ($m = 1, \ldots, 12$). These 24 weather variables help control for local weather events, such as spring freezes, extreme heat, or rain during pollination, all of which can affect the productivity of labor and nonlabor inputs.

Although it is plausible that the OLS estimate of Ω, say Ω_{OLS}, provides an improvement over Γ_{OLS} due to the model's bias mitigation strategy, it may still suffer from upward bias due to the employment-labor supply mismatch. As a result, one can reasonably expect that $\xi_1 \leq \Omega_{\mathrm{OLS}}$, so we interpret Ω_{OLS} as an upper bound for the elasticity of labor-intensive crop production with respect to the labor supply.

In order to estimate the impact of shifts in the farm labor supply on the total value of production, we also estimate the following model:

$$\ln R_{ct} = \Psi \ln A_{ct} + \phi_c + \phi_t + \alpha_1^c t_c + \alpha_2^c t_c^2 + \sum_{m=1}^{12} \left(\tau^m Temp_{ct}^m + \pi^m Precip_{ct}^m \right) + \mu_{ct}, \tag{19}$$

where $R_{ct} = \sum_{i=1}^{I} \overline{p}_{ic} Q_{ict}$ denotes the total value of hand-harvested crops in a county in a year, calculated by multiplying the production of each crop in each county by its average price (calculated separately for each crop in each county), and summing up over the crops grown in a county. The average crop price is defined as $\overline{p}_{ic} = 1/T_{ic} \times \sum_{t=1}^{T_{ic}} p_{ict}$, where T_{ic} identifies the number of years a crop was grown in a county, and p_{ict} is the yearly price. We use average crop prices, as opposed to yearly crop prices, as decreases in output may be offset by price increases even at the county level, and the ultimate concern is about the social value of crop production rather than farmer revenue. Unlike Hagerty (2020), we allow the price average to vary systematically by county in order to capture permanent differences in crop value arising from geographic factors (e.g., closeness to processing/packing plants) and possibly harvest time during the year. Again, the coefficient of interest (Ψ_{OLS}) is interpreted as an upper bound for the effect on the total value of production. Other variables in Equation (19) are defined above except for μ_{ct}, which is the error term.

In panel settings that have a natural regional clustering of observations, such as the county-level data used in this analysis, it is common to use standard errors that are clustered at the region level (Rogers, 1993). In order to conduct valid inference with cluster-robust standard errors, the errors must not be correlated across clusters. This assumption may be difficult to justify when the clusters are geographic regions located within close proximity to each other. The counties included in our study, depicted in Figure 2, are the top 10 labor-intensive crop producing counties in California.

Using the Frees test, which is appropriate for use with static panel models when the number of years in the data is less than the number of cross-sectional units and year fixed effects are included (De Hoyos & Sarafidis, 2006; Frees, 1995), we test for cross-sectional dependence in the error term. The Frees tests provide strong evidence of cross-sectional dependence, suggesting that standard error estimates clustered at the county level would be biased. Inference based on clustered standard errors is also not valid in our setting because the number of clusters should be large for the standard error estimates to be consistent, yet we consider 10 counties at most. Instead, we use Driscoll-Kraay standard errors (Driscoll & Kraay, 1998; Hoechle, 2007), which are robust to general forms of cross-sectional dependence, heteroskedasticity, and serial correlation 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, 1990). For comparability purposes, for each set of regressions within a table (e.g., for the top 5 counties) we choose the most conservative degree of serial correlation as determined by the Cumby-Huizinga tests across the entire set. We also report county-clustered standard error estimates for reference.

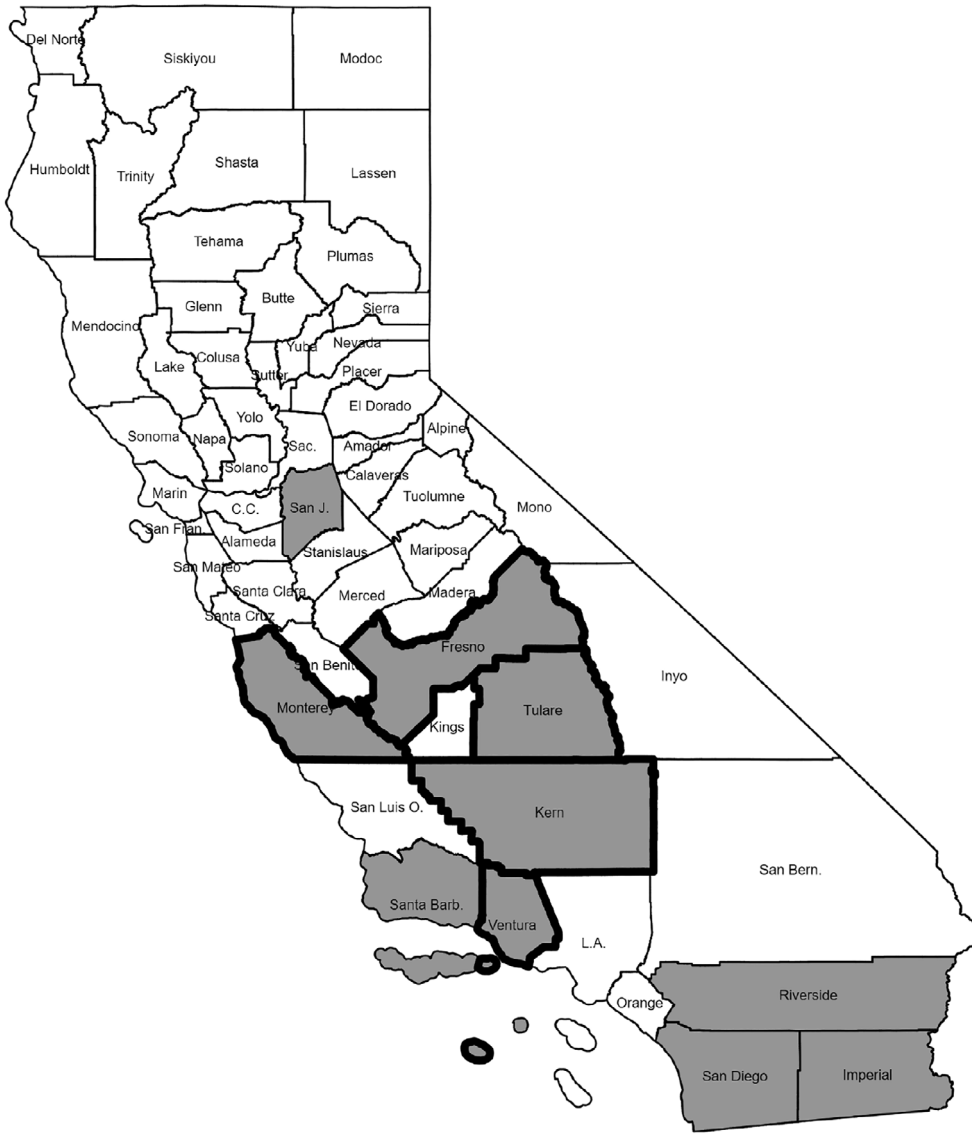


FIGURE 2 Geography of the top labor-intensive FV producing counties in California. The top 10 labor-intensive FV producing counties are shaded in gray. The top five counties are outlined with a thick black border.

3 | DATA

Our data span the period from 1990 to 2019 and cover 10 of the 44 FV crop producing counties in California.[18] We exclude the more marginal counties, for which there is a greater potential for measurement error in the employment variable due to a larger share of workers not involved in

[18]Other major FV producing states, such as Florida, have significant data limitations that make it infeasible to conduct a comparative analysis. For example, Florida does not include H-2A workers in its QCEW employment measures, whereas California does. In FY 2020, Florida had about 40,000 H-2A jobs certified for work in the state, whereas annual QCEW employment was about 48,000, so Florida's QCEW employment measures significantly understate actual farm employment (Castillo et al., 2022). Nevertheless, an exercise using FLS hired labor data in conjunction with the USDA-NASS production and harvested acreage data generates results that are of similar magnitude to those we find in California. The results are available upon request to the authors.

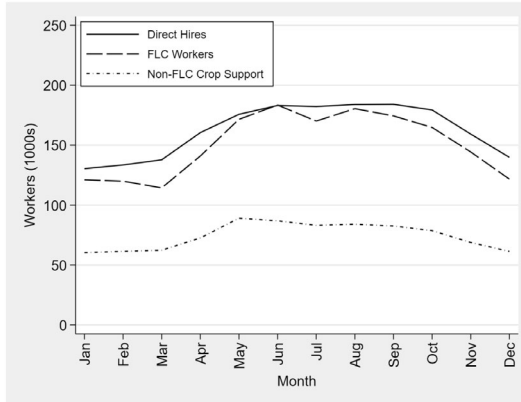


FIGURE 3 Average monthly employment by worker type in California, 2019

labor-intensive crop production. Counties are selected in descending order of importance with respect to the total value of labor-intensive FV crops grown across the sample period. Calculations exclude FV crops with a viable option for mechanical harvest. The top 10 counties produce about 86% of the value of all hand-harvested FV crops in the state. There are 69 such crops used in the analysis, which are listed in Appendix C, Appendix S1.

The data were assembled from three separate sources. The crop production data were obtained from the California County Agricultural Commissioners' reports (NASS, 2021), which include the value (in US dollars) and quantity (in US tons) of production, the number of acres harvested, and the average yield per acre harvested for each crop in each county in each year.

The county-level crop employment data were obtained from the public Quarterly Census of Employment and Wages (QCEW) data files (USBLS, 2021a). In 2019, California crop farmers employed an average of 387,000 workers each month. California's farm workers can be classified into three broad categories: (i) those recruited and hired directly by farmers (direct hires), (ii) those hired by farm labor contractors (FLCs) and then brought to farms to perform certain tasks (e.g., pruning, weeding, or harvesting), and (iii) non-FLC crop-support workers contracted to perform certain tasks, such as tilling the soil or providing mechanical harvesting services. Unlike direct hires and FLC workers, non-FLC crop-support workers generally do not hand harvest FV crops and are not considered in the analysis.

Due to the seasonal nature of agriculture, the number of workers employed at any given time fluctuates throughout the year. Figure 3 shows the average crop employment for each month during 2019, broken down by type of worker, revealing that statewide employment peaks during the summer months when the bulk of the harvest activities take place. The employment measures used in the analysis identify the average employment during a county's "peak employment quarter," assumed to be the period of time when the majority of the harvest activities take place. This peak quarter was identified by determining the quarter during which the county had its highest average employment over the time period 1990–2019. Once the peak quarter was defined for a county, the employment values from that quarter were assigned to the county for the entire sample period. The peak quarter is generally stable for most counties, although there are a handful of cases where a county's peak quarter fluctuates between adjacent quarters.[19]

Importantly for our identification strategy, statewide employment statistics mask significant heterogeneity among local labor markets, as can be seen in Figure 4, which shows employment trends for a selection of counties constructed using the administrative employment data from the QCEW.

[19]When these values differ, the difference in employment between the assigned quarter and the county's actual peak quarter for that year is usually nominal. The empirical estimates are nearly identical if we allow the peak employment quarter to vary from year to year.

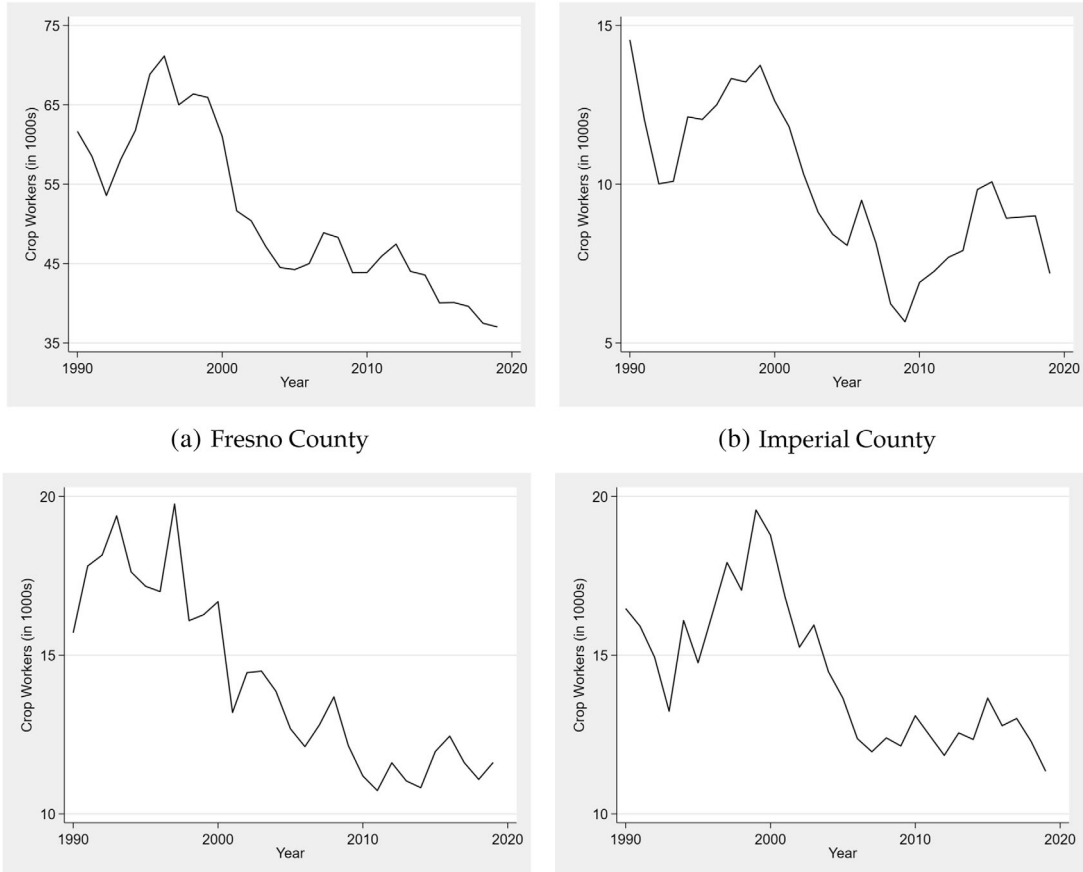


FIGURE 4 Average direct hire and FLC employment during the peak employment quarter, selected counties 1990–2019

Finally, weather data were obtained from the National Oceanic and Atmospheric Administration Climate Data Online website (NOAA, 2021).

Detailed information regarding how variables were constructed from the raw data is provided in Appendix D, Appendix S1, where we also show a selection of summary statistics.

4 | RESULTS

4.1 | Labor-intensive crops

The results from estimating Equation (18) are reported in Tables 2 and 3.[20] Table 2 shows the estimates from a balanced panel of crops that, for a given county, are grown in all sample years. Table 3

[20]Appendix E.4 shows results from a sample that uses the share of FV production value, as opposed to the total FV production value, to identify the top 10 FV counties. This procedure causes five of the counties to drop out of the previously selected set and five new ones to be added. Our results are robust to this selection procedure. In Appendix E.5, we also provide a set of results for an expanded sample that includes mechanically harvested FV crops (representing 28 additional crops). Those results are similar in terms of magnitude and significance level.

TABLE 2 Effects of a change in farm labor supply on hand-harvested FV production for crops grown in all sample years

	(1)	(2)	(3)	(4)	(5)	(6)
	Top 5 counties					
Production	0.524***	0.609***	0.560***	0.661***	0.661***	0.661***
	(0.143)	(0.078)	(0.142)	(0.103)	(0.104)	(0.105)
	[0.270]	[0.266]	[0.265]	[0.275]	[0.278]	[0.279]
R^2	0.064	0.064	0.064	0.065	0.737	0.901
Harvested acres	0.285***	0.352***	0.364***	0.418***	0.418***	0.418***
	(0.082)	(0.071)	(0.080)	(0.081)	(0.082)	(0.083)
	[0.144]	[0.126]	[0.107]	[0.134]	[0.135]	[0.136]
R^2	0.066	0.066	0.066	0.066	0.742	0.919
Yield	0.239***	0.258***	0.197**	0.243***	0.243***	0.243***
	(0.078)	(0.062)	(0.082)	(0.061)	(0.061)	(0.062)
	[0.156]	[0.159]	[0.170]	[0.147]	[0.149]	[0.149]
R^2	0.138	0.141	0.139	0.142	0.765	0.789
N	1890	1890	1890	1890	1890	1890
	Top 10 counties					
Production	0.304***	0.287***	0.340***	0.323***	0.323***	0.323***
	(0.076)	(0.049)	(0.069)	(0.048)	(0.049)	(0.049)
	[0.183]	[0.183]	[0.187]	[0.189]	[0.191]	[0.193]
R^2	0.155	0.155	0.155	0.156	0.651	0.894
Harvested acres	0.285***	0.268***	0.308***	0.287***	0.287***	0.287***
	(0.036)	(0.038)	(0.040)	(0.044)	(0.044)	(0.044)
	[0.106]	[0.108]	[0.117]	[0.118]	[0.119]	[0.120]
R^2	0.130	0.130	0.130	0.130	0.661	0.906
Yield	0.019	0.020	0.032	0.036	0.036	0.036
	(0.063)	(0.033)	(0.058)	(0.028)	(0.028)	(0.028)
	[0.115]	[0.099]	[0.132]	[0.105]	[0.105]	[0.106]
R^2	0.120	0.122	0.121	0.123	0.752	0.832
N	3649	3649	3649	3649	3649	3649
Year f.e.	X	X	X	X	X	X
Quadratic county trends	X	X	X	X	X	X
Monthly temp. controls	–	X	–	X	X	X
Monthly precip. controls	–	–	X	X	X	X
County f.e.	X	X	X	X	X	–
Crop f.e.	–	–	–	–	X	–
Crop-by-county f.e.	–	–	–	–	–	X

Note: Significance levels are based on Driscoll–Kraay standard errors, which are reported in parentheses. Driscoll–Kraay standard errors in the top five (resp. 10) counties correct for serial correlation up to three (resp. four) lags. Standard errors clustered at the county level are reported in brackets for reference.
$^{**}p < 0.05$. $^{***}p < 0.01$.

shows estimates from a larger, unbalanced panel that includes the set of crops that, for a given county, are grown in at least half of the sample years. Each table includes two panels: one for the top five producing counties and the other for the top 10 producing counties. The top five (resp. 10)

TABLE 3 Effects of a change in farm labor supply on hand-harvested FV production for crops grown in at least 15 of the 30 sample years

	(1)	(2)	(3)	(4)	(5)	(6)
	Top 5 counties					
Production	0.393***	0.376***	0.448***	0.430***	0.417***	0.476***
	(0.143)	(0.074)	(0.126)	(0.069)	(0.071)	(0.077)
	[0.190]	[0.169]	[0.168]	[0.203]	[0.255]	[0.246]
R^2	0.026	0.027	0.027	0.027	0.621	0.894
Harvested acres	0.168	0.154**	0.217**	0.206***	0.246**	0.285***
	(0.108)	(0.065)	(0.099)	(0.074)	(0.097)	(0.066)
	[0.080]	[0.061]	[0.035]	[0.090]	[0.151]	[0.135]
R^2	0.042	0.042	0.042	0.042	0.611	0.908
Yield	0.225***	0.221***	0.231***	0.224***	0.170**	0.191**
	(0.067)	(0.082)	(0.069)	(0.076)	(0.074)	(0.079)
	[0.138]	[0.113]	[0.146]	[0.118]	[0.121]	[0.122]
R^2	0.104	0.107	0.105	0.108	0.742	0.779
N	3342	3342	3342	3342	3342	3342
	Top 10 counties					
Production	0.450***	0.452***	0.522***	0.515***	0.508***	0.420***
	(0.071)	(0.051)	(0.060)	(0.053)	(0.054)	(0.040)
	[0.129]	[0.103]	[0.113]	[0.090]	[0.129]	[0.113]
R^2	0.114	0.115	0.115	0.115	0.528	0.903
Harvested acres	0.296***	0.294***	0.327***	0.332***	0.364***	0.281***
	(0.045)	(0.056)	(0.045)	(0.059)	(0.054)	(0.041)
	[0.083]	[0.073]	[0.075]	[0.058]	[0.118]	[0.080]
R^2	0.119	0.119	0.119	0.120	0.523	0.911
Yield	0.154**	0.157***	0.195***	0.184***	0.144***	0.139***
	(0.065)	(0.039)	(0.063)	(0.040)	(0.039)	(0.039)
	[0.099]	[0.067]	[0.109]	[0.074]	[0.062]	[0.071]
R^2	0.078	0.080	0.079	0.081	0.720	0.823
N	6018	6018	6018	6018	6018	6018
Year f.e.	X	X	X	X	X	X
Quadratic county trends	X	X	X	X	X	X
Monthly temp. controls	–	X	–	X	X	X
Monthly precip. controls	–	–	X	X	X	X
County f.e.	X	X	X	X	X	–
Crop f.e.	–	–	–	–	X	–
Crop-by-county f.e.	–	–	–	–	–	X

Note: Significance levels are based on Driscoll–Kraay standard errors, which are reported in parentheses. Driscoll–Kraay standard errors in the top five (resp. 10) counties correct for serial correlation up to three (resp. four) lags. Standard errors clustered at the county level are reported in brackets for reference.
**$p < 0.05$. ***$p < 0.01$.

counties produce 67% (resp. 86%) of the value of all labor-intensive FV 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 displays estimates from models that include a different set of control variables. With the exception of Column (3), moving from left to right in a table, each column pertains to a model

specification that is progressively more demanding. The results from our preferred specification, which includes crop-by-county fixed effects and all monthly weather controls, are presented in Column (6).

When focusing on the production results for the top five counties in Table 2 (resp. Table 3), the upper bound indicates that a 1% decrease in the farm labor supply causes at most a 0.66% (resp. 0.48%) decrease in hand-harvested specialty crop production. Reduced production is primarily channeled through a decrease in the number of acres harvested, although there is a significant, yet smaller, effect on the average yield. One potential explanation for the yield effect is that farmers may be constrained by the number of times they can get crews to harvest crops, such as strawberries, that do not ripen uniformly and require multiple rounds of harvest. According to one California farmer, if there are not enough workers to maintain a timely rotation from field to field, "eventually you get so far behind that the crop gets overripe and you have to jump ahead and abandon sections" (Estrabrook, 2021). A related explanation could be that farmers instruct scarce crews to only harvest higher quality fruit, leaving lower value product in the field. Some farmers report losing "5%–10% of [their] crop yield every day because [they don't] have enough workers in the field" (Stoicheff, 2018). According to a recent study conducted in northern and central California, selective picking of FV in the field (and the five tons of food loss per acre that accompanies it) occurs even under normal circumstances (Baker et al., 2019). As a result, yield losses due to labor supply constraints could contribute to food waste in a time where nearly 5% of US households suffer from food insecurity (ERS, 2020). Because we do not observe planted acres, it is not possible to determine the extent to which the effect we find on harvested acres is due to the difficulty to recruit workers at the time of harvest, which would further contribute to food waste, rather than reduced planting of labor-intensive FV crops in rational anticipation of labor shortages.

In the top five counties, the results from Table 2 (resp. Table 3) indicate that a 1% decrease in the farm labor supply causes at most a 0.42% (resp. 0.29%) reduction in harvested acres and at most a 0.24% (resp. 0.19%) decrease in the average yield. If the labor supply decreases at a rate of 1% per year, as suggested by Charlton and Taylor (2016), our more conservative estimates indicate that 2500 acres of FV crops could be lost per annum. At that rate of decline, the joint reduction in harvested acreage and yield could generate 60,000 tons of loss each year.

We extend the analysis to the top 10 counties to provide a more comprehensive view of California FV production. In the top 10 counties, the results from Table 2 (resp. Table 3) indicate that a 1% reduction in the farm labor supply causes at most a 0.32% (resp. 0.42%) reduction in production, at most a 0.29% (resp. 0.28%) reduction in harvested acres and at most a 0.04% (resp. 0.14%) reduction in the average yield. Thus, when considering this broader set of counties, the estimates are consistently smaller, warranting further discussion. It is plausible that the smaller production effects in the top 10 counties are driven by smaller production effects in the top 6–10 counties. For example, the upper bound for production in the top 6–10 counties with the unbalanced panel is 0.24, which is half as large as that in the top five counties. Smaller production estimates in the top 6–10 counties may result from intensive-margin labor adjustments that offset lower employment levels, key differences in the dominant crops produced, and attenuation bias.

Evidence from the confidential NAWS data indicates that, relative to the top five counties, workers in the top 6–10 counties worked 13% more hours over the course of our study, so it is likely that intensive-margin labor adjustments have been more pronounced there. Additionally, if we define the set of dominant crops for the top five (resp. top 6–10) counties as the top dozen revenue generating crops, which together generate 74% (resp. 71%) of the value of production in those counties over our sample period, the intersection of the two sets of dominant crops only contains five crops. For example, avocado is the most valuable commodity produced in the top 6–10 counties, but it ranks 18th in the top five counties. Avocado is a perennial crop with a very long harvest season (Bender, 2012), so harvest can potentially be performed by fewer workers over a longer period of time. Finally, the less prominent FV counties produce a smaller amount of FV crops, so there is greater potential for a mismatch between crop employment and FV employment. Thus, attenuation bias from classical measurement error may also play a role.

TABLE 4 Effects of a change in farm labor supply on the value of hand-harvested FV crops

	(1)	(2)	(3)	(4)
	Top 5 counties			
Value	0.558***	0.527***	0.575***	0.550***
	(0.166)	(0.119)	(0.176)	(0.135)
	[0.233]	[0.198]	[0.189]	[0.192]
R^2	0.926	0.942	0.945	0.955
N	150	150	150	150
	Top 10 counties			
Value	0.227*	0.139	0.235*	0.141
	(0.123)	(0.113)	(0.120)	(0.114)
	[0.186]	[0.182]	[0.182]	[0.175]
R^2	0.971	0.974	0.973	0.976
N	299	299	299	299
Year f.e.	X	X	X	X
County f.e.	X	X	X	X
Quadratic county trends	X	X	X	X
Monthly temp. controls	–	X	–	X
Monthly precip. controls	–	–	X	X

Note: Significance levels are based on Driscoll–Kraay standard errors, which are reported in parentheses. Driscoll–Kraay standard errors in the top five (resp. 10) counties correct for serial correlation up to one lag (resp. two lags). Standard errors clustered at the county level are reported in brackets for reference.
$^{*}p < 0.1$. $^{***}p < 0.01$.

Note that secondary effects could emerge as the labor supply shrinks. For example, American farmers could lose market share to neighboring countries like Mexico, who have a competitive advantage in labor (Johnson, 2018). On the other hand, if fresh produce prices rise as a result of higher labor costs, healthy food options could become less accessible to those on the lower end of the income distribution. Although higher labor costs may not be ideal for American farmers or consumers, farmworkers who remain in the workforce could benefit as employers increase compensation. However, access to foreign guest workers via the H-2A visa program could limit the amount farmers are willing to pay US-based workers because the Adverse Effect Wage Rate (AEWR), a super-minimum wage rate that must be paid to H-2A workers, could act as a wage ceiling.

The results for the total value of labor-intensive FV production, presented in Table 4, are consistent with the production results yet suggest that the effects are concentrated in the top five counties. The estimates are based on the value of all labor-intensive crops grown within a county regardless of how many years each crop appears in the sample. Moving from left to right in the table, regressions include the same control variables as those presented in Columns (1) through (4) of Tables 2 and 3. The results in Column (4) indicate that a 1% decrease in the farm labor supply in the top five counties could cause as much as a 0.55% decrease in the total value of labor-intensive crop production. Over the course of a decade, such losses could add up to $3.7 billion (or 2.9% of the total value of production).[21] The results for the top 10 counties are not statistically significant in the most

[21]This calculation assumes that the farm-gate revenue for the labor-intensive crops we consider in the top five counties in 2019 ($12.5 billion) would have been maintained at that level over the course of the decade in the absence of the declining labor supply trend and that the effects are compounded each year. For example, the losses experienced in Year 1 (resp. Year 2) result from a 1% (resp. 1.99% = 1% + 1% × 99%) reduction in the labor supply relative to the amount that would have been produced in that year if there were no labor supply shocks. The calculation ignores crops that are both hand harvested and mechanically harvested, such as wine and raisin grapes. Wine grapes, for example, generate about $3.5 billion in farm-gate revenue each year, and a significant proportion (perhaps 50%) is harvested by hand.

demanding specification, but the coefficients are smaller than those for the top five counties, which is consistent with the production results.

4.2 | Dual labor markets

Dual labor markets are relevant in the agricultural sector because undocumented workers comprise a significant share of the labor force. To the extent that employers are unwilling to hire undocumented workers, that undocumented workers are unable or unwilling to present false legal documents, or that undocumented workers have lower education, experience, or English language ability, they face inherent labor market frictions that impede their ability to move across employers (Manning, 2003; Richards, 2018). Thus, undocumented labor may not be perfectly substitutable for documented labor.

Mérel and Rutledge (2021) note that low-skilled sectors are notorious for having high rates of "under the table" employment, where workers are paid in cash and employment is not reported to the government. This type of informal employment is particularly attractive to undocumented workers who are apprehensive about providing personal information to the government and are willing to perform low-skilled, manual-intensive labor (Peri & Sparber, 2009). Additionally, workers who work under the table are in a position to accept lower wages because payroll taxes, workman's compensation, and unemployment insurance contributions are not deducted from informal cash wage payments.

The existence of a wage gap between documented and undocumented immigrants in US labor markets has been well documented (see e.g., Borjas & Cassidy, 2019; Durand et al., 2016; Massey & Gentsch, 2014; Rivera-Batiz, 1999), pointing to the existence of a distinct labor market for unauthorized workers. Taylor (1992) finds econometric evidence that California's farm labor market is segmented along such lines, with undocumented farmworkers experiencing a significant earnings gap. He concludes that undocumented status may act as a barrier to mobility in terms of gaining access to higher paying, specialized farm jobs; thus, a productivity gap may emerge as a result of differential job assignment. Fan, Alves Pena, and Perloff (2016)'s findings reinforce this notion by concluding that the wages of documented workers have increased more than undocumented workers in recent years, suggesting that documented workers could be more productive.

Although the QCEW employment data do not provide information about documented status, they do enable us to identify whether workers were hired directly by farmers (NAICS code 111) or were brought to farms by FLCs (NAICS code 115115). According to the NAWS, California's FLC workers have consistently had higher shares of undocumented workers (ranging from 10 pp to 30 pp more) over the course of our study, but undocumented workers still comprise about 40% of the direct hires. To gain some insight into the predicted differences in the labor supply effects between documented and undocumented workers, we run separate sets of regressions that focus either on direct hires or on FLC workers.

The results are reported in Appendix F, Appendix S1. They show larger upper bounds for the workers directly hired by farmers, suggesting that reductions in the supply of legally authorized workers create larger production losses. For example, Table F.1.1 (resp. Table F.2.1), Appendix S1 indicates that the upper bound for the production-labor supply elasticity in the top five counties is a statistically significant 0.54 for direct hires (resp. 0.31 for FLC workers). In the top 10 counties, the upper bound for production is 0.45 for direct hires and 0.11 for FLC workers.

Another factor that may contribute to this finding is that workers hired directly by farmers are more likely to have worked for their current employer for a longer period of time and may have accumulated human capital specific to their current job, whereas workers who are brought to a farm by an FLC have less relevant work experience. Data from the NAWS support this hypothesis, as California farmworkers who were hired directly by farmers had an average of two additional years of farm work experience relative to FLC workers over our sample period. Additionally, direct hires were

15% points more likely to have had only one farm employer in the previous 12 months, suggesting that workers directly hired by farmers were more likely to have gained a work experience premium specific to their current place of employment.

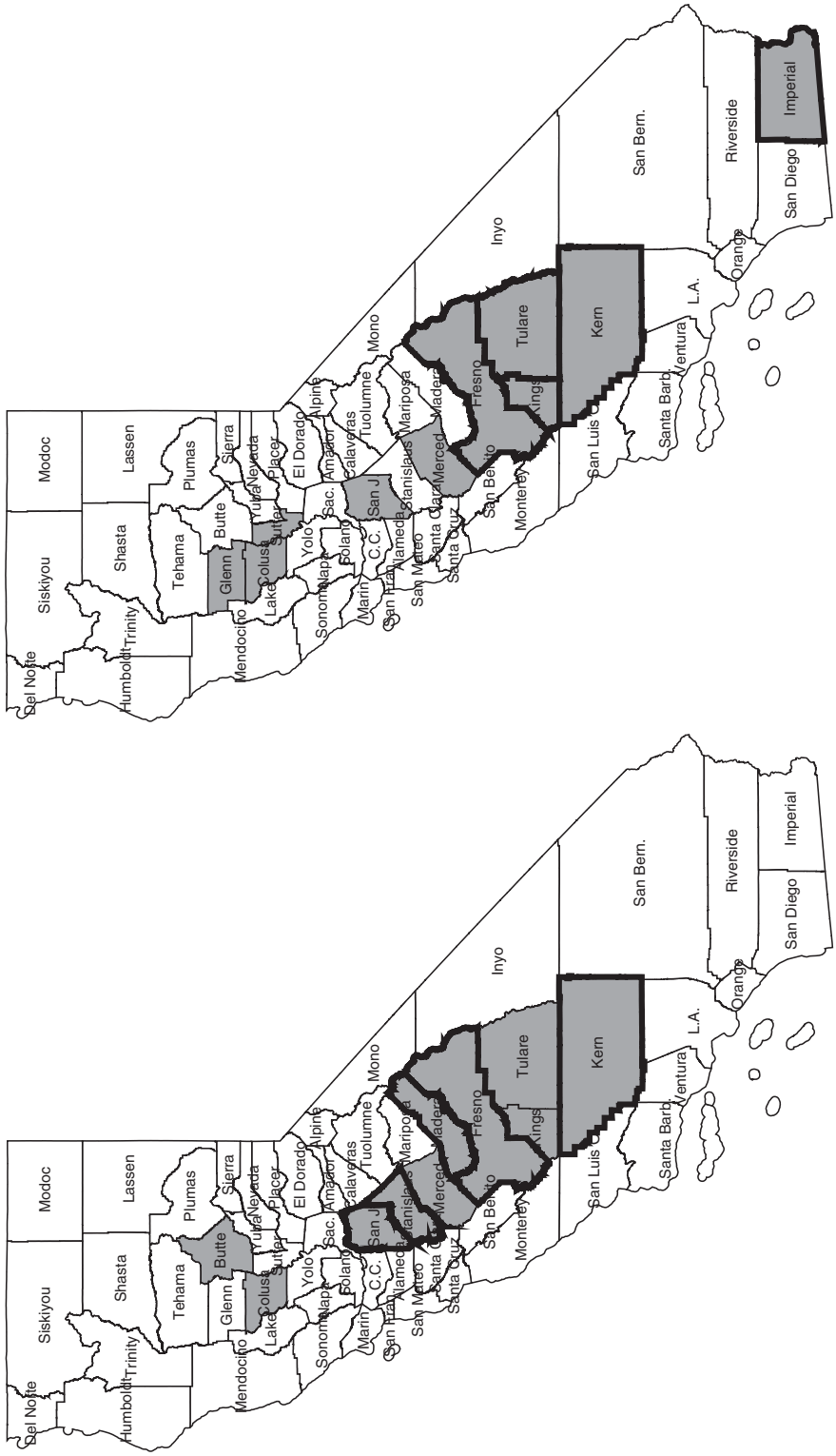
4.3 | Mechanically harvested nut and field crops

Nut and field crops are harvested by machines and thus require much less labor than hand-harvested crops to produce. For example, according to a 2016 cost study for almond production in the San Joaquin valley, labor only accounts for 3.2% of total production costs (Yaghmour et al., 2016). As a result, one should not expect to find labor availability effects on the production of mechanically harvested crops as large as those found in labor-intensive crops. Formally, the elasticity of crop production with respect to the labor supply, ξ_1, has a limit of zero as k_A approaches zero (see Equation (7)). Thus, when the labor input only accounts for a small share of the production costs, labor supply shocks only induce small production effects. In order to test this hypothesis, and as a falsification test for our results regarding labor-intensive crops, we estimate the elasticity of production with respect to the farm labor supply separately for nut and field crops, using the same regression framework as in Section 3.1. We focus on the top five and top 10 nut or field crop producing counties, which have some geographic overlap with the top labor-intensive crop producing counties but are not located in the coastal regions (see Figure 5).

The estimated impacts for nut and field crops (considered separately) using an unbalanced panel of data are shown in Tables 5 and 6. The unbalanced panels include crops grown within a county in at least half of the sample years. There are only four major nut crops produced in California: almonds, walnuts, pistachios, and pecans. Almond production, which has increased three-fold since the turn of the millennium, accounts for the lion's share of nut production in terms of weight (nearly 60%) and had a farm-gate value of roughly $7 billion in 2019. In terms of field crops, alfalfa hay was the top revenue generator, whereas corn silage was the leading crop in terms of tonnage. As with the hand-harvested crops, we also generated a set of results using a smaller, balanced panel of data, which are shown in Appendix G, Appendix S1. There, we also show regression results for samples that include both nut and field crops.

A review of these tables reveals two important facts. First, the magnitudes of the coefficients, when positive, are much smaller than those found in the FV crop analysis, and they are never positive and statistically significant. The positive coefficients for nut crops (resp. field crops) range from a statistically insignificant 0.001 to a statistically insignificant 0.169 (resp. 0.022 to 0.095). These estimates are less than half the magnitude of any of those produced by the FV analysis. Positive coefficients for the combined nut and field crop sample range from 0.005 to 0.247 (see Tables G.3 and G.4 in Appendix G). Second, in some instances, the production coefficients are negative, although when they are, they are only statistically significant for certain specifications using the unbalanced panel of data for field crops. For instance, the elasticity estimate for the top 10 counties in column (4) of Table 6 reveals an upper bound of −0.323. A negative elasticity would imply that a decline in the farm labor supply causes an increase in the production of mechanically harvested crops. Although a negative elasticity would confirm anecdotal evidence that indicates some farmers are switching production out of hand-harvested crops toward crops that can be mechanically harvested (e.g., CFBF and UC Davis, 2019; Martin, 2019; Rutledge and Taylor, 2019; Ryssdal, 2017), the results presented here do not provide a uniform body of evidence to support that hypothesis.[22]

[22]In the top 10 field crop producing counties, 42% of the value of production comes from fruits and vegetables, so demand for FV labor is still prevalent there. The statistically significant negative coefficients for field crop yields in Table 6 could then be the result of reverse causality. For example, a production shock early in the season could reduce the demand for field crop cultivation and machine harvest workers, causing some field crop workers to seek employment on FV farms performing cultivation work or operating tractors and machinery. Moreover, lower field crop yields would almost certainly lead to lower demand for post-harvest field crop workers, who comprise the largest group not included in our employment measure. Lower field crop yields could thus induce a nontrivial increase in FV employment, leading to reverse causality.



(a) Top nut producing counties

(b) Top field crop producing counties

FIGURE 5 Geography of top nut and field crop producing counties. The top 10 counties are shaded in gray. The top five counties are outlined with a thick black border.

TABLE 5 Effects of a change in farm labor supply on the production of nut crops grown in at least 15 of the 30 sample years

	(1)	(2)	(3)	(4)	(5)	(6)
	Top 5 counties					
Production	0.169	0.016	0.113	0.001	0.001	0.001
	(0.203)	(0.181)	(0.208)	(0.204)	(0.204)	(0.206)
	[0.082]	[0.031]	[0.124]	[0.058]	[0.059]	[0.059]
R^2	0.280	0.281	0.281	0.282	0.630	0.942
Harvested acres	0.171	0.127	0.150	0.165	0.165	0.165
	(0.109)	(0.112)	(0.118)	(0.119)	(0.119)	(0.120)
	[0.149]	[0.122]	[0.188]	[0.159]	[0.159]	[0.161]
R^2	0.210	0.210	0.210	0.210	0.721	0.969
Yield	−0.002	−0.111	−0.036	−0.164	−0.164	−0.164
	(0.202)	(0.152)	(0.193)	(0.157)	(0.158)	(0.160)
	[0.114]	[0.107]	[0.175]	[0.108]	[0.108]	[0.109]
R^2	0.165	0.182	0.172	0.189	0.625	0.646
N	380	380	380	380	380	380
	Top 10 counties					
Production	−0.083	−0.103	−0.125	−0.135	−0.126	−0.054
	(0.098)	(0.097)	(0.116)	(0.115)	(0.110)	(0.077)
	[0.095]	[0.105]	[0.130]	[0.129]	[0.119]	[0.087]
R^2	0.267	0.268	0.268	0.268	0.524	0.949
Harvested Acres	−0.201**	−0.213**	−0.180*	−0.185**	−0.177**	−0.110*
	(0.093)	(0.086)	(0.094)	(0.090)	(0.086)	(0.063)
	[0.124]	[0.141]	[0.114]	[0.130]	[0.124]	[0.112]
R^2	0.219	0.219	0.219	0.220	0.581	0.968
Yield	0.118*	0.110	0.055	0.050	0.051	0.056
	(0.069)	(0.076)	(0.073)	(0.070)	(0.070)	(0.069)
	[0.085]	[0.087]	[0.074]	[0.073]	[0.072]	[0.072]
R^2	0.187	0.194	0.198	0.203	0.660	0.694
N	775	775	775	775	775	775
Year f.e.	X	X	X	X	X	X
Quadratic county trends	X	X	X	X	X	X
Monthly temp. controls	–	X	–	X	X	X
Monthly precip. controls	–	–	X	X	X	X
County f.e.	X	X	X	X	X	–
Crop f.e.	–	–	–	–	X	–
Crop-by-county f.e.	–	–	–	–	–	X

Note: Significance levels are based on Driscoll–Kraay standard errors, which are reported in parentheses. Driscoll–Kraay standard errors in the top five and 10 counties do not correct for any degree of serial correlation. Standard errors clustered at the county level are reported in brackets for reference.
$^*p < 0.1$. $^{**}p < 0.05$.

The results for the total value of nut and field crop production (considered separately), which can be found in Table 7, are generally consistent with the production results. All of the coefficients are small in magnitude, and none of them are statistically significant. Overall, these falsification results indicate that the labor supply constraints FV farmers have expressed concern about in recent

TABLE 6 Effects of a change in farm labor supply on the production of field crops grown in at least 15 of the 30 sample years

	(1)	(2)	(3)	(4)	(5)	(6)
	Top 5 counties					
Production	−0.080	−0.163	−0.080	−0.209	0.093	−0.021
	(0.234)	(0.245)	(0.217)	(0.188)	(0.154)	(0.140)
	[0.301]	[0.370]	[0.268]	[0.291]	[0.135]	[0.152]
R^2	0.033	0.034	0.034	0.035	0.837	0.903
Harvested acres	−0.050	−0.166	−0.030	−0.165	0.066	0.005
	(0.215)	(0.230)	(0.169)	(0.164)	(0.154)	(0.127)
	[0.235]	[0.287]	[0.206]	[0.226]	[0.128]	[0.151]
R^2	0.060	0.061	0.062	0.064	0.656	0.794
Yield	−0.029	0.004	−0.049	−0.044	0.027	−0.026
	(0.122)	(0.146)	(0.132)	(0.138)	(0.061)	(0.058)
	[0.113]	[0.135]	[0.105]	[0.132]	[0.047]	[0.048]
R^2	0.039	0.039	0.039	0.039	0.967	0.975
N	1401	1401	1401	1401	1401	1401
	Top 10 counties					
Production	−0.319**	−0.297*	−0.323**	−0.323**	−0.145	−0.139
	(0.134)	(0.167)	(0.131)	(0.149)	(0.113)	(0.116)
	[0.154]	[0.185]	[0.172]	[0.197]	[0.188]	[0.162]
R^2	0.092	0.092	0.092	0.093	0.795	0.923
Harvested acres	−0.084	−0.116	−0.083	−0.137	−0.079	−0.056
	(0.098)	(0.135)	(0.094)	(0.114)	(0.109)	(0.110)
	[0.060]	[0.097]	[0.082]	[0.118]	[0.132]	[0.109]
R^2	0.142	0.143	0.143	0.143	0.597	0.847
Yield	−0.235**	−0.181**	−0.240***	−0.186**	−0.066**	−0.083***
	(0.095)	(0.083)	(0.090)	(0.078)	(0.032)	(0.029)
	[0.098]	[0.096]	[0.096]	[0.089]	[0.057]	[0.054]
R^2	0.046	0.046	0.046	0.046	0.961	0.973
N	2592	2592	2592	2592	2592	2592
Year f.e.	X	X	X	X	X	X
Quadratic county trends	X	X	X	X	X	X
Monthly temp. controls	–	X	–	X	X	X
Monthly precip. controls	–	–	X	X	X	X
County f.e.	X	X	X	X	X	–
Crop f.e.	–	–	–	–	X	–
Crop-by-county f.e.	–	–	–	–	–	X

Note: Significance levels are based on Driscoll–Kraay standard errors, which are reported in parentheses. Driscoll–Kraay standard errors in the top five and 10 counties correct for serial correlation up to three lags. Standard errors clustered at the county level are reported in brackets for reference.
*$p < 0.1$. **$p < 0.05$. ***$p < 0.01$.

years do not have a detectable impact on the production and value of mechanically harvested crops. Therefore, mechanization could provide a viable alternative to manual harvest labor if technologies were available and advanced enough to prevent the types of damage that consumers consider unacceptable. Other possible short-to-medium term solutions include the mechanization of labor-

TABLE 7 Effects of a change in farm labor supply on the value of nut and field crops

	(1)	(2)	(3)	(4)
	Top 5 counties			
Nut value	−0.049	−0.065	−0.060	−0.065
	(0.192)	(0.153)	(0.186)	(0.161)
	[0.161]	[0.127]	[0.170]	[0.145]
R^2	0.981	0.986	0.983	0.987
N	146	146	146	146
Field crop value	−0.009	−0.020	−0.004	−0.071
	(0.116)	(0.152)	(0.124)	(0.149)
	[0.166]	[0.233]	[0.167]	[0.200]
R^2	0.858	0.872	0.876	0.888
N	145	145	145	145
	Top 10 counties			
Nut value	0.028	0.058	0.021	0.041
	(0.074)	(0.073)	(0.087)	(0.081)
	[0.089]	[0.069]	[0.076]	[0.049]
R^2	0.983	0.984	0.984	0.985
N	277	277	277	277
Field crop value	−0.147	−0.109	−0.159	−0.133
	(0.108)	(0.125)	(0.100)	(0.116)
	[0.129]	[0.155]	[0.125]	[0.150]
R^2	0.934	0.938	0.937	0.940
N	252	252	252	252
Year f.e.	X	X	X	X
County f.e.	X	X	X	X
Quadratic county trends	X	X	X	X
Monthly temp. controls	–	X	–	X
Monthly precip. controls	–	–	X	X

Note: Significance levels are based on Driscoll–Kraay standard errors, which are reported in parentheses. Driscoll–Kraay standard errors in the nut crop analysis and the analysis of the top five field crop counties do not correct for any degree of serial correlation. In the analysis of the top 10 field crop counties, the Driscoll–Kraay standard errors correct for serial correlation up to one lag. Standard errors clustered at the county level are reported in brackets for reference.

intensive tasks that complement the harvesting process. For example, mechanical engineers are developing automated, self-guided carts for strawberry crops that drive into the middle of the field to pick up trays of berries and bring them back to packing crews at the edge of the field (UC Davis, 2021). This technology eliminates the need for workers to walk back and forth to deliver trays, increasing the amount of time they can spend picking fruit.[23]

5 | CONCLUSION

Recent studies point to a decline in the US farm labor supply driven by demographic and structural changes in Mexico, increased US border security measures, and a decline in the number of farm

[23]Hamilton et al. (2021) argue that the adoption of mechanical harvest aids, which serve as technical complements in production, has lagged behind because these technologies increase productivity and push wages up, thus disincentivizing their use.

workers willing to engage in follow-the-crop migration, which has reduced the geographic reach of local farm labor markets. A smaller farm labor supply has the potential to reduce access to safe and healthy produce, increase the nation's reliance upon foreign producers, and reduce the profitability of US farm operations. To examine the extent to which changes in the farm labor supply may affect crop production, we estimate panel regressions using a rich set of production and employment data from California counties. We use an equilibrium displacement model to gain insight into the bias likely to affect our empirical estimates. Our regression results reveal statistically significant upper bounds for the effects of labor supply shifts on the production of hand-harvested FV crops but, as expected, not on that of mechanically harvested crops.

California is the leading FV producer in the United States, contributing two-thirds of the domestically produced fruits and one-third of the vegetables. As a result, labor-supply driven production effects in California would likely reverberate throughout the nation. Although the bounds for FV production we find are economically meaningful, they indicate that the impacts of a declining farm labor supply will likely be limited in California over the next decade. These effects are perhaps best exemplified by focusing on the top five producing counties, which produce 67% of the value of all labor-intensive crops in the state. According to Charlton and Taylor (2016), the US farm labor supply is shrinking by about 1% each year. A decline in the farm labor supply of that magnitude in the top five counties could cause a loss of 60,000 tons (or 0.48%) of hand-harvested FV each year. Production value losses of 0.55% per year for the crops we consider in those counties could add up to as much as $3.7 billion, or 2.9% of the total value of state production, over the course of a decade.

Importantly, our results reveal that there does not exist a one-to-one relationship between farm labor and labor-intensive fruit and vegetable production, suggesting that other inputs could potentially substitute for labor. At least two factors may contribute to this finding. First, the farm labor supply in this study only considers the number of workers and does not account for adjustments on the intensive margin, such as changes in the number of weeks worked or hours of work per week. Data from the NAWS indicate that, on average, farm workers have been supplying more units of labor each year (US Department of Labor, 2021). Over the past few decades, farmers have become increasingly reliant upon farm labor contractors to reduce frictions in the farm labor market (USBLS, 2021a, 2021b; Thilmany, 1996; Thilmany & Blank, 1996). The use of farm labor contractors helps reduce the burden associated with finding harvest workers, which can increase the number of employee-employer matches throughout the year. An increase in the number of these matches can translate into intensive margin adjustments as workers find more employment. As a result, a 1% decrease in the supply of workers may correspond to a smaller decrease in the supply of labor units, thus estimates based on units of labor could potentially be larger than those uncovered by the present analysis. It is not clear to us, however, that an elasticity with respect to labor units would necessarily be more relevant for policy purposes than one based on worker counts.

Second, farmers are increasingly making use of labor-saving technologies (CFBF & UC Davis, 2019; Rutledge & Taylor, 2019). Although mechanical harvesters are currently not available for the vast majority of FV crops, other technologies, such as hydraulic platforms in tree orchards and conveyor belts in lettuce fields, are readily available and can help stretch the remaining workforce by increasing efficiency and reducing the physical difficulty associated with harvesting, enabling workers to maintain high levels of productivity. Our falsification tests on nut and field crops suggest that harvest mechanization could provide an alternative to the use of hand-harvest labor in a time of labor scarcity, provided that technologies are advanced enough to prevent unacceptable damage to crops.

REFERENCES

Baker, Gregory, Leslie Gray, Michael Harwood, Travis Osland, and Jean Tooley. 2019. "On-Farm Food Loss in Northern and Central California: Results of Field Survey Measurements." *Resources, Conservation, and Recycling* 149: 541–9.

Basso, Gaetano and Giovanni Peri. The Association Between Immigration and Labor Market Outcomes in the United States (Working Paper). IZA Discussion Paper, No. 9436, 2015: 1–34.

Bender, Gary S. 2012. *Avocado Production in California: A Cultural Handbook for Growers*. San Diego: The University of California Cooperative Extension and The California Avocado Society.

BLS. Consumer Price Index, 2021a. Retrieved April 23, 2021 from https://www.bls.gov/cpi/data.htm.

BLS. Quarterly Census of Employment and Wages, Average Annual and Quarterly Employment [dataset], 2021b. Retrieved April 23, 2021 from https://www.labormarketinfo.edd.ca.gov/cgi/dataanalysis/areaselection.asp?tablename=industry.

Borjas, George J. 2014. *Immigration Economics*. Cambridge: Harvard University Press.

Borjas, George J., and Hugh Cassidy. 2019. "The Wage Penalty to Undocumented Immigration." *Labour Economics* 61.

Boucher, Stephen R., Aaron Smith, and J. Edward Taylor. 2007. "Impacts of Policy Reforms on the Supply of Mexican Labor to U.S. Farms: New Evidence from Mexico." *Review of Agricultural Economics* 29(1): 4–16.

Brady, Michael P., R. Karina Gallardo, Syed Badruddozza, and Xioajiao Jiang. 2016. "Regional Equilibrium Wage Rate for Hired Farm Workers in the Tree Fruit Industry." *Western Economics Forum* 15(1): 20–31.

Brown, Randall S., and Laurits R. Christensen. Estimating Elasticities of Substitution in a Model of Partial Static Equilibrium: An Application to U.S. Agriculture, 1947-1974. Social Systems Research Institute Workshop Series, No. 8007, 1980.

California Farm Bureau Federation (CFBF), and UC Davis. 2019. *CFBF News*: 1–11. http://www.cfbf.com/wp-content/uploads/2019/06/LaborScarcity.pdf

Cassey, Andrew J., Kwanyoung Lee, Jeremy Sage, and Peter R. Tozer. 2018. "Assessing Post Harvest Labor Shortages, Wages, and Welfare." *Agricultural and Food Economics* 6(17): 1–24.

Castillo, Marcelo, Philip Martin, and Zachariah Rutledge. "The H-2A Program in 2020." *USDA-ERS Economic Information Bulletin*, 2022.

CDFA. California Agricultural Production Statistics: 2019 Crop Year Report, 2021. Retrieved April 23, 2021 from https://www.cdfa.ca.gov/Statistics/.

CFBF, and UC Davis. Still Searching for Solutions: Adapting to Farm Worker Scarcity Survey 2019. CFBF News, 2019. Retrieved May 1, 2021 from http://www.cfbf.com/wp-content/uploads/2019/06/LaborScarcity.pdf.

Charlton, Diane, and J. Edward Taylor. 2016. "A Declining Farm Workforce: Analysis of Panel Data from Rural Mexico." *American Journal of Agricultural Economics* 98(4): 1158–80.

Charlton, Diane, J. Edward Taylor, Stavros Vougioukas, and Zachariah Rutledge. 2019. "Can Wages Rise Quickly Enough to Keep Workers in the Fields?" *Choices Magazine* 34(2): 1–7.

Clemens, Michael A., Ethan G. Lewis, and Hannah M. Postel. 2018. "Immigration Restrictions as Active Labor Market Policy: Evidence from the Mexican Bracero Exclusion." *American Economic Review* 108(6): 1468–87.

Congressional Research Service. The U.S. Trade Situation for Fruit and Vegetable Products. Report RL34468, 2016 Retrieved May 18, 2021 from https://fas.org/sgp/crs/misc/RL34468.pdf.

Congressional Research Service. U.S. Food and Agricultural Imports: Safeguards and Selected Issues. Report R46440. 2020. Retrieved May 18, 2021 from https://crsreports.congress.gov/product/pdf/R/R46440.

Cumby, Robert E., and John Huizinga. 1990. "Testing the Autocorrelation Structure of Disturbances in Ordinary Least Squares and Instrumental Variables Regressions." NBER Technical Working Paper No. 92, 185–195.

De Hoyos, Rafael, and Vasilis Sarafidis. 2006. "Testing for Cross-Sectional Dependence in Panel-Data Models." *The Stata Journal* 6(4).

della Cava, Marco, and Ricardo Lopez. 2019. Could California Produce Soon Cost You More? Farms Face Labor Shortages, Immigration Woes, USA Today. Retrieved Feb 23, 2020 from https://www.usatoday.com/story/news/2019/01/27/could-california-produce-soon-cost-you-more/2594964002/?fbclid=IwAR0clU-zge5QHNCgz0oDPa6yplQrrILS6lpf1HrKS_pmVe_3CTJfOk7xlbA.

Driscoll, John C., and Aart C. Kraay. 1998. "Consistent Covariance Matrix Estimation with Spatially Dependent Panel Data." *The Review of Economics and Statistics* 80(4): 549–60.

Durand, J., D. Massey, and K. Pren. 2016. "Double Disadvantage: Unauthorized Mexicans in the U.S. Labor Market." *The Annals of the American Academy of Political and Social Science* 666(1): 78–90.

Edward Taylor, J., Diane Charlton, and Antonio Yúnez-Naude. 2012. "The End of Farm Labor Abundance." *Applied Economic Perspectives and Policy* 34(4): 587–98.

Ejimakor, Godfrey, Obed Quaicoe, and Fafanyo Asiseh. 2017. "Agricultural Factor Use and Substitution in the South-Eastern United States." *Studies in Agricultural Economics* 119: 156–9.

ERS. Food Insecurity in the United States: How Do States Compare?, 2020. USDA Economic Research Service. Retrieved May 6, 2021 from https://www.ers.usda.gov/topics/food-nutrition-assistance/food-security-in-the-us/interactive-charts-and-highlights/#States.

Estrabrook, Barry. Farmers Can't Find Enough Workers to Harvest Crops - and Fruits and Vegetables Are Literally Rotting in Fields. Eating Well, 2021.Retrieved May 6, 2021 from https://www.eatingwell.com/article/291645/farmers-cant-find-enough-workers-to-harvest-crops-and-fruits-and-vegetables-are-literally-rotting-in-fields/.

Fan, Maoyong, Susan Gabbard, Anita Alves Pena, and Jeffrey M. Perloff. 2015. "Why Do Fewer Agricultural Workers Migrate Now?" *American Journal of Agricultural Economics* 97(3): 665–79.

Fan, Maoyong, Anita Alves Pena, and Jeffrey M. Perloff. 2016. "Effects of the Great Recession on the U.S. Agricultural Labor Market." *American Journal of Agricultural Economics* 98(4): 1146–57.

Frees, Edward. 1995. "Assessing Cross-Sectional Correlation in Panel Data." *Journal of Econometrics* 69: 393–414.

Gardner, Bruce L. 1975. "The Farm-Retail Price Spread in a Competitive Food Industry." *American Journal of Agricultural Economics* 57: 399–409.

Glaister, Dan. 2006. US Crops Left to Rot as Mexicans Leave the Fields for Better-Paid Jobs, The Guardian. Retrieved December 30, 2018 from https://www.theguardian.com/world/2006/feb/04/usa.uk.

Goldsmith-Pinkham, Paul, Isaac Sorkin, and Henry Swift. 2020. "Bartik Instruments: What, When, Why, and How." *American Economic Review* 110(8): 2586–624.

Gunter, Lewell F., Josepth C. Jarett, and James A. Duffield. 1992. "Effect of U.S. Immigration Reform on Labor-Intensive Agricultural Commodities." *American Journal of Agricultural Economics* 74(4): 897–906.

Gunter, Lewell, and Uptal Vasavada. 1988. "Dynamic Labour Demand Schedules for US Agriculture." *Applied Economics* 20: 803–12.

Hagerty, Nick. The Scope for Climate Adaptation: Evidence from Irrigated Agriculture in California, 2020.Working paper. Retrieved May 1, 2021 from https://hagertynw.github.io/webfiles/Scope_for_Climate_Adaptation.pdf.

Hamilton, Stephen F., Timothy J. Richards, Aric Shafran, and Kathryn N. Vasilaky. 2021. "Farm Labor Productivity and the Impact of Mechanization." *American Journal of Agricultural Economics*. Retrieved December 28, 2021 from https://onlinelibrary.wiley.com/doi/pdf/10.1111/ajae.12273.

Hertz, Tom, and Steven Zahniser. 2012. "Is There a Farm Labor Shortage?" *American Journal of Agricultural Economics* 95(2): 476–81.

Hill, Alexandra. 2020. "California Crop Labor Supply and Demand During COVID-19." *ARE Update* 24(3): 9–11.

Hoechle, Daniel. 2007. "Robust Standard Errors for Panel Regressions with Cross-Sectional Dependence." *The Stata Journal* 7(3): 281–312.

Jaeger, David A., Joakim Ruist, and Jan Stuhler. 2018. Shift-Share Instruments and the Impact of Immigration. NBER, Working Paper No. 24285: 1–42. Retrieved April 5, 2018 from http://www.nber.org/papers/w24285.

Johnson, Renée. 2018. The U.S. Trade Situation for Fruit and Vegetable Products. Congressional Research Service, Report No. RL34468. Retrieved May 6, 2021 from https://fas.org/sgp/crs/misc/RL34468.pdf.

Kenner, Bart. U.S. Fruit Imports Grew By $8.9 Billion Over the Last Decade to Meet Rising Demand. Amber Waves, 2021. Retrieved July 20, 2021 from https://www.ers.usda.gov/amber-waves/2020/september/us-fruit-imports-grew-by-89-billion-over-the-last-decade-to-meet-rising-demand.

Kostandini, Genti, Elton Mykerezi, and Cesar Escalante. 2013. "The Impact of Immigration Enforcement on the U.S. Farming Sector." *American Journal of Agricultural Economics* 96(1): 172–92.

Manning, Alan. 2003. *Monopsony in Motion: Imperfect Competition in Labor Markets*. New Jersey: Princeton University Press.

Martin, Philip. 2007.Backgrounder. *Farm Labor Shortages: How Real? What Response?* Washington DC: Center for Immigration Studies.

Martin, Philip. Farm Labor Shortages. Rural Migration News, 2019.Retrieved May 1, 2021 from https://migration.ucdavis.edu/rmn/blog/post/?id=2264.

Martin, Philip. California Farm Employment: 2019 versus 2020.Rural Migration News, 204, 2020.

Martin, Philip. 2021. "COVID-19 and California Farm Labor." *California Agriculture* 74(2): 67–8.

Massey, D. S., and K. Gentsch. 2014. "Undocumented Migration to the United States and the Wages of Mexican Immigrants." *International Migration Review* 48(2): 482–99.

Mérel, Pierre R. 2009. "On the Deadweight Cost of Production Requirements for Geographically Differentiated Agricultural Products." *American Journal of Agricultural Economics* 91(3): 642–55.

Mérel, Pierre, and Zachariah Rutledge. 2021. Unpublished version. "The Short-Run Impacts of Immigration on Native Workers: A Sectoral Approach." In *World Scientific Encyclopedia of Global Migration*, edited by Robert Sauer. World Scientific Publishing Co Pte Ltd. https://www.zachrutledge.com/uploads/1/2/5/6/125679559/versionbook.pdf.

Muth, Richard F. 1964. "The Derived Demand Curve for a Productive Factor and the Industry Supply Curve." *Oxford Economic Papers, New Series* 16(2): 221–34.

NASS. Quickstats [website], 2021. Retrieved April 23, 2021 from https://quickstats.nass.usda.gov/.

NOAA. Climate Data Online [website], 2021. 2021 from https://www.ncdc.noaa.gov/cdo-web/.

Okrent, Abigail M., and Julian M. Alston. 2012. "The Effects of Farm Commodity and Retail Food Policies on Obesity and Economic Welfare in the United States." *American Journal of Agricultural Economics* 94(3): 611–46.

Peri, Giovannni, and Chad Sparber. 2009. "Task Specialization, Immigration, and Wages." *American Economic Journal: Applied Economics* 1(3): 135–69.

Peter Timmer, C. 1988. "Chapter 8, The Agricultural Transformation." In *Handbook of Development Economics*, edited by H. Chenery and T.N. Srinivastan. Vol 1 275–331. Elsevier, Amsterdam. https://www.sciencedirect.com/science/article/pii/S1573447188010113.

Piggott, Roley R., Nicholas E. Piggott, and Vic E. Wright. 1995. "Approximating Farm-Level Returns to Incremental Advertising Expenditure: Methods and an Application to the Australian Meat Industry." *American Journal of Agricultural Economics* 77(3): 497–511.

Plummer, Brad. We're Running Out of Farm Workers. Immigration Reform Won't Help. 2013.Washington Post. Retrieved Feb 23, 2020 from https://www.washingtonpost.com/news/wonk/wp/2013/01/29/the-u-s-is-running-out-of-farm-workers-immigration-reform-may-not-help/?utm_term==.85a4c6595cb2.

Richards, Timothy J. 2018. "Immigration Reform and Farm Labor Markets." *American Journal of Agricultural Economics* 100 (4): 1050–71.

Richards, Timothy J. 2020. "Income Targeting and Farm Labor Supply." *American Journal of Agricultural Economics* 102(2): 419–38.

Richards, Timothy J., and Paul M. Patterson. 1998. "Hysteresis and the Shortage of Agricultural Labor." *American Journal of Agricultural Economics* 80: 683–95.

Ridley, William, and Stephen Devadoss. 2021. "The Effects of COVID-19 on Fruit and Vegetable Production." *Applied Economic Perspectives and Policy* 43(1): 329–40.

Rivera-Batiz, F. L. 1999. "Undocumented Workers in the Labor Market: An Analysis of the Earnings of Legal and Illegal Mexican Immigrants in the United States." *Journal of Population Economics* 12: 91–116.

Rogers, Williams. 1993. "Regression Standard Errors in Clustered Samples." *Stata Technical Bulletin* 13.

Rutledge, Zachariah, Marcelo Castillo, Timothy Richards, and Philip Martin. The Impact of Minimum Wage Shocks on Low-Skilled Workers in the United States: Evidence from the H-2A Visa Agricultural Guestworker Program, 2021. Working paper. Retrieved July 21, 2021 from https://www.zachrutledge.com/uploads/1/2/5/6/125679559/aewr_paper_current_draft.pdf.

Rutledge, Zachariah, and J. Edward Taylor. 2019. "California Farmers Change Production Practices as the Farm Labor Supply Declines." *ARE Update* 22(6).

Ryssdal, Kai. As Farmers Grow Scarce, Wages Are on the Rise.Marketplace.org, 2017.Retrieved May 1, 2021 from https://www.marketplace.org/2017/03/23/farmworkers-grow-scarce-farm-wages-go/.

Stoicheff, Lily. The Impact of Santa Cruz County Agriculture's Labor Shortage. Good Times, 2018.Retrieved May 6, 2021 from https://goodtimes.sc/cover-stories/impact-santa-cruz-county-agriculture-labor-shortage/.

Taylor, J. Edward. 1992. "Earnings and Mobility of Legal and Illegal Immigrant Workers in Agriculture." *American Journal of Agricultural Economics* 74(4): 91–116.

Thilmany, Dawn. 1996. "FLC Usage among California Growers under IRCA: An Empirical Analysis of Farm Labor Market Risk Management." *American Journal of Agricultural Economics* 78(4): 37–49.

Thilmany, Dawn, and Steven C. Blank. 1996. "FLCs: An Analysis of Labor Management Transfers among Agricultural Producers." *Agribusiness: An International Journal* 12(1).

UC Davis. 2021. FRAIL-Bots: Fragile Crop Harvest Aiding Mobile Robots. UC Davis Biological and Agricultural Engineering. Retrieved May 7, 2021 from https://faculty.engineering.ucdavis.edu/vougioukas/research/projects/nrismall-frail-bots-fragile-crop-harvest-aiding-mobile-robots.

US Department of Labor. National Agricultural Workers Survey - Confidential Version [dataset], 2021.

Wohlgenant, Michael K. 1989. "Demand for Farm Output in a Complete System of Demand Functions." *American Journal of Agricultural Economics* 71(2): 241–52.

Yaghmour, Mohammad, David Haviland, Elizabeth Fichtner, Black Sanden, Mario Viveros, Daniel Sumner, Donald Stewart, and Christine Gutierrez. Sample Costs to Establish an Orchard and Produce Almonds, 2016. UC ANR. Retrieved May 7, 2021 from https://coststudyfiles.ucdavis.edu/uploads/cs_public/87/3c/873c1216-f21e-4e3e-8961-8ece2d647329/2016_almondsjv_south_final_10142016.pdf.

Zahniser, Steven, Tom Hertz, Peter Dixon, and Maureen Rimmer. 2011. "Immigration Policy and its Possible Effects on U.S. Agriculture and the Market for Hired Farm Labor: A Simulation Analysis." *American Journal of Agricultural Economics* 94(2): 477–82.

Zahniser, Steven J. Edward Taylor, Thomas Hertz, and Diane Charlton. Farm Labor Markets in the United States and Mexico Pose Challenges for U.S. Agriculture. USDA-ERS Economic Research Bulletin, No. 201, 46 pp., 2018.

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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