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Farm Labor Scarcity and its Uneven Impacts on U.S. Crop Producers

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Abstract

This paper is the first to evaluate the nationwide impacts of farm labor scarcity on U.S. crop producers between 2002 and 2017, by disentangling its effects from other market forces such as rising demand for agricultural commodities, factor-biased technological change, and changes in the supply of other inputs. To accomplish this, we leverage insights from a stylized theoretical framework, that shows labor market outcomes are determined by the interaction between input-specific productivity changes, factor substitutability and endogenous relative price changes. We implement a two-step empirical strategy. First, we use a novel constrained optimization approach to simultaneously estimate changes in input-biased factor productivity and labor substitutability for nine Farm Resource Regions. Second, with these estimates in hand, we use a spatially explicit partial equilibrium model of the crop sector, to replicate observed labor market outcomes, and estimate their responsiveness to changes in farm labor supply across widely differing production systems, between 2002 and 2017. Our estimates of regional changes in factor-biased productivity and labor substitutability underscore the difference in capacity to adjust to labor shortages across production systems. We estimate that a 1% annual decline in farm labor supply can increase hiring costs by 11.1% for specialty crop growers and 6.1% for field crop producers over 10 years. These can be further aggravated if trade policies increase demand from domestic producers and immigration policy exaggerates the shock to farm workers. Addressing labor scarcity will be key to ensuring the long-term sustainability and resilience of U.S. agriculture.

1. Introduction

Farm labor supply for crop producers in the United States (U.S.) has been constrained by declining migration flows due to structural changes in the Mexican economy and tightening immigration enforcement at the border (Zahniser et al. 2018; Charlton and Taylor 2016). There is a rich literature on the role of farm wages (Win et al. 2025; Costa and Martin 2020; Charlton et al. 2019a), mechanization (Charlton et al. 2019b; Charlton and Kostandini 2021; Hamilton et al. 2022) and immigration policies for guest workers (Rutledge et al. 2024; Charlton and Kostandini 2021; Castillo et al. 2021; Steven Zahniser et al. 2012) to alleviate farm labor scarcity. Yet there is little evidence of how producers across different production systems have adapted to farm labor scarcity. What has been the impact on farm wages and employment? To what extent have productivity changes, for labor and other inputs, played a mitigating role? Answers to these questions are critical for effective policy design in an era of increasing farm labor shortages.

This paper develops a novel two-step empirical approach to estimate the impacts of farm labor scarcity for the nine Farm Resource Regions (Heimlich 2000) across continental U.S.. In this study, an "increase in farm labor scarcity" or a "reduction in farm labor supply", imply that fewer workers are willing to take farm jobs at the going wage rate.[1] In the first step, drawing on key insights from a stylized theoretical framework and the Simplified International Model for agricultural Prices, Land use and the Environment, Gridded version with Commuting Zones (SIMPLE-G-CZ) (Ray and Hertel 2025b; Ray et al. 2023), we simultaneously estimate changes in partial factor productivity (PFP) for labor, resources and intermediate inputs as well as elasticity of substitution for labor, which interacts with relative input price changes, to jointly govern

[1] Also described as a backward shift in the labor supply schedule in standard microeconomic theory

producers' input use decisions. In the second step, we use these estimates to quantify the responsiveness of labor market outcomes to labor supply shocks, input-biased productivity changes and output demand across the Farm Resource Regions between 2002 and 2017. While the analysis covers all nine regions, we focus our discussion on four regions with contrasting production systems.

Our findings indicate that producers in the Heartland and Northern Great Plains, benefiting from more mechanized systems, were able to substitute scarce farm workers more easily in response to labor supply shocks, leading to a 0.8 to 1.7% reduction in employment for each 1% reduction in labor supply. In contrast, producers in the Northern Crescent and Fruitful Rim exhibited much less flexibility. Limited mechanization options forced producers to rely on raising wages to attract and retain labor, with smaller reductions in employment. This confirms the findings in a recent study by Win, Rutledge, and Maredia (2025) who find that raising wages is the most common response to farm labor shortages amongst California farmers.

Our analysis also suggests, that if a 1% annual decline in farm workers were sustained over the next 10 years, labor costs would increase by 6.1% in the grain based production systems and 11% in the Northern Crescent and Fruitful Rim regions.[2] These increases in hiring cots costs are likely to be further reinforced by changes in immigration policies (Martin and Rutledge 2025) and proposed import tariffs (Najmabadi 2025), since it could aggravate both labor scarcity and demand from domestic producers. Further, it could intensify the concentration of larger farms with

[2] Charlton and Taylor (2016) document a roughly 1% annual decline in rural Mexicans joining the U.S. farm labor force from 1982 to 2010. We benchmark predictions from our model by assuming this translates to a 1% annual decline in the U.S. farm workforce, which is reasonable given that these workers comprise the majority of the workforce, and that this trend continued, which we believe is reasonable and likely a lower bound.

important implications for the fruits and vegetable producers with a higher representation of smaller farm (Lacy et al. 2023; MacDonald 2020).

Our theoretical framework shows that while labor shortages increase the cost of production, enhanced worker productivity can mitigate these effects. We estimate that 1% increase in labor productivity led to a proportionate decrease in labor costs and employment (1 and 1.05% respectively) in the Fruitful Rim. In the Heartland it led to a smaller reduction in wages (0.3%) and greater reduction in employment (1.2%) since labor constitutes a smaller share of production costs. These results underscore the need for region-specific labor market policies and technological innovations because of the important and sizable regional disparities in the impacts of labor shortages as well as producers' capacities for adaptation.

Estimating the impact of labor scarcity across different production systems using available data is challenging since it reflects the interplay of multiple market forces as well as the adaptability of producers. While reduced supply of farmworkers workers puts upward pressure on wages, it is confounded by the increased global demand for labor-intensive crops and changes in input-biased productivity. This study is the first to disentangle the impacts of labor supply shocks on labor market outcomes, as distinct from the overlapping effects of demand growth, land supply changes, and shifts in productivity, across the diverse agricultural regions in the U.S. The novel empirical strategy in this paper leverages the SIMPLE-G-CZ model, where the underlying structural framework is driven by foundational principles of economic theory, and includes site-specific details with granular data as well as empirically estimated behavioral parameters that govern producer decisions (Haqiqi and Baldos 2025; Baldos et al. 2020). The SIMPLE-G-CZ model also incorporates the recent evidence on agricultural labor market dynamics in the US, which is particularly relevant in this study (Ray and Hertel 2025b; Ray et al. 2023).

Our paper contributes to the literature on farm labor markets in the U.S. First, this study meaningfully extends the literature on the impacts of labor scarcity on the agricultural sector beyond California (Rutledge and Mérel 2023; Richards 2018). Other papers have presented national level analysis (Castillo and Charlton 2023; Kostandini et al. 2014; Hertz and Zahniser 2013; Zahniser et al. 2012), to the best of our knowledge this is the first study to present regionally disaggregated analysis to deepen our understanding of the impacts of changing labor market dynamics for crop producers in different regions. Second, the study examines the role—and limitations—of input-biased productivity growth in mitigating the effects of labor scarcity. We extend this literature, where the focus is often on Total Factor Productivity (TFP) growth (Wang et al. 2024; Ball et al. 2016), by simultaneously estimating geographically heterogenous changes in Partial Factor Productivity (PFP) for labor, resources and intermediate inputs for the crop sector across the Farm Resource Regions in the U.S.

The remainder of this paper proceeds as follows: Section 2 presents a literature review. Section 3 outlines the theoretical framework and Section 4 describes the empirical strategy. Section 5 presents the empirical results for four major crop growing regions, i.e., Heartland, Northern Great Plains, Northern Crescent and Fruitful Rim, with the complete set of results available in the online Supplementary Materials (SM). Section 6 concludes with a discussion of implications for policy and future research.

2. Literature Review

A large literature examines the consequences of agricultural labor scarcity in the U.S., much of it focused on California and other parts of the Fruitful Rim where production is highly labor intensive. The decline in availability of farmworkers, particularly those of Mexican origin, has been attributed to long-term demographic and economic shifts in Mexico. Charlton and Taylor (2016) show that the supply of Mexican agricultural workers declined by 1% (approximately 150,000 workers) annually between 1980 and 2010, driven by declining birth rates, expanded access to education, and the growth of non-agricultural employment. These findings are reinforced by Taylor, Charlton, and Yúnez-Naude (2012) and Zahniser et al. (2018), who document a contraction in the overall supply of hired farmworkers in the U.S. as a result of these changes.

Domestic factors such as intensified immigration enforcement further contribute to a shrinking and less mobile farm workforce. Richards (2018) and Kostandini, Mykerezi, and Escalante (2014) note that stricter immigration policies, particularly those targeting unauthorized workers, have compounded the scarcity of farm labor. Fan et al. (2015) highlight the declining mobility of the farm labor force, which has become older, more settled, and less willing to migrate for work. In this context, the role of policy in shaping labor flows has been highlighted in research on guest worker programs, including Rutledge et al. (2025), Charlton and Kostandini (2021), and Castillo et al. (2021), who document the expansion of the H-2A program and its growing role in U.S. agriculture.

Studies of producer responses emphasize three key strategies for addressing labor scarcity: wage increases, mechanization, and the use of contract labor. Costa and Martin (2020) estimate that a 40% increase in farmworker wages would translate to only modest increases in food prices for consumers, suggesting that wage increases are feasible under certain market conditions. Similarly, Win, Rutledge, and Maredia (2025) provide evidence that producers do raise wages in response to scarcity, though not always at levels sufficient to offset labor shortages. Hamilton et al. (2022), Charlton and Kostandini (2021) and Charlton et al. (2019b) examine how producers adopt labor-saving technologies, particularly in crops where automation is more readily feasible. Yet at present, the potential for cost-effective mechanization remains limited for many specialty crops, due to perishability and quality concerns.

Attracting additional workers through the H-2A guest worker program along with Farm Labor Contractors (FLCs) has helped to fill some of the gap in farm labor scarcity. Hill et al. (2024) estimate that, nationally the share of H-2A workers out of all migrant workers has increased from 1 in 10 in 2006 to close to 6 in 10 by 2022. In the grain-production regions like the Heartland and Northern Great Plains, 67 – 89% of migrant workers were hired through the H-2A program in 2022. Castillo, Martin, and Rutledge (2022) estimate that the share of H-2A wage bill to total labor expenditure, was higher in states like Michigan, Ohio, North and South Dakota, relative to California. Latest estimates for Illinois show that labor costs has been the primary driver of increase in overhead costs which has tripled between 2005 – 2025 (Paulson and Valencia 2025). They also find that H-2A workers have been predominantly employed for general farm operations, even for low-labor intensive field crop producers. Bronars (2015) reported that less than 6% of field crop workers in the Midwest had immigrated to the US in the four years prior to 2008-2012, compared to 16% in California. This suggests that the pool of migrant workers in the Midwest was being replenished at a much lower rate—adding to anecdotal evidence of labor shortages emerging beyond the Western US (Tran 2025; Bardenhagen et al. 2025; Jones 2023).

These geographical patterns identify a gap in the literature on farm labor scarcity that often focusses on labor intensive production systems that overlooks impacts elsewhere (Win et al. 2025; Rutledge and Mérel 2023; Richards 2018) or national-level analyses (Castillo and Charlton 2023; Kostandini et al. 2014; Hertz and Zahniser 2013; Zahniser et al. 2012) that offer broad assessments but lack the granularity needed to assess heterogeneity across regions. As the overall supply of new immigrant workers has dwindled, regions that were not popular destinations for immigrant farmworkers have seen a greater decline in labor supply in relative terms, compounded by the declining mobility of the existent pool of farmworkers (Fan et al. 2015).

Our study builds on and extends this literature by providing the first regionally disaggregated analysis of the impacts of farm labor scarcity and mitigating impacts of input-biased productivity growth, depending on the substitutability of labor with other inputs, using a structural model that distinguishes among different drivers of change in input use and factor payments. We conduct our analysis at a geographically disaggregated scale for nine Farm Resource Regions (Heimlich 2000) that captures distinct production systems constituting. We present our discussion on four regions, i.e., the Heartland and Northern Great Plains, characterized by large-scale mechanized grain production, the Fruitful Rim with more labor-intensive production systems specialized in fruits, nuts and vegetable production and the Northern Crescent, where production systems are mixed with a growing share of grains production during our study period: 2002-2017. Results for all nine regions are available in the SM.

3. Theoretical Framework

Understanding the impacts of farm labor scarcity requires disentangling the effects of labor supply shocks from other concurrent forces—such as rising commodity demand, input substitution, changes in land use, and input-biased technological change—that jointly determine observed labor market outcomes. For example, between 1990 and 2023, real farm wages rose by over 36% (USDA 2025), while the real value of fruit and nut production increased by 127%, and total crop production by 17.5% (Authors' calculation). These trends reflect not just labor scarcity but also structural shifts in demand and productivity lead to the observed changes in wages and employment.

To address this challenge, we build on the stylized theoretical framework developed in Ray and Hertel (2025a), which draws on and extends classic models of input demand (e.g., Muth 1964). Our objective is to provide a tractable, yet insightful representation of the underlying economic 'drivers' shaping producers' input use decisions across diverse spatial contexts. Our stylized theoretical framework identifies three drivers of observed changes in factor markets, i.e., changes in commodity demand (expansion effect), changes in input supply and changes in factor-biased productivity (PFP) that depends on endogenous changes in relative prices and factor substitutability.

Consider a stylized two input production model, where cost-minimizing producers in a spatial unit Z, use Labor $\left(Q_{LZ}\right)$ and non-labor input, say Resources $\left(Q_{RZ}\right)$, to produce crop output $\left(Q_{Z}\right)$ with a Constant Elasticity of Supply (CES) production function.[3] In this framework, a change in demand for input j (Equation 1) is the difference between the 'expansion effect' and the 'substitution effect' (Gohin and Hertel 2003) in the linearized form:

$$(1)\quad q_{jZ}^{d} = q_{Z} - a_{jZ} - \sigma_{Z}\left(p_{jZ} - a_{jZ} - p^{*}\right), j = L\, or R$$

$$(2)\quad q_{jZ}^{s} = e_{j} p_{jZ} - \phi_{jZ}$$

In our notation, percentage changes in input use, output as well as input and output prices are depicted in lower case. We conduct our analysis at the Commuting Zone (CZ) level indexed by Z (Fowler and Jensen 2020), which refers to a group of counties that delineate the local labor-sheds

[3] For simplicity, we describe the theoretical framework with two inputs. The same approach can be applied to a multi-input production system which underlies the SIMPLE-G framework.

and widely used (Autor et al. 2021; Orsatti et al. 2020). Although most of the data used in this analysis are available at the county level, county boundaries may not accurately reflect local labor markets. Without readily available delineation for agricultural labor-sheds, we use CZs as the best available alternative. Moreover, our analysis focusses on the percentage *changes* in input use and factor prices due to percentage *changes* in the drivers of input use. Aggregating over the 3100+ counties to 605 CZs smooths over some random noise in the data.

The expansion effect for input j is driven by the changes in crop production $\left(q_Z\right)$ net of input-biased productivity changes $\left(a_{jZ}\right)$. Given the competitive nature of agricultural markets in the U.S., we assume that producers are price takers who respond to commodity prices determined at the national level. Commodity demand depends on changes in domestic and international population, income growth and policy changes such as biofuel mandates that impacted field crop production during the period of our study. While the national price changes reflect changes in commodity demand, the principle of duality implies that observed changes in production can serve as a proxy for the expansion effect. This is useful for our study, because it captures the impact of the expansion effect at a granular scale incorporating the spatially heterogenous impact of changes in commodity demand, say on grain producers in the Midwest relative to specialty crop producers in California.

The substitution effect refers to the re-optimization of the input-mix driven by input-biased productivity-adjusted changes in relative prices and, critically, labor substitutability $\left(\sigma_Z\right)$, which determines the ability of producers to adjust input use decisions to changes in relative prices.

Changes in input supply $\left(q_{jZ}^{s}\right)$ are determined by the price elasticity of input supply $\left(e_{jZ}\right)$ and changes in input price $\left(p_{jZ}\right)$ net of input supply shocks $\left(\phi_{jZ}\right)$ (Equation 2). In our notation, a positive value for ϕ_{jZ} represents a backward shift in the supply of input *j*.

(3) $q_{L,Z\in F}^{*} = q_{Z\in F}\beta_{q,F} + a_{L,Z\in F}\beta_{aL,F} + a_{R,Z\in F}\beta_{aR,F} + \phi_{L,Z\in F}\beta_{\phi L,F} + \phi_{R,Z\in F}\beta_{\phi R,F}$

(4) $p_{L,Z\in F}^{*} = q_{Z\in F}\lambda_{q,F} + a_{L,Z\in F}\lambda_{aL,F} + a_{R,Z\in F}\lambda_{aR,F} + \phi_{L,Z\in F}\lambda_{\phi L,F} + \phi_{R,Z\in F}\lambda_{\phi R,F}$

(5) $\beta_q = \dfrac{e_L\left(e_R+\sigma\right)}{D}, \beta_{aL} = -e_L\dfrac{\theta_L\sigma\left(1+e_R\right)+e_R\left(1-\sigma\right)}{D}, \beta_{aR} = -\dfrac{\theta_R e_L\sigma\left(e_R+1\right)}{D}, \beta_{\phi L} = -\dfrac{\sigma e_R\theta_R}{D}, \beta_{\phi R} = \dfrac{e_L\sigma\theta_R}{D}$

(6) $\lambda_q = \dfrac{\beta_q}{e_L}, \lambda_{aL} = \dfrac{\beta_{aL}}{e_L}, \lambda_{aR} = \dfrac{\beta_{aR}}{e_L}, \lambda_{\phi L} = -\beta_{\phi L}\dfrac{e_R+\theta_L\sigma}{\sigma e_R\theta_R}, \lambda_{\phi R} = \dfrac{\beta_{\phi R}}{e_L}$

$and\ D = \theta_L\left(e_L-e_R\right)+e_R\left(e_L+\sigma\right)$

Equating input demand and input supply (Equations 1 and 2) and assuming free entry and exit, we can analytically decompose the changes in the factor markets into three key drivers of change in input use and factor payment as: the expansion effect $\left(q_Z\right)$; changes in input-biased factor productivity $\left(a_{jZ}\right)$; and changes in input supply $\left(\phi_{jZ}\right)$ (Equations 3 and 4). Equations 3 and 4, are the main equations of interest in our analysis, focusing on changes in the labor market i.e., employment and real wages respectively for each of the nine Farm Resource Regions (F) regions. The interaction terms (between the driver and its coefficient) on the right-hand side of Equations 3 and 4 capture the impact of the driver on the outcome of interest on the left-hand side for Region F between 2002 and 2017. For example, in Equation 3, $\phi_{L,Z\in FR}\beta_{\phi L,FR}$ represents the change in employment due to the labor supply shock in the Fruitful Rim (FR).

The direction of change for each driver depends on the sign of the coefficient. Equations 5 and 6 show the coefficients of Equations 3 and 4, in terms of the structural parameters. We expect that an increase in labor scarcity is likely to reduce employment $\left(\beta_{\phi L} < 0 \text{ in Equation 5}\right)$, since it drives up the cost of hiring in Equation 4 $\left(\lambda_{\phi L} > 0 \text{ in Equation 6}\right)$. Appendix A provides further details on the derivations including the analytical equations for the non-labor input (Equations A7 and A8), as well as define each of the coefficients in terms of the structural parameters (Equations A9, A10 and A11), along with the expected signs for the coefficients (Table A1).

The coefficients in Equations 3 and 4, should be interpreted as the *average* impact of a 1% change in the driver on the outcome of interest on the left-hand side for region F. The magnitude of the coefficients varies across Farm Resource Regions depending on the structural parameters of production, i.e., cost shares $\left(\theta_j\right)$, price elasticity of either input supply and the elasticity of input substitution (Equation 5 and 6), that underlies each region's responsiveness to the drivers of input use. With perfect information on each of the structural parameters, we could simply calculate the coefficients in the system of equations. However, empirical estimates of changes in input-biased productivity and the labor-substitutability parameter are not well researched in the literature.

An important aspect of the theoretical framework developed here is to explicitly model input biased productivity changes. In the literature, changes in PFP are often defined as the difference between change in output and the change in specific input use. This definition overlooks productivity changes in other inputs and the production structure that allows some degree of factor substitutability. This has led to the use of TFP as the preferred measure of productivity changes, defined as the ratio of change in output to the change in composite input use.

Our theoretical framework identifies a key limitation of using TFP as a measure of changes in factor productivity. When faced with an input specific shock, factor-neutral productivity changes merely adjust the output prices by the change in TFP and do not accurately capture the change in *relative prices* that ultimately determines the substitution effect in Equation 1 (Ray and Hertel 2025a). Further, cross-input impacts of input biased productivity changes are overlooked. Ceteris paribus, the cross-input impacts of input-biased technical change $\left(a_{jZ} > 0\right)$ are always input-conserving, since the other input becomes relatively more expensive. The own-input impacts of input-biased technical change depend on factor substitutability. This further highlights the importance of the factor substitutability parameter, σ.

In this stylized, CES theoretical framework, σ is constant and it dictates the ability of producers to adopt labor-saving technologies. The substitution between capital and labor may be more flexible for field crops in the Mid-West than for labor-intensive crops in California. Prior studies have used national level estimates of capital-labor substitutability for the agricultural sector that are around 0.26 (Aguiar et al. 2019; Wei 2013), and similarly for California (Rutledge and Mérel 2023). This is a critical variable capturing the geographical heterogeneity in our coefficients of interest. To the best of our knowledge, there are no disaggregated empirical estimates of this parameter to explore the potential geographical heterogeneity of agriculture in the US.

Changes in observed employment and input prices reflect a combination of these drivers. Equilibrium conditions require that input demand equals input supply in each region, with supply schedules reflecting both observed price responsiveness and exogenous shifts in supply. We model labor supply shocks as backward shifts in the supply curve for hired workers, due to reduced immigration of fewer Mexican workers (Charlton and Taylor 2016) or due to non-farm activities, such as the construction sector, competing for the same pool of workers through higher wages

(Castillo and Charlton 2023). For land use changes we model the net change in availability of cropland due to localized trends of urbanization and land-use changes in response to bio-fuel policies.

Our theoretical framework emphasizes the interplay between the three drivers of changes in input use which in turn depends on the key structural parameters that shape regional adaptation capacity to labor scarcity. In the next section, we discuss the empirical implementation of this theoretical framework using the SIMPLE-G-CZ model, where we describe our constrained optimization strategy for simultaneously estimating productivity and substitutability parameters (first step) and our decomposition approach (second step) for attributing observed changes to their underlying drivers. The foundations of the SIMPLE-G modelling framework (Haqiqi and Hertel 2025) is based on a multi-input generalization of the stylized two-input framework developed here, which makes it an excellent fit.

4. Empirical strategy

Insights from our theoretical model highlight key challenges in estimating our equations of interest. A major challenge of using econometric methods is omitted variable bias, since we do not observe changes in input-biased productivity. Local unobservable conditions are likely to impact both shocks to input supply and changes in factor-biased productivity. For example, land owners facing stagnation in productivity and low returns to agricultural production may seek alternative land use with higher earnings potential leading to a backward shift in land supply. More dynamic regions may attract more agricultural workers which impacts the labor supply variable. If these changes in productivity are not explicitly accounted for—as formalized in Equations (7) and (8)—

then the error terms $(\varepsilon, \tau, \vartheta, \nu)$ may be endogenous, leading to biased estimates for the coefficients of interest.

(7) $q_{L,Z\in F} = q_{Z\in F}\tilde{\beta}_{q,F} + \phi_{L,Z\in F}\tilde{\beta}_{\phi L,F} + \phi_{R,Z\in F}\tilde{\beta}_{\phi R,F} + \varepsilon_{Z\in F}, where\, \varepsilon_{Z\in F} = \beta_{L,F}a_{L,Z\in F} + \beta_{R,F}a_{R,Z\in F}$

(8) $p_{L,Z\in F} = q_{Z\in F}\tilde{\lambda}_{q,F} + \phi_{L,Z\in F}\tilde{\lambda}_{\phi L,F} + \phi_{R,Z\in F}\tilde{\lambda}_{\phi R,F} + \vartheta_{Z\in F}, where\, \vartheta_{Z\in F} = \lambda_{L,F}a_{L,Z\in F} + \lambda_{R,F}a_{R,Z\in F}$

Some studies have used instrumental variables (Rutledge et al. 2024; Basso and Peri 2015) to address the endogeneity challenge which often leverages geographic variation (Jaeger et al. 2018; Basso and Peri 2015) while acknowledging that they can exacerbate bias (Rutledge and Mérel 2023) and it is nearly impossible to find truly exogenous instruments. The aim of this study is to estimate Equations 3 and 4 as a system, for each of the Farm Resource Regions, specifically to investigate if the impacts of labor scarcity vary across production systems. In this context, econometric estimation also leads to spatial autocorrelation in the error term since the changes in PFP are likely to be correlated across spatial units with similar cropping systems.

Our study adopts a two-step estimation strategy using a numerical simulation approach that leverages the underlying structure of producer decisions. The methodology developed here complements previous econometric efforts and provides a comprehensive analysis of the impacts of labor scarcity across different production systems in the US.

In the first Step, we use a novel constrained optimization strategy to simultaneously estimate changes in factor-biased productivity for labor, resources and intermediate inputs and labor substitutability for each of the Farm Resource Regions, which leverages the cost-minimizing structure of producer decision at a spatially explicit scale embedded in the SIMPLE-G-CZ (Ray et al. 2023) model. We employ the Nelder-Mead Algorithm (Nelder and Mead 1965) which exploits mathematical properties of a N-dimensional Simplex to solve this optimization problem without requiring derivatives, similar to a recent application in Wang (2024). We call this the estimation stage.

In the second Step, we use the estimates from Step 1, additional data on input supply shocks and the SIMPLE-G-CZ model to replicate the observed level of wages and employment in 2017.[4] At the solution, the model reports each element of the interaction terms in Equations 3 and 4 using the decomposition technique documented by Harrison, Horridge, and Pearson (1999). This in turn allows for the identification of each coefficient in our equations of interest.

We discuss each element of this estimation strategy in this Section. We start with the SIMPLE-G-CZ model since it underlies the overall estimation strategy followed by a description of the data used in this study. Then we describe the two-step estimation strategy. We also discuss our approach to systematic sensitivity analysis to handle the different sources of uncertainty in our study (ref Appendix B for additional details).

4.1 SIMPLE-G-CZ: Numerical Model

We use the SIMPLE-G-CZ model (Ray et al. 2023) from the suite of gridded SIMPLE models (Haqiqi and Hertel 2025), which is based on a partial equilibrium framework for the crop producing sector that incorporates spatially explicit details for multiple inputs across different spatial scales. While our theoretical framework is developed with a stylized two-input model, our empirical analysis models aggregate crop output with a nested CES production tree for multiple inputs for each of the 75,000+ grid-cells[5], engaged in crop production in continental U.S. The

[4] The model also replicates changes in land use and rental rates from which we can identify the coefficients in Equations A7 and A8. These are included in discussed in the SM.

[5] We use 5 arc-minute grid cells with uniform arc dimensions (from 6 to 8 km each side) ranging between 36 – 64 square kilometers.

multi-input production structure of the SIMPLE-G model is a higher order generalization of the theoretical framework described above. Aggregate crop output (measured in price-weighted corn-equivalent terms) in a grid-cell is produced with three composite inputs i.e., hired farm workers, resources comprising of land and water inputs and composite intermediate inputs including machinery, seeds, fertilizers, chemicals and other expenditures. Demand for each composite input is as a result of cost-minimization by producers (Equations 1), that interacts with the input supply in each grid-cell (Equation 2) to determine the equilibrium input use and factor prices observed from various data sources, and a zero-profit condition imposes the free entry and exit condition for the crop sector.

This underlying structure of the SIMPLE-G-CZ model is useful in disentangling the different market forces that drive changes in input use as well as the fundamentally unobservable interactions between producer behavior in response to the expansion effect due to higher commodity demand and the substitution effect in response to changes in productivity adjusted relative prices. The parameters introduced in the theoretical section can be considered as a generalized representation of the gridded structure of the SIMPLE-G models capturing location-specific heterogeneity underpinning producer behavior, biophysical constraints on input availability and differences in input intensity across Farm Resource Regions.

In this study, crop output aggregated over grid-cells in the U.S. is sold to both domestic and international commodity demand[6] through an Armington (Armington 1969) trade structure, which differentiates goods by origin and captures bilateral trade flows consistent with structural gravity models of agricultural trade (Grant and Lambert 2008). This structure links producer decisions at

[6] Other countries are aggregated into 16 global regions.

the grid-cell level to the global commodity markets through commodity price changes. The non-linear system of equations is solved[7] to allow for dynamic adjustments in cost shares based on producers' input use decisions.

The SIMPLE-G-CZ model incorporates the recent evidence on restricted labor mobility (Fan et al. 2015; Taylor et al. 2012), by introducing spatially explicit labor markets limiting mobility of workers across CZs and modelling labor supply with an upward sloping supply curve[8], which is in contrast to earlier applications of the SIMPLE-G model (Haqiqi et al. 2023a; Liu et al. 2022; Baldos et al. 2020) that assume perfect mobility of farm workers. The labor markets clear at the local labor-shed level with free mobility of workers within the labor shed. Our analysis models hired labor as an aggregate of different types of hired workers to get accurate estimates of input-biased productivity changes. This simplifying assumption implies that our results do not differentiate the impacts of changes in labor supply for key categories of workers, such as domestic workers, those hired through FLCs or the H-2A program. We focus our analysis at this level due primarily to data availability and low incidences of employment for some worker types (like H-2A guest workers) in the first half of our study period (Hill et al. (2024). Considering labor at this aggregated level, our analysis provides important insights on the impacts of labor scarcity for the average farmworker, abstracting away from a key adaptation strategy of changes in the mix of hired workers typologies. The changes in real wages does reflect the higher cost of hiring through the H-2A program and/or FLCs at the aggregate.

Natural resource inputs, both land and water, are explicitly modelled in the SIMPLE-G-CZ model considering a detailed nested CES structure informed by observations and biophysical simulations.

[7] The SIMPLE suite of model is solved with the GEMPACK software designed for economic models defined by algebraic representation of model equations (Horridge et al. 2025) .
[8] Based on latest review by Hill, Ornelas, and Taylor (2021)

We obtain data to inform cropland area from satellite (NLCD and MIrAD) and yield from the CoA and crop models; water withdrawal information is from USGS, and the value of water is approximated considering irrigated yield gap for all crops at each grid cell (Wickham et al. 2021; Pervez and Brown 2010; Haqiqi et al. 2023b; Haqiqi 2023). The markets for resource inputs clear at the grid-cell level.

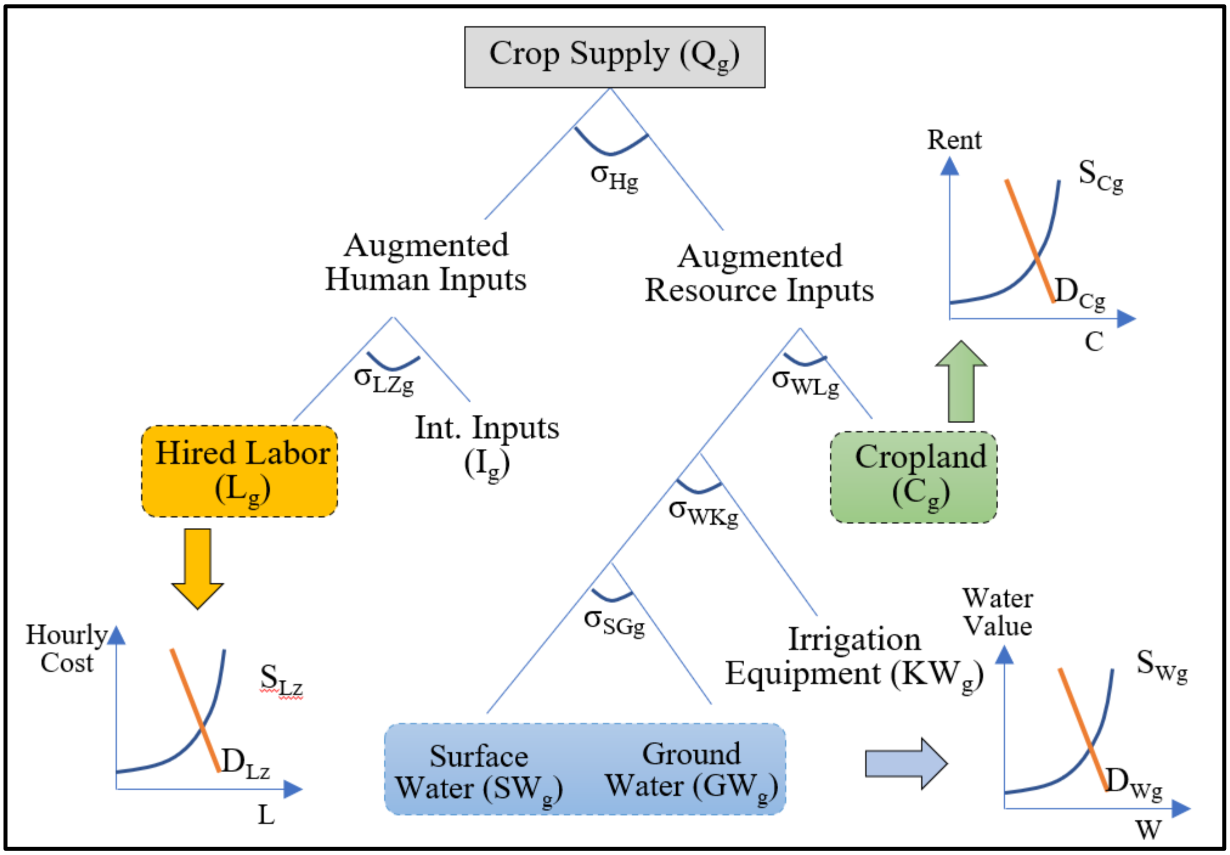

Figure 1: Structure of the CES production structure in SIMPLE-G-CZ (Ray et al. 2023). The supply of each input is modelled with an upward sloping supply curve where the slope depends on price elasticity of supply i.e., e_j, substitution between the pair of inputs in a nest is determined by the substitution elasticity i.e., σ, changes to input supply are modelled with shifts in the supply curves and changes in PFP i.e., a_j, is applies to each input.

Other inputs—including machinery, seeds, chemical inputs, and unpaid labor—are modeled as a composite intermediate input to keep the model tractable. Under tightening labor market conditions, the ability to substitute hired labor with non-resource inputs represents a key adaptation pathway for producers. We model this substitution potential using a Farm Resource Region–specific labor substitutability parameter in the nest for Augmented Labor (Figure 1). This allows substitutability to vary across regions in line with differences in production systems and labor intensity. Ref Haqiqi and Baldos (2025) for detailed discussion of benchmark parameters estimated across several peer-reviewed papers.

4.2 Data

The benchmark data for the SIMPLE-G-CZ model draws from various sources. The Census of Agriculture (CoA) provides details on crop output, harvested cropland, land rents, payroll costs for hired workers, and use of intermediate inputs. We supplement this data with hired labor wages (US DOL NAWS 2023) from the National Worker Sample Survey (NAWS) and details on water use from the United States Geological Survey (USGS). We focus our discussion on measuring the changes in labor markets including employment, wages and labor supply shock. Additional details on other variables are included in Appendix C in the SM.

We measure employment in terms of hours to account for differences in the intensity of work across types of hired labor. While the CoA provides data on the number of directly hired workers, it only reports the payroll costs of contract workers. Moreover, directly hired and contract workers differ significantly in duration of employment over the year, making headcounts an incomplete measure of hired labor use (Hill et al. 2024). We estimate hours of employment of directly hired workers in each county by dividing payroll costs of hired workers in the county (available from the CoA) with the average wages for hired workers in the corresponding Farm Resource Region (author's calculations from the NAWS). We use a similar approach for contract hours. We consider that the hourly cost of hiring contract workers is equivalent to hired wages, inflated by additional costs to the employer due to contracting fees, administrative costs and living costs. To the best of our knowledge there is no data on commission rates for contract farm labor services, but existing estimates in California suggest that these range from 30 to 50 percent (Martin, 2014; Martin, 2025). Because these rates are likely to differ across states, due to differences in payroll tax rates and business operating expenses, we apply the lower bound of these commission rates (assuming a 30% inflation of costs for contract labor) but consider a range from 20 to 50 percent to account for measurement error. Finally, we calculate long term change (10-year average around the end-points) in employment and real cost of hiring labor between 2002 and 2017 for each CZ.

The supply shock to the hired farm workforce is not directly observable. We approximate it by considering the distinct drivers affecting domestic and immigrant labor. For domestic workers, demographic and structural shifts have reduced mobility (Fan et al. 2015), while rising real wages in construction—an alternative local employment option—have drawn workers away from agriculture. Castillo and Charlton (2023) show that construction booms reduce the availability of local crop workers, increasing reliance on H-2A contract labor. Accordingly, we use changes in real construction wages from the QCEW (BLS 2025b) to proxy shifts in domestic labor supply at the CZ level.

The supply of immigrant workers, primarily from rural Mexico, has declined due to economic transformation in Mexico and stricter immigration policies in the US. Charlton and Taylor (2016), using nationally representative rural household panel data, estimate an average annual decline of over 150,000 Mexican farmworkers from 1982 to 2010, driven by falling rural fertility, expanded non-farm employment, and rising education. While their estimated supply trend for US agriculture is imprecise (0.4% annually; 95% CI: -1.8 to 2.6), we adopt a central estimate of a 1% annual decline and consider two additional scenarios: -0.6% and -1.7%. The aggregate labor supply shift in each CZ is computed as the weighted sum of changes in real construction wages and reduced immigrant labor, using domestic employment shares from the US Decennial Census.

Between 2002 and 2017, government subsidies for ethanol production and blending mandates led to a boom in the demand for corn and soybeans (Wang and Khanna 2023; Duffield and Xiarchos 2015). This led to an increase in acreage under field grains which impacted the major grain growing regions. We estimate the change in land use as the share of cropland what was being used as pastureland or was fallow (including under the Conservation Reserve Program) in a county in 2002 and was converted to cropland in 2017. We also consider the impacts of urbanization that reduced available land for agriculture using high resolution data from the USGS.

4.3 Simultaneous Estimation of Unknown Parameters: First-step of empirical strategy

In the first step of our empirical strategy, our goal is to simultaneously estimate a vector of unknown parameters, i.e., changes in input-biased factor productivity $\left(a_{jF}\right)$ and labor substitutability $\left(\sigma_F\right)$. In the multi-input structure of the numerical model, we estimate, changes in productivity of three major inputs i.e., hired labor $\left(a_{L,F}\right)$, resources $\left(a_{R,F}\right)$ and intermediate inputs $\left(a_{I,F}\right)$ which includes machinery amongst other manufactured inputs, for each Farm Resource Region (F).

We design a constrained optimization approach (Equation 9) to estimate $X = \left(a_L, a_I, a_R, \sigma\right)$, by minimizing deviations between simulated and observed input use in 2017. The objective function is defined as the cost-share weighted sum of absolute deviations between observed and simulated input use $\left(Q_L^{sim}, Q_C^{sim}, V_I^{sim}\right)$ across all CZs within each Farm Resource Region, constrained by the observed factor prices and aggregate production in each CZ $\left(\overline{P_L^{17}}, \overline{P_I^{17}}, \overline{P_C^{17}}, \overline{Q^{17}}\right)$ in 2017. The simulated values are calculated by updating the observed data on input use in 2002 with the predicted percentage change simulated from the SIMPLE-G-CZ model for the period 2002 to 2017. At the global minimum of our objective function (where $\Im(X)=0$), we find the best fit for the vector of unknown parameters, conditional on model parameters (Ω).

(9) $$X_F^*\left(a_L^*, a_Z^*, a_R^*, \sigma_L^* \mid \Omega\right) = \underset{runs=30}{median}\left[\min_X \Im(X)\right]$$

where, $\Im(X) = \sum_{CZ\in F}\left(\tilde{Q}_{L,CZ} * \theta_{L,CZ}\right) + \sum_{CZ\in F}\left(\tilde{V}_{Z,CZ} * \theta_{Z,CZ}\right) + \sum_{CZ\in F}\left(\tilde{Q}_{C,CZ} * \theta_{C,CZ}\right)$ subject to $\tilde{Q}_{L,Z}=0, \tilde{V}_{I,Z}=0, \tilde{Q}_{C,Z}=0, P_{L,Z}=\overline{P_L^{17}}, P_{I,Z}=\overline{P_I^{17}}, P_{C,Z}=\overline{P_C^{17}}, Q_W=\overline{Q_W^{17}} \text{ and } Q=\overline{Q^{17}}$ for Farm Resource Region (F)

Since the objective function is defined over model generated values, it is not differentiable precluding us from using traditional derivative based optimization methods. Here the Nelder-Mead algorithm (Nelder and Mead 1965) offers a derivative free optimization approach, exploiting the properties of a N-dimensional 'simplex', recently used to estimate unknown parameters that govern land-use decisions (Wang 2024). The algorithm is initialized with N+1 values for a vector of N unknown parameters. We use regionally disaggregated estimates of TFP by Haqiqi et al. (2023) for the unknown PFP parameters and 0.26 for the labor substitutability parameter to initialize the algorithm. The algorithm updates the initial values by exploring the solution space, determined by the initial values, to minimize the value of the objective function.

4.4 Historical Replication: Second step of empirical strategy

Having estimated the PFP and labor substitution parameters, we are in a position to analyze the historical period of interest: 2002-2017. In Step 2, we test the unconstrained model's ability to endogenous reproduce observed levels of input use and factor prices. We employ the numerical integration technique developed by Harrison, Horridge and Pearson (1999) which allows us to isolate the magnitude of each of the interaction terms on the RHS of Equations 3 and 4. We identify the coefficients of interest by normalizing the interaction terms over the corresponding driver.

The combination of data sources used in this study provides a comprehensive description of the long-term trends in input use and factor payments for crop production between 2002 – 2017. However, there exists some uncertainty in key data points that are based on survey data, as in the NAWS, or is fundamentally unobservable in which case we use the next best alternative like in case of the shocks to labor supply. Further, our coefficient estimates are based on the first stage estimates from a constrained optimization strategy that can stabilize around a local minimum based on the initial values. In these cases, we conduct bounding analysis using 3 (low- median – high) values. The coefficient estimation for Equations 3 and 4 discussed in the next Section is based on 81 potential parameter combinations. Using the methodology developed in Arndt (2000), we run the historical replication for the 81 potential parameter combinations and present the median and 90 percentile range around it. The median is more representative of the range of values since it is less sensitive to extreme values (ref Appendix B for further details).

5. Empirical Findings

This section discusses the results for four Farm Resource Regions which exemplify contrasting responses to labor scarcity due to differences in cropping systems. While our discussion here focuses on the Heartland, Northern Great Plains, Northern Crescent and Fruitful Rim, Appendix D includes detailed analysis for all nine Farm Resource Regions.

5.1 Changes in crop production, input use, input prices and supply shocks 2002 – 2017

Before discussing the empirical results, we present a brief discussion of the long-run trends in the commodity and labor markets, disaggregated by Farm Resource Regions over the 15-year study period. The changes are calculated as multi-year averages (based on available data) centered around 2002 and 2017..

Between 2002 and 2017, aggregate crop production rose by 17.5% (Authors' calculation), while real, quality-adjusted prices increased by close to three times, at 49.7% (Wang et al. 2024), with notable crop specific variation (Figure 2). The real grain price increase (46.5%) was around the average for aggregate crops. The increase in the real price for vegetables, fruits and nuts was much higher at 72.5% and 127.7% respectively. Despite these sharper price increases for non-grain crops, grain production increased at a higher rate by 27.3%, while vegetable production declined by 15.8% and fruits and nuts production remained flat (a 5.2% increase). This implied that increases in grain production dominated the increases in value and production from the crop sector (Figures D1.1 and D1.2 in Appendix D in SM).

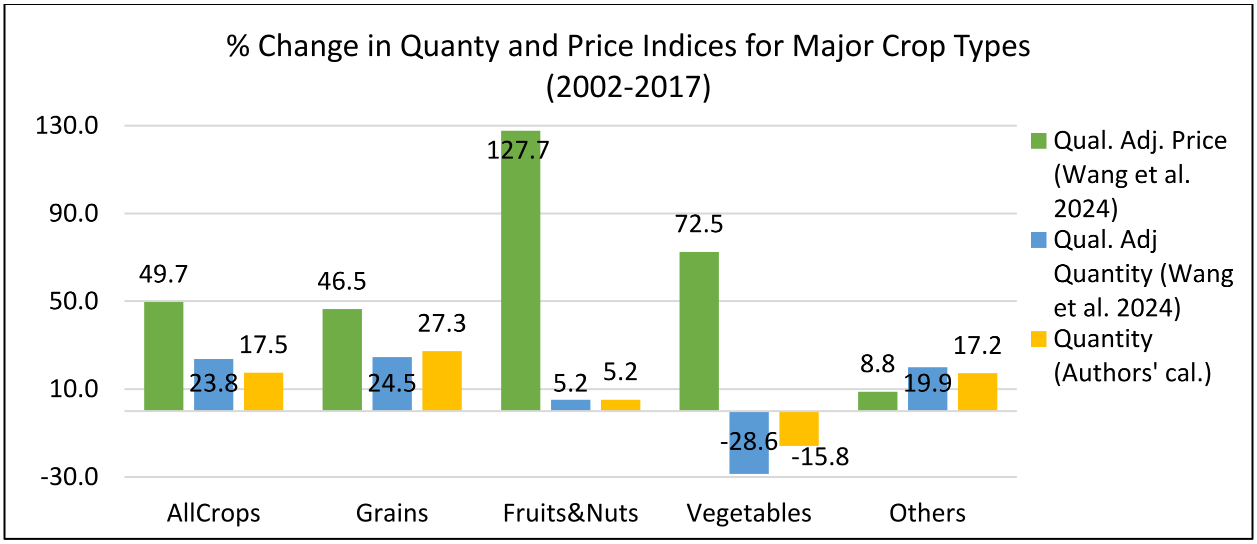

Figure 2: A comparison of the changes in quality adjusted commodity prices and production for major crop categories. The analysis in this study uses county level data from the CoA and quality adjusted national price indices (green bars) for major crop types reported by USDA (Wang et al. 2024), to calculate CZ level changes in production and real prices for grains, fruits & nuts, vegetables and other crops. This figure shows a comparison of the national level aggregate based on these calculations (yellow bars) and the corresponding reported values from the USDA (blue bars) presented in Wang et al. 2024. Appendix C in SM provides additional details.

These crop-specific differences in the changes in production, implies important regional variation in the expansion effect (Table 2). The expansion effect had an above average impact on the Heartland and Northern Great Plains (18.1 – 50.5%) where grain production was dominant (83 – 91% of the value of all crops) as well as the Northern Crescent (29.1%) where grain production increased by 60.1% displacing specialty crop production which fell by 15.8 – 79% during the study period. The increases in grains production (blues in Figure 3B) versus decline in specialty crops (reds in Figure 3C) production in the Northern Crescent, particularly in Western Michigan and Upstate New York indicate a change in the crop-mix, where labor -intensive fruits, nuts and vegetable is replace by more filed crop production. Recently, Bardenhagen et al. (2025) also reported a 11% loss in specialty crop acreage in the state of Michigan within the Northern Crescent.

Table 2: Characteristics of production systems and long-term trends for the crop sector (2002 – 17)

	Heartland	**Northern Great Plain**	**Northern Crescent**	**Fruitful Rim**	**US**
(1)	(2)	(4)	(4)	(5)	(6)
% Change in aggregate crop output	18.10	50.50	29.10	5.40	17.50
% Change in grains output	19.80	46.10	60.10	-10.60	27.30
% Change in fruit and nuts output	-72.00	7.00	-79.00	15.00	5.20
% Change in vegetable output	-28.30	-23.60	-15.90	-14.80	-15.80
% Change in other crop output	5.30	86.60	31.00	13.20	17.20
% Change in employment of hired labor hours	31.20	19.00	12.50	3.10	7.00
% Change in real cost of hiring labor	11.90	31.50	20.10	26.30	23.00
% Change in labor supply	0.41	0.55	0.30	0.74	
Labor supply shock (in million hours)	13.7	6.0	42.1	720.1	
% Change in harvested cropland	0.78	10.64	-0.62	-4.96	0.59
% Change in real rental rate	81.2	68.3	57.9	66.8	38.5
% Cropland supply shock	-2.13	-5.81	-0.91	0.65	-4.28
Cropland supply shock (in million ha)	-0.99	-1.70	-0.12	0.08	7.42

Note: This tables shows key trends in the input and output markets for four production regions. Consistent with the theoretical framework, where backward shift in input supply shock is introduced in Equation 2, positive values for the supply shock should be interpreted as is backward shift and vice versa. Details for all production regions are included in Table D2.3 in SM.

As national growth in fruits and nuts production stagnated and contracted for vegetables, it translated to a lower-than-average expansion effect in Fruitful Rim (5.4%) which is the largest producer of specialty crops and along with Northern Crescent contributes 88% of the national value of these crops. Within-region spatial variation in specialty crop production in the Fruitful Rim (Figure 3C) suggest increased concentration in the Central Valley where production grew by up to 40% and contracted in other parts of the region, including traditional specialty crop growing regions in Oregon, Washington and Florida (Figure 3C).

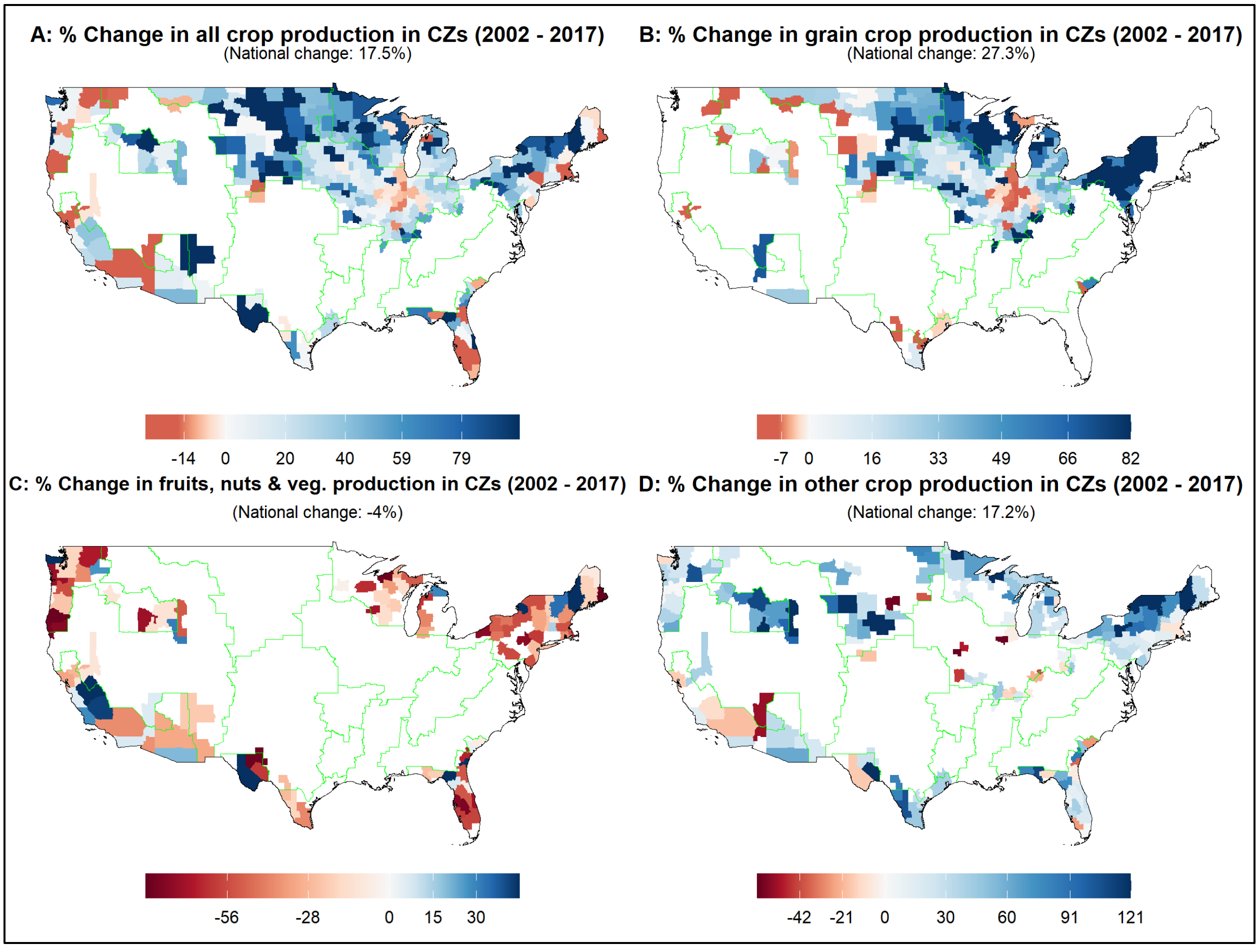

Figure 3: Percentage change in aggregate and major crop production (2002-2017) at the CZ level for four Farm Resource Regions. Panel A shows the change in aggregate (price weighted, corn-equivalent) crop production and Panels B, C and D shows disaggregated the changes in grains, specialty crops and other crop production respectively. Panel B, C and D shows the CZs where the value share of corresponding crops is greater than 15% in the CZ to suppress large percentage changes over small base values.

While grain-producing regions broadly experienced expansion during the study period, driven in part by biofuel policy shifts (Hertel and Baldos 2016; Hertel and Tyner 2013), the Northern Great Plains stands out. Since it accounted for a smaller share (10%) of national grain production, it experienced higher percentage increases compared to the Heartland, the nation's primary grain-producing region. Further, harvest cropland area in Northern Great Plains increased by 10.6% and 1.7 million hectares of land was converted into cropland, which is by far the largest across all other Farm Resource Regions. During the same period, the expansion of hydraulic fracturing in the

Northern Great Plains (Fitzgerald et al. 2020) intensified competition for labor by drawing from the same pool of workers that supply farm labor. As a result, crop producers undertaking expansion in production faced compounded labor shortages—amplifying national trends due to additional pressure from non-agricultural employers.

Nationally, the average cost of hired farm labor rose by 23% over the study period. In the Fruitful Rim and Northern Great Plains, labor costs increased even more—by 26.3% and 31.5%, respectively. The disproportionate increase in hourly hiring costs in the Northern Great Plains may reflect the combined effects of expanding agricultural output and intensified competition for labor from the fracking sector. Further, employment in Heartland (31.2%) and Northern Great Plains (19%) also increased more than the national level average (7%). In the Fruitful Rim region, the cost of hiring labor increased more than the national average (26.3%) while employment (3.1%) increased by less than the national average, suggesting tightening labor market.

The within-region spatial variation in changes in employment, provides further evidence for increased concentration of specialty crop production in the Central Valley where employment increased modestly (Figure 4B) and fell in Southern California and Florida where specialty crop production also fell (Figure 3C). Note that in some regions of the Fruitful Rim in the Pacific Northwest, overall crop production decreased (reds in Figure 3A) and hired labor hours appears to have increased (blues in Figure 4A), suggesting higher hired labor requirement for each unit of output.

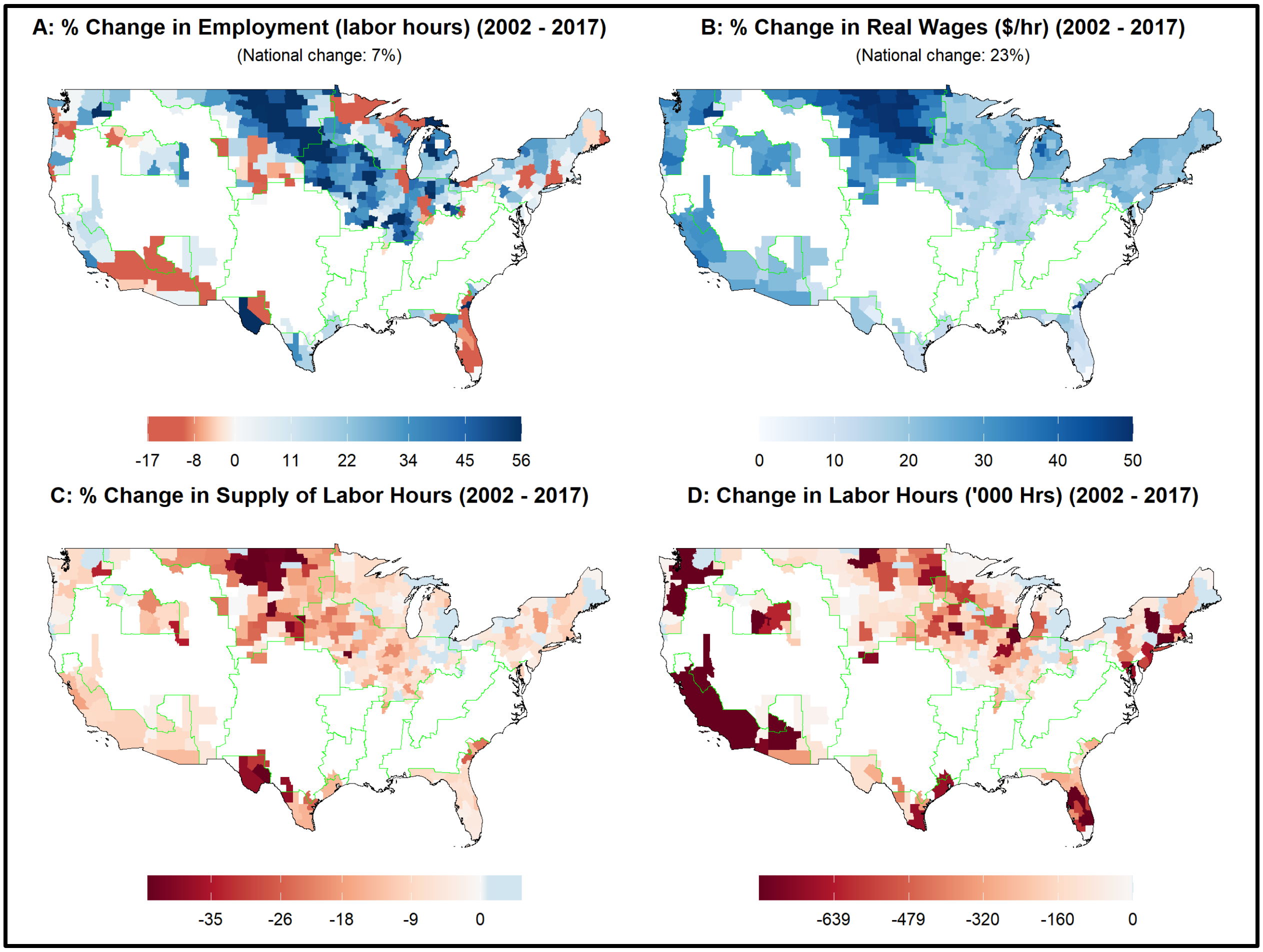

Figure 4: Changes in the labor market between 2002 – 2017. Panel A shows that percentage change in hired labor hour. Panel B shows the percentage change in real wages. Panels C and D shows the changes in labor supply. The reduction in labor supply is measured as the shift in the labor supply schedule. Panel C shows the relative changes in labor supply. Panel D shows the number of fewer labor hours available.

Across all regions, workers hired through FLCs contributed disproportionately to the increase in hired labor hours (Figure D1.4 in SM). This is consistent with other studies that show a decline in directly hired workers as well as a steady increase in the role of FLCs to match employers with scarce farmworkers (Hill et al. 2024; Wang et al. 2024). This underscores the importance of including all hired workers including through FLCs, since ignoring it would severely undercount the contribution of hired labor in the total cost of crop production and the direction of change in employed labor hours would be imprecise in some cases.

The relative impact of labor supply shock, measured as the number of fewer labor hours available to hire relative to 2002 baseline of employed labor hours, is the largest in the Fruitful Rim region at 0.74%, followed by the Northern Great Plains at 0.55%. In relative terms, regions in North Dakota show the highest impact of the labor supply shock at more than 35% fewer labor hours available. In absolute terms, the largest impacts are observed in the Fruitful Rim region. However, some CZs in Northern Great Plains, Heartland and Northern Crescent also show modest impacts of labor scarcity even in absolute terms. This provides further evidence, that states beyond California and regions other than the Fruitful Rim have been grappling with labor scarcity. Agricultural land supply in the Fruitful Rim region declined by 0.65% or a net of 80,000 fewer hectares in crop production which can be attributed either to fallow cropland due to declining water availability or conversion to developed land due to urbanization. In other regions cropland supply increased, primarily in response to biofuel polices.

5.2 First Stage Results: Changes in Partial Factor Productivity and Labor Substitutability

The first stage estimation results of this study show stark geographical heterogeneity in input-biased productivity changes across Farm Resource Regions in the U.S. between 2002 and 2017 (Figure 5). The TFP changes in crop productivity from our analysis tracks the geographical heterogeneity reported in overall agricultural productivity changes in Wang et al. (2024)[9]

[9] Note, that state wise TFP reported in Wang et al. (2024) includes the livestock sector while our analysis focuses on the crop sector. Since crop-sector specific sub-national estimates of TFP are not available from an alternative source, this is the next best alternative to compare the implied TFP from our first stage PFP estimates.

Amongst the focus regions for our analysis, the highest increase in labor productivity is estimated in the Northern Great Plains at 50.1% and quite low (5 – 7%) for the other regions over the 15-year period. We find that the increase in TFP (9 – 10%) for the specialty crop growing regions are mainly driven by increases in resource productivity. In the Heartland, our analysis suggests that TFP growth was stagnated due to low PFP growth for all three inputs. Nationally, our analysis suggests that the highest growth in TFP (28 – 58%) for the crop sector was observed in the Southeastern regions (including Eastern Uplands, Southern Seaboard and Mississippi Portal) with relatively higher increases in labor productivity (62.9 – 85.3%) (ref Figure D2.1 in SM). However, these regions together contribute to less than 13% of national value of crop output and employ less than 15% of hired labor hours.

Our earlier discussion of changes in output and input use across Farm Resource Regions provides some intuition to explain the region pattern in productivity changes. In the Fruitful Rim region, we find that the increase in production and employment was relatively small and cropland use decreased (Table 2). This suggests that producers in the region continued to meet the demand for fruits, nuts and vegetables while conserving (or fallow/retire/build-up) cropland and faced with severe scarcity in water for irrigation, which is reflected in higher resource productivity but inherent limitations in the production system from substituting away from scarce labor inputs is likely to have limited growth in labor productivity. In contrast producers in the Norther Great Plains could adapt to compounding sources of labor scarcity while they responded to the expansionary pressures for output demand such that growth in output was disproportionately higher than the increase in input use. This is reflected in higher PFP growth in the region. The stark geographical variation in productivity change, implies that the ability of producers to adapt to labor scarcity varies across the Farm Resource Regions

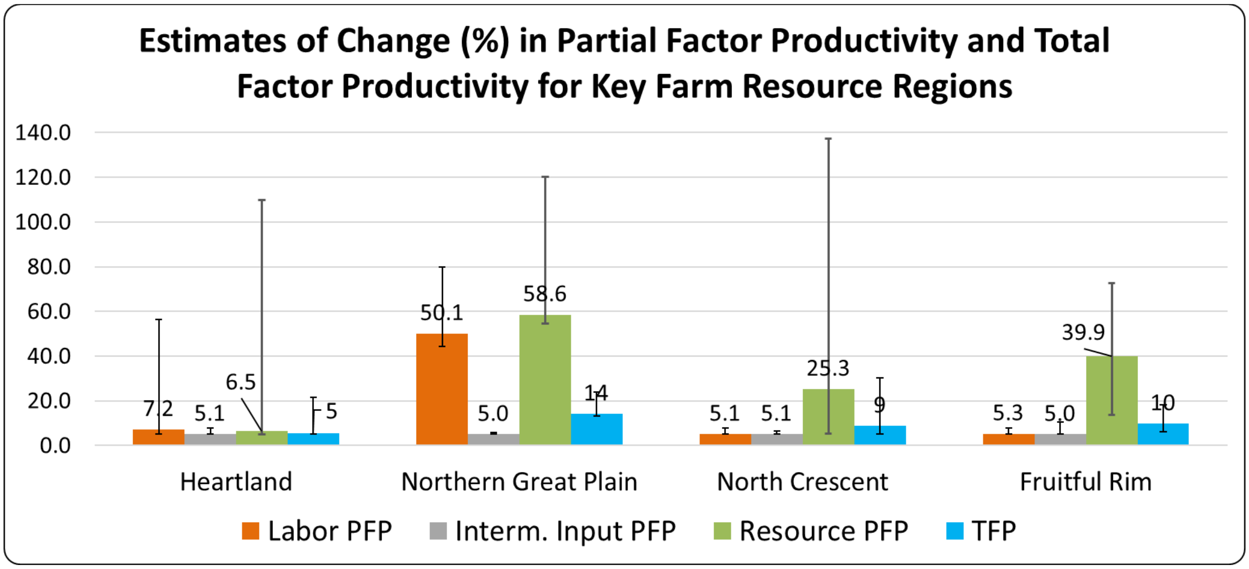

Figure 5: Changes in partial factor productivity in the crop sector for three major inputs (bars) and the estimates of labor substitutability for ten Labor-sheds. The bars and points show the median value and the whiskers show the range of solutions over thirty iterations of the Nelder-Meade algorithm.

While we find stark geographical variation in productivity changes, estimates of labor substitutability is notably stable across the production regions around previous estimates in the literature of 0.26 (Figure D2.2 in SM). However, the potential range is systematically large suggesting the labor substitutability parameter between 0.15 – 0.4 fits with the observed changes in the crop sector during our study period. This finding does not necessarily tell us about regional differences in labor substitutability parameter but it also does not reject the hypothesis that it varies across regions.

5.3 Second Stage Results: Validation, historical decomposition and responsiveness to drivers of change

To validate the full model using the estimates from the first stage, we show that the simulated number of hired labor hours (Figure 6A) and cost of hired labor for 2017 (Figure 6B) track closely with the estimates from the observed data, across Farm Resource Regions. In this comparison we present uncertainty introduced in our first stage estimation as well as uncertainty in the data (ref Appendix B for details on uncertainty analysis in this study). It is important to note here, that these may not fully capture the measurement error because of data limitations related to the workers included and excluded in the NAWS sample—the NAWS does not include H-2A workers and includes a smaller share of contract workers than other data sources suggest—and due to reporting and measurement error in the NAWS—alternative data sources produce very different measures of farm wages and employment that are not rectified using within sample standard errors alone (see, discussions in Costa et al. 2020 and Hill et al. 2024).

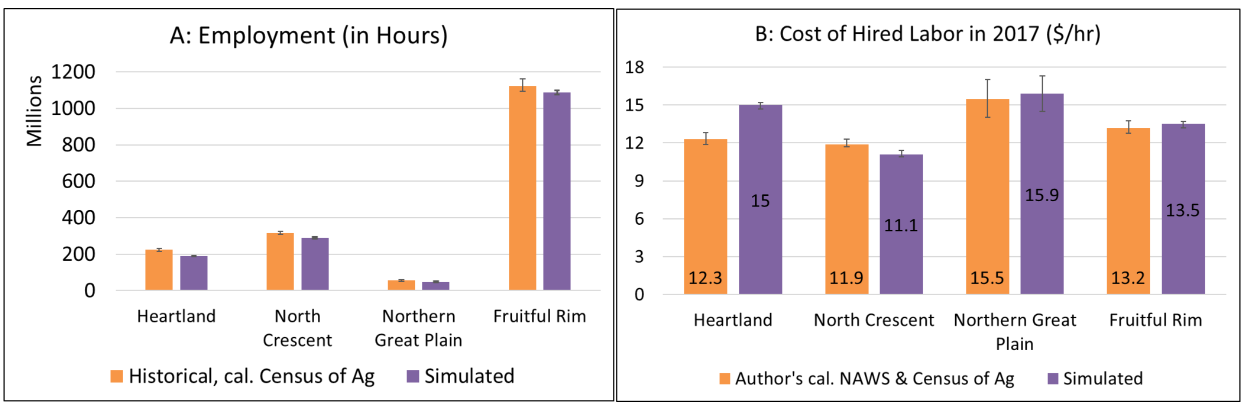

Figure 6: Comparison between observed and simulated employment and hourly cost of hired labor in 2017. The bars show the average calculated (orange) and the simulated employment of labor hours (purple) around the mean and median estimates respectively. The whiskers show the 95% confidence interval around the mean and percentile around the median. Ref Appendix D in SM for similar figures for other inputs.

In the second stage of our analysis, we decompose the observed changes (Harrison et al. 1999) in terms of three drivers (Table 3), i.e., interaction terms in Equations 3 and 4. Finally, we report the coefficient estimates (Figure 7) for the drivers on labor market outcomes, which normalizes the interaction term by the magnitude of the driver. These coefficient estimates capture the responsiveness of labor market outcomes to the drivers.

Table 3: Decomposition of changes in real cost of hiring labor and employment between 2002 and 2017

		Heartland	Northern Great Plains	Northern Crescent	Fruitful Rim
1	Cost of hired labor in 2002 $\left(P_{LF}^{2002}\right)$ (2002 \$/hour)	8.0	8.6	7.2	7.6
2	Cost of hired labor in 2017 $\left(P_{LF}^{2017}\right)$ (2017 \$/hour)	12.3	15.5	11.9	13.2
3	% Change in real cost of hiring labor $\left(p_{LF}\right)$	15.3	37.3	22.3	27.3
4	Expansion effect $\left(q_{F}\right)$	12.5	50.1	20.1	23.7
5	Labor productivity $\left(a_{LF}\right)$	-2.3	-30.4	-6.7	-5.3
6	Resource productivity $\left(a_{RF}\right)$	-0.5	-1.2	-1.2	-0.8
7	Intermediate input productivity $\left(a_{IF}\right)$	-0.2	-2.6	-0.8	-1.3
8	Land supply shock $\left(\phi_{CF}\right)$	-0.1	-0.7	0.1	0.1
9	Labor supply shock $\left(\phi_{LF}\right)$	3.6	17.1	5.3	12.5
10	Employment in 2002 $\left(Q_{LF}^{2002}\right)$ (Million Hours)	171	46	281	1091
11	Employment in 2017 $\left(Q_{LF}^{2017}\right)$ (Million Hours)	224	55	316	1124
12	% Change in Employment $\left(q_{LF}\right)$	31.6	19.2	12.9	2.9
13	Expansion effect $\left(q_{F}\right)$	39.7	135.8	17.9	13.1
14	Labor productivity $\left(a_{LF}\right)$	-8.9	-98.0	-8.6	-4.6
15	Resource productivity $\left(a_{RF}\right)$	-2.1	-3.7	-1.5	-0.6
16	Intermediate input productivity $\left(a_{IF}\right)$	-0.7	-8.1	-0.9	-1.1
17	Land supply shock $\left(\phi_{CF}\right)$	-0.3	-1.9	0.2	0.1
18	Labor supply shock $\left(\phi_{LF}\right)$	-5.0	-19.9	-1.0	-2.7

Note: Rows 1,2 show the hourly cost of hiring labor in 2002 and 2017 in current dollars and Row 3 shows the percentage change, assuming an 37% consumer price inflation (BLS 2025a). Rows 10, 11 and 12 shows similar calculation for employment. For each Farm Resource region, aggregating across Rows 4 – 9 approximately equals to the relative change in hourly cost of hiring labor. Any difference is due to other exogenous controls (change in water use and cost of using intermediate inputs) in the historical validation run that are suppressed here for conciseness. Similarly, Rows 13 – 18, approximately equal the relative change in employment for each Farm Resource region.

The expansion effect is the largest driver of employment and hiring costs for each of the four production regions with the largest impact in the Northern Great Plains during its expansionary period (Table 3). The expansionary market forces in the region led to a 50% increase in cost of hiring workers and 135% increase in total hired labor hours. In contrast the expansion effect has a relatively muted impact in the Fruitful Rim, which increased wages by 23.5% and employment by

13.1%. However, since the magnitude of the expansion effect varied across regions, the coefficient estimates in Figure 7 is a more accurate measure for the responsiveness of labor market outcomes to the expansion effect.

We find that wages are more responsive to expansion effect in the Fruitful Rim, where 1% increase in demand for specialty crops leads to a 4.4% increase in hourly wages, relative to the other regions (0.6% - 0.8%). This suggests that even modest increases in future demand for domestic production of fruits and vegetable, which may be expected under the proposed import tariffs (Najmabadi 2025), could significantly increase cost of production amongst specialty crop producers. The median estimates for responsiveness of employment, to 1% increase in commodity demand is about 2 – 2.9%, with the exception of Northern Crescent at 0.5%. This suggests that producers across all production systems rely on hiring additional workers to meet higher commodity demand. In case of Northern Crescent, the smaller coefficient estimate may reflect the changing crop-mix in the region away from labor intensive production systems.

Following the expansion effect, the labor supply shock is the second most important driver of wage increases while reducing employment. The magnitude of impact of the labor supply shock is the highest in the Northern Great Plains leading to a 17.1% increase in wages and 19.9% reduction in employment.

In the Fruitful Rim region, that faced the highest absolute impacts of the labor supply shock (Figure 4D), it led to a 12.5% increase in wages and relatively small impact on employment at -2.9%. This suggests that given the nature of labor-intensive production systems and limited availability of labor savings technologies, producers in the region tend to bid up wages to retain workers. Coefficient estimates for the labor supply shock shows wages are more responsive and

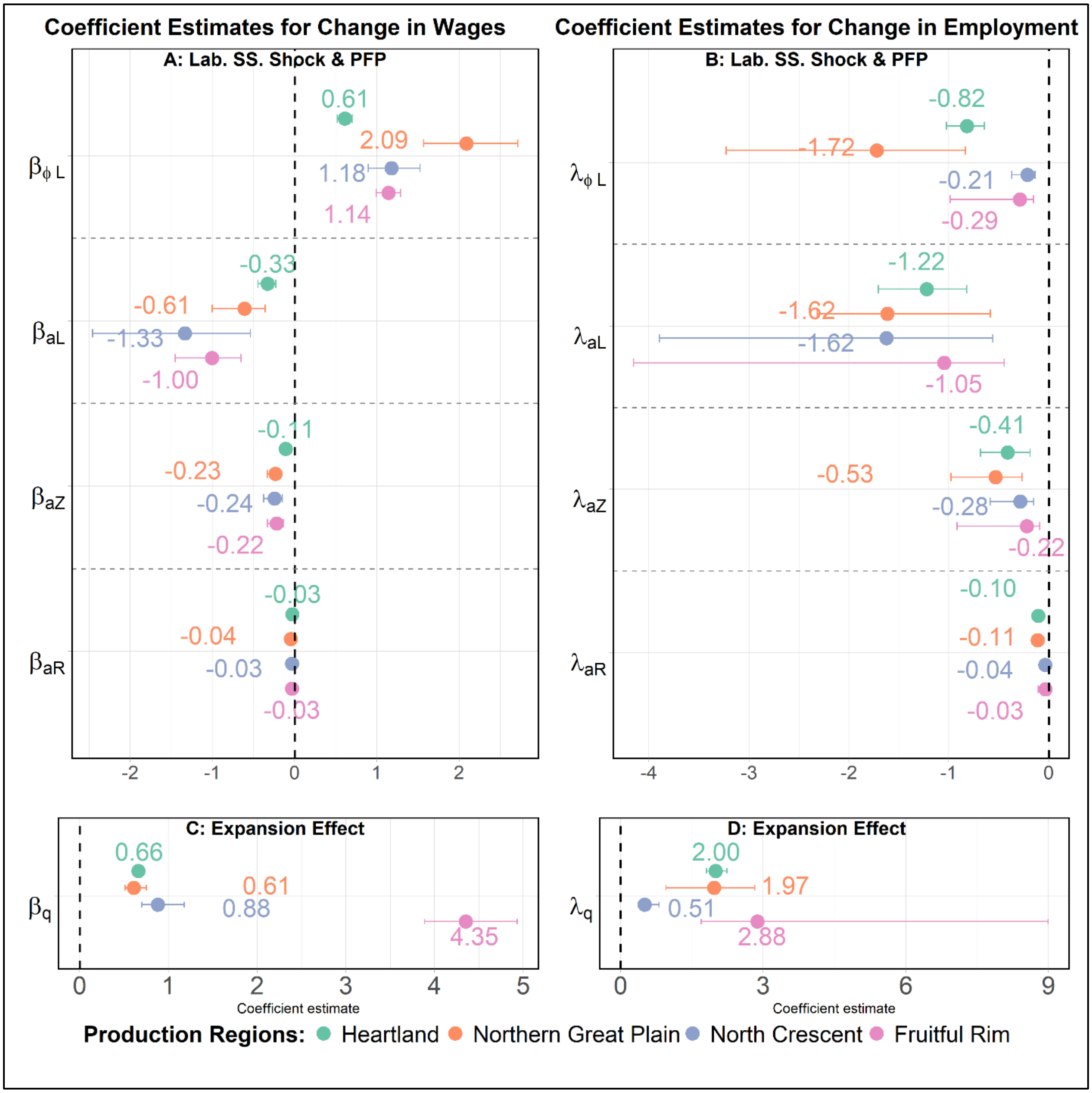

Figure 7: Coefficient estimates for Equations 3 and 4. The point estimates, i.e., the median value for 81 parameter combinations and their 90th percentile range are color coded for the four major Farm Resource Regions. Panel A shows the coefficient estimates for changes in cost of hiring (Equation 3) and Panel B shows the coefficient estimates for changes in hired labor hours (Equation 4). Similar plots for cropland and intermediate inputs are included in Appendix D in the SM.

employment is less responsive in labor-intensive production systems, with the notable exception of Northern Great Plains which faced compounding sources of labor scarcity during the period of our study (Figure 7). For a 1% increase in labor supply shock, wages increased by 1.1 – 1.2% and employment fell by 0.2 – 0.3% in the Fruitful Rim and Northern Crescent relative to 0.6% increase in wages and 0.8% reduction in employment in the Heartland. The implied price elasticity of labor to labor supply shock ranges between 0.18 – 0.23 in labor intensive production systems which are within the range of recent estimates by Li and Reimer (2021), Richards (2020), and Hill (2020). It also reinforces recent evidence from California that highlights wage increases as the primary adaptation strategy to labor scarcity among these producers (Win et al. 2025).

Our theoretical framework shows that the input supply shock increases own- and cross-input factor prices (ref: Figure D2.6 in SM). The empirical estimates imply that if the 1% increase in labor scarcity estimated by Charlton and Taylor (2016) is sustained over the next 10 years, it would increase hiring costs by 11.4% in the Fruitful Rim and 6% in the Heartland.

While the expansion effect and labor supply shock increase wages, higher productivity of workers leads to a reduction in hiring costs and conservation of workers, as expected from the theoretical framework. The larger increases in labor productivity in the Northern Great Plains (Figure 5) lead to relatively higher labor conservation (-98%) and lowers hiring costs (-30.5%) in the region. This suggests that as agricultural production expanded in the region, labor productivity also improved, leading to more output per hired labor hour. The impacts of labor productivity were more modest in the other regions given the smaller estimates of labor-biased productivity growth. The magnitude of impact of PFP changes in resources and intermediate goods are small across all regions.

The estimated coefficients for labor productivity indicate that, in the Fruitful Rim, wages and employment respond proportionately to a 1% reduction in labor supply. In contrast, the Heartland shows a smaller wage response (-0.3%) and a larger employment response (-1.2%), suggesting different adjustment mechanisms across regions (Figure 7). In large-scale, grain-dominated systems like the Heartland, gains in labor productivity tend to have a stronger labor-conserving effect but a weaker cost-saving effect. The coefficient estimates for the Northern Crescent stands out with a disproportionate reduction in wages and employment which may reflect the previously discussed changes in the crop-mix during the study period. The general pattern observed here imply that improving labor productivity in labor-intensive systems—such as those in the Fruitful Rim—can help offset the employment pressures associated with limited farm labor supply, while also lowering production costs. However, the adoption of labor-saving technologies remains challenging for highly perishable fruit and vegetable crops, where maintaining product quality adds further constraints.

6. Discussion and Conclusion

This study provides the first spatially disaggregated, theoretically grounded analysis of how U.S. crop producers are adapting to long-term agricultural labor scarcity. Using a novel estimation strategy to distinguish the impacts of three drivers of changes in labor market outcomes—commodity demand, labor conserving technological change facilitating labor substitution, and input supply—we uncover region-specific vulnerabilities and adjustment strategies.

Our analysis shows that labor intensive production systems have greater potential to offset the disproportionately higher impacts of labor scarcity and commodity demand on hiring costs through labor-saving technological change. However, growth in labor specific productivity in the Fruitful Rim—home to the nation's most labor-intensive crops—stagnated while producers continue to rely heavily on wage adjustments in response to shrinking labor supply. At the same time, employment responded less sharply to labor scarcity than wages, aligning with findings by Win, Rutledge, and Maredia (2025). In the Northern Crescent, responsiveness of employment to labor productivity reflects similar patterns observed in mechanized systems which captures the changes in crop-mix away from labor intensive crops also reported by Bardenhagen et al. (2025).

We find that regions beyond the Fruitful Rim face challenges associated with rising labor shortages. In the Northern Great Plains, where the biofuel boom and growth of the fracking industry intensified competition for semi-skilled labor, a 1% reduction in the supply of hired agricultural workers led to more than twice the impact on hiring costs relative to the Fruitful Rim region. In more mechanized production systems, employment was also more responsive to labor shortages and labor specific technological change. These findings suggest that mechanization alone may not fully insulate producers from labor market pressures. As supply to the pool of farm workers continue to diminish, regions beyond the traditional hubs of immigrant farm employment may nonetheless confront acute labor shortages during peak agricultural seasons, which have recently been met by contract workers hired though FLCs, often at a premium. This underscores the growing labor constraints in regions that employ a smaller share of hired farmworkers and traditionally less dependent on immigrant workers.

Our analysis shows that over the next 10 years if there is an annual drop in labor supply by 1% (Charlton and Taylor 2016), it would lead to a 6% increase in hiring costs in mechanized production systems. While this is a modest increase over a relatively smaller share of labor costs, it can impact the competitiveness of U.S. agricultural output, that producers typically operate within narrow profit margins (Blank 2018).

In the case of the Fruitful Rim, a similar increase in labor scarcity over the next 10 years would lead to a 11.4% increase in hiring costs due to contracting fees for FLC services with or without the H-2A program which also includes different fees and requires employers provided benefits. Ongoing deportation policies of unauthorized workers, 850,000 of whom are employed as farmworkers (Martin and Rutledge 2025), could lead to much sharper increases in production costs. Steep increase in labor costs can be prohibitive for smaller operations—reinforcing ongoing structural shifts in farm sizes in the sector (MacDonald 2020). While grain production is already concentrated among large farms, Lacy, Orazem, and Schneekloth (2023) document a bimodal size distribution among fruit and vegetable producers in the Fruitful Rim. Sustained increases in cost of production due to scarcity in labor supply, amplified by trade and immigration policy changes, risk reducing the competitiveness of smaller farms and accelerate the concentration of large farms.

This study models hired labor as an aggregate category, potentially glossing over labor-type specific impacts of native-born vs immigrant workers, local vs migrant workers and directly vs contract workers. This is partly because estimates for sub-categories of hired workers are not readily available and ongoing work is focused on improving this understanding with a combination of data sources (Hill et al. 2024). This study and the larger project of which it is part highlight uncertainty in estimating hired farm employment, even at a considerably aggregated level, since high-quality data sources on employment contain critical gaps for accurate measurement.

The results carry several implications. Given our findings that rising labor scarcity is likely to increase production costs across diverse farming systems, a comprehensive strategy is needed—one that combines reliable policy solutions like the H2A program that facilitates producers' access to hired labor with targeted investments in technological innovation that enable quality-preserving automation, particularly in labor-intensive crops less amenable to mechanization. Such measures will be essential for adapting to a future where farm labor scarcity is likely to be the norm.

For researchers, the findings highlight the importance of modeling labor heterogeneity and regional dynamics when assessing agricultural resilience to market and policy shocks. Future work should integrate disaggregated labor types and finer spatial data to better capture how adaptation unfolds across labor markets and production systems. As labor scarcity deepens, understanding these differentiated regional responses will be critical for designing both effective policy and robust models of agricultural adjustment.

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