Understanding the Relationship between U.S. Agricultural Labor and Machinery

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1 Background

Farmers and ranchers in the United States have struggled to find workers willing to harvest and process the goods that feed the nation, which pose a significant threat to the domestic food supply chain and undermines U.S. food security. According to the American Farm Bureau Federation, more than 2.4 million farm jobs need to be filled annually. However, the agricultural labor pool, consisting of hired workers, self-employed individuals, and family workers, has declined significantly over the past several decades. Duvall (2019) indicated the shrinking availability of farm labor as one of the most critical constraints facing U.S. agriculture.

Labor shortages not only affect production capacity, but also contribute to food waste. The Natural Resource Defense Council (NRDC) reported that insufficient labor is one of the reasons crops are left unharvested in the field (Gunders, 2012). For example, in 2011, the

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Georgia Fruit and Vegetable Growers Association estimated that labor shortages for harvest and packing would cost the state $ 140 million in crop losses, accounting for roughly 25 percent of total production value for these crops (McKissick & Kane, 2011).

Another straightforward piece of evidence demonstrating the domestic farm labor shortage is the increasing number of H-2A based positions (a federal visa program that aims to bring foreign-born workers to the United States to perform seasonal farm labor on a temporary basis). According to the United States Department of Agriculture Economic Research Service, the number of H-2A positions requested and approved has increased more than sevenfold in the past 19 years, from just over 48,000 positions certified in fiscal year (FY) 2005 to around 385,000 in FY 2024 (Castillo et al., 2025). As part of the H-2A application process, farm operators are required to demonstrate that their efforts to recruit domestic workers were unsuccessful. There are various reasons explaining why Americans no longer want to work on farms, including but not limited to harsh working conditions, wages, preference for immediate employment, and dissatisfying employee compensation packages.

While many studies have explored the potential of immigrant labor as a solution to the farm labor shortage (Kostandini et al., 2014; Martin, 2013; Richards, 2018; Rutledge et al., 2025), this paper builds on the work of Hamilton et al. (2022) by empirically examining whether technological innovation can serve as an alternative or complementary approach. We aim to address this problem from a production economics perspective by directly quantifying the degree of substitutability between farm labor and mechanization. If machinery and labor are substitutes, that means technologies are labor-saving; thus, machinery reduces the need for human labor in production. [1] Conversely, if machinery and labor complement each other, technological adoption enhances the productivity of labor rather than replacing it.

Numerous studies within neoclassical economic literature have examined the interrelationships among production inputs, particularly the relationship between labor and capital. The

[1] Gallardo and Sauer (2018) provide a literature review of the adoption of labor-saving technologies within the agricultural sector.

seminal work *The Theory of Wages* argues that changes in the relative prices of production factors can serve as a catalyst for technological innovation (Hicks, 1932). Habakkuk (1962) builds on Hicks's idea to explain the effective search for and adoption of labor-saving technologies in nineteenth-century America. According to the Habakkuk hypothesis, labor scarcity was the primary driver of mechanization in antebellum America. Similarly, Allen (2009) argues that the comparatively high wages in Britain were the main catalyst for the Industrial Revolution.

More recently, Acemoglu (2010) characterizes the conditions under which input factor scarcity can induce technological advancement—either through innovation or the adoption of more productive technologies. His analytical framework shows that if machinery is strongly labor-complementary, labor scarcity discourages technology adoption. Conversely, if technology is strongly labor-saving, labor scarcity can induce and accelerate technological progress by reducing the marginal product of labor. This paper complements Acemoglu (2010) by conducting an empirical analysis of the relationship between labor and technology.

2 Literature Review

2.1 Flexible Functional Forms and Share Equations

The concept of flexible functional forms is well-established in the literature and has been extensively discussed by numerous authors. As discussed by Caves and Christensen (1980) and Diewert (1974), researchers applying neoclassical economic theory to analyze consumer/producer behavior using parametric methods must specify a functional form to describe the underlying relationships. Chambers (1988) states that the most likely contribution of the flexible forms lie not in their approximation properties, but they impose fewer restrictions prior to estimation than traditional functional forms, such as Leontief and Cobb-Douglas. In other words, it also allows measures like the elasticity of size and elasticities of substitution that depend on the data, which echoes today's data-driven approach in machine learning and

modeling.

Some of the notable examples of flexible functional forms are CES (Arrow et al., 1961), translog form (Berndt & Christensen, 1973; Christensen et al., 1973, 1975), the generalized Leontief form (Diewert, 1971, 1973), the Fourier flexible form (Gallant, 1981), and the minflex Laurent flexible function form (Barnett et al., 1987).

By applying Roy's identity or Shephard's lemma, researchers can derive and estimate systems of consumer demand or production factor equations [2]. These systems also make it possible to estimate key parameters, such as price elasticity of demand and elasticities of substitution. While much of the theoretical literature focuses on the deterministic forms of demand systems resulting from various functional forms, Chavas and Segerson (1987) focus on the statistical inference and offer a theoretical justification of stochastic specification of singular share equations. As argued, the hypothesis test can yield biased results if a homoscedastic stochastic error term is added to each deterministic share equation.

2.2 Translog Cost Function Empirical Work

The translog (transcendental logarithmic) cost function, originally called the translog price possibility frontier, was introduced by Christensen et al. (1973) as a flexible alternative to estimate a twice-differentiable cost function allowing for variable elasticities of substitution. Berndt and Wood (1975) use the translog cost function to study energy demand with the U.S. manufacturing data and reveal substitution possibilities among energy and non-energy inputs. Christensen and Greene (1976) use the same model to estimate economies of scale for U.S. electricity power generation firms. This study concludes that in 1955, there were significant scale economies available to nearly all firms; however, in 1970, many firms were operating in the essentially flat area of the average cost curve.

In the agricultural sector, Ray (1982) was among the first to estimate a multi-output translog

[2]Parallel argument from the consumer demand side can be found in (Phaneuf & Requate, 2016) centering on willingness to pay (WTP) and willingess to accept (WTA).

cost function using time-series data on U.S. agriculture from 1939-1977. This study uses joint generalized least squares (GLS) estimation of cost and share equations, showing a declining trend in the degree of substitutability between capital and labor. In addition, price elasticity of demand for all inputs was found to increase over time.

Similarly, Ball and Chambers (1982) use annual data from the meat products industry spanning 1954 to 1976 to estimate a translog cost function derived from its dual aggregated production function. Their empirical findings indicates increasing returns to scale, suggesting potential deviations from the assumptions of a perfectly competitive market. This result aligns with contemporaneous concerns raised in Congress regarding structural changes within the meat products industry, which may have facilitated non-competitive market behavior. Ollinger et al. (2005) revisit the economies of scale in the U.S. poultry industry and use a translog cost function to examine technological change. The results suggest large and extensive scale economies and that firms had the potential to further reduce processing costs if they could build and fully utilize larger plants.

Akridge and Hertel (1986) estimate a multi-output, short-run (variable) translog cost function using data from 24 retail fertilizer plants in Indiana and Illinois, covering the years 1975 to 1982. Their study focuses on evaluating economies of scale, scale efficiency, and scope, concluding that these plants can reduce average costs by increasing total output and diversifying their product offerings, such as expanding into anhydrous ammonia.

Babin et al. (1982) estimate a translog cost function to analyze the cross-price elasticity of demand for various inputs with respect to water prices across U.S. manufacturing sectors. Their findings suggest that changes in water prices have minimal impact on the usage of other inputs within individual sectors, such as food and kindred products and paper and allied products.

Kuroda (1988) specifies a multi-output translog cost function to estimate the demand elasticities with respect to output quantities. This study uses aggregate farm data for all of

Japan, excluding the Hokkaido region, for the period 1958-1984. The paper concludes that an expansion of livestock production requires a relatively smaller amount of labor than an expansion of crop production. In conclusion, the sharp increase in livestock production had a positive effect on the rapid transfer of agriculture to nonagricultural sectors during the study period.

More recently, Holtkamp and Peter (2025) estimate a translog cost function using USDA Agricultural Resource Management Survey (ARMS) Phase III data to analyze labor demand in American livestock production. Their study finds that livestock producers' demand for domestic labor is elastic, while the demand for H-2A workers is even more elastic.

3 Theoretical Foundation

Suppose a price-taking firm produces a scalar output y using n inputs, $x = (x_1, x_2, ...x_n)$ described by a production function, $y = f(x)$. [3] The dual cost function is defined as:

$$C(w, y) = \min_x \{w \cdot x : f(x) \geq y\} \tag{1}$$

which is a function of a vector of input prices $w = (w_1, w_2, \ldots, w_n)$ and output y. We assume that the cost function is continuous, twice differentiable, and well-behaved. It satisfies linear homogeneity in input prices, which means that for any scalar $\lambda > 0$, we have the following:

$$\lambda C(w) = C(\lambda w) \tag{2}$$

The cost share of input i is defined as:

$$s_i = \frac{w_i x_i}{C(w, y)} \tag{3}$$

[3] We assume cost-minimizing farms in this paper because cost-minimization aligns well with farm management goals like reducing expenses. Profit maximization will be more suitable if the study focuses on revenue strategies, marketing decisions, or risk management, etc.

By Shephard's Lemma, we have:

$$x_i = \frac{\partial C(w,y)}{\partial w_i} \tag{4}$$

Therefore,

$$s_i = \frac{w_i}{C(w,y)} \cdot \frac{\partial C(w,y)}{\partial w_i} \tag{5}$$

By summing over all input shares, we have:

$$\sum_{i=1}^{n} s_i = \sum_{i=1}^{n} \frac{w_i}{C(w,y)} \frac{\partial C(w,y)}{\partial w_i} = \frac{1}{C(w,y)} \sum_{i=1}^{n} w_i \frac{\partial C(w,y)}{\partial w_i} \tag{6}$$

By Euler's Theorem for linearly homogeneous functions, we know our cost function is homogeneous of degree 1 in input prices, thus:

$$\sum_{i=1}^{n} w_i \frac{\partial C(w,y)}{\partial w_i} = C(w,y)$$

Therefore, the cost share sums to one:

$$\sum_{i=1}^{n} s_i = \frac{C(w,y)}{C(w,y)} = 1 \tag{7}$$

The translog cost function is a flexible specification that approximates any arbitrary cost function using a second-order Taylor series expansion. It can also be regarded as a generalized quadratic function expressed in logarithmic form. To estimate the parameters at the mean of the data, this study follows the common practice of normalizing all input prices and output quantities by their respective means. This ensures that the estimated translog cost function reflects local behavior around the average values $(\bar{w}, \bar{y})$.

The resulting translog cost function evaluated at the mean is:

$$\begin{aligned}\ln C(w,y) \approx\ & \ln C(\bar{w},\bar{y}) + \sum_{i=1}^{n} \left.\frac{\partial \ln C}{\partial \ln w_i}\right|_{(\bar{w},\bar{y})} \ln\left(\frac{w_i}{\bar{w}_i}\right) + \left.\frac{\partial \ln C}{\partial \ln y}\right|_{(\bar{w},\bar{y})} \ln\left(\frac{y}{\bar{y}}\right) \\ & + \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} \left.\frac{\partial^2 \ln C}{\partial \ln w_i \partial \ln w_j}\right|_{(\bar{w},\bar{y})} \ln\left(\frac{w_i}{\bar{w}_i}\right)\ln\left(\frac{w_j}{\bar{w}_j}\right) \\ & + \sum_{i=1}^{n} \left.\frac{\partial^2 \ln C}{\partial \ln w_i \partial \ln y}\right|_{(\bar{w},\bar{y})} \ln\left(\frac{w_i}{\bar{w}_i}\right)\ln\left(\frac{y}{\bar{y}}\right) + \frac{1}{2}\left.\frac{\partial^2 \ln C}{\partial (\ln y)^2}\right|_{(\bar{w},\bar{y})} \left(\ln\left(\frac{y}{\bar{y}}\right)\right)^2\end{aligned} \tag{8}$$

Following Uzawa (1962), the Allen-Uzawa elasticity of substitution (AES) between inputs i and j is defined as:

$$AES_{ij}(w,y) = \frac{c_{ij}(w,y)c(w,y)}{c_i(w,y)c_j(w,y)} = \frac{c_{ij}(w,y)c(w,y)}{x_i(w,y)x_j(w,y)} \tag{9}$$

where subscripts of c denote partial derivatives. AES is a symmetric measure of how easily one input can be substituted for another in a cost-minimizing production process, holding output constant.

On the other hand, the Morishima elasticity of substitution (MES) measures the percentage change in the ratio of two inputs used in response to a percentage change in their relative prices, holding output constant (Morishima, 1967). It is asymmetric and defined as:

$$MES_{ij}(w,y) = w_j\left(\frac{c_{ij}(w,y)}{c_i(w,y)} - \frac{c_{jj}(w,y)}{c_j(w,y)}\right) \tag{10}$$

As argued by Blackorby and Russell (1989), careful consideration is required when using elasticities of substitution to characterize production relationships. Hicks originally defined the elasticity of substitution in the context of a two-input production model. While this concept can be extended to cases involving more than two inputs, doing so requires holding output and all other inputs constant except for the pair being analyzed. The Hicks-Allen elasticity (also referred to as the Allen-Uzawa elasticity) was developed to address the limi-

tations of Hicks's original formulation in multi-input settings. However, it has been shown to be an inadequate measure in such contexts. The information it provides is largely embedded in the estimated parameters and offers limited insight into substitution behavior.

In contrast, the Morishima elasticity of substitution is a more robust and informative measure when multiple inputs are involved. This measure not only captures the ease of substitution between inputs but also provides complete comparative statics regarding relative factor shares. It more effectively fulfills the original intent of Hicks' elasticity in a multi-input production system while maintaining the assumption of cost-minimization. In this study, both the Hicks-Allen and Morishima elasticities are computed to illustrate the implications of choosing one measure over the other.

4 Elasticity Estimations through Translog Cost Function

Elasticities of substitution serve as critical indicators of the interrelationships among inputs in production processes. When input demand functions are derived from a cost function, it is handy to jointly estimate elasticities of substitutions alongside price elasticities and scale elasticity. In the context of a single-output production function, price elasticity refers to the percentage change in the quantity demanded of a particular input resulting from a one percent change in the price of that input (own-price elasticity) or the price of another input (cross-price elasticity).

The general nonhomothetic symmetric translog cost function $\ln C$ in terms of $\ln w_i$ and $\ln y$ is defined as:

$$\ln C = a_0 + \sum_{i=1}^{N} a_i \ln w_i + a_y \ln y + \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} a_{ij} \ln w_i \ln w_j + \sum_{i=1}^{N} a_{iy} \ln w_i \ln y + \frac{1}{2} a_{yy} (\ln y)^2 \quad (11)$$

By Young's theorem, the symmetry conditions imply:

$$\frac{\partial^2 \ln C}{\partial x_i \partial x_j} = a_{ij} = a_{ji} \tag{12}$$

The output elasticity of cost is:

$$\eta_y = \frac{\partial \ln C}{\partial \ln y} = a_y + a_{yy} \ln y + \sum_{i=1}^{N} a_{iy} \ln w_i > 0 \tag{13}$$

The marginal cost is:

$$\frac{\partial C}{\partial y} = \frac{\partial C}{\partial \ln C} \cdot \frac{\partial \ln C}{\partial \ln y} \cdot \frac{\partial \ln y}{\partial y} = C \cdot \eta_y \cdot \frac{1}{y} = \frac{C \cdot \eta_y}{y} > 0 \tag{14}$$

By Shephard's Lemma, the derived factor share equations are:

$$s_i = \frac{\partial \ln C}{\partial \ln w_i} = a_i + \sum_{j=1}^{N} a_{ij} \ln w_j + a_{iy} \ln y > 0 \tag{15}$$

Thus, by the linear homogeneity of the cost function in input prices:

$$\sum_{i=1}^{N} s_i = 1 \tag{16}$$

By the definition of the share equation, we can derive the conditional input demand or factor demand:

$$x_i = s_i \cdot \frac{C}{w_i} > 0 \tag{17}$$

which yields the following relationship by taking logs:

$$\ln x_i = \ln s_i + \ln C - \ln w_i \tag{18}$$

The price elasticity of demand is therefore:

$$\eta_{ij} = \frac{\partial \ln x_i}{\partial \ln w_j} = \frac{\partial \ln s_i}{\partial \ln w_j} + \frac{\partial \ln C}{\partial \ln w_j} - \frac{\partial \ln w_i}{\partial \ln w_j} \tag{19}$$

The cross-price elasticity of demand for input i with respect to the price of input j is therefore:

$$\eta_{ij} = \frac{a_{ij}}{s_i} + s_j \tag{20}$$

because by Shephard's lemma

$$\frac{\partial \ln C}{\partial \ln w_j} = s_j \tag{21}$$

and by chain rule

$$\frac{\partial \ln s_i}{\partial \ln w_j} = \frac{1}{s_i} \cdot \frac{\partial s_i}{\partial \ln w_j} = \frac{a_{ij}}{s_i} \tag{22}$$

Similarly, the own price elasticity of demand is:

$$\eta_{ii} = \frac{a_{ii}}{s_i} + s_i - 1 < 0 \tag{23}$$

The Morishima elasticity of substitution is simply computed as:

$$MES_{ij} = \eta_{ij} - \eta_{jj} \tag{24}$$

In terms of the cost share and using the translog cost function, the Allen-Uzawa elasticity of substitution can be expressed as:

$$AES_{ij} = \frac{a_{ij} + s_i s_j - \delta_{ij} s_i}{s_i s_j} \tag{25}$$

where δ_{ij} is the Kronecker delta, equal to 1 if $i = j$ and 0 otherwise.

By simplification, we get [4]

$$AES_{ij} = \frac{1}{s_i s_j} a_{ij} + 1 \quad \text{for all } i \neq j \tag{26}$$

$$AES_{ii} = \frac{a_{ii} + s_i^2 - s_i}{s_i^2} \quad \text{for all } i \tag{27}$$

5 Graphical Interpretation

Understanding the relationship between inputs and commodities—whether they are substitutable or complementary—is a foundational concept in microeconomic theory, studied even at the introductory level, and further investigated in production and consumer analysis. The elasticity of substitution serves as a key metric to quantify the ease with which one input (e.g., labor) can be replaced by another (e.g., capital) while maintaining a constant level of output. In extremes, perfect substitutes exhibit infinite elasticity of substitution, implying that inputs can be exchanged at a constant rate without affecting output. This is represented graphically by straight line isoquants, as illustrated in Figure 1. In contrast, perfect complements, modeled by the Leontief production function, have zero elasticity of substitution, indicating that inputs must be used in fixed proportions. This input relationship is represented by L-shaped isoquants in Figure 2.

Between these two extremes lie more nuanced cases of substitution and complementarity, where the curvature of isoquants reflects varying degrees of substitutability. Algebraically, in the two-input case, the elasticity of substitution is defined as the percentage of their marginal rate of technical substitution (MRTS). For a production function with two inputs K and L, the elasticity of substitution can be expressed as:

$$\sigma = \frac{d \ln \left(\frac{K}{L}\right)}{d \ln \left(MRTS_{LK}\right)} = \frac{d \left(\frac{K}{L}\right) / \left(\frac{K}{L}\right)}{d \left(MRTS_{LK}\right) / \left(MRTS_{LK}\right)} \tag{28}$$

[4] A similar derivation is noted in the example SAS code provided in the documentation, *Calculating Elasticities from a Translog Cost Function* (last updated November 29, 2023).

where in a perfectly competitive input market, the firm is in equilibrium when it chooses the input combination at which the MRTS is equal to the factor price ratio.

$$MRTS_{LK} = \frac{w}{r} \tag{29}$$

Therefore

$$\sigma = \frac{d\left(\frac{K}{L}\right)/\left(\frac{K}{L}\right)}{d\left(\frac{w}{r}\right)/\left(\frac{w}{r}\right)} \tag{30}$$

The higher the value of σ, the more easily the two inputs can be substitutable.

Graphically, elasticity of substitution can be understood by referring to Figure 3. Suppose that we are moving from point A (K_A, L_A) to point B (K_B, L_B) on the isoquant. At Point A, the marginal rate of technical substitution (MRTS) is the slope of the line tangent to the point (slope of the green line). When we move to Point B, the MRTS decreases as the slope of the line tangent to the point becomes flatter. The labor-capital ratio, which is the slope of the blue dashed line, decreases as we move from Point A to B. The elasticity of substitution, thus, compares the change of labor-capital ratios to the change of MRTS. In other words, the elasticity of substitution quantifies the degree to which the labor-capital ratio responds to changes in MRTS.

It is also straightforward to see from Figure 3 that the greater the curvature or convexity of the isoquant, the smaller the change in input proportions resulting from a given change in the marginal rate of technical substitution. In other words, when the isoquant exhibits high curvature, small changes in input ratios lead to rapid shifts in the marginal rate of technical substitution (MRTS), yet the labor-capital ratio remains relatively stable, indicating a low elasticity of substitution. In contrast, flatter isoquants are associated with more gradual changes in MRTS and greater responsiveness in the labor-capital ratio, reflecting a higher elasticity of substitution.

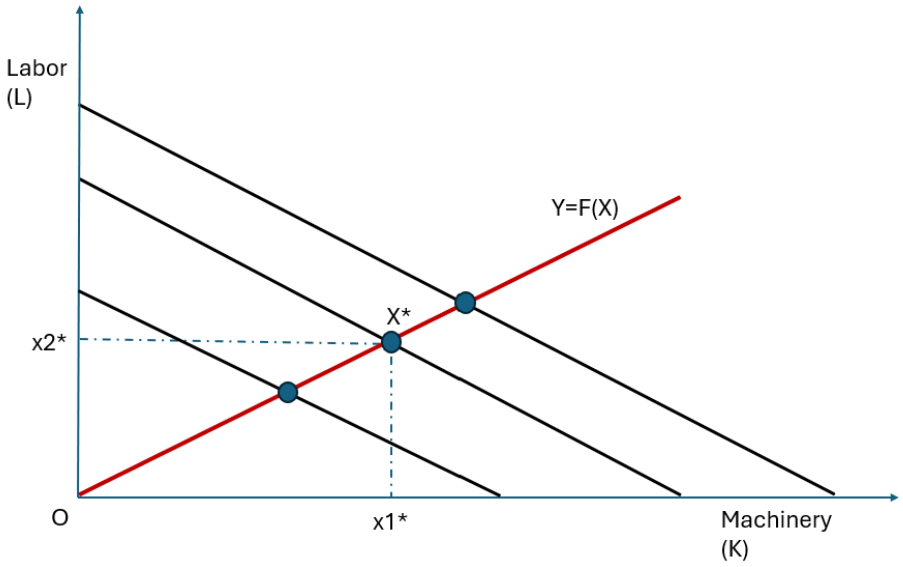


Figure 1: Perfect Substitutes

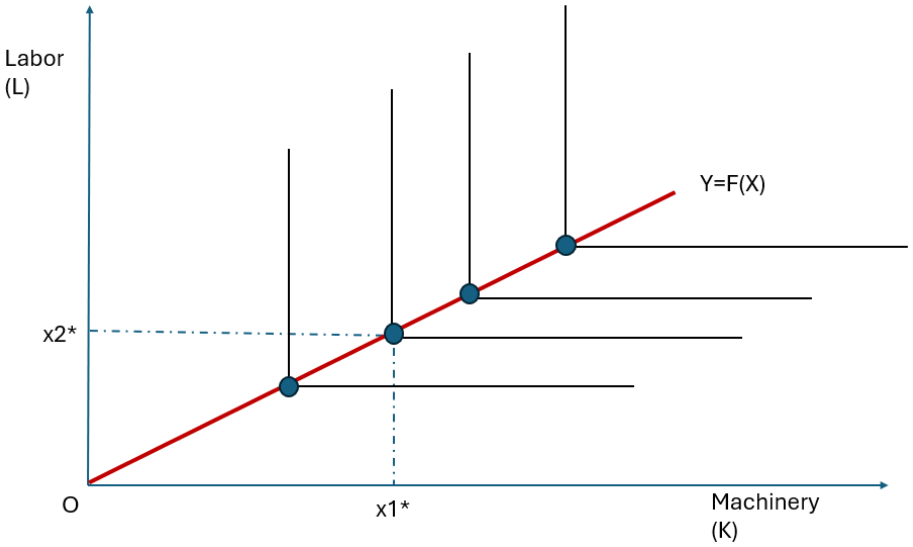


Figure 2: Perfect Complement

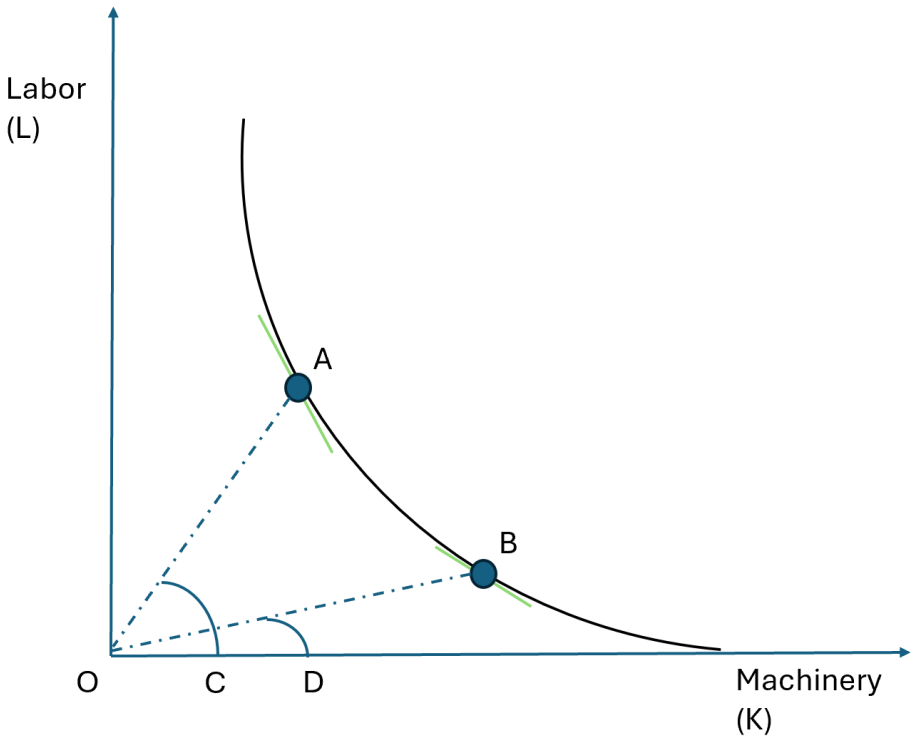


Figure 3: Complement

6 Dataset

We utilize county-level data from the 2002 and 2022 Census of Agriculture for the 48 continental U.S. states, excluding Hawaii and Alaska. Conducted every five years by the United States Department of Agriculture (USDA), the Census of Agriculture offers the only source of uniform, comprehensive, and impartial agriculture data for every county in the nation. It is a complete count of American farms and ranches and the people who operate them.

For this study, we use the aggregated data published by the National Agricultural Statistics Service (NASS), along with the count of farm operations, to construct a representative farm of each county. [5]

We use the variable *Commodity Totals – Sales ($ per Operation)* as a proxy for output quantity, denoted by Y.

[5]Data Source: https://www.nass.usda.gov/datasets/, file name: qs.census2002.txt.gz last modified Tue. March 7th, 2023 - 09:16am and qs.census2022.txt.gz last modified Wed. February 14th, 2024 - 02:25pm

For input quantities:

- **Land (Z)**: Represented by *Farm Operations – Area Operated (measured in Acres per Operation)*.
- **Labor (L)**: The count of labor hired per farm is calculated as the ratio of *Labor, Hired – Number of Workers* to *Labor, Hired – Operations with Workers*, representing the number of hired workers per operation.
- **Machinery (K)**: Approximated by dividing *Machinery Totals – Asset Value ($)* by *Machinery Totals – Operations with Asset Value*, yielding machinery value per operation.

Input prices are constructed as follows:

- **Land Price (P_Z)**: Represented by *Ag Land, Including Buildings – Asset Value ($ per Acre)*.
- **Labor Price (P_L)**: We first calculated the total labor expense per farm as *Labor, Hired – Expense ($)* divided by *Labor, Hired – Operations with Workers*. Then we calculate the expense per labor as the ratio of *the total labor expense per farm* divided by *the count of labor hired per farm*.
- **Machinery Price (P_K)**: Approximated using *Fuels, Including Lubricants – Expense ($)* divided by *Fuels, Including Lubricants – Operations with Expense*.

We further classified each representative farm according to the ARMS III farm production expenditure regions shown in Figure 4 to account for regional variation.

7 Estimation Method

We are estimating a three-input one-output translog cost function with input labor (L), machinery (K), and land (Z), with the corresponding prices P_L, P_K, P_Z. Following the

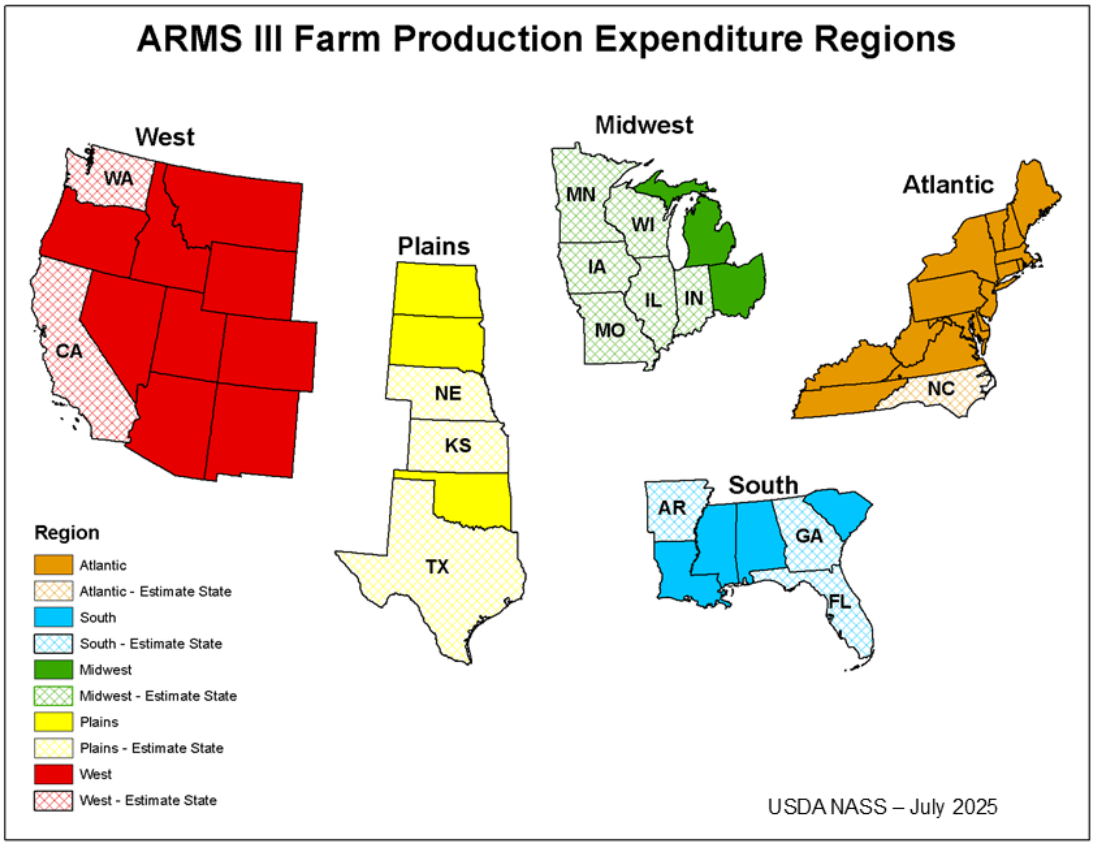


Figure 4: ARMS Production Region Map

general nonhomothetic translog cost function formulation and symmetry condition, we would get:

$$\begin{aligned}\ln(C) = a_0 + a_y \ln(y) + \frac{1}{2}a_{yy}[\ln(y)]^2 \\ + a_Z \ln(P_Z) + a_K \ln(P_K) + a_L \ln(P_L) \\ + \frac{1}{2}a_{ZZ}[\ln(P_Z)]^2 + \frac{1}{2}a_{KK}[\ln(P_K)]^2 + \frac{1}{2}a_{LL}[\ln(P_L)]^2 \\ + a_{ZK} \ln(P_Z)\ln(P_K) + a_{ZL} \ln(P_Z)\ln(P_L) + a_{KL} \ln(P_K)\ln(P_L) \\ + a_{yZ} \ln(y)\ln(P_Z) + a_{yK} \ln(y)\ln(P_K) + a_{yL} \ln(y)\ln(P_L)\end{aligned} \tag{31}$$

By homogeneous of degree 1 in the input price, we would get the normalized version:

$$\begin{aligned}\ln(\frac{C}{P_Z}) = a_0 + a_y \ln(y) + \frac{1}{2}a_{yy}[\ln(y)]^2 \\ + a_Z \ln(\frac{P_Z}{P_Z}) + a_K \ln(\frac{P_K}{P_Z}) + a_L \ln(\frac{P_L}{P_Z}) \\ + \frac{1}{2}a_{ZZ}[\ln(\frac{P_Z}{P_Z})]^2 + \frac{1}{2}a_{KK}[\ln(\frac{P_K}{P_Z})]^2 + \frac{1}{2}a_{LL}[\ln(\frac{P_L}{P_Z})]^2 \\ + a_{ZK} \ln(\frac{P_Z}{P_Z})\ln(\frac{P_K}{P_Z}) + a_{ZL} \ln(\frac{P_Z}{P_Z})\ln(\frac{P_L}{P_Z}) + a_{KL} \ln(\frac{P_K}{P_Z})\ln(\frac{P_L}{P_Z}) \\ + a_{yZ} \ln(y)\ln(\frac{P_Z}{P_Z}) + a_{yK} \ln(y)\ln(\frac{P_K}{P_Z}) + a_{yL} \ln(y)\ln(\frac{P_L}{P_Z})\end{aligned} \tag{32}$$

After simplification, terms containing $\ln(\frac{P_Z}{P_Z})$ evaluate to zero and therefore drop out of the equation. For clarification, we denote normalized prices $\frac{P_K}{P_Z}$ and $\frac{P_L}{P_Z}$ as w_K and w_L, respectively. The normalized total cost is denoted as c. Then for each cross-sectional dataset, we are using Seemingly Unrelated Regression (SUR) and linear restrictions [6] to estimate the

[6]The formal econometric algorithm can be found in Chapter "Estimating Systems of Equations by OLS and GLS" in Wooldridge (2002).

following translog cost function and the corresponding share equations:

$$\begin{aligned}\ln(c) = a_0 + a_y \ln(y) + \frac{1}{2} a_{yy} [\ln(y)]^2 \\ + a_K \ln(w_K) + a_L \ln(w_L) \\ + \frac{1}{2} a_{KK} [\ln(w_K)]^2 + \frac{1}{2} a_{LL} [\ln(w_L)]^2 \\ + a_{KL} \ln(w_K) \ln(w_L) \\ + a_{yK} \ln(y) \ln(w_K) + a_{yL} \ln(y) \ln(w_L)\end{aligned} \tag{33}$$

By Shephard's lemma, the estimated cost share equations are:

$$\hat{S}_K = \frac{\partial \ln(c)}{\partial \ln(w_K)} = a_K + a_{KK} \ln(w_K) + a_{KL} \ln(w_L) + a_{yK} \ln(y) \tag{34}$$

$$\hat{S}_L = \frac{\partial \ln(c)}{\partial \ln(w_L)} = a_L + a_{LL} \ln(w_L) + a_{KL} \ln(w_K) + a_{yL} \ln(y) \tag{35}$$

Note that we are allowing variable returns to scale (VRS) as we are using micro-level data. The main argument was that farms differ in size, management, and agro-climate conditions. Thus, we want the translog model to be flexible enough to capture enough relationships between inputs and outputs. If we are using aggregate data, the assumption of constant returns to scale would be more appropriate.

The cross-price elasticity of demand for machinery with respect to labor price is therefore:

$$\eta_{KL} = \frac{a_{KL}}{\hat{S}_k} + \hat{S}_L \tag{36}$$

and should have the same sign of cross-price elasticity of demand for labor with respect to machinery price:

$$\eta_{LK} = \frac{a_{LK}}{\hat{S}_L} + \hat{S}_K \tag{37}$$

A positive cross-price elasticity indicates that two inputs or goods are substitutes, while a

negative value suggests complementarity.

The own-price elasticity of demand for machinery and labor would be negative, with estimated values as follows:

$$\eta_{LL} = \frac{a_{LL}}{\hat{S}_L} + \hat{S}_L - 1 \tag{38}$$

$$\eta_{KK} = \frac{a_{KK}}{\hat{S}_K} + \hat{S}_K - 1 \tag{39}$$

The Allen-Uzawa elasticity of substitution between machinery and labor is therefore:

$$AES_{LK} = AES_{KL} = \frac{1}{\hat{S}_L \hat{S}_K} a_{LK} + 1 \tag{40}$$

The Morishima elasticity of substitution between machinery and labor is

$$MES_{KL} = \eta_{KL} - \eta_{LL} \tag{41}$$

And the Morishima elasticity of substitution between labor and machinery is

$$MES_{LK} = \eta_{LK} - \eta_{KK} \tag{42}$$

A positive Allen-Uzawa elasticity implies that inputs are substitutes—specifically, an increase in the marginal rate of technical substitution leads to an increase in the input ratio. Conversely, a negative value indicates complementarity. The Morishima elasticity of substitution offers the same insight: a positive index suggests that input is substituted, and a negative index suggests complementary.

8 Results

To assess the robustness of the translog cost function specification, we estimate the model parameters using alternative scales of machinery asset values: reported in millions of dollars (1×10^6), hundred thousand dollars (1×10^5), and ten thousand dollars (1×10^4).

Our demand elasticities using 2002 and 2022 nationwide cross-sectional datasets suggest that labor and machinery are substitutes in U.S. agriculture. As shown in Table 1 and Table 2, mean values of all indices, including Allen-Uzawa elasticity of substitution, Morishima elasticity of substitution, and cross-price elasticity, suggest a strong substitutable relationship, which reflects the ability of farms to replace human labor with mechanical equipment to perform tasks like planting, harvesting, and processing. Machinery, which is estimated to be labor-saving, can perform repetitive and physically demanding tasks more efficiently than labor; therefore, innovations in agricultural equipment have made it easier to automate tasks that previously required manual labor. Another possible reason is that farms have already been relying on machinery to mitigate labor shortages. With fewer available workers, especially in rural areas, farms turn to machines to maintain the level of production.

Table 1: Demand Elasticities – 2002 Nationwide Machinery by Value Scale

Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Machinery in Million Dollars					
$AES_{FuelLabor}$	2,906	3.2496	48.2408	1.1093	2527.8880
$\eta_{FuelLabor}$	2,906	0.3949	0.1234	-3.9559	2.9358
$\eta_{LaborFuel}$	2,906	0.4182	0.5062	-22.4832	7.9817
$MES_{FuelLabor}$	2,906	0.9062	0.6617	-10.2723	30.5953
$MES_{LaborFuel}$	2,906	0.9318	0.3801	-15.6450	8.1113
$\eta_{LaborLabor}$	2,906	-0.5113	0.7525	-34.5512	10.8236
$\eta_{FuelFuel}$	2,906	-0.5136	0.1758	-6.8383	3.2949
Machinery in Hundred Thousand Dollars					
$AES_{FuelLabor}$	2,906	2.6169	17.8054	1.1053	769.4702
$\eta_{FuelLabor}$	2,906	0.3896	0.1291	-3.1561	4.6596
$\eta_{LaborFuel}$	2,906	0.4214	0.3320	-13.1864	5.9828
$MES_{FuelLabor}$	2,906	0.8945	0.4462	-7.5801	19.8798
$MES_{LaborFuel}$	2,906	0.9181	0.2684	-9.9454	6.0658
$\eta_{LaborLabor}$	2,906	-0.5049	0.5076	-21.2720	8.1206
$\eta_{FuelFuel}$	2,906	-0.4967	0.2008	-6.0383	6.3909
Machinery in Ten Thousand Dollars					
$AES_{FuelLabor}$	2,906	1.5293	16.9841	-885.0417	170.7609
$\eta_{FuelLabor}$	2,906	0.3295	0.1645	-2.3249	5.8527
$\eta_{LaborFuel}$	2,906	0.4177	0.1455	-4.7745	3.3338
$MES_{FuelLabor}$	2,906	0.8139	0.3687	-5.6921	16.1085
$MES_{LaborFuel}$	2,906	0.7997	0.5462	-17.9549	8.7438
$\eta_{LaborLabor}$	2,906	-0.4845	0.2917	-11.3991	6.1278
$\eta_{FuelFuel}$	2,906	-0.3820	0.4912	-8.1214	16.4977

Table 2: Demand Elasticities – 2022 Nationwide Machinery by Value Scale

Variable	Observations	Mean	Std. Dev.	Min	Max
Machinery in Million Dollars					
$AES_{FuelLabor}$	2,928	2.4685	14.9288	-358.3221	556.5497
$\eta_{FuelLabor}$	2,928	0.4010	0.4352	-18.9764	3.0104
$\eta_{LaborFuel}$	2,928	0.4340	0.2129	-4.6683	3.6729
$MES_{FuelLabor}$	2,928	0.8683	0.5009	-16.2085	11.0554
$MES_{LaborFuel}$	2,928	0.9823	0.5379	-7.3683	22.9821
$\eta_{LaborLabor}$	2,928	-0.4674	0.3215	-8.0450	4.4808
$\eta_{FuelFuel}$	2,928	-0.5483	0.5293	-24.1376	2.7000
Machinery in Hundred Thousand Dollars					
$AES_{FuelLabor}$	2,928	1.7035	30.7205	-1587.7310	184.5855
$\eta_{FuelLabor}$	2,928	0.3889	0.1651	-3.7365	3.6697
$\eta_{LaborFuel}$	2,928	0.4250	0.4966	-23.8532	8.0023
$MES_{FuelLabor}$	2,928	0.8558	0.8604	-11.2952	42.8547
$MES_{LaborFuel}$	2,928	0.9254	0.5880	-26.5502	7.6829
$\eta_{LaborLabor}$	2,928	-0.4668	0.8190	-40.4130	12.1464
$\eta_{FuelFuel}$	2,928	-0.5004	0.2467	-6.5904	4.5581
Machinery in Ten Thousand Dollars					
$AES_{FuelLabor}$	2,928	1.4668	6.6075	-66.1744	316.2667
$\eta_{FuelLabor}$	2,928	0.2404	0.0997	-1.0117	3.3579
$\eta_{LaborFuel}$	2,928	0.3730	0.1684	-3.8848	3.9587
$MES_{FuelLabor}$	2,928	0.6358	0.8020	-20.6003	21.6614
$MES_{LaborFuel}$	2,928	0.6741	0.7083	-24.8790	5.1009
$\eta_{LaborLabor}$	2,928	-0.3954	0.8020	-22.6730	20.7968
$\eta_{FuelFuel}$	2,928	-0.3010	0.6932	-8.9857	25.0983

Thus, we saw a declining substitutability from 2002 to 2022, as evidenced by decreasing elasticity of substitution (both AES and MES) shown in Table 3. This can be explained by technological saturation. As basic tasks are mechanized, the remaining labor-intensive tasks (such as fruit picking and livestock care) are harder to automate, reducing substitutability. In addition, while machinery improved rapidly in earlier decades, recent innovations may not have significantly expanded the range of tasks that can be automated.

Over the two-decade period from 2002 to 2022, our analysis, as detailed in Table 3, also reveals a noticeable decline in the own-price elasticity of labor. This trend indicates that farm operators' demand for labor has become less sensitive to changes in wage rates, suggesting that even as wages fluctuate, farms are less likely to adjust their labor input proportionally.

One plausible explanation for this reduced responsiveness is the increasing reliance on skilled farm labor. As farming becomes more specialized, certain tasks, such as livestock care may require skilled labor that cannot be easily substituted or reduced by mechanization, even if wages rise.

Table 3: Comparison of Nationwide Elasticities: 2002 vs. 2022

Variable	**2002**	**2022**	**Difference**	**Percent Change**
Machinery in Million Dollars				
$AES_{FuelLabor}$	3.2496	2.4685	-0.7811	-24.04%
$MES_{FuelLabor}$	0.9062	0.8683	-0.0379	-4.18%
$\eta_{LaborLabor}$	-0.5113	-0.4674	0.0439	8.59%
Machinery in Hundred Thousand Dollars				
$AES_{FuelLabor}$	2.6169	1.7035	-0.9134	-34.90%
$MES_{FuelLabor}$	0.8945	0.8558	-0.0387	-4.33%
$\eta_{LaborLabor}$	-0.5049	-0.4668	0.0381	7.54%
Machinery in Ten Thousand Dollars				
$AES_{FuelLabor}$	1.5293	1.4668	-0.0625	-4.09%
$MES_{FuelLabor}$	0.8139	0.6358	-0.1781	-21.88%
$\eta_{LaborLabor}$	-0.4845	-0.3954	0.0891	18.39%

We also observe a notable regional variation in the elasticities of the demand for labor and machinery. As demonstrated by Table 4, both the Allen-Uzawa and Morishima elasticities of substitution in the West Region are positive regardless of the unit of the machinery value in 2002 and 2022. Thus, their magnitudes have declined over the past two decades, suggesting labor and machinery have become less substitutable in this region. A similar downward trend in substitutability is observed in the Midwest, where the decline is even more pronounced than in the West. In contrast, the South Region exhibits a clear increase in the degree of substitutability between labor and machinery, with elasticity values increasing significantly over time. These findings highlight the importance of considering geographic context when evaluating agricultural production technology and labor-capital dynamics.

Table 4: Comparison of Regional Elasticities: 2002 vs. 2022

Variable	**2002**	**2022**	**Difference**	**Percent Change**
West Region — Machinery in Million Dollars				
$AES_{FuelLabor}$	0.9389	0.9008	-0.0380	-4.05%
$MES_{FuelLabor}$	0.9710	0.9556	-0.0153	-1.58%
West Region — Machinery in Hundred Thousand Dollars				
$AES_{FuelLabor}$	0.9293	0.8736	-0.0557	-5.99%
$MES_{FuelLabor}$	0.9650	0.9380	-0.0269	-2.79%
West Region — Machinery in Ten Thousand Dollars				
$AES_{FuelLabor}$	0.8362	0.6744	-0.1618	-19.35%
$MES_{FuelLabor}$	0.9134	0.8268	-0.0866	-9.49%
South Region — Machinery in Million Dollars				
$AES_{FuelLabor}$	-10.9425	0.9607	11.9032	108.78%
$MES_{FuelLabor}$	0.2093	0.5566	0.3474	165.99%
South Region — Machinery in Hundred Thousand Dollars				
$AES_{FuelLabor}$	-7.3986	-6.4208	0.9778	13.22%
$MES_{FuelLabor}$	0.3617	0.4093	0.0476	13.17%
South Region — Machinery in Ten Thousand Dollars				
$AES_{FuelLabor}$	-5.3569	44.4443	49.8012	929.66%
$MES_{FuelLabor}$	0.5297	1.9592	1.4295	269.87%
Midwest Region — Machinery in Million Dollars				
$AES_{FuelLabor}$	4.5369	-33.0839	-37.6208	-829.23%
$MES_{FuelLabor}$	0.4720	-1.4280	-1.9001	-402.53%
Midwest Region — Machinery in Hundred Thousand Dollars				
$AES_{FuelLabor}$	3.1246	-20.9921	-24.1167	-771.83%
$MES_{FuelLabor}$	0.4203	-0.7148	-1.1351	-270.05%
Midwest Region — Machinery in Ten Thousand Dollars				
$AES_{FuelLabor}$	-1.3168	-9.9089	-8.5921	-652.50%
$MES_{FuelLabor}$	0.1066	-0.5460	-0.6527	-612.02%

9 Policy Implication

First of all, the estimated results can provide empirically grounded statistics that support evidence-based policymaking, especially in advancing the goal of the United States Department of Agriculture's Agriculture Innovation Agenda (AIA). The estimated elasticity of substitution between labor and capital offers direct insight into the technological flexibility of U.S. farm production. A positive elasticity of substitution suggests that farmers can substitute labor with capital efficiently. This result strengthens the economic justification for public policies that support technological innovation, including subsidies, tax incentives for machinery, robotics, or precision agriculture tools. The result also informs the prioritization of R&D funding priorities for agricultural innovation.

Second, the estimates explore the option of using mechanization as the solution to persistent labor shortages in the U.S. agriculture. As discussed in the background section, this sector heavily relies on seasonal and migrant labor, making it particularly vulnerable to labor supply disruptions. When the elasticity of substitution between labor and machinery is low, labor cannot be easily replaced by machinery. In such cases, policies that restrict labor supply (such as tighter immigration controls or fewer young immigrants entering agriculture) would severely disrupt production. Conversely, when the elasticity of substitution is high, investments in mechanization may partially offset labor shortages, suggesting that policy efforts should focus on facilitating technology adoption and diffusion.

Third, the estimated parameters, such as the elasticity of substitution between labor and machinery, can be used for calibration in the macroeconomic/structural models of the U.S. agricultural sector. Accurate parameterization ensures that the models reflect the behavior of real-world farm operators, allowing for more reliable forecasts and scenario analysis.

Fourth, the findings of a declining own-price elasticity of labor emphasize the critical role of specialized farm labor in modern agricultural production, with meaningful implications for education and workforce development policy. As agricultural production undergoes struc-

tural transformation, farm productivity depends not solely on labor availability but on the quality, experience, and task-specific knowledge embodied in workers. Highly skilled farm labor, such as livestock technicians and precision equipment operators, possesses human capital developed through intensive on-the-job learning and is closely tied to specific technologies, crops, and even production environments. This form of human capital is not easily replaceable in the short run and is often weakly transferable to non-agricultural sectors. Therefore, education and workforce development policies play a crucial role to support the accumulation of ag-specific human capital. In addition, many modern agricultural technologies are skill-biased and generate productivity gains only when operators possess sufficient technical competence. Without complementary investments in training, farms may underutilize existing capital or delay adoption altogether, weakening the returns to publicly funded agricultural research. Therefore, skill-based training becomes a necessary complement to innovation policy, rather than a secondary consideration. Job-ready training programs that are accessible and linked to extension services can broaden access to skill acquisition, reduce barriers to entry, and prevent human capital constraints from accelerating structural consolidation in the U.S. agricultural sector. In this way, investments in ag-specific education and training of highly skilled farm labor contribute not only to productivity and profitability but also to resilience and inclusiveness.

Fifth, the empirical results show that substitution patterns between labor and capital vary significantly across different agricultural regions in the United States. These regional differences reflect heterogeneity in demographic, climate, commodity, and production practices, calling for region-specific strategies rather than one-size-fits-all solutions. By aligning policy interventions with regional substitution patterns, decision-makers can optimize resource allocation and enhance the effectiveness of agricultural innovation initiatives.

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