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Economics of Inequity in Agricultural, Food, and Environmental Systems

Ethnic and gender disparities in U.S. agriculture: An analysis of technology and technical efficiency differentials

Eric Njuki[1] | **Michée A. Lachaud**[2] | **Boris E. Bravo-Ureta**[3] | **Nigel Key**[1]

[1]Economic Research Service, USDA, Washington, District of Columbia, USA

[2]Florida A&M University, Tallahassee, Florida, USA

[3]Department of Agricultural and Resource Economics, University of Connecticut, Storrs, Connecticut, USA

Correspondence
Eric Njuki, Economic Research Service, USDA, Washington, DC, USA.
Email: eric.njuki@usda.gov

Abstract

We explore ethnic and gender disparities in U.S. agriculture by comparing productivity gaps between male- and female-headed family farms, and between non-Hispanic White and minority-headed family farms. Using Agricultural Resource Management Survey data from 2017 to 2020, propensity score matching techniques are applied to obtain comparable samples based on observable covariates. Statistical tests reveal structural differences in production technologies between male- and female-headed farms, and between non-Hispanic White and minority-headed farms, thus requiring the estimation of separate production technologies for each group. Accordingly, a stochastic metafrontier framework is used to envelop the group frontiers and assess technology gaps. The results indicate that female and minority-principal operators not only use different production technologies but are also less proficient at combining inputs to maximize farm output. The results also reveal within-group gender and ethnic differences—ceteris paribus, among non-Hispanic White and minority-led farms, female producers generated substantially less output compared to their male counterparts. Similarly, among male principal operators, Hispanic producers generated more output compared to their non-Hispanic White and non-Hispanic non-White counterparts.

KEYWORDS

metatechnical efficiency, ethnic and gender disparities, stochastic metafrontier, stochastic production frontiers, technical efficiency, technology gap ratio, U.S. agriculture

JEL CLASSIFICATION
D22, Q12, Q16

1 | INTRODUCTION

The U.S. Department of Agriculture (USDA) defines socially disadvantaged farmers and ranchers (SDFR) as those belonging to groups that have been subject to historical racial or ethnic discrimination and gender discrimination (USCRS, 2021). The SDFR community includes Native Americans, Asians, Blacks or African Americans, Hispanic Americans, and women. The 2022 Census of Agriculture reported 3.37 million producers across the United States, of whom 1.26 million were female producers. Furthermore, 56,203 were American Indian, 22,788 were Asian American, 41,807 were recorded as Black or African American, and 112,379 were listed as of Hispanic origin (USDA, 2024). On average, SDFR operations were smaller and generated less total revenue compared to non-SDFR farms. Operations for which a SDFR was the primary producer represented 30% of all farms but accounted for only 13% of the market value of agricultural products sold in 2017 (USGAO, 2019). Further, only 21% of SDFR operations received government agricultural payments, compared to 36% of non-SDFR operations.

Historical events have shaped the current pattern of farmland ownership in the U.S. and explain why farms operated by SDFRs, on average, own less land, have less access to irrigation water, are clustered in areas less conducive to farming, and are situated further from markets and infrastructure. For years, many SDFRs have received lower levels and poorer quality education, inferior quality agricultural extension services, and restricted access to key public resources (Huffman, 1981). Some tenure systems on land controlled by SDFRs, such as those governing some American Indian reservations and heirs property, may have also contributed to the differential outcomes by inhibiting farm investment and growth (Deaton, 2012; Leonard et al., 2020). Horst and Marion (2019) find that historical disparities associated with race, ethnicity, and gender have persisted over time, leaving many SDFRs at an economic disadvantage.

Unequal treatment and access to public support and programs may also help explain some of the disparities between SDFR and non-SDFR farms (Ackerman et al., 2012; Feder & Cowan, 2013). Historical discrimination has been documented by the United States Commission on Civil Rights (USCCR, 1965; USCCR, 1982) and the USDA's Civil Rights Action Team (USDA, 1997). The Civil Rights Action Team has linked significant losses of land and income to discriminatory actions from USDA agencies. Ayazi and Elsheikh (2015) argue that past farm bills have contributed to a food system characterized by social, economic, political, and environmental inequalities as well as racial/ethnic and gender disparities.

Increasing racial and social equity is a high priority for the Biden administration as evidenced by Executive Order 13985 signed on January 20, 2021, which articulated the federal government's commitment to advancing equity (Biden Jr, 2021). In response to this executive order, the USDA developed an Equity Action Plan that includes equity criteria as an element in its farm, family, and food policies (Vilsack & Bronaugh, 2022).

The USDA Equity Action Plan builds on recent efforts to improve access to USDA programs and services by SDFRs (USDA, 2005). For instance, the 2018 Farm Bill reauthorized and expanded support for SDFRs across a range of USDA initiatives including farm credit programs, crop insurance, and conservation programs. More recently, the American Rescue Plan Act of 2021 and the Inflation Reduction Act of 2022 have targeted debt relief and financial assistance to producers who have experienced discrimination in USDA farm lending (U.S. Congress, 2021; U.S. Congress, 2022).

Farm productivity is a critical determinant of farm profitability and farm business growth and survival (Islam et al., 2014; Mugera et al., 2016). An important unanswered question is whether farms headed by SDFR operators are as productive as similar farms headed by non-SDFR operators.

Evidence of a productivity gap would suggest that SDFR-headed farms continue to suffer from discrimination or face other barriers in access to government programs or private sector resources. Understanding the reasons for differences in productivity between groups could provide useful information for the design of agricultural programs and policies.

There are no studies that we are aware of in the context of U.S. agriculture that have estimated differences in productivity between farms operated by SDFRs and other groups. In contrast, recent literature illustrates how restrictive access to production inputs, credit, and asset ownership can lead to productivity differentials across ethnic and gender groups in developing countries (e.g., Julien et al., 2023; Kilic et al., 2015; Owusu & Bravo-Ureta, 2022; Songsermsawas et al., 2023). These studies show the importance of controlling for observed and unobserved heterogeneity across groups to identify disparities in productivity.

This paper addresses this major gap in the literature by exploring productivity differentials between male- and female-headed family farms, and between non-Hispanic White (NHW) and minority-headed family farms[1] in the U.S. The data are drawn from the USDA Agricultural Resource Management Survey (ARMS) conducted between 2017 and 2020. These farm-level data include information on farm characteristics, production practices, costs, and returns. We apply propensity score matching (PSM) to obtain comparable samples based on observable covariates (Bravo-Ureta et al., 2021; Caliendo & Kopeinig, 2008). We find that statistical tests support the hypothesis that the production technologies are not similar across groups, so we implement the stochastic metafrontier framework to establish a robust basis to investigate technology gaps and technical efficiency differences across groups of producers (Amsler et al., 2017; Cillero et al., 2021; Huang et al., 2014; O'Donnell et al., 2008).

Differences in production technology are partly explained by operators' ability to acquire and adopt new methods, systems, and processes for transforming inputs into outputs. Differences in technical efficiency are determined by operators' proficiency at maximizing output given available inputs and are thus linked to their managerial skills.

Our results indicate that female- and minority-principal operators not only use different production technologies but are also less proficient at combining inputs to maximize farm output compared to their male and non-Hispanic White (NHW) counterparts. We also find within-group gender and ethnic differences—that is, among NHW and minority-led farms, female producers generated substantially less output compared to their male counterparts. Similarly, among male principal operators, Hispanic producers generated more output relative to their NHW, and non-Hispanic Non-White (NHNW) counterparts.

The remainder of the paper is organized into five additional sections. Section 2 continues with an assessment of the prior literature; Section 3 outlines the theoretical framework and the empirical model; Section 4 contains a discussion of the data; Section 5 focuses on the results and analysis, and the paper ends with a summary and concluding remarks in Section 6.

2 | EXPLAINING DIFFERENCES IN FARM PRODUCTIVITY

Several themes emerge in the literature pointing to the likelihood that SDFRs have lower farm productivity than similar farms operated by non-Hispanic White farmers. These themes include: (1) inferior agricultural resource endowments; (2) fractional tenure systems that inhibit investment and efficient land use; (3) lower rates of educational attainment and training; (4) barriers that limit access to USDA programs; and (5) discrimination that restricts the use of private-sector loans.

There are many historical reasons why SDFRs may own or have access to lower quality land (e.g., fertility, grade, soil retention), have insufficient water for irrigation, be in a climate less

[1]In this study, we define minority-headed family farms as those with principal operators of Asian, Black or African American, Hispanic, or Native American racial ancestry.

conducive to farming, or be situated further from markets or transportation infrastructure. In the case of Native Americans, the early postcolonial period was characterized by their forced movement from land considered desirable by European settlers for agriculture to areas further from markets and infrastructure (Horst & Marion, 2019). For example, the 1830 Indian Removal Act forcibly relocated Cherokee, Creeks, and other eastern Indian tribes to west of the Mississippi River to make room for European immigrants. After the Civil War, settlers moved west in large numbers, leading to demands that Indian reservation land be opened to settlement. From 1887 to 1934 the amount of Indian land supervised by the federal government declined from 136 to 52 million acres, with much of that being arid land in the Southwest or timberland in the Northwest (Carlson, 1983). Cornell and Kalt (1994) cite poor natural resources, distance from markets, and high transportation costs among the main explanations for relatively slow economic growth on American Indian reservations.

Historical events suggest that contemporary African American farmers have also inherited land poorly suited for agriculture. Many of the ancestors of Black farmers were freed slaves who faced discrimination and lacked the economic resources to purchase or hold onto high quality agricultural land. This forced some former slaves to settle in less fertile areas (Horst & Marion, 2019; Mitchell, 2001). Using data from the 2007 Census of Agriculture and the 1997 National Resources Inventory, Nickerson and Hand (2009) find that socially disadvantaged farms are more likely to be in counties where a substantial proportion of cropland is highly erodible.

Historically, women have faced numerous obstacles relative to men in obtaining access and control over land (Amott & Matthaei, 1996; Horst & Marion, 2019; Pilgeram & Amos, 2015). It was not until 1900 that every state had enacted legislation granting married women the right to keep their wages and property in their own name. Access to credit was limited prior to the passage of the Equal Credit Opportunity Act (1974) that ended discrimination against credit applicants based on gender. Furthermore, the traditional practice of land being passed from father to son made it difficult for women to inherit land—even that owned jointly with the husband—a limitation that only ended in 1982 (Jensen, 1991).

Tenure systems on land controlled by SDFRs may also reduce farm productivity. Land within American Indian reservations held in trust by the federal government has significant restrictions on its use and development, which could inhibit investments and lead to lower productivity (Leonard et al., 2020). Anderson and Lueck (1992) estimate that the per-acre value of agricultural output is 85%–90% lower on tribal trust land. They hypothesize that this is explained by the inability to use trust land as collateral, as well as higher transaction costs resulting from multiple owners of small parcels. After controlling for land quality, Leonard et al. (2020) estimate that ownership fractionation resulting from trusteeship substantially reduces per capita income on reservations. Ge et al. (2018) use a fuzzy regression discontinuity design to explore how tenure systems on American Indian lands affect agricultural land use, irrigation levels, and irrigation investment. They estimate that, compared to similar land outside tribal boundaries, tribal land is 18% points less likely to be irrigated, and existing irrigation is significantly less capital intensive.

Farm productivity may also suffer when farmland is jointly owned as heirs' property, which is a form of ownership created when land is passed from someone who dies—usually without a will—to multiple individuals with legal claim to the property. This is the case on a substantial number of African American owned farms in the South and Appalachia (Gilbert et al., 2002). The joint ownership that characterizes heirs' property makes it more difficult to secure loans and coordinate management of the land (Deaton, 2012; Winters-Michaud et al., 2024).

Research also indicates that SDFRs historically have received lower levels and poorer quality education as well as inferior quality extension services compared to non-SDFRs (Huffman, 1981). Recent data from the USDA's Agricultural Resource Management Survey indicates that the education gap persists. For example, between 2017 and 2020, an average of 60% of non-Hispanic White (NHW) farmers had attended college compared to only 50% of Hispanic farmers and 51% of non-Hispanic non-White (NHNW) farmers.

Studies have found that SDFRs use USDA programs at lower rates than NHW farmers, which can be partly explained by farm size, commodity specialization, or other farm or operator characteristics. Dismukes et al. (1997) report that farms operated by SDFRs are less likely to participate in USDA crop insurance programs because they tend to raise livestock or specialty crops (e.g., fruits and vegetables) for which there are few or no such programs. Asaare-Baah et al. (2018) use survey data to investigate the reasons for participation and nonparticipation in USDA programs by African American farmers in the South and find that the lower rates of participation were explained by farmers' belief that they would not qualify for these benefits or lacked collateral for loans. Hargrove and Jones (2004) find that lack of awareness of existing programs and the inability to fully comprehend rules and regulations also limited SDFR participation.

Several studies reveal that, within the private sector, minority-owned operations have been charged higher interest rates or have been less likely to be offered credit than similar non-minority businesses contributing to lower rates of farm investment and productivity (e.g., Asiedu et al., 2012; Blanchard et al., 2008; Blanchflower et al., 2003). According to the U.S. General Accountability Office (GAO) there have been few analyses of discrimination in private-sector agricultural lending mainly because regulations prohibit lenders from collecting information on personal characteristics except for mortgage loans (USGAO, 2019). The GAO investigation reveals that SDFRs face challenges obtaining private agricultural credit because they are more likely to operate smaller lower revenue farms, have weaker credit history, and lack clear title to their land (USGAO, 2019). SDFR advocacy groups reported to the GAO that some SFDRs believe they receive unfair treatment in lending and others have been dissuaded from applying for credit because of past instances of alleged discrimination.

The federal government has been the defendant in several civil rights lawsuits filed against the USDA Farm Service Agency (FSA), which is the department's main entity charged with farm lending. For example, the *Pigford v. Glickmann* lawsuit filed by African American farmers and the *Keepseagle v. Vilsack* lawsuit by Native American farmers (Feder & Cowan, 2013). In the *Garcia* and *Love* cases, Hispanic and women farmers alleged discrimination and received cash compensation, tax, and debt relief in 2012. The federal budget for these settlements comprised more than $2 billion allocated for African American farmers, $680 million for Native American farmers, and $1.33 billion earmarked for Hispanic and women farmers (Feder & Cowan, 2013).

The USDA has enacted several reforms designed to improve minority farmers' program access (USDA, 2005). The FSA currently targets funding under various programs to historically underserved farmers and ranchers, who include minorities and women (e.g., Guaranteed, Direct operating, and Direct farm ownership loans). The Transition Incentives Program provides additional payments to landowners with expiring Conservation Reserve Program contracts who sell or rent land to an SDFR. The 2021 American Rescue Plan Act authorized debt relief for socially disadvantaged producers with farm loans.

In addition to the FSA, USDA's Natural Resource Conservation Service (NRCS) allocates 5% of the Environmental Quality Incentives Program funds to SDFRs. USDA's Office of Advocacy and Outreach manages the *2501 Program*, which distributes funds for technical assistance and outreach to SDFRs and veteran farmers. USDA's Rural Development Agency provides grants to deliver technical assistance to socially disadvantaged groups in rural areas. The USDA Office of Civil Rights also maintains the voluntary Minority Farm Register to promote equal access to USDA farm programs and services. In sum, there is substantial evidence that SDFRs face discrimination in access to financial resources and inputs that may lead to lower farm productivity relative to non-SDFRs.

3 | ANALYTICAL FRAMEWORK

The methodology used in this paper entails two main steps. First, we use propensity score matching (PSM) to define the samples (Caliendo & Kopeinig, 2008). Second, we estimate separate stochastic production frontier (SPF) models for family farms with minority and non-Hispanic White (NHW) principal operators, as well as for male and female principal operators. Subsequently, we test the null hypothesis that the production technologies are similar across these different groups. Rejection of the null hypothesis would provide sufficient support for implementing the stochastic metafrontier framework—a common technology benchmark.

3.1 | Propensity score matching (PSM)

We use PSM to preprocess the data and match minority-headed family farms with NHW family farms, as well as female- with male-headed family farms to find groups that are comparable based on observables (Ho et al., 2007). A major rationale for doing this is to mitigate *model dependence* relating to functional forms and other assumptions that could yield different causal effects and thus to improve the statistical efficiency of the estimated parameters (Ho et al., 2007; Ñopo, 2008; Owusu & Bravo-Ureta, 2022). Conducting data preprocessing through PSM before model estimation ensures the doubly robust nature of our findings. That is, even with potential misspecification in the metafrontier production function, our causal estimates are reliable given accurate matching. Similarly, if the matching is suboptimal but the metafrontier is properly specified, the consistency of causal estimates is upheld (Ho et al., 2007; Robins & Rotnitzky, 2001).

The propensity scores, P_i, are derived from a probit model of the likelihood for a farm to have a minority or female principal operator. Following Frölich (2007) and Mishra et al. (2017) this is expressed as:

$$P_i = \Phi(X'\gamma) + \varepsilon_{i,} \tag{1}$$

where P_i equals 1 for minority- or female-headed family farms and 0 for NHW- or male-headed family farms; X is a set of covariates including age, gender, education, experience, ethnicity, value of farm assets, government payments received, farm specialization, ratio of farm household to total household income, ratio of owned to operated acres, farm business debt to asset ratio, value of total current assets, farm resource regions that depict areas with similar commodity specialization, and year fixed-effects; γ is a parameter vector to be estimated; and $\Phi(\cdot)$ is the cumulative distribution function. The results of the probit model make it possible to calculate propensity scores to determine the area of common support (Caliendo & Kopeinig, 2008). The aim is to define a data set in which minority- and female-headed family farms and NHW- and male-headed family farms exhibit similar observable characteristics. More formally:

$$\tilde{P} = (X|T=1) = \tilde{P} = (X|T=0), \tag{2}$$

where $\tilde{P}$ is the observed empirical density of the data, $T=1$ for minority- and female-headed farms and 0 otherwise. For Equation (2) to be satisfied, each minority- or female-headed farm should be matched with their NHW or male counterparts such that the distributions of the observed characteristics across groups are equivalent. This can be accomplished using several alternative matching algorithms (Caliendo & Kopeinig, 2008), and here, we rely on radius matching within a caliper of 0.25 standard deviations of the propensity score and without replacement. All NHW- and male-headed family farms that cannot be matched with a minority- or female-headed family farm are discarded.

3.2 | Stochastic production frontiers (SPF)

In the second step of the estimation process, we approximate the production technologies used by minorities and female operators vis-à-vis their non-Hispanic white and male operators. We assume that farm operators produce a strictly positive scalar output denoted $y \in \Re_{++}$ using a vector of inputs denoted by $x = (x_1, x_2, \ldots, x_k) \in \Re_{+}^{K}$, in a production environment characterized by $z = (z_1, z_2, \ldots, z_s) \in \Re_{+}^{S}$ that is beyond the control of the producer. The technology set that represents all feasible input–output combinations can be characterized as follows (e.g., Chambers & Pieralli, 2020; O'Donnell, 2016):

$$\mathbb{T}(z) = \{(y, x) : x \text{ can produce } y \text{ in environment } z\}, \tag{3}$$

Following Aigner et al. (1977) and Meeusen and Broeck (1977), the SPF for farm operator i at time $-t$ from the $j-$th group is given by:

$$y_{it}^{j} = X_{kit}^{j\prime}\beta_k^j + Z_{sit}^{j\prime}\gamma_s^j + v_{it}^j - u_{it}^j, \tag{4}$$

where y_{it}^{j}, X_{kit}^{j}, and Z_{sit}^{j} are respectively, a scalar output, a column vector of k inputs, and a vector of s environmental variables, in logs, for the $i-$th farm in the $j-$th group at time $-t$; β_k^j and γ_s^j are vectors of k- and $s-$parameters to be estimated; v_{it}^j is the standard two-sided normally distributed error term, and u_{it}^j is a one-sided error denoting inefficiency that is assumed here to follow an exponential distribution. Technical efficiency (TE) for the $i-$th farm in the $j-$th group, $\left(TE_i^j\right)$, is given by $\exp\left(u_{it}^j\right)$ (Jondrow et al., 1982). In other words, each group can utilize its own technology set given by:

$$\mathbb{T}^j\left(z^j\right) = \left\{\left(y^j, x^j\right) : x^j \text{ can be used by group } j \text{ farm operators to produce } y^j \text{ in environment } z^j\right\} \tag{5}$$

3.3 | Stochastic metafrontier production framework

We start by testing the null hypothesis that the production technologies used by the different groups are equal, and if statistical tests reject the null, then we implement a stochastic metafrontier production framework to generate a common technology benchmark. First proposed by Hayami and Ruttan (1971), the metafrontier framework envelopes an array of individual production technologies each representing a unique group based on a specific set of circumstances—such as access to production inputs, new technologies, and capacity to properly use them. Specifically, the metafrontier represented, by $y^M = f^M(x^M)$, envelops the individual group frontiers, $y^j = f^j(x^j)$ where each $j-$th production group exhibits a specific production technology based on gender and ethnicity. Following Huang et al. (2014), the first step in estimating the stochastic metafrontier involves fitting each of the $j-$th group stochastic production frontiers separately as follows:

$$\ln y_{it}^j = \ln f^j\left(x_{it}^j, z_{it}^j\right) + v_{it}^j - u_{it}^j, \tag{6}$$

Thereafter, the estimates from all individual group frontiers are pooled and used to estimate the overarching stochastic metafrontier, which is represented as:

$$\ln f^j\left(x_{it}^j, z_{it}^j\right) = \ln f^M\left(x_{it}^M, z_{it}^M\right) + v_{jit}^M - u_{jit}^M, \tag{7}$$

From Equation (7) we can infer the technology gap ratio (TGR), which is defined as the distance between the $j-$th group production frontier and the metafrontier, as $\mathrm{TGR}^j = f^j\left(x_{it}^j, z_{it}^j\right)/f^M\left(x_{it}^M, z_{it}^M\right) = \exp\left(u_{it}^M\right) \leq 1$. Finally, we generate the metatechnical efficiency (MTE), which is defined as the distance from the $i-$th farm to the metafrontier production technology. The MTE is the product of the individual farm's distance from the group frontier (u_{it}^j), and the technology gap ratio (u_{it}^M), and is given by: $\mathrm{MTE}_{it}^j = u_{it}^j \times u_{it}^M$.

4 | DATA

This study relies on data from the Agricultural Resource and Management Survey (ARMS). The ARMS is a cross-sectional,[2] multiphased, multiframed, stratified, probability weighted survey that is conducted jointly by the Economic Research Service (ERS) and the National Agricultural Statistics Service (NASS) of the U.S. Department of Agriculture. The surveys are administered annually on a diverse national sample of crop and livestock farm operations. The surveys used in this study cover 4 years—from 2017 to 2020; thus, we analyze a pooled cross-sectional data.[3] As the focus of this study is on family farms, we exclude farms that are designated as legal partnerships, estates, trusts, cooperatives, or corporations. Furthermore, we exclude family farms where the principal operator was retired or spent most of their time working off farm.

The ARMS also includes information on principal operator characteristics (age, gender, ethnicity, years of farming experience, years of education), type of farming specialization (high-value crops, cash grains, or livestock), value of farm assets, government payments received, ratio of farm household to total household income, ratio of owned to operated acres, farm business debt to asset ratio, and value of total current assets.

A second set of variables is used to approximate the production technology. This set includes output and input variables defined as follows: Output is the monetary value of total agricultural output; land comprises the sum of harvested acres plus acres of pastureland, and forage; labor encompasses the labor hours for both paid and unpaid workers; intermediate materials include expenditures on fuel and oil, electricity, fertilizers and pesticides, seeds, purchased feed, and custom services; and capital is the sum of depreciation, interest rates paid, rent and lease on tractors, vehicles, equipment or storage structures, and value of livestock inventory. All nominal monetary values are expressed in 2020 dollars using producer price index for farm products generated by NASS (NASS, 2020).

The input–output data are augmented with contemporaneous temperature and precipitation data from the parameter-elevation Regressions on Independent Slopes Model (PRISM) Climate group. PRISM utilizes a climate mapping system, applying inverse-distance squared weighting to interpolate maximum and minimum temperatures over 4-by-4 kilometer grid cells across the conterminous United States. This method incorporates information from nearby weather stations considering distance, elevation, topographic position, and coastal proximity (Daly et al., 2008, 2015). Weather variables derived from PRISM include daily measures of mean, maximum, and minimum temperature, and precipitation over the typical growing season from March to August. Time-invariant production environment characteristics are captured using state-level fixed effects depicting areas with similar physiographic, topography, and agricultural policy.

[2]The ARMS is a lengthy and time-intensive survey that collects a substantial quantity of information from respondents. To track the same farm households and businesses every year would be burdensome to the respondents and may lead to attrition. Furthermore, the ERS and NASS are guided by the Paperwork Reduction Act (1980), which mandates information collection burdens on respondents be minimized.

[3]Mundlak (1978) and Wooldridge (2010) note that in a pooled cross section, the independence (but not identical) distribution assumption still holds.

TABLE 1 Descriptive statistics of farms by gender of principal operator.

Variable	Male Mean (*SD*)	Female Mean (*SD*)
Output and production inputs		
Value of agricultural products ($'000)	724.05 (1541.55)	386.96 (854.55)
Land (Acres)	709.73 (1118.31)	412.21 (895.06)
Labor hours	4401.24 (14333.33)	3463.14 (6914.26)
Capital ($'000)	243.54 (544.52)	139.99 (287.14)
Materials ($'000)	193.11 (493.74)	96.04 (224.30)
Livestock units ('000)	210.91 (814.17)	115.36 (422.73)
Production environment characteristics		
Spring precipitation (in.)	12.03 (5.67)	11.91 (6.44)
Summer precipitation (in.)	12.18 (6.48)	11.15 (7.79)
Spring temperature (°Fahrenheit)	53.42 (8.67)	54.39 (9.04)
Summer temperature (°Fahrenheit)	74.29 (5.46)	74.36 (6.34)
Principal operator demographics		
Non-Hispanic White (NHW)	0.94 (0.23)	0.88 (0.32)
Non-Hispanic non-White (NHNW)	0.02 (0.15)	0.05 (0.22)
Hispanic	0.02 (0.15)	0.05 (0.21)
Principal operator experience	32.63 (14.40)	27.47 (16.57)
Principal operator age	59.24 (12.56)	61.21 (13.15)
Principal operator education class	2.84 (0.91)	3.10 (0.87)
Principal operator college	0.29 (0.46)	0.41 (0.49)
Farm operation characteristics		
Cash grain specialization	0.39 (0.49)	0.21 (0.41)
Other field crop specialization	0.13 (0.33)	0.15 (0.36)
High value crop specialization	0.09 (0.28)	0.18 (0.38)
Ratio of farm household to total household income	0.20 (2.63)	0.02 (2.11)
Value of total current assets ($'000)	296.41 (642.53)	184.00 (573.69)
Government payments ($'000)	32.20 (75.08)	22.80 (74.88)
Ratio of owned to operated acres	0.66 (0.84)	0.84 (0.70)
Farm business debt to asset ratio	0.17 (0.38)	0.14 (0.51)
N	15,355	628

A summary of input–output, and weather variables used in this study is provided in Tables 1 and 2 for male- and female-headed farms, and NHW- and minority-headed farms, respectively. Maximum and minimum values have been suppressed to preserve anonymity of survey respondents.

5 | RESULTS

As discussed above, PSM is used to ensure that individuals across the various groups—minorities and non-Hispanic White, as well as male and female—are comparable in terms of key observable characteristics that do not directly affect farm output. The PSM probit models are estimated separately for each year included in the study—2017, 2018, 2019, and 2020—to match male and female

TABLE 2 Descriptive statistics of farms by ethnicity of principal operator.

Variable	Non-Hispanic Whites Mean (*SD*)	Minorities Mean (*SD*)
Output and production inputs		
Value of agricultural products ($'000)	694.44 (1481.86)	786.13 (2106.46)
Land (acres)	693.58 (1114.90)	482.21 (890.72)
Labor hours	4266.72 (14170.73)	6004.54 (13301.05)
Capital ($'000)	236.06 (526.36)	233.55 (631.75)
Materials ($'000)	183.49 (462.41)	195.63 (706.23)
Livestock units ('000)	203.99 (781.27)	164.83 (590.82)
Production environment characteristics		
Spring precipitation (in.)	12.09 (5.66)	10.81 (6.43)
Summer precipitation (in.)	12.19 (6.39)	9.97 (8.83)
Spring temperature (°Fahrenheit)	53.51 (8.62)	57.21 (9.00)
Summer temperature (°Fahrenheit)	74.32 (5.41)	75.82 (6.52)
Principal operator demographics		
Female	0.04 (0.19)	0.08 (0.27)
Male	0.96 (0.19)	0.92 (0.27)
Principal operator experience	32.25 (14.47)	28.66 (14.93)
Principal operator age	59.14 (12.65)	59.21 (12.29)
Principal operator education class	2.84 (0.91)	2.77 (0.99)
Principal operator college	0.30 (0.46)	0.30 (0.46)
Farm operation characteristics		
Cash grain specialization	0.37 (0.48)	0.21 (0.41)
Other field crop specialization	0.13 (0.33)	0.15 (0.35)
High value crop specialization	0.08 (0.28)	0.28 (0.45)
Ratio of farm household to total household income	0.19 (2.64)	0.02 (2.85)
Value of total current assets ($'000)	286.31 (620.92)	284.26 (934.00)
Government payments ($'000)	31.16 (72.22)	26.37 (86.62)
Ratio of owned to operated acres	0.65 (0.56)	0.69 (0.58)
Farm business debt to asset ratio	0.16 (0.32)	0.13 (0.26)
N	14,365	755

principal operators, and separately non-Hispanic White (NHW) and minority principal operator categories. These models incorporate observed covariates that explain differences between groups but do not necessarily or directly affect the production technology as discussed above. The results of the probit models are shown in Tables 3 and 4 for selection into the male and NHW principal operator category, respectively. The associated kernel densities of the propensity scores are provided in the online Supplementary Appendix in panels of Figures A1 and A2 for the gender and ethnic categories, respectively. Additional results on the balancing statistics and tests for the matched and unmatched samples are presented in the online Supplementary Appendix in Tables S1–S4, and Figures A3 and A4.

Each matched group is pooled across the years to estimate the stochastic production frontier, and metafrontier models. Separate stochastic production frontiers are estimated for male- and female-headed farms, as well as for NHW- and minority-headed farms, and the results are discussed

TABLE 3 First stage probit estimates for selection into male principal operator category—2017, 2018, 2019, and 2020.

Parameter/variables		2017 Coefficient (*SD*)	2018 Coefficient (*SD*)	2019 Coefficient (*SD*)	2020 Coefficient (*SD*)
γ_0	Constant	−2.0350** (1.0080)	−1.6302* (0.9468)	−2.8468*** (0.8485)	−2.6380** (1.1570)
γ_1	Heartland	−0.2198 (0.2484)	−0.2426 (0.2113)	0.0107 (0.2299)	0.1393 (0.2798)
γ_2	Northern crescent	−0.2492 (0.2828)	−0.1568 (0.2465)	0.2115 (0.2561)	−0.0496 (0.3247)
γ_3	Northern great plains	0.0066 (0.3065)	−0.4099 (0.3052)	0.7111** (0.2868)	−0.1098 (0.4382)
γ_4	Prairie gateway	−0.0455 (0.2492)	−0.0834 (0.2040)	0.3189 (0.2333)	−0.1150 (0.2918)
γ_5	Eastern uplands	−0.3916 (0.2619)	−0.3338 (0.2043)	0.1034 (0.2315)	0.0665 (0.2842)
γ_6	Southern seaboard	0.0559 (0.2353)	−0.3545* (0.2010)	−0.1965 (0.2310)	−0.3378 (0.2857)
γ_7	Fruitful rim	−0.0778 (0.2567)	−0.0572 (0.2234)	0.2817 (0.2391)	0.1345 (0.2947)
γ_8	Basin and range	0.1194 (0.3149)	−0.4659 (0.3142)	0.6784** (0.2964)	0.2914 (0.3687)
γ_9	Principal operator experience	−0.0201*** (0.0034)	−0.0216*** (0.0032)	−0.0135*** (0.0036)	−0.0188*** (0.0043)
γ_{10}	Principal operator age	0.0263*** (0.0041)	0.0227*** (0.0039)	0.0102** (0.0042)	0.0168*** (0.0051)
γ_{11}	Principal operator education	0.1489** (0.0758)	0.0824 (0.0808)	0.1714** (0.0796)	0.2305** (0.1005)
γ_{12}	Principal operator college	−0.1797 (0.1434)	0.0506 (0.1492)	−0.0979 (0.1443)	−0.3136* (0.1792)
γ_{13}	Non-Hispanic White	−0.1705 (0.5053)	−0.5313 (0.4509)	0.1830 (0.2074)	−0.0849 (0.4988)
γ_{14}	Non-Hispanic non-White	0.1137 (0.5430)	−0.3499 (0.4906)	0.7417*** (0.2659)	0.0346 (0.5486)
γ_{15}	Hispanic	0.3069 (0.5459)	−0.4484 (0.4860)	0.1817 (0.2789)	0.1976 (0.5394)
γ_{16}	High value crops specialization	0.1179 (0.1549)	0.0204 (0.1290)	0.0722 (0.1209)	−0.1965 (0.1574)
γ_{17}	Cash grains specialization	−0.1411 (0.0967)	−0.2742** (0.1107)	−0.1254 (0.0973)	−0.2873** (0.1274)
γ_{18}	Ratio of farm household to total household income	0.0396 (0.0405)	−0.0035 (0.0127)	0.0085 (0.0168)	0.0001 (0.0017)
γ_{19}	Ratio of owned to operated acres	0.0107 (0.0250)	0.0659* (0.0388)	0.0299 (0.0381)	0.0286 (0.0643)
γ_{20}	Value of total current assets	−0.0000 (0.0000)	−0.0000 (0.0000)	−0.0000 (0.0000)	−0.0000 (0.0000)
γ_{21}	Farm business debt to asset ratio	−0.3015 (0.1904)	0.1780** (0.0841)	0.0747 (0.0661)	−0.0303 (0.1323)
γ_{22}	Government payments	−0.0000 (0.0000)	−0.0000 (0.0000)	0.0000*** (0.0000)	−0.0000 (0.0000)

(Continues)

TABLE 3 (Continued)

Parameter/variables		2017 Coefficient (SD)	2018 Coefficient (SD)	2019 Coefficient (SD)	2020 Coefficient (SD)
γ_{23}	Farm typology	−0.0573* (0.0304)	−0.0986*** (0.0298)	−0.0779*** (0.0287)	−0.1085*** (0.0359)
γ_{24}	Precipitation	0.0034 (0.0031)	0.0007 (0.0031)	0.0030 (0.0035)	0.0014 (0.0031)
γ_{25}	Temperature	0.0033 (0.0363)	−0.0444 (0.0356)	−0.0143 (0.0352)	0.0006 (0.0422)
Log likelihood		−644.28	−666.00	−669.40	−424.67
N		4991	4534	3998	3023

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

below. We use the Cobb–Douglas functional form; therefore, the parameter estimates are partial production elasticities.

The rationale for defining groups that are similar in terms of observables is to account for possible inherent structural differences in production technologies across the groups studied. Following the estimation of the j-group stochastic production frontiers, we test the null hypothesis (H_0) that the production technologies across groups are equal. For the male and female $j-$group production technologies, a Wald test with chi-squared distribution, $\left(\chi^2_\rho\right)$ with $\rho = 17$ degrees of freedom, generates a test statistic of 32.84 with a p-value of 0.0118. Therefore, we reject the null hypothesis that female-headed and male-headed farms use the same technology. Similarly, for the production technologies for the NHW and minority groups, a Wald test with a chi-squared distribution, $\left(\chi^2_\rho\right)$ with $\rho = 16$ degrees of freedom, yields a test statistic of 27.16 with a p-value of 0.0397. Thus, again we reject the null hypothesis that these two groups have equal production technologies. Simply stated, both statistical tests reveal structural differences in production technologies across ethnic and gender groups.

Comparing stochastic production frontier estimates for male- and female-headed farms in Table 5 reveals some differences and similarities in magnitude and sign. For example, the parameter estimate representing material inputs, $\widehat{\beta}_4$, ceteris paribus, indicate that a 1% increase in material inputs contributed to 0.55%, and 0.59% in agricultural output for female- and male-headed farms, respectively, demonstrating that material inputs were the primary driver of agricultural output across both groups. Similarly, the parameter estimate for labor input, $\widehat{\beta}_2$, reveals that a 1% addition in labor hours contributed to 0.16%, and 0.13% increase in agricultural output for female- and male-headed farms, respectively. On the other hand, a 1% increase in land, $\widehat{\beta}_1$, contributed to a 0.27% increase in agricultural output for female-headed farms compared to a 0.15% increase in agricultural output for male-headed farms.

In addition, the parameter estimates, $\widehat{\alpha}_1$ and $\widehat{\alpha}_2$ representing the indicator variable for ethnicity of the principal operator, reveal that male-headed farms where the principal operator was of Hispanic ethnicity generated nearly 7.8% more agricultural output compared to their NHW counterparts. By contrast, male-headed farms with the principal operator being of non-Hispanic non-White (NHNW) ethnicity—a group that comprises Native American, Asians, Blacks or African Americans—produced approximately 11.9% less agricultural output compared to their NHW counterparts.

The estimated parameter $\lambda = \sigma_u/\sigma_v$ measures the relative contribution of inefficiency to the composed error term. The corresponding stochastic metafrontier estimates for male- and female-headed family farms are also provided in the third column of Table 5. All the estimated parameters are

TABLE 4 First stage probit estimates for selection into non-Hispanic White (NHW) principal operator category—2017, 2018, 2019, and 2020.

Parameter/variables		2017 Coefficient (*SD*)	2018 Coefficient (*SD*)	2019 Coefficient (*SD*)	2020 Coefficient (*SD*)
γ_0	Constant	−3.0593*** (0.8629)	−1.1441 (0.8078)	−1.6834** (0.7963)	−0.8824 (0.9282)
γ_1	Heartland	−0.5433*** (0.2125)	−0.8476*** (0.1837)	−0.5978*** (0.2117)	−0.7373*** (0.2498)
γ_2	Northern crescent	−0.2820 (0.2509)	−0.6968*** (0.2305)	−0.3458 (0.2409)	−0.7548*** (0.2962)
γ_3	Northern great plains	−0.2107 (0.2701)	−0.3744 (0.2550)	0.1619 (0.2781)	−0.2905 (0.3559)
γ_4	Prairie gateway	−0.3982* (0.2121)	−0.6410*** (0.1755)	0.0432 (0.2039)	−0.2218 (0.2445)
γ_5	Eastern uplands	−0.1947 (0.2146)	−0.5379*** (0.1739)	−0.0647 (0.2018)	−0.1165 (0.2453)
γ_6	Southern seaboard	−0.2263 (0.1994)	−0.5349*** (0.1627)	−0.1890 (0.1927)	0.1877 (0.2247)
γ_7	Fruitful rim	0.0774 (0.2147)	−0.4915** (0.2021)	0.4096** (0.2065)	0.1591 (0.2491)
γ_8	Basin and range	−0.0416 (0.2779)	−0.4151 (0.2696)	0.0563 (0.2969)	−0.2906 (0.3429)
γ_9	Principal operator experience	−0.0104*** (0.0037)	−0.0078** (0.0033)	−0.0087** (0.0036)	−0.0028 (0.0042)
γ_{10}	Principal operator age	0.0029 (0.0043)	0.0025 (0.0039)	0.0023 (0.0042)	−0.0027 (0.0050)
γ_{11}	Principal operator education	−0.1224 (0.0668)	−0.2034*** (0.0699)	−0.2776*** (0.0724)	−0.3531*** (0.0814)
γ_{12}	Principal operator college	0.0254 (0.1387)	0.2432* (0.1399)	0.5036*** (0.1475)	0.3303** (0.1651)
γ_{13}	Female	0.3845** (0.1542)	0.0926 (0.1486)	0.3371** (0.1369)	0.2660 (0.1824)
γ_{14}	High value crops specialization	0.5202*** (0.1298)	0.4280*** (0.1218)	0.2048* (0.1113)	0.3136** (0.1275)
γ_{15}	Cash grains specialization	−0.0201 (0.0964)	−0.1486 (0.1012)	0.1273 (0.0989)	0.1096 (0.1192)
γ_{16}	Ratio of farm household to total household income	−0.0248 (0.0212)	−0.0098 (0.0088)	−0.0024 (0.0148)	−0.0025 (0.0099)
γ_{17}	Ratio of owned to operated acres	−0.0343 (0.0689)	−0.0438 (0.0654)	−0.0698 (0.0687)	0.0702 (0.0736)
γ_{18}	Value of total current assets	0.0000 (0.0000)	−0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)
γ_{19}	Farm business debt to asset ratio	0.0734 (0.1203)	−0.2656* (0.1605)	−0.1874 (0.1453)	0.0269 (0.0991)
γ_{20}	Government payments	−0.0000 (0.0000)	−0.0000 (0.0000)	−0.0000 (0.0000)	0.0000 (0.0000)
γ_{21}	Farm typology	−0.0289 (0.0284)	−0.0099 (0.0273)	−0.0217 (0.0287)	−0.0998*** (0.0315)
γ_{22}	Precipitation				

(Continues)

TABLE 4 (Continued)

Parameter/variables	2017 Coefficient (*SD*)	2018 Coefficient (*SD*)	2019 Coefficient (*SD*)	2020 Coefficient (*SD*)
	−0.0035 (0.0033)	−0.0123*** (0.0035)	−0.0008 (0.0034)	−0.0003 (0.0029)
γ_{23}				
Temperature	−0.0166 (0.0342)	0.0505 (0.0340)	0.0009 (0.0337)	−0.0757** (0.0364)
Log likelihood	−689.28	−752.85	−701.52	−549.63
N	4900	4238	3769	2889

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

significant at the 1% level of significance except for the parameter associated with the spring precipitation, which is significant at the 5% level.

As a robustness check we evaluate if the production environment characteristics, that is, weather, and state-level fixed effects belong in the model. Thus, we test the null hypotheses (H_0) that the parameters are jointly zero, that is, $\varphi_1 = \varphi_2 = \ldots = \varphi_{10} = 0$ and $\gamma_1 = \gamma_2 = \ldots \gamma_{48} = 0$. A likelihood ratio test with chi-squared distribution, $\left(\chi^2_\rho\right)$ with $\rho = 57$ degrees of freedom generate a test statistic of 116.66 with a p-value of 0.000; therefore we reject the null hypothesis and conclude that the factors characterizing the production environment are important drivers in productivity differences between male- and female-headed farms. We also note the stability of the parameter estimates compared to the alternative specification depicted in the online Supplementary Appendix Table S5.

Technical efficiency (TE) measures the distance of a single farm from its group frontier, the technological gap ratio (TGR) reflects the distance of the group frontier from the metafrontier, and the metatechnical efficiency (MTE) measures the distance of an individual farm from the metafrontier. Table 6 shows the estimates for TE, TGR, and MTE. The findings indicate that the average female- and male-headed farms had TE estimates of 64.1% and 75.8%, respectively. The TGR results reveal that the average group frontiers were close to the metafrontier, at 91.2% and 97.1% for female and male group frontiers, respectively. Meanwhile, the MTE shows that the average female- and male-headed farms were 58.5% and 73.7% efficient, respectively. A statistical test of the equality of the means of the TE, TGR, and MTE reveals that the means are significantly different from zero (see Table S6 in the Supplementary Appendix).

Table 7 presents estimates of stochastic production frontier for non-Hispanic White (NHW) and minority-headed farms. The estimated parameters show some differences and similarities in magnitude and sign between the two ethnic groups. For example, the parameter estimate, $\widehat{\beta}_4$, reveals that material inputs were the primary drivers of agricultural output for both groups—a 1% increase in material inputs contributed to a 0.59% and 0.68% increase in agricultural output for NHW- and minority-headed farms, respectively. Conversely, the parameter estimate, $\widehat{\beta}_1$, reveals that a 1% increase in land contributed to 0.17% increase in farm output for NHW-headed farms, and only 0.09% increase in agricultural output for minority-headed farms.

Furthermore, the parameter for gender of the principal operator, $\widehat{\alpha}_1$, shows that relative to NHW principal operators who were male, NHW principal operators who were female generated 12.9% less agricultural output than their male NHW counterparts. Similarly, ceteris paribus, minority principal operators who were female generated 41.2% less agricultural output compared to their minority male counterparts. The stochastic metafrontier estimates related to weather variables display signs and magnitude akin to those revealed in the stochastic metafrontier regression for both male-

TABLE 5 Stochastic production frontier and metafrontier results for male and female principal operator farms.

Parameters/variables		Male operators Coefficient (*SD*)	Female operators Coefficient (*SD*)	Metafrontier Coefficient (*SD*)
β_0	Constant	1.1108 (1.4481)	−9.8797 (7.7370)	0.9737*** (0.1063)
β_1	Land	0.1583*** (0.0078)	0.2669*** (0.0411)	0.1620*** (0.0006)
β_2	Labor	0.1327*** (0.0065)	0.1609*** (0.0414)	0.1351*** (0.0005)
β_3	Capital	0.1503*** (0.0065)	0.0381 (0.0360)	0.1441*** (0.0005)
β_4	Materials	0.5919*** (0.0083)	0.5586*** (0.0442)	0.5893*** (0.0006)
α_1	Hispanic	0.0776* (0.0473)	−0.3242 (0.2174)	0.0575*** (0.0034)
α_2	Non-Hispanic non-White	−0.1191** (0.0500)	−0.0805 (0.2012)	−0.1162*** (0.0036)
τ_1	2018	−0.0305 (0.0242)	−0.1862 (0.1390)	−0.0375*** (0.0018)
τ_2	2019	−0.0555** (0.0233)	−0.2492* (0.1378)	−0.0623*** (0.0017)
τ_3	2020	0.0510** (0.0242)	−0.0633 (0.1474)	0.0452*** (0.0018)
φ_1	Spring precipitation	−0.0006 (0.0122)	0.0781 (0.0762)	0.0018** (0.0009)
φ_2	Spring precipitation squared	0.0002 (0.0002)	0.0001 (0.0007)	0.0002*** (0.0000)
φ_3	Spring precipitation × spring temperature	−0.0001 (0.0002)	−0.0015 (0.0012)	−0.0002*** (0.0000)
φ_4	Summer precipitation	−0.0478** (0.0233)	−0.1701 (0.1431)	−0.0511*** (0.0017)
φ_5	Summer precipitation squared	−0.0002* (0.0001)	−0.0009 (0.0006)	−0.0002*** (0.0000)
φ_6	Spring temperature	−0.0468** (0.0208)	0.0379 (0.1258)	−0.0480*** (0.0015)
φ_7	Spring temperature squared	0.0005** (0.0002)	−0.0002 (0.0011)	0.0005*** (0.0000)
φ_8	Summer temperature	0.0783* (0.0454)	0.2906 (0.2363)	0.0849*** (0.0033)
φ_9	Summer temperature squared	−0.0006* (0.0003)	−0.0019 (0.0016)	−0.0006*** (0.0000)
φ_{10}	Summer precipitation × summer temperature	0.0008** (0.0003)	0.0024 (0.0020)	0.0008*** (0.0000)
γ_1	Arizona	0.7187*** (0.2298)	2.4227*** (0.9193)	0.8051*** (0.0181)
γ_2	Arkansas	0.1368** (0.0717)	1.5265** (0.6254)	0.1453*** (0.0052)
γ_3	California	0.5986*** (0.0887)	1.8880*** (0.6787)	0.6186*** (0.0065)
γ_4	Colorado	0.0783 (0.1263)	0.9218 (0.8519)	0.0626*** (0.0092)
γ_5	Connecticut	0.5030 (0.3192)	1.8712 (1.2145)	0.4754*** (0.0225)
γ_6	Delaware	0.6568* (0.3393)	−2.4852** (1.1806)	0.6111*** (0.0247)
γ_7	Florida	−0.1057 (0.0938)	1.6454** (0.6961)	0.0767*** (0.0068)
γ_8	Georgia	0.0519 (0.0739)	1.4668** (0.6389)	0.0635*** (0.0054)
γ_9	Idaho	0.0664 (0.1188)	0.9637 (0.8374)	0.0560*** (0.0087)
γ_{10}	Illinois	−0.0129 (0.0783)	1.1607* (0.6676)	−0.0192*** (0.0057)
γ_{11}	Indiana	−0.0971 (0.0794)	0.6422 (0.7037)	−0.1083*** (0.0058)
γ_{12}	Iowa	0.0737 (0.0849)	1.0276 (0.6948)	0.0598*** (0.0062)
γ_{13}	Kansas	−0.1577** (0.0783)	1.0119 (0.6461)	−0.1629*** (0.0057)
γ_{14}	Kentucky	−0.0820 (0.0864)	1.2372* (0.7002)	−0.0789*** (0.0063)
γ_{15}	Louisiana	−0.2154** (0.0913)	0.6316 (0.7315)	−0.2141*** (0.0067)
γ_{16}	Maine	0.1147 (0.1931)	1.3971 (0.9691)	0.0918*** (0.0138)
γ_{17}	Maryland	0.2512 (0.2044)	0.9031 (0.8560)	0.2192*** (0.0148)
γ_{18}	Massachusetts	0.7117** (0.3387)	—	0.6974*** (0.0252)
γ_{19}	Michigan	−0.1420 (0.1042)	0.3457 (0.8184)	−0.1593*** (0.0077)

(Continues)

TABLE 5 (Continued)

Parameters/variables		Male operators	Female operators	Metafrontier
		Coefficient (*SD*)	Coefficient (*SD*)	Coefficient (*SD*)
γ_{20}	Minnesota	−0.0382 (0.0931)	1.2594* (0.7548)	−0.0522*** (0.0068)
γ_{21}	Mississippi	−0.1348 (0.0868)	1.2103* (0.6847)	−0.1194*** (0.0063)
γ_{22}	Missouri	−0.0983 (0.0742)	1.1196* (0.6300)	−0.0984*** (0.0054)
γ_{23}	Montana	−0.3421*** (0.1122)	1.4330* (0.7699)	−0.3176*** (0.0082)
γ_{24}	Nebraska	−0.0211 (0.0846)	0.9182 (0.6808)	−0.0360*** (0.0062)
γ_{25}	Nevada	0.6731*** (0.1920)	0.7683 (0.9172)	0.6462*** (0.014)
γ_{26}	New Hampshire	0.0286 (0.2382)	—	0.0145 (0.0175)
γ_{27}	New Jersey	0.1026 (0.2062)	−0.0478 (0.9494)	0.0766*** (0.0150)
γ_{28}	New Mexico	−0.1582 (0.1685)	0.9536 (0.8824)	−0.1616*** (0.0121)
γ_{29}	New York	−0.2465** (0.1347)	1.3986* (0.7684)	−0.2155*** (0.0098)
γ_{30}	North Carolina	0.4204*** (0.0717)	1.9426*** (0.6368)	0.4325*** (0.0052)
γ_{31}	North Dakota	−0.2832** (0.1149)	1.1715 (0.8724)	−0.2942*** (0.0084)
γ_{32}	Ohio	−0.0257 (0.0925)	0.6719 (0.7546)	−0.0373*** (0.0068)
γ_{33}	Oklahoma	−0.2616*** (0.0919)	1.0210 (0.6622)	−0.2457*** (0.0067)
γ_{34}	Oregon	0.0795 (0.1133)	1.4863** (0.7601)	0.0895*** (0.0083)
γ_{35}	Pennsylvania	0.2984*** (0.0980)	1.5860* (0.9596)	0.2943*** (0.0072)
γ_{36}	Rhode Island	0.4873 (0.3659)	−0.0229 (0.9107)	0.4045*** (0.0261)
γ_{38}	South Carolina	−0.1851 (0.1296)	1.8096 (1.1850)	−0.1824*** (0.0096)
γ_{39}	South Dakota	−0.0658 (0.1094)	1.1547 (0.7696)	−0.0809*** (0.0080)
γ_{40}	Tennessee	−0.1402 (0.0871)	1.1314 (0.7630)	−0.1399*** (0.0064)
γ_{41}	Texas	−0.1950*** (0.0732)	1.0511* (0.6291)	−0.2090*** (0.0059)
γ_{42}	Utah	0.2448* (0.1468)	1.3982 (0.9136)	0.2362*** (0.0107)
γ_{43}	Vermont	−0.0180 (0.3681)	4.1330 (1.2202)	2.1891*** (0.0435)
γ_{44}	Virginia	−0.3312*** (0.1008)	1.0544 (0.6729)	−0.3209*** (0.0073)
γ_{45}	Washington	0.2258** (0.0984)	1.3312* (0.7181)	0.2201*** (0.0072)
γ_{46}	West Virginia	0.3171** (0.1419)	1.3388* (0.7367)	0.3001*** (0.0100)
γ_{47}	Wisconsin	−0.2157** (0.0918)	0.9051 (0.7130)	−0.2296*** (0.0067)
γ_{48}	Wyoming	0.2234 (0.1444)	3.0574** (1.4111)	0.2356*** (0.0108)
σ_v	Sigma (v)	0.8185*** (0.0070)	0.9074 (0.0457)	0.0591*** −0.0004
σ_u	Sigma (u)	0.3201*** (0.0143)	0.5647 (0.0788)	0.0334*** (0.0005)
λ	Lambda	0.3911*** (0.0195)	0.6222 (0.1142)	0.5657*** (0.0006)
Log likelihood		−19,844.31	−930.72	19,894.16
N		15,355	628	15,983

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

and female-headed family farms. A robustness check is conducted to assess if the production environment characteristics influence productivity of NHW- and minority-headed farms. That is, we test the null hypothesis (H_0) that $\varphi_1 = \varphi_2 = \ldots = \varphi_{10} = 0$ and $\gamma_1 = \gamma_2 = \ldots \gamma_{48} = 0$. A likelihood ratio test with chi-squared distribution, $\left(\chi^2_\rho\right)$ with $\rho = 58$ degrees of freedom generate a test-statistic of 153.20 with a p-value of 0.000. Therefore, we reject the null hypothesis that the production environment characteristics do not influence differences in productivity between NHW- and minority-

TABLE 6 Average technical efficiency, technological gap ratio, and metatechnical efficiency estimates by gender of principal operator.

	Group	Observations	Mean (%)	*SD*	Min	Max
Technical efficiency (TE)	Female	628	64.1	(0.124)	0.022	0.862
	Male	15,355	75.8	(0.071)	0.010	0.920
Technological gap ratio (TGR)	Female	628	91.2	(0.153)	0.021	0.997
	Male	15,355	97.1	(0.017)	0.116	0.982
Metatechnical efficiency (MTE)	Female	628	58.5	(0.150)	0.014	0.857
	Male	15,355	73.7	(0.071)	0.009	0.895

headed farms, and conclude that they are important drivers in productivity differences between NHW- and minority-headed farms (see Table S7 in the Supplementary Appendix).

In Table 8 we present estimates of TE, TGR, and MTE. The average TE scores were 69.3% and 74.9% for minority- and NHW-headed family farms farmers, respectively. The TGR, which measures the distance from the *j*-group frontier to the metafrontier, average 93.2% and 97.5% for both minority- and NHW-headed family farms, revealing that both *j*-group frontiers were close to the metafrontier. On the other hand, the MTE estimates of 64.6% and 73.1% for minority- and NHW-headed family farms, respectively, reveal that the structural differences originate from differences in technical efficiency between both groups. A test of the equality of the means of the TE, MTE, and TGR shows that they are statistically different across minority- and NHW-headed farms (see Table S8 in the Supplementary Appendix).

Finally, we re-estimate the model using an alternative specification comprising ERS farm resource regions (FRR) fixed effects in lieu of the state-level fixed effects. These farm resource regions—Basin and Range, Northern Great Plains, Heartland, Northern Crescent, Eastern Uplands, Southern Seaboard, Mississippi Portal, Prairie Gateway, and Fruitful Rim—depict areas of geographic specialization where producers are likely to focus on similar agricultural commodities (Heimlich, 2000). We find that the main results are consistent across specifications: Minority- and female-headed farms show structural differences in their production technologies compared with NHW- and male-headed farms. Similarly, minority- and female-headed farms are less technically efficient that their NHW and male counterparts. Thus, we are confident that our results are not driven by our choice of fixed effects. The parameter estimates of the alternative specifications and estimates of TE, TGR, and MTE scores for male- and female-headed family farms are shown in the Supplementary Appendix in Tables S9 and S10, respectively. And those of NHW- and minority-headed farms are shown in Tables S11 and S12, respectively.

6 | SUMMARY AND CONCLUDING REMARKS

This study investigates ethnic and gender disparities in technical efficiency and technology in U.S. agriculture. We apply propensity score matching techniques to data from the 2017 to 2020 Agricultural Resource Management Surveys (ARMS) to create observationally similar groups of family farms. We then estimate separate stochastic production frontiers representing for male- and female-headed farms, and for non-Hispanic White (NHW) and minority-headed farms to evaluate whether different gender and ethnic groups share similar production technologies. Although our models account for heterogeneity across farms, including weather effects, and state-level characteristics, we do not explicitly consider soil quality and other agroecological conditions at the farm level. We also do not account for production shocks—notably the negative effects of COVID-19, which were more pronounced in 2020. However, because we preprocess the data using propensity score matching

TABLE 7 Stochastic production frontier and metafrontier results for non-Hispanic White and minority principal operator farms.

Parameters/variables		Non-Hispanic White operators	Minority operators	Metafrontier
		Coefficient (std. err)	Coefficient (*SD*)	Coefficient (*SD*)
β_0	Constant	0.6294 (1.5935)	5.3010 (5.7137)	1.0254*** (0.1048)
β_1	Harvested acres and pasture	0.1651*** (0.0081)	0.0855** (0.0354)	0.1588*** (0.0005)
β_2	Labor	0.1360*** (0.0068)	0.0999*** (0.0336)	0.1359*** (0.0005)
β_3	Capital	0.1457*** (0.0067)	0.1277*** (0.0341)	0.1439*** (0.0005)
β_4	Materials	0.5876*** (0.0086)	0.6791*** (0.0392)	0.5940*** (0.0006)
α_1	Female	−0.1294*** (0.0396)	−0.412*** (0.1487)	−0.1439*** (0.0026)
τ_1	2018	−0.0479* (0.0256)	0.1530 (0.1200)	−0.0363*** (0.0017)
τ_2	2019	−0.0941*** (0.0245)	0.0979 (0.1166)	−0.0811*** (0.0016)
τ_3	2020	0.04070 (0.0253)	−0.0952 (0.1211)	0.0369*** (0.0017)
φ_1	Spring precipitation	0.0029 (0.0131)	0.0375 (0.0635)	0.0026*** (0.0009)
φ_2	Spring precipitation squared	0.0002 (0.0002)	0.0016 (0.0010)	0.0002*** (0.0000)
φ_3	Spring precipitation × spring temperature	−0.0002 (0.0002)	−0.0017* (0.0009)	−0.0002*** (0.0000)
φ_4	Summer precipitation	−0.0321 (0.0250)	−0.2608** (0.1312)	−0.0445*** (0.0017)
φ_5	Summer precipitation squared	−0.0002* (0.0001)	−0.0006 (0.0005)	−0.0002*** (0.0000)
φ_6	Spring temperature	−0.0723*** (0.0222)	0.1539 (0.1059)	−0.0580*** (0.0015)
φ_7	Spring temperature squared	0.0007*** (0.0002)	−0.0014 (0.0009)	0.0006*** (0.0000)
φ_8	Summer temperature	0.1065** (0.0499)	−0.1522 (0.1828)	0.0889*** (0.0033)
φ_9	Summer temperature squared	−0.0007** (0.0003)	0.0009 (0.0012)	−0.0006*** (0.0000)
φ_{10}	Summer precipitation × summer temperature	0.0006* (0.0003)	0.0037** (0.0018)	0.0007*** (0.0000)
γ_1	Arizona	0.6589*** (0.2413)	0.8628 (0.7239)	0.7492*** (0.0170)
γ_2	Arkansas	0.1508** (0.0737)	0.4659 (0.3905)	0.1625*** (0.0049)
γ_3	California	0.6583*** (0.0927)	0.4342 (0.4390)	0.6503*** (0.0062)
γ_4	Colorado	0.0500 (0.1308)	0.1184 (0.6256)	0.0591*** (0.0088)
γ_5	Connecticut	0.5067 (0.3238)	—	0.5008*** (0.0223)
γ_6	Delaware	0.3713 (0.3633)	−0.1276 (1.0597)	0.3491*** (0.0233)
γ_7	Florida	−0.1272 (0.0967)	0.4649 (0.4699)	−0.0893*** (0.0065)
γ_8	Georgia	0.0715 (0.0760)	0.1602 (0.3936)	0.07309*** (0.0051)
γ_9	Idaho	0.0755 (0.1230)	0.1009 (0.5977)	0.0751*** (0.0083)
γ_{10}	Illinois	0.0019 (0.0814)	0.1604 (0.4651)	0.0025 (0.0055)
γ_{11}	Indiana	−0.0889 (0.0827)	−0.6545 (0.6479)	−0.0969*** (0.0055)
γ_{12}	Iowa	0.0600 (0.0885)	−0.0053 (0.5533)	0.0555*** (0.0059)
γ_{13}	Kansas	−0.1429* (0.0808)	−0.0295 (0.44987)	−0.1399*** (0.0054)
γ_{14}	Kentucky	−0.0614 (0.0887)	−0.8876 (0.6810)	−0.0674 (0.0059)
γ_{15}	Louisiana	−0.2232** (0.0941)	−0.1289 (0.4693)	−0.2150 (0.0063)
γ_{16}	Maine	0.0772 (0.1924)	—	0.0763 (0.0131)
γ_{17}	Maryland	0.1495 (0.2036)	—	0.1397 (0.0139)
γ_{18}	Massachusetts	0.5816 (0.3687)	1.7278 (1.0974)	1.0061*** (0.0589)
γ_{19}	Michigan	−0.1775* (0.1080)	−0.1703 (0.5973)	−0.1755*** (0.0073)

TABLE 7 (Continued)

Parameters/variables		Non-Hispanic White operators	Minority operators	Metafrontier
		Coefficient (std. err)	Coefficient (*SD*)	Coefficient (*SD*)
γ_{20}	Minnesota	−0.0631 (0.0977)	0.2050 (0.6227)	−0.0551*** (0.0066)
γ_{21}	Mississippi	−0.1292 (0.0900)	0.0666 (0.4114)	−0.1222*** (0.0059)
γ_{22}	Missouri	−0.0847 (0.0767)	0.0719 (0.4187)	−0.0796*** (0.0051)
γ_{23}	Montana	−0.3147*** (0.1156)	−0.3058 (0.5919)	−0.3072*** (0.0078)
γ_{24}	Nebraska	−0.0264 (0.0875)	0.0827 (0.5040)	−0.0261 (0.0059)
γ_{25}	Nevada	0.5417*** (0.1985)	0.8260 (0.6938)	0.6110*** (0.0141)
γ_{26}	New Hampshire	0.0272 (0.2424)	—	0.0214 (0.0165)
γ_{27}	New Jersey	−0.0007 (0.2058)	0.1905 (1.0689)	−0.0060 (0.0138)
γ_{28}	New Mexico	0.0975 (0.1980)	−0.8381* (0.4984)	0.0088 (0.0129)
γ_{29}	New York	−0.2061 (0.1362)	−0.1749 (1.1287)	−0.2111*** (0.0092)
γ_{30}	North Carolina	0.4604*** (0.0741)	0.3271 (0.3703)	0.4503*** (0.0049)
γ_{31}	North Dakota	−0.2937** (0.1191)	−0.0680 (0.6966)	−0.2859*** (0.0080)
γ_{32}	Ohio	0.0031 (0.0969)	−0.2772 (0.5651)	−0.0052 (0.0065)
γ_{33}	Oklahoma	−0.2443** (0.0996)	−0.2613 (0.3819)	−0.2194*** (0.0065)
γ_{34}	Oregon	0.1546 (0.1170)	−0.2305 (0.5891)	0.1176*** (0.0079)
γ_{35}	Pennsylvania	0.3207*** (0.1015)	0.3644 (0.7092)	0.3172*** (0.0068)
γ_{36}	Rhode Island	0.0478 (0.3159)	—	0.0426** (0.0211)
γ_{38}	South Carolina	−0.1808 (0.1318)	—	−0.1819*** (0.0090)
γ_{39}	South Dakota	−0.0608 (0.1132)	−0.0597 (0.5878)	−0.0548*** (0.0076)
γ_{40}	Tennessee	−0.1134 (0.0897)	−0.4041 (0.4767)	−0.1229*** (0.0060)
γ_{41}	Texas	−0.2149*** (0.0764)	0.0251 (0.3821)	−0.1966*** (0.0051)
γ_{42}	Utah	0.3024** (0.1494)	−0.5317 (0.8421)	0.2747*** (0.0102)
γ_{43}	Vermont	−0.3606 (0.3577)	—	−0.3595*** (0.0239)
γ_{44}	Virginia	−0.2545** (0.1025)	−1.2936*** (0.4901)	−0.2698*** (0.0069)
γ_{45}	Washington	0.2901*** (0.1029)	−0.2857 (0.4918)	0.2550*** (0.0069)
γ_{46}	West Virginia	0.3092** (0.1425)	0.3396 (0.6006)	0.3113*** (0.0093)
γ_{47}	Wisconsin	−0.2314** (0.0954)	−0.1411 (0.5350)	−0.2278*** (0.0064)
γ_{48}	Wyoming	0.2584* (0.1523)	0.1869 (0.6416)	0.2563*** (0.0102)
σ_v	Sigma (v)	0.8255*** (0.0074)	0.9113*** (0.0363)	0.0565*** (0.0004)
σ_u	Sigma (u)	0.3363*** (0.0149)	0.4476*** (0.0667)	0.0279*** (0.0005)
λ	Lambda	0.4074*** (0.0205)	0.4912*** (0.0934)	0.4939*** (0.0006)
Log likelihood		−18,022	−1083.9	20,025.51
N		14,365	755	15,120

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

prior to estimating the frontier models, we believe these omitted factors are unlikely to substantially alter our main results. Nonetheless, these data refinements do suggest areas for future work.

Our estimates yield several insights with potential policy implications. First, we establish that the production technologies for farms with minority and NHW principal operators, and male and female principal operators are structurally different. Such disparities may emanate from difficulties in acquiring and adopting productive resources, the provision and access to public support and programs. Furthermore, these results are consistent with disparities documented in the literature in

TABLE 8 Average technical efficiency, technological gap ratio, and metatechnical efficiency estimates by ethnicity of principal operator.

	Group	Observations	Mean (%)	*SD*	Min	Max
Technical efficiency (TE)	Minority	755	69.3	(0.097)	0.011	0.900
	Non-Hispanic Whites	14,365	74.9	(0.076)	0.009	0.902
Technological gap ratio (TGR)	Minorities	755	93.2	(0.111)	0.353	0.997
	Non-Hispanic Whites	14,365	97.5	(0.006)	0.689	0.985
Metatechnical efficiency (MTE)	Minorities	755	64.6	(0.120)	0.011	0.888
	Non-Hispanic Whites	14,365	73.1	(0.074)	0.008	0.879

access to productive resources across ethnic and gender groups. For example, recent research has found that socially disadvantaged farmers and ranchers (SDFRs) receive fewer loans and are less likely to participate in government agricultural programs (Hendricks et al., 2024; Todd et al., 2024; Yu & Lim, 2024). These limitations may hinder SDFRs access to technologies and various opportunities available to their non-SDFR counterparts.

Consequently, our findings suggest that SDFRs—Native Americans, Asians, Blacks or African Americans, Hispanic Americans, and female farm operators—could enhance their farm output and close their technological gaps through policies aimed at expanding their access to a wider array of USDA programs, facilitating credit access, or providing greater financial assistance that would aid in overcoming barriers and challenges within private credit markets.

Another key result is that, given their production technologies, minority- and female-headed family farms operate at a considerable distance from their own group frontiers. This suggests that in addition to the structural disparities, there are substantial differences in managerial performance relative to NHW- and male-headed farms. These results imply that it may help to target support towards strategies that foster improved managerial skills and capacity building to promote the effective use of the best available technologies. We note that these findings are consistent with the evidence from studies showing that SDFRs have experienced lower levels and lower quality of education, subpar agricultural extension services, and less awareness and uptake of available USDA programs.

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SUPPORTING INFORMATION

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

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