ETHNICITY AND GENDER IN US AGRICULTURE: PRELIMINARY RESULTS OF TECHNOLOGY AND TECHNICAL EFFICIENCY DIFFERENTIALS

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Abstract

This paper explores productivity gaps between family farms managed by male and female. operators, and by socially disadvantaged farmers and ranchers (SDFR) and non-socially disadvantaged farmers and ranchers (non-SDFR) operators. We use data from the Agricultural Resource Management Surveys (ARMS) conducted between 2017 and 2020 and propensity score matching techniques to obtain comparable samples based on observable covariates. Then, stochastic production frontier methods are implemented to test for technology differentials and perform a technical efficiency (TE) analysis. The results reveal that the production technologies of SDFR and non-SDFR farm operators, and male and female are structurally different. In addition, given their production technologies, TE estimates for SDFR and female headed farms are significantly lower compared to their non-SDFR and male counterparts providing evidence that these groups may not have similar access to USDA programs, or they are not as adept at combining various inputs to maximize output.

Keywords: US agriculture; family farms, ethnic and gender disparities; stochastic production frontiers; technical efficiency

Disclaimer: *The findings and conclusions in this publication are those of the authors and should not be construed to represent any official USDA or U.S. government determination or policy.*

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1. INTRODUCTION

The USDA defines socially disadvantaged farmers and ranchers (SDFR) as those belonging to groups that have been subject to racial or ethnic prejudice in some USDA programs. The SDFR community includes Native American, Asians, Blacks or African Americans, Hispanic Americans, and Women. According to the 2017 US Census of Agriculture, 4.6% of all producers are non-white, 3.3% are Hispanic (of any race) and 36.1% are female (USDA, 2019).

Research indicates that SDFRs typically have received lower levels and poorer quality education, inferior quality extension services, and restricted access to key resources such as irrigation water (Huffman 1981; Burton 1987). Horst and Marion (2019) report that findings drawn from recent data reveal that historical disparities based on race, ethnicity, and gender have exhibited little change over time, leaving the SDFR community at a socio-economic disadvantage and likely lagging in terms of productivity relative to their non-SDFR counterparts. These disparities have been a matter of concern and the subject of numerous reports published over the years (e.g., Ackerman, Bustos, and Muller, 2012).

Over the past few decades, the USDA has enacted reforms designed to improve access to USDA programs by minority farmers (USDA. 2005). Several USDA agencies now have programs that target SDFRs, but it remains an open question whether and to what extent current differences in lending - and USDA program participation more generally - are the result of ongoing racial discrimination (e.g., Escalante et al. 2018). In 2021, the American Rescue Plan Act authorized debt relief to socially disadvantaged producers holding direct or guaranteed farm loans as well as Farm Storage Facility Loans. Moreover, SDFRs may also suffer from discrimination in the private sector, contributing to lower rates of farm investment and productivity. For example, several studies of small business loans have found evidence that minority-owned operations were charged higher interest rates or were less likely to be offered credit than similar non-minority businesses (e.g., Asiedu, et al. 2012; Blanchard et al. 2008; Blanchflower, et al. 2003).

Despite an extensive literature focusing on the problems faced by the SDFRs in the US, there is a dearth of econometric analysis of these issues. An important unanswered question is whether farms operated by SDFRs are as productive as otherwise similar farms operated by non-SDFRs. Evidence of a productivity gap would suggest that SDFRs continue to suffer from discrimination in access to government programs or private sector resources. In contrast to the lack of studies in the U.S., an extensive literature has emerged concerning disparities in developing countries focusing on female-male productivity differentials (e.g., Owusu and Bravo-Ureta 2021; Ben Yishay et al. 2020; Kilic, Palacios-López, and Goldstein (2015).

In sum, there is substantial evidence that SDFRs have faced discrimination in access to financial resources and inputs to production which could be expected to have adverse consequences for their farm productivity relative to non-SDFRs. However, rigorous econometric analyses to evaluate and compare the productivity of these two groups of producers is a major gap in the literature. Therefore, the objective and novelty of this paper is to explore productivity gaps between family farms managed by male and female operators, and by SDFRs and non-SDFR operators applying state of the art econometric procedures using rich micro level data.

The data used comes from the Agricultural Resource Management Surveys (ARMS) conducted between 2017 and 2020. These data comprise production practices, and cost and returns for several commodities. We apply propensity score matching (PSM) to obtain comparable samples based on observable covariates. Stochastic production frontier methods are implemented to test for technology differentials and perform a technical efficiency analysis.

The remainder of the paper is organized into five additional sections. Section 2 outlines the methodology and section 3 contains a discussion of the data and the empirical model. Section 4 displays the results and analysis, and the paper ends with a summary and concluding remarks in Section 5.

2. METHODOLOGY

The methodology used in this paper entails two main steps. First, we use Propensity Score Matching (PSM) to define the sample. Second, we estimate separate SPF models for the SDFR and non-SDFR operators, as well as for male and female principal operators then test the null hypothesis that the technologies used across the different groups are the same.

2.1 Propensity Score Matching (PSM)

We use PSM to pre-process the data and match SDFR and non-SDFR farms as well male and female farms in order to find comparable control groups (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 and Bravo-Ureta, 2021).

As explained in the results section, statistical tests indicate an unbalanced distribution of observable attributes between SDFR and non-SDFR headed farms, and male and female headed farms pre matching. Propensity scores, P_i, are derived from a Probit model of the likelihood for a farmer to belong to SDFR or female and is expressed, following Frölich (2007) and Mishra et al. (2017), as:

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

where P_i equals 1 for SDFR or female and 0 for non-SDFR or male; X is a set of covariates which include age, gender, education, experience, ethnicity, value of farm assets, government payments received, farm specialization, and regional specific and year 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 and then determine the area of common support (Caliendo and Kopeinig 2008; Lachaud, et al. 2018). The aim is to define a data set in which the treated (SDFR and female) and control groups (non-SDFR and male) exhibit similar characteristics (Ho et al., 2007). 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 treated and 0 otherwise. For equation (2) to be satisfied, each SDFR or female farm should be matched with non-SDFR or male counterparts, so that the distributions of the observed characteristics across groups are equivalent. This can be accomplished using several alternative matching algorithms (Caliendo and Kopeinig, 2008). Here we rely on radius matching within a caliper of 0.25 standard deviations of the propensity score and without replacement. All non-SDFR and male observations that cannot be matched with an SDFR or female counterparts are discarded.

***2.2 Stochastic Production Frontiers* (SPF)**

In the second step we assume that farm operators use a non-negative vector of inputs denoted by $x = (x_1, x_2, \dots, x_n) \in \Re_+^K$ to produce a strictly positive scalar output denoted $y \in \Re_{++}$. The set of all feasible input-output combinations can be characterized as follows:

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

Following Aigner et al., (1977) and Meeusen and van den Broeck (1977), given the technology set, the SPF for farm operator i from group g is given by:

$$Y_{ig}^F = X'_{kig}\beta_{kg} + v_{ig} - u_{ig} \tag{4}$$

where Y_{ig}^{F} and X'_{kig} are respectively, a scalar output and a column vector of k inputs, in logs, for the ith farm in the gth group; β_{kg} is a vector of parameters to be estimated; v_{ig} is the standard 2-sided normally distributed error term and u_{ig} the one-sided error denoting inefficiency that is assumed to follow a half-normal distribution. The TE for the ith unit in group g, TE_i^g, is given by $e^{-u_{ig}}$ (Jondrow et al., 1982). In other words, we allow for each group to utilize its own technology set given by:

$$\mathbb{T}^g = \{(y, x)\text{: } x \text{ can be used by farm operators of ethnic group } g \text{ to produce } y\}. \qquad (5)$$

If statistical tests support the hypothesis that the technologies exhibited by the different groups are different, then the stochastic meta-frontier technology framework is implemented to generate a common technology benchmark.

3. DATA AND EMPIRICAL MODEL

This study relies on data generated from the Agricultural Resource and Management Survey (ARMS). The ARMS is a cross-sectional, multi-phased, multi-framed, 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 used in this study cover four years, from 2017 to 2020. They were administered on a diverse national sample of crop and livestock farm operations. The focus of this study is on family farms therefore we exclude farms that are designated corporate, legal partnerships, estates, trusts and cooperatives. A summary of input-output variables used in this study is provided in Tables 1 and 2 for the SDFR and non-SDFR farms, and the male and female farms, respectively, where farms are classified by the ethnicity or gender of the farm's principal operator. Maximum and minimum values have been suppressed to preserve anonymity.

The output and input variables are defined as follows: output is equal to the value of total agricultural output; land corresponds to harvested acres; labor comprises both paid and unpaid labor hours; intermediate materials include expenditures on fuel and oil, fertilizers and pesticides, seeds, and purchased feed; and capital is the sum of depreciation expenses, value of livestock inventory, and maintenance and repair expenses. All monetary values were converted to implicit quantities using price indices generated by the National Agricultural Statistics Service.

4. RESULTS

As mentioned above propensity score matching is used to restrict estimation to a region of common support. Several recent stochastic production frontier studies have utilized propensity score matching including Bravo-Ureta et al. (2020) and Owusu and Bravo-Ureta (2021). A PSM approach helps to improve comparability of productivity outcomes across the various groups: SDFR and non-SDFR, as well as male and female. The Probit results for selection into non-SDFR, and male principal operator categories are provided in Tables 3 and 4, respectively. Similarly, the kernel densities of the propensity scores are shown in the panels of Figure 1 and Figure 2 for the ethnic, and gender categories, respectively. Additional results on the balancing statistics and balancing tests for the matched and unmatched samples are presented in the Appendix Tables A1, A2, A3 and A4 and Figures A1 and A2.

Separate stochastic production frontiers are estimated for the SDFR and non-SDFR (Table 5), and for the male and female headed farms (Table 6). The individual group production technologies assume that there are inherent structural differences in the production technologies across the groups. Following estimation of the *j*-group stochastic production frontiers we test the null hypothesis (H_0) that the *j*-group production technologies are equal. For the SDFR and non-SDFR j-group production technologies a Wald test with chi-squared distribution, (χ^2_ρ) with $\rho = 16$

degrees of freedom, generates a test-statistic of 20.70 with a p-value of 0.190 indicating a failure to reject the null hypothesis.

Similarly, for the male and female production technologies a Wald test, with a chi-squared distribution, (χ^2_ρ) with $\rho = 18$ degrees of freedom, yields a test-statistic of 31.37 with a p-value of 0.261 suggesting the no-rejection of the null hypothesis. Simply stated, both statistical tests reveal structural differences in production technologies across ethnic groups and gender. We use a Cobb-Douglas functional form so that the parameter estimates for inputs can be interpreted directly as partial production elasticities.

The findings suggest that a 1-percent increase in land results in a 0.121 and 0.170 percent augmentation in output for the SDFR and non-SDFR groups, respectively. The parameter estimates γ_j and τ_t capture regional and year fixed effects. The evidence suggests, in general, that the production environment in the Southern Seaboard, Fruitful Rim, and Basin Range is more favorable for farm operators compared to those in the other regions and in particular Prairie Gateway. This difference in production environments is more significant for males across both groups. Estimates of σ_u and σ_v where $\sigma_u/\sigma_v = \lambda$ measure the relative contribution of inefficiency to the composed error term or output variability.

Similarly, a 1-percent increase in land leads to a 0.233 and 0.161 percent increase in output for the female and male farm operators, respectively. It is worth noting that there is a statistically significant decline in output in female operated non-SDFR farms, and in non-Hispanic Non-White (NHNW) operated male farms.

Average technical efficiency (ATE) estimates, which measure where the average farm operates relative to its group frontier are provided in Table 7 and 8 for the SDFR and non-SDR, and male and female headed farms, respectively.

The within-group estimates of technical efficiency indicate that the average SDFR and non-SDFR headed farms had technical efficiency estimates of 66.4 percent and 75.0 percent, respectively. Meanwhile, relative to their specific group frontiers, the average female and male headed farms have technical efficiency estimates of 62.9 and 75.4 percent, respectively.

5. SUMMARY AND CONCLUSIONS

The results generated in this study establish that the production technologies of farms with SDFR and non-SDFR principal operators, and male and female principal operators are structurally different. We also observe that, given their production technologies, the technical efficiency estimates for SDFR and female headed farms are significantly lower compared to their non-SDFR and male headed farms providing evidence that these groups are not as adept at combining various inputs to maximize output.

The preliminary results presented in this study provide the basis for additional research, including the estimation of stochastic metafrontiers and the decomposition of total factor productivity, to generate more refined evidence of productivity differentials across the various groups. Most important is to generate results that can be used to inform public policy and stakeholders.

Table 1: Descriptive statistics of farms by ethnicity of principal operator

	non-SDFR		SDFR	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
Value of farm assets ('000)	3,026.52	6,167.34	2,861.88	6,683.46
Value of agricultural products	6,542.99	19,320.52	6,769.84	20,425.28
Land acres	1,100.96	2,320.87	776.35	2,117.47
Cropland acres	708.07	1,260.26	418.84	884.41
Harvested acres	624.43	1,126.44	348.75	783.12
Labor hours	3,246.55	2,255.28	2,961.43	2,060.83
Capital ($)	1,885.39	9,375.71	1,928.24	6,955.67
Materials ($)	2,144.79	6,681.79	1,935.68	7,049.66
Livestock units	1,217.21	8,490.70	1,276.68	6,357.83
Principal operator education class	2.81	0.90	2.74	0.99
Principal operator college	0.28	0.45	0.30	0.46
Principal operator age	60.05	12.87	59.95	12.42
Principal operator retired indicator	0.05	0.21	0.05	0.22
Principal operator experience	32.91	14.81	27.90	15.20
Received government payment	0.55	0.50	0.35	0.48
Government payments received	112.03	316.69	69.72	260.32
Value of land and buildings ('000)	2,296.46	5,209.81	2,257.51	5,932.29
Cash grain specializations	0.38	0.48	0.17	0.38
Other field crops specialization	0.11	0.32	0.13	0.33
High value crops specialization	0.08	0.27	0.29	0.46
Beef specialization	0.30	0.46	0.29	0.45
Other livestock specialization	0.13	0.34	0.12	0.33
Limited resource farm indicator	0.05	0.21	0.07	0.26
N	25,040		1,257	

Table 2: Descriptive statistics of farms by gender of principal operator

	Male		Female	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
Value of farm assets ('000)	2,869.01	4,261.03	2,192.59	3,971.24
Value of agricultural products	6,478.51	17,623.34	3,314.22	10,182.73
Land acres	1,077.89	2,192.83	640.94	1,382.75
Cropland acres	687.84	1,180.22	350.00	900.83
Harvested acres	604.22	1,044.56	277.46	768.61
Labor hours	3,244.07	2,232.77	2,616.24	2,140.23
Capital ($)	1,851.66	5,933.78	1,096.91	2,469.18
Materials ($)	2,100.52	5,566.61	970.57	3,096.38
Livestock units	1,196.07	5,269.06	694.73	2,008.21
Principal operator education class	2.81	0.90	3.03	0.87
Principal operator college	0.28	0.45	0.37	0.48
Principal operator age	59.98	12.78	63.42	13.38
Principal operator retired indicator	0.05	0.21	0.08	0.27
Principal operator experience	32.87	14.75	28.68	17.37
Received government payment	0.55	0.50	0.36	0.48
Government payments received	107.83	299.16	57.42	227.57
Value of land and buildings ('000)	2,158.90	3,646.31	1,796.03	3,601.75
Cash grain specializations	0.37	0.48	0.17	0.37
Other field crops specialization	0.12	0.32	0.12	0.33
High value crops specialization	0.09	0.29	0.19	0.39
Beef specialization	0.29	0.46	0.38	0.49
Other livestock specialization	0.13	0.34	0.14	0.35
Limited resource farm indicator	0.04	0.21	0.10	0.31
N	25,358		1,079	

Table 3: Probit results for selection into non-SDFR principal operator category

Ethnicity	Coefficient	Std. Err.
Gender	0.1276**	0.0533
Value of farm assets	-0.0000	0.0000
Heartland	-0.6420***	0.0663
Northern crescent	-0.6426***	0.0778
Northern great plains	-0.1316*	0.0787
Prairie gateway	-0.0987	0.0651
Eastern uplands	-0.2803***	0.0700
Southern seaboard	-0.1200	0.0640
Fruitful rim	0.2455***	0.0648
Basin range	0.0578	0.0838
Principal operator experience	-0.0109***	0.0012
Principal operator age	0.0041***	0.0014
Principal operator college	0.2427***	0.0518
Principal operator education class	-0.2094***	0.0253
High value crops specialization	0.3527	0.0409
Cash grain specializations	-0.1059***	0.0362
Government payments received	-0.0001*	0.0000
2018	0.0623*	0.0348
2019	0.0365	0.0364
2020	0.0986***	0.0384
Constant	-0.9101***	0.1060
Log likelihood	-5398.12	
N	29,188	

Table 4: Probit results for selection into male principal operator category

Gender	Coefficient	Std. Err.
Value of farm assets	-0.0000***	0.0000
Heartland	0.0020	0.0755
Northern crescent	0.0794	0.0809
Northern great plains	0.0505	0.0934
Prairie gateway	0.0600	0.0777
Eastern uplands	0.0131	0.0802
Southern seaboard	-0.0849	0.0780
Fruitful rim	0.1524*	0.0784
Basin range	0.2637	0.0924
Principal operator experience	-0.0186***	0.0011
Principal operator age	0.0241***	0.0014
Principal operator college	-0.1781***	0.0524
Principal operator education class	0.1757***	0.0282
Nonhispanic white	0.1502	0.1184
Nonhispanic Nonwhite	0.3500***	0.1354
Hispanic	0.2312***	0.1364
High value crops specialization	0.0372	0.0453
Cash grain specializations	-0.3227***	0.0374
Government payments received	-0.0001	0.0001
2018	0.0496	0.0361
2019	0.1145***	0.0368
2020	0.0401	0.0403
Constant	-3.1735***	0.1712
Log likelihood	-5020.6969	
N	29,316	

Table 5: Stochastic production frontier estimates by ethnicity of principal operator

		SDFR		non-SDFR	
Coefficient/Variable		Coefficient	Std. Err.	Coefficient	Std. Err.
β_1	Harvested acres	0.1208***	0.0270	0.1701***	0.0063
β_2	Labor hours	0.1533***	0.0470	0.1387***.	0.0095
β_3	Capital	0.1657***	0.0233	0.1192***	0.0045
β_4	Materials	0.6584***	0.0288	0.6367***	0.0065
α_1	Gender	-0.1042	0.1207	-0.0828***	0.0298
τ_1	2018	0.0359	0.0852	0.0459***	0.0147
τ_2	2019	0.0855	0.0879	0.0905***	0.0156
τ_3	2020	0.0447	0.0921	0.1991***	0.0169
γ_1	Heartland	0.1498	0.1561	0.1174***	0.0278
γ_2	Northern crescent	0.0854	0.1913	0.0451	0.0313
γ_3	Northern great plains	0.1885	0.1831	-0.0502	0.0352
γ_4	Prairie gateway	-0.1246	0.1481	-0.0546*	0.0307
γ_5	Eastern uplands	0.1845	0.1656	0.0371	0.0326
γ_6	Southern seaboard	0.2548*	0.1418	0.2475***	0.0306
γ_7	Fruitful rim	0.5575***	0.1345	0.4536***	0.0318
γ_8	Basin range	0.4885**	0.1929	0.2029***	0.0430
β_0	Constant	0.6216*	0.3571	0.8015***	0.0706
σ_v	Sigma (v)	0.9545	0.0318	0.8276	0.0056
σ_u	Sigma (u)	0.5087	0.0576	0.3346	0.0114
λ	Lambda	0.5329	0.0819	0.4044	0.0157
	Log likelihood	-1881.4722		-32745.51	
	N	1,257		25,040	

Table 6: Stochastic production frontier estimates by gender of principal operator

		Female		Male	
	Coefficient/Variable	Coefficient	Std. Err.	Coefficient	Std. Err.
β_1	Harvested acres	0.2334***	0.0308	0.1614***	0.0062
β_2	Labor hours	0.0800**	0.0443	0.1467***	0.0095
β_3	Capital	0.0834***	0.0250	0.1218***	0.0045
β_4	Materials	0.6255***	0.0322	0.6412***	0.0064
α_1	Nonhispanic white	-0.1642	0.2906	-0.0563	0.0506
α_2	Hispanic	-0.3933	0.3332	0.0123	0.0619
α_3	Nonhispanic Nonwhite	0.0849	0.3314	-0.1331**	0.0632
τ_1	2018	0.0208	0.0945	0.0448***	0.0148
τ_2	2019	-0.0805	0.0962	0.0941***	0.0155
τ_3	2020	0.0894	0.1062	0.1939***	0.0168
γ_1	Heartland	-0.0590	0.1942	0.1311***	0.0277
γ_2	Northern crescent	0.0085	0.2113	0.0516***	0.0313
γ_3	Northern great plains	-0.0552	0.2400	-0.0324***	0.0351
γ_4	Prairie gateway	-0.0571	0.2015	-0.0578*	0.0305
γ_5	Eastern uplands	0.1232	0.2099	0.0420	0.0325
γ_6	Southern seaboard	0.2434	0.2095	0.2586***	0.0304
γ_7	Fruitful rim	0.4615	0.1960	0.4565***	0.0314
γ_8	Basin range	0.3319	0.2339	0.2234***	0.0428
β_0	Constant	1.6376***	0.4600	0.7812***	0.0870
σ_v	Sigma (v)	0.9696	0.0363	0.8306	0.0056
σ_u	Sigma (u)	0.5933	0.0627	0.3272	0.0117
λ	Lambda	0.6119	0.0904	0.3939	0.0159
	Log likelihood	-1665.41		-33161.69	
	N	1,079		25,358	

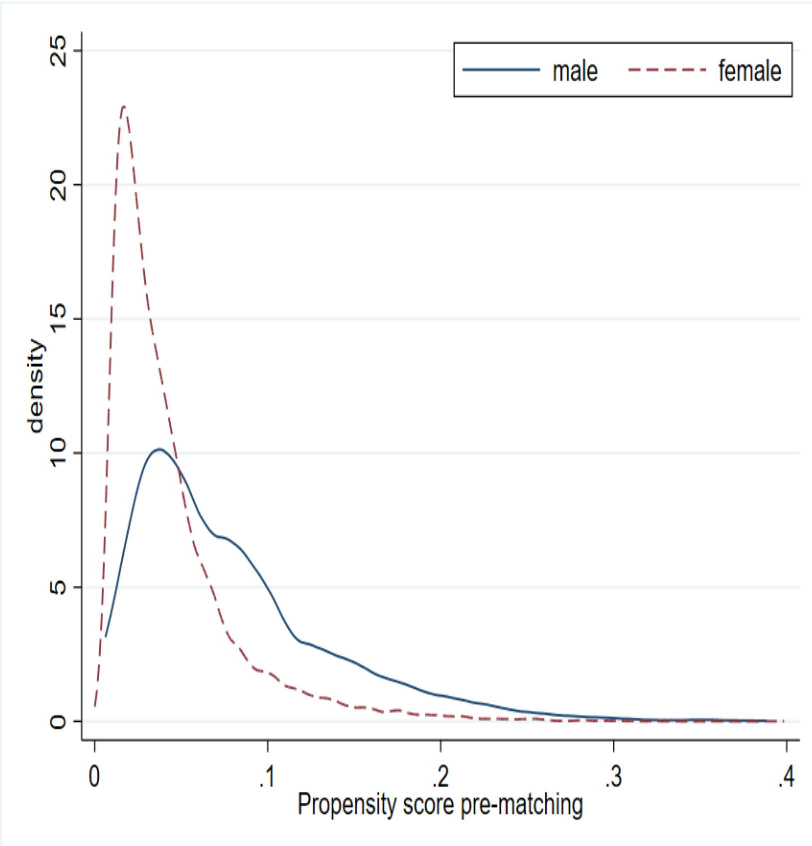
Table 7: Average technical efficiency estimates by ethnicity of principal operator

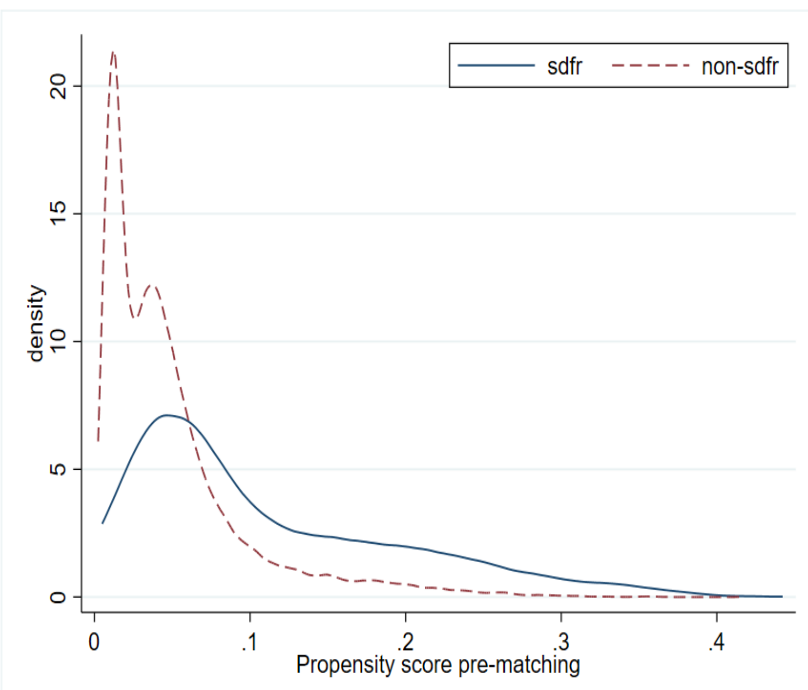
Variable	Observation	Mean	Std. dev.	Min	Max
SDFR	1,257	0.664	0.108	0.012	0.889
non-SDFR	25,040	0.750	0.075	0.005	0.916

Table 8: Average technical efficiency estimates by gender of principal operator

Variable	Observations	Mean	Std. dev.	Min	Max
Female	1,079	0.629	0.124	0.030	0.867
Male	25,358	0.754	0.073	0.014	0.916

Figure 1: Kernel density of propensity scores by gender, and ethnicity of principal operator





REFERENCES

Ackerman, L., D. Bustos, and M. Muller. 2012. Disadvantaged Farm-ers: Addressing Inequalities in Federal Programs for Farmers of Color. Institute for Agriculture and Trade Policy. http://www.iatp.org/sites/default/files/2018-1/%234.%20Disadvantaged%20Farmers.%20 Addressing%20Inequalities%20in%20Federal%20Programs%20for%20Farmers%20of% 20Color.pdf. Accessed December 2021.

Agriculture Improvement Act. 2018. H.R. 2 Agricultural Improvement Act of 2018. Accessed 12/21 at: https://www.congress.gov/bill/115th-congress/house-bill/2

American Rescue Plan. 2021. H.R. 1319. American Rescue Plan Act of 2021. Accessed 12/21 at: https://www.congress.gov/bill/117th-congress/house-bill/1319/text

Anderson, T. L. and Lueck, D. 1992. Land tenure and agricultural productivity on Indian reservations. *The Journal of Law and Economics 35*(2): 427-454.

Asare-Baah, L., R. Zabawa and H. Findlay. 2018. Participation in Selected USDA Programs by Socially Disadvantaged Farmers in Selected Black Belt Counties in Georgia. *Journal of Rural Social Sciences* 33(1): Article 2. https://egrove.olemiss.edu/jrss/vol33/iss1/2

Asiedu, E., Freeman, J. A., and Nti-Addae, A. 2012. Access to credit by small businesses: How relevant are race, ethnicity, and gender? *American Economic Review 102*(3): 532-37.

Ayazi, H., and E. Elsheikh. 2015. The Farm Bill Report: Corporate Power and Structural Racialization in the United States Food System. Haas Institute for a Fair and Inclusive Society at the University of California. https://haasinstitute.berkeley.edu/globa l-justice/glocal-food-systems/farm-bill-report-corporate-power -and-structural-racialization-us-food-system. Accessed December 2021.

Blanchard, L., B. Zhao, and J. Yirager. 2008. Do Lenders Discriminate against Minority and Woman Entrepreneurs? *Journal of Urban Economics* 63(2): 467-97.

Blanchflower, D. G., P. B. Levine, and D. J. Zimmerman. 2003. Discrimination in the Small-Business Credit Market. *Review of Economics and Statistic* 85 (4): 930-4

Ben Yishay, A., Jones, M., Kondylis, F., and Mobarak, A. M. (2020). Gender Gaps in Technology Diffusion. *Journal of Development Economics* 1–26. https://doi.org/10.1016/j.jdeveco.2019.102380.

Bravo-Ureta, B.E., W. Greene, and D. Solis. 2012. “Technical Efficiency Analysis Correcting for Biases from Observed and Unobserved Variables: An Application to a Natural Resource Management Project.” *Empirical Economics* 43(1):55–72.

Burton, l. 1987. The American Indian Water Rights Dilemma: Historical Perspective and Dispute-Settling Policy Recommendations. *Journal of Environmental Law* 7-1: 1-66.

Caliendo, M., & Kopeinig, S. 2008. Some practical guidance for the implementation of propensity score matching. *Journal of economic surveys* 22(1): 31-72.

Carlson, L.A., 1983. Federal Policy and Indian Land: Economic interests and the sale of Indian allotments, 1900-1934. *Agricultural history 57*(1): 33-45.

Cornell, S.E. and Kalt, J.P. eds., 1992. *What can tribes do?: Strategies and institutions in American Indian economic development*. Los Angeles, CA: American Indian Studies Center, University of California, Los Angeles.

Deaton, B.J., 2012. A review and assessment of the heirs' property issue in the United States. *Journal of Economic Issues 46*(3): 615-632.

Dehejia, R.H., and S. Wahba. 1999. “Causal Effects in nonexperimental Studies: Reevaluating the Evaluation of Training Programs.” *Journal of the American Statistical Association* 94:1053–1062.

Dismukes, Robert, Joy L. Harwood, and Susan E. Bentley. 1997. Characteristics and Risk Management Needs of Limited-Resource and Socially Disadvantaged Farmers. USDA Economic Research Service. *Agriculture Information Bulletin* No. 733. April.

Escalante, C.L., Osinubi, A., Dodson, C. and Taylor, C.E., 2018. Looking beyond farm loan approval decisions: Loan pricing and nonpricing terms for socially disadvantaged farm borrowers. *Journal of Agricultural and Applied Economics 50*(1): 129-148.

Feder, J. and T. Cowan. 2013. *Garcia v. Vilsack: A Policy and Legal Analysis of a USDA Discrimination Case.* Congressional Research Service, CRS Report for Congress, 7-5700.

Food, Agriculture, Conservation, and Trade Act of 1990. (1990, November 28). https://www.congress.gov/bill/101st-congress/senate-bill/2830.

Frölich, M. 2007. Propensity score matching without conditional independence assumption—with an application to the gender wage gap in the United Kingdom. *The Econometrics Journal* 10(2): 359–407. https://doi.org/10.1111/j.1368-423X.2007.00212.x.

Ge, M., Edwards, E.C., and S. Akhundjanov. 2018. Land Ownership and Irrigation on American Indian Reservations. (CEnREP Working Paper No. 18-017). Raleigh, NC: Center for Environmental and Resource Economic Policy.

Gilbert, J., Sharp, G. and Felin, M.S., 2002. The loss and persistence of black-owned farms and farmland: A review of the research literature and its implications. *Journal of Rural Social Sciences 18*(2): 1.

Hargrove, T. and B. L. Jones. 2004. A Qualitative Case Study Analysis of the Small Farmers Outreach Training and Technical Assistance (2501) Program from 1994-2001: Implications for African American Farmers. *Journal of Agricultural Education* 45(2):72–82.

Heckman, J., H. Ichimura, and P.E. Todd. 1997. "Matching as an Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Programme." *The Review of Economic Studies* 64(4):605–654.

Ho, D. E., Imai, K., King, G., & Stuart, E. A. 2007. Matching as nonparametric preprocessing for Reducing model dependence in parametric causal inference. *Political Analysis* 15(3): 199–236. https://doi.org/10.1093/pan/mpl013.

Horst, M. and A. Marion. 2019. Racial, Ethnic and Gender Inequities in Farmland Ownership and Farming in the U.S. *Agriculture and Human Values* 36:1–16.

Huang, C., T.H. Huang, and N.H. Liu. 2014. "A New Approach to Estimating the Metafrontier Production Function Based on a Stochastic Frontier Framework." *Journal of Productivity Analysis* 42(3):241–254.

Huffman, W. 1981. Black-White Human Capital Differences: Impact on Agricultural Productivity in the U.S. South. *American Economic Review* 71: 94-107.

Kilic, T., Palacios-López, A. and Goldstein, M. (2015). Caught in a Productivity Trap: A Distributional Perspective on Gender Differences in Malawian Agriculture. *World Development 70*: 416–463. https://doi.org/10.1016/j.worlddev.2014.06.017.

Lachaud, M. A., Bravo-Ureta, B. E., Fiala, N., & Gonzalez, S. P. 2018. The impact of agri-business skills training in Zimbabwe: an evaluation of the Training for Rural Economic Empowerment (TREE) programme. *Journal of Development Effectiveness* 10(3): 373-391.

Leonard, B., D. P. Parker, T. L. Anderson. 2020. Land quality, land rights, and indigenous poverty", *Journal of Development Economics* 143: https://doi.org/10.1016/j.jdeveco.2019.102435.

Mishra, A. K., Khanal, A. R., & Mohanty, S. 2017. Gender differentials in farming efficiency and profits: The case of rice production in the Philippines. *Land Use Policy* 63: 461–469. https://doi.org/10.1016/j.landusepol.2017.01.033

Mitchell, T.W. 2000. From reconstruction to deconstruction: Undermining black landownership, political independence, and community through partition sales of tenancies in common. *Northwestern Univ. Law Review* 95: 505.

Nickerson, C. and M. Hand. 2009. Participation in Conservation Programs by Targeted Farmers: Beginning, Limited-Resource, and Socially Disadvantaged Operators' Enrollment Trends. USDA Economic Research Service. *Economic Information Bulletin*. Number 62 December.

Ñopo, H. (2008). Matching as a tool to decompose wage gaps. *The Review of Economics and Statistics* 90(2): 290–299.

O'Donnell, C. J., Rao, D. S. P., & Battese, G. E. 2008. Metafrontier frameworks for the study of firm-level efficiencies and technology ratios. *Empirical Economics* 34(2): 231–255. https://doi.org/10.1007/s00181-007-0119-4

Owusu, E. S. and B. E. Bravo-Ureta. 2021. Gender and Productivity Differentials: An Analysis of Groundnut Farmers in Malawi. *Journal of Development Studies*: Forthcoming.

Rubin, D.B. 1991. "Practical Implications of Modes of Statistical Inference for Causal Effects and the Critical Role of the Assignment Mechanism." *Biometrics* 47:1213–1234.

USCCR. 1965. *Equal Opportunity in Farm Programs: An Appraisal of Services Rendered by Agencies of the United States Department of Agriculture*. U.S. Commission on Civil Rights. Washington, DC: U.S. Government Printing Office.

USCCR. 1982. *The Decline of Black Farming in America: A Report of the United States Commission on Civil Rights*. U.S. Commission on Civil Rights. Washington, DC: U.S. Government Printing Office.

USDA. 1997. *Civil rights at the United States Department of Agriculture: A report of the Civil Rights Action Team*. Washington, DC.: USDA Civil Rights Action Team.

USDA. 2005. *Minority Participation in Farm Service Agency's Farm Loan Programs.* (No. 03601-11-AT). Washington, D.C.: USDA Office of Inspector General.

USDA. 2019. 2017 United States Census of Agriculture: United States Summary and State Data. U.S. Department of Agriculture. National Agricultural Statistics Service. AC-17-A-51.

USGAO. 2019. "Agricultural lending Information on Credit and Outreach to Socially Disadvantaged Farmers and Ranchers Is Limited". Government Accountability Office**.** GAO-19-539. https://www.gao.gov/products/gao-19-539

Appendix

Table A1: Balancing statistics for matched and unmatched samples for gender

Variable	Unmatched Matched	Mean Treated	Control	%bias	%reduct |bias|	t-test t	p>|t|	V(T)/ V(C)
Heartland	U	0.155	0.272	-28.9		-9.49	0	.
	M	0.155	0.153	0.5	98.3	0.15	0.884	.
Value of farm assets ('000)	U	2200.000	3100.000	-16	0.7	-5.06	0	0.39*
	M	2200.000	2200.000	0.8	95.4	-0.28	0.777	1.31*
Northern crescent	U	0.094	0.102	-2.5		-0.89	0.374	.
	M	0.094	0.092	0.8	66.9	0.22	0.825	.
Northern great plains	U	0.038	0.054	-7.5		-2.51	0.012	.
	M	0.038	0.039	-0.2	97.2	-0.06	0.953	.
Prairie gateway	U	0.131	0.128	0.9		0.34	0.734	.
	M	0.131	0.130	0.1	88.6	0.03	0.978	.
Eastern uplands	U	0.111	0.098	4.4		1.61	0.107	.
	M	0.111	0.113	-0.7	83.7	-0.18	0.858	.
Southern seaboard	U	0.128	0.140	-3.5		-1.23	0.219	.
	M	0.128	0.129	-0.5	85.5	-0.13	0.894	.
Fruitful rim	U	0.252	0.132	30.8		12.48	0	.
	M	0.252	0.250	0.4	98.8	0.08	0.933	.
Basin range	U	0.058	0.029	14.5		6.19	0	.
	M	0.058	0.057	0.5	96.5	0.12	0.908	.
Principal operator experience	U	28.668	32.866	-26.1		-10.09	0	1.39*
	M	28.668	29.059	-2.4	90.7	-0.62	0.535	1.31*
Principal operator age	U	63.444	59.915	26.9		9.83	0	1.1

	M	63.444	63.515	-0.5	98	-0.15	0.885	1.22*
Prinicpal operator college	U	0.366	0.278	18.9		6.98	0	.
	M	0.366	0.370	-0.8	95.6	-0.21	0.837	.
Prinicpal operator education	U	3.028	2.806	25.1		8.85	0	0.93
	M	3.028	3.030	-0.1	99.5	-0.03	0.975	0.99
Non-Hispanic White	U	0.895	0.936	-15		-6.03	0	.
	M	0.895	0.894	0.3	98.2	0.06	0.949	.
Non-Hispanic Non-White	U	0.049	0.024	13.4		5.73	0	.
	M	0.049	0.050	-0.3	97.7	-0.07	0.946	.
Hispanic	U	0.043	0.026	9.3		3.75	0	.
	M	0.043	0.043	0.1	98.9	0.02	0.981	.
High value crop specialization	U	0.187	0.090	28.4		11.9	0	.
	M	0.187	0.187	-0.2	99.4	-0.04	0.971	.
Cash grains specialization	U	0.168	0.374	-47.7		-15.39	0	.
	M	0.168	0.169	-0.2	99.6	-0.05	0.957	.
Total payment received	U	57.382	113.760	-20.1		-6.29	0	0.49*
	M	57.382	59.847	-0.9	95.6	-0.29	0.772	1.14*
2018	U	0.282	0.281	0.1		0.04	0.966	.
	M	0.282	0.280	0.3	-132.7	0.07	0.942	.
2019	U	0.270	0.237	7.6		2.78	0.005	.
	M	0.270	0.272	-0.5	93.7	-0.12	0.904	.
2020	U	0.193	0.183	2.5		0.92	0.36	.
	M	0.193	0.190	0.8	68.6	0.2	0.838	.

* if variance ratio outside [0.90; 1.11] for U and [0.90; 1.11] for M

Table A2: Balancing test for matched and unmatched samples for gender

Sample	Ps R2	LR chi2	p>chi2	Mean Bias	Med Bias	B	R	%Var
Unmatched	0.079	857.23	0.000	16	14.8	83.2*	1.16	60
Matched	0.000	1.08	1.000	0.5	0.5	4.0	1.15	80

* if B>25%, R outside [0.5; 2]

Figure A1: Standardized percentage bias plots

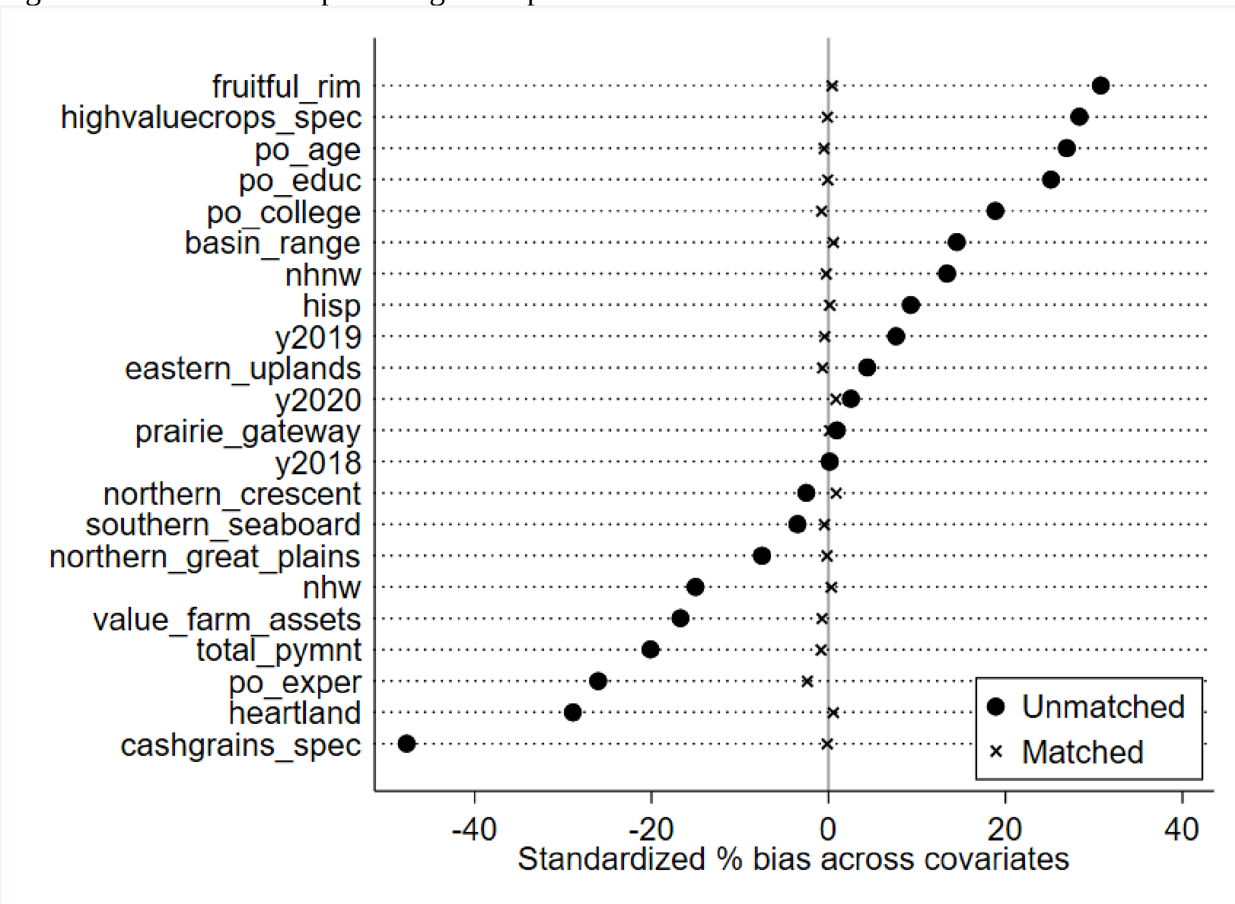


Table A3: Balancing statistics for matched and unmatched samples for ethnicity

Variable	Unmatched Matched	Mean Treated	Mean Control	%bias	%reduct |bias|	t-test t	t-test p>|t|	V(T)/ V(C)
Heartland	U	0.07	0.28	-57		-18.13	0.000	.
	M	0.07	0.09	-5.2	90.9	-1.93	0.053	.
Value of farm assets ('000)	U	2900.00	3000.00	-2	0.7	-1.08	0.278	1.16*
	M	2900.00	2900.00	0.2	92.7	-0.05	0.958	0.99
Northern crescent	U	0.04	0.11	-27.4		-8.83	0.000	.
	M	0.04	0.04	-2.4	91.3	-0.87	0.384	.
Northern great plains	U	0.04	0.05	-5.4		-1.97	0.049	.
	M	0.04	0.04	0.7	87	0.21	0.835	.
Prairie gateway	U	0.12	0.13	-1.8		-0.67	0.505	.
	M	0.12	0.11	2.5	-45	0.73	0.468	.
Eastern uplands	U	0.08	0.10	-6.4		-2.35	0.019	.
	M	0.08	0.08	0.7	89.3	0.2	0.842	.
Southern seaboard	U	0.16	0.14	5.1		2.01	0.044	.
	M	0.16	0.15	2.6	49.2	0.71	0.475	.
Fruitful rim	U	0.39	0.12	64.9		30.66	0.000	.
	M	0.39	0.39	-0.9	98.6	-0.22	0.829	.
Basin range	U	0.05	0.03	8.8		3.75	0.000	.
	M	0.05	0.04	1.9	78.2	0.49	0.621	.
Principal operator experience	U	27.91	32.95	-33.6		-13.01	0.000	1.05
	M	27.94	27.87	0.5	98.6	0.13	0.899	0.99
Principal operator age	U	59.96	60.08	-1		-0.37	0.714	0.93
	M	59.95	60.42	-3.6	-275.1	-1.00	0.318	0.88*
Principal operator college	U	0.30	0.28	3.5		1.33	0.182	.
	M	0.30	0.30	-1.8	48.2	-0.49	0.623	.
Principal operator education	U	2.74	2.82	-7.8		-3.14	0.002	1.24*
	M	2.75	2.78	-4.1	47.6	-1.11	0.267	1.1
Gender	U	0.08	0.04	15.3		6.77	0.000	.
	M	0.08	0.09	-6.2	59.2	-1.48	0.138	.
High value crops specialization	U	0.29	0.08	56.8		28.63	0.000	.
	M	0.29	0.31	-4.1	92.8	-0.93	0.352	.
Cash grains specialization	U	0.17	0.38	-48.1		-16.66	0.000	.
	M	0.17	0.18	-2.7	94.4	-0.85	0.395	.
Total payment received	U	69.72	113.33	-14.9		-5.23	0.000	0.65*
	M	69.85	71.13	-0.4	97.1	-0.14	0.889	1.08
2018	U	0.29	0.28	0.6		0.21	0.831	.
	M	0.29	0.29	-0.1	84.1	-0.02	0.980	.

2019	U	0.24	0.23	2		0.77	0.444	.
	M	0.24	0.24	0.8	57.5	0.23	0.815	.
2020	U	0.21	0.18	6.7		2.63	0.008	.
	M	0.21	0.22	-2.6	60.6	-0.71	0.476	.

* if variance ratio outside [0.91; 1.10] for U and [0.91; 1.10] for M

Table A4: Balancing test for matched and unmatched samples for gender

Sample	Ps R2	LR chi2	p>chi2	Mean Bias	Med Bias	B	R	%Var
Unmatched	0.109	1314.24	0.000	18.5	7.3	94.9*	1.31	60
Matched	0.003	13.8	0.841	2.2	2.2	13.4	0.85	20

* if B>25%, R outside [0.5; 2]

Figure A2: Standardized percentage bias plots