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The Impact of Soybean Adoption on Households' Crop Production Value in Mozambique: A Genetic Matching Approach

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Abstract
This research demonstrates that soybean adoption has a positive effect on the crop production value of households. Employing a genetic matching ap- proach, the estimated impact amounts to 11,000 Mozambican Meticals (MT). On average, households embracing soybean adoption exhibit a roughly 60% higher crop production value compared to those that have not done so. These findings hold statistically significant at the 99% confidence level, confirmed through various robustness checks. Furthermore, regional analysis reveals that households in the northeast experience a 40% higher difference in crop produc- tion value compared to those in the northwest. The study also explores different scenarios related to estimating crop production value in married households, particularly when responses from spouses, despite farming together, vary. No- tably, considering only the wife's response as indicative of true household pro- duction yields the smallest average treatment effect for the treated (ATT). Moreover, the study finds that the impact of soybean adoption on the crop production value of women is half that of men. Finally, the research includes a theoretical section justifying the preference for the genetic matching approach over common matching techniques such as propensity score matching, Maha- lanobis distance, and exact matching.

Keywords: *Genetic matching; propensity score; balance, soybean; crop production; value; adoption; self-selection; survey, ATT; Mozambique*

1 Introduction

1.1 Background

The soybean industry in Mozambique traces its beginnings to the 1980s when plan- tations were established (Findeis, 2018). Despite decades of promotion, the adoption rate of soybeans by farmers remained low until the late 1990s. This slow adoption can be attributed to several factors.

Firstly, soybean was a novel crop, and farmers lacked knowledge about its nutri- tional benefits and lacked adequate training for its cultivation. Additionally, small- holder farmers were hesitant to replace their staple food crops with soybeans, as it was primarily seen as a cash crop. Furthermore, the entire crop production was con- sumed by farmers' households, with no surplus for trading or selling (Findeis, 2016). Moreover, farmers resisted initiatives aimed at soybean development due to concerns about land ownership. Numerous cases of land grabbing were reported during the initial years of soybean introduction, exacerbating farmers' reluctance to adopt soy- bean cultivation (Findeis, 2016).

However, in the early 2000s, soybeans resurfaced with a focus on nutrition and quickly became essential for private businesses. The Mozambican government en- acted laws to address land grabbing issues. Additionally, international non-profit organizations (NPOs) played a crucial role in shaping the sector by providing train- ing to farmers' associations and establishing seed banks. These efforts, coupled with government protection of land rights and support from NPOs, instilled confidence in farmers to venture into soybean cultivation (Findeis, 2016).

As of now, the impact of soybean adoption by Mozambican farmers has not been fully evaluated. Different farming practices are observed across regions, with small- holder farmers in the northeast adopting improved seeds with assistance from the international donor community and research centers. However, farmers in the north- west and central regions continue to face challenges in adopting efficient and sustain- able soybean production practices (Findeis, 2018). Furthermore, variations in crop prices across regions, along with differences in farmers' practices and seed availability, influence crop production value.

According to the USDA, crop production value represents the monetary value of production at the farm gate level. This aggregate value includes all agricultural products' market value at the time of production, without subtracting intermediate inputs like seeds and feed (USDA, 2019).

The goal of this essay is to study the impact on farmer's income of soybean adoption across the different regions of Mozambique, and also across gender.

The literature on soybean adoption in Africa underscores its potential to positively impact farmer welfare, household income, and economic development (Sanginga et al, 1999; Tesfa and Teshale, 2019). While there is consensus on the overall positive out- comes of soybean adoption, disagreements or nuances exist regarding gender-specific impacts, market challenges, and sustainability issues (Mubichi, 2017; Kamara et al, 2021). Addressing these challenges requires strategic interventions, inclusive policies, and collaborative efforts among stakeholders to maximize the welfare benefits of soy- bean adoption among smallholder farmers in Africa. This study contributes to the existing literature on the socio-economic impact of soybean adoption by assessing regional variations in the impact of soybean adoption in Mozambique and examining gender-related income disparities in the country.

2 Literature review on the socio - economic impact of soybean adoption in Subsaharan Africa

Soybean adoption has garnered significant attention due to its potential to enhance farmer welfare and contribute to economic development. This literature review syn- thesizes findings from various studies to provide a comprehensive understanding of the social and economic implications of soybean adoption among smallholder farmers across Subsaharan Africa.

Studies conducted in Nigeria and Ethiopia on the social impact of soybean (Sanginga et al, 1999; Tesfa and Teshale, 2019), reveal positive impacts of soybean adoption on household welfare and income generation. In Nigeria's southern Guinea savanna, soy- bean adoption has positively impacted farmers' income, household welfare, and food security (Sanginga et al, 1999). Similarly, in northwestern Ethiopia, the adoption of improved soybean varieties has led to increased farm income and productivity among smallholder farmers (Tesfa and Teshale, 2019). Women's participation in soybean pro- duction has widened equity and distributional effects within households, contributing to improved social welfare. Additionally, women's involvement in soybean production has widened equity and distributional effects within households, emphasizing the im- portance of gender inclusivity in agricultural development (Sanginga et al, 1999).

In Ethiopia, soybean cultivation has been instrumental in combating food inse- curity, malnutrition, and poverty (Acevedo-Siaca and Goldsmith, 2020). The com- mercialization of soybean farming presents opportunities for smallholder farmers to increase their income, enhance food security, and contribute to economic growth. Moreover, soy-maize crop rotations in sub-Saharan Africa have the potential to im- prove agricultural productivity, soil health, and food security (Acevedo-Siaca and Goldsmith, 2020).

There is a consensus among studies regarding the positive impacts of soybean adoption on farmers' welfare, including increased productivity, income, food security, and nutritional status (Manda, 2016; Kamara, 2021). However, gender disparities in income and the simultaneous impact on crop diversity conservation remain areas of uncertainty (Coromaldi et al., 2015; Mubichi.,2017).

Economically, soybean adoption has shown promising outcomes in enhancing ru- ral livelihoods and economic development across various regions in Africa. Findings from Chianu et al. (2009) highlight increased farm income, productivity, and market opportunities associated with soybean adoption. The collaborative efforts of stake- holders, including governments, research institutes, and NGOs, have played a crucial role in promoting soybean adoption and driving economic growth within the agri- culture sector (Chianu et al, 2009). Improved soybean technologies in Malawi have significantly reduced poverty among adopters, leading to higher gross farm incomes and improved food security (Tufa et al., 2021). The adoption of improved soybean varieties has particularly benefited female-headed households, households with higher education levels, and larger cultivated land areas.

However, challenges such as sustainable production practices and gender-based income disparities persist (Kamara et al, 2021). While the adoption of improved soy- bean varieties has generally led to positive economic outcomes, there is evidence of gender gaps in soybean net revenue, indicating disparities in market access or other factors affecting income levels (Kamara et al, 2021). Gendered preferences in legume diversification choices among smallholder farmers in Mozambique and Malawi, as highlighted by Mubichi (2017), underscored disparities in cropping patterns, income, and decision-making processes within farming households. Such gender dynamics necessitate inclusive agricultural policies to address gender-specific needs and con- straints.

3 Survey Design and Data Collection

3.1 Study Site

The Mozambique Women's Empowerment in Agriculture Index (WEAI5) survey was conducted across three distinct regions of the country: the northeast, the northwest, and the center. The selection of participating villages within each region was meticu- lously undertaken by the collaborative efforts of the Soybean Innovation Lab and the Social Impacts team (SIL ESI), comprising esteemed researchers from the Mozam- bique Institute for Agricultural Research (IIAM). Given the critical role of agrocli- matic conditions in soybean cultivation, the selection process meticulously considered factors such as soil organic matter diversity, pH levels, and climatic variations. The chosen sites are strategically located across two of Mozambique's primary agrocli- matic zones (Findeis, 2016).

Figure 1 in Appendix A delineates the geographical distribution of village sites across Manica Province (east of Zimbabwe), Tete Province (west of Malawi), and Zambezia and Nampula Provinces (east of Malawi). Notably, villages in the North- west (Tete Province) region exhibit significantly higher elevations, with a minimum altitude of 304.8 meters (1,000 ft) above sea level (MASL) compared to those in the Central and Northeast regions. The highest elevation village site, located in Tete Province, stands at an impressive 1,406 meters (4,613 ft) MASL, while the lowest ele- vation village, situated in the Northeast region, lies at 523 MASL (1,715 ft). Villages in the Central region, nestled within Manica Province, span altitudes ranging from 621 MASL (2,037 ft) to 898 MASL (2,945 ft). Mozambique's annual rainfall typically falls within the range of approximately 500-900mm, exhibiting variations based on altitude. Similarly, the average temperature oscillates between 15-34C (59-93F), with altitude also contributing to variances in climatic conditions (Findeis, 2016).

3.2 Survey Enumeration

Male and female survey enumerators were trained by the research teams from the University of Missouri, Mississippi State University, and IIAM-Mozambique. Enu- merators who could understand local dialects were chosen to form the team, and a single team was used across all villages to enhance consistency in survey enumera- tion. Enumerators from outside the villages were employed because study participants may have concern about sharing personal information with local surveyors whom they know (Findeis, 2016). In each village, the (traditional) village chief and municipal chief were consulted prior to the survey, and permissions were secured. Prior to visiting each village, Google Earth and Bing maps were made showing the landscape of each village, including village compounds.

A random sample of households was developed, based on Google Earth/Bing im- agery. Random sampling was used to reduce sample selection bias. Permissions being secured from the village and municipal chiefs, the sample households were asked if they wanted to participate in the survey. Consent procedures approved through IRB were used.

One adult female and one adult male decision-maker were asked to participate in each household, if both present. If no adult male was part of the household, only the adult female was interviewed. Similarly, if no adult female was part of the household, only the male decision-maker was interviewed. In the case when the household male or female decision-maker was not at home at the time of the interview, enumerators set up an appointment for a later time to return to the household to conduct the in- terview. Two appointments were made for this follow-up. The goal was to maximize the number of households in which both a male and female were interviewed, if both part of the household. Survey respondents were free to refuse to be interviewed, skip any questions and/or stop the interview at any time (Findeis, 2016).

Within a household, female and male survey respondents received the same survey instrument. The woman in the household was interviewed by a female enumerator. A male enumerator interviewed the male respondent. This makes it possible to gain insights into perceptions and knowledge – both from him and from her. Previous sur- veys conducted among agricultural households in the US, China and Africa (Zhang 2011, Smith and Findeis 2013, Sevilla 2013), have used this approach, allowing the research team to better understand differences in responses across the household. In- dividuals were not interviewed with others present or nearby, again to avoid concern that responses could be shared with others.

4 Conceptual Framework and the Genetic Matching algorithm

4.1 The Conceptual Framework:The Rubin Causal Model

Estimating the impact of soybean adoption on households' crop production value is equivalent to estimating the causal effect of adopting soybean on crop production value.

The Rubin causal model conceptualizes causal inference in terms of potential out- comes under treatment and control, only one of which is observed for each unit. A causal effect is defined as the difference between an observed outcome and its coun- terfactual. The model will be put in the context of an observational study because the data available is not experimental (Rubin,2010).

In this study, the observed outcome Y_i is the crop production value for household i. Treatment T_i is whether or not household i has grown soybean the last season. $T_i = 1$ for adoption, and 0 otherwise. Therefore, farmers having adopted soybean are in the treatment regime, and those who have not done so are in the control regime

(Rubin,2010).

Let Y_{i1} denote the potential outcome for household i if the household has grown soybean the last growing season, and let Y_{i0} denote the potential outcome for house- hold i in the control regime. The treatment effect for observation i is defined by $\tau_i = Y_{i1} - Y_{i0}$.

However, Y_{i1} and Y_{i0} are never both observed. Since T_i is a treatment indicator, the observed outcome for household i observation is then $Y_i = T_i * Y_{i1} + (1 - T_i) * Y_{i0}$. In an observational setting, covariates are almost never balanced across treatment and control groups because the two groups are not ordinarily drawn from the same population. Thus, a common quantity of interest is the average treatment effect for the treated (ATT):

$$\tau|(T = 1) = E(Y_{i1}|T_i = 1)\text{-}E(Y_{i0}|T_i = 1) \tag{1}$$

Equation 1 cannot be directly estimated because Y_{i0} is not observed for the treated. Progress can be made by assuming that selection into treatment depends on observ- able covariates X. one can assume that conditional on X, treatment assignment is unconfounded $(Y_0, Y_1 \perp T \mid X)$ and that there is overlap: $0 < Pr(T = 1 | X) < 1$.

Together, unconfoundedness and overlap constitute a property known as strong ignorability of treatment assignment which is necessary for identifying the average treatment effect. The overlap assumption for ATT only requires that the support of X for the treated be a subset of the support of X for control observations (Rubin, 2010).

$$E(Y_{ij}|X_i, T_i = 1) = E(Y_{ij}|Xi, T_i = 0) = E(Y\,i|Xi, T_i = j) \tag{2}$$

By conditioning on observed covariates, X_i, treatment and control groups are exchangeable. The average treatment effect for the treated is estimated as

$$\tau|(T = 1) = E(E(Y_i|X_i, T_i = 1)\text{-}E(Y_i|Xi, T_i = 0)|T_i = 1) \tag{3}$$

where the outer expectation is taken over the distribution of X_i $(T_i = 1)|$ which is the distribution of baseline variables in the treated group (Rubin, 2010).

4.2 Motivation for the Genetic Matching algorithm

The goal of this section is to explain why genetic matching is an appropriate technique for our estimation. Let's start with the most straightforward and nonparametric way to condition on X, exact matching. This approach fails in finite samples if the di- mensionality of X is large or if X contains continuous covariates. For this study, the dataset contains continuous variables. Thus, in general, alternative methods have to be used (Sekhon,2011).

The most common method of multivariate matching is based on Mahalanobis distance. If the set of covariates X consists of more than one continuous variable, mul-tivariate matching estimates contain a bias term which does not asymptotically go to zero at rate $\sqrt{n}$ (Abadie and Imbens, 2006). Therefore, simply applying mahalanobis

matching to this dataset will give bias results because the sample is finite and con-

An alternative way to condition on X is to match on the probability of assign- ment to treatment, known as the propensity score. As one's sample size grows large, matching on the propensity score produces balance on the vector of covariates X (Rubin,2010).The propensity score model is generally unknown. The issue with the propensity score is that the model needs to be specified. When the model is not misspecified, the results are significantly biased.

A significant shortcoming of common matching methods such as Mahalanobis dis- tance and propensity score matching is that they may frequently make balance worse across measured potential confounders. These methods may make balance worse, in practice, even if covariates are distributed ellipsoidally. In a finite sample there may be departures from an ellipsoidal distribution, which makes the results bias. Propen- sity score matching has good theoretical properties if and only if the true propensity score model is known and the sample size is large, which is not the case in this study (Sekhon,1998).

Finally, the Equal percent Bias Reduction (EPBR) property is violated because the sample is finite, and the distributions of covariates are not normal. EPBR implies that improving balance in the difference in means on one variable also improves it on all their linear combinations) by a proportional amount. The violation of this property will make mahalanobis and propensity score matching increase the bias of some linear functions of the covariates even if all univariate means are closer in the matched data than the unmatched (Rubin, 2010).

Because of the limited theoretical properties for matching when the propensity score is not known and the sample is finite, one approach is to algorithmically impose additional properties, and this is the approach used by genetic matching.

Genetic Matching is a generalization of propensity score and Mahalanobis dis- tance matching, and it has been used by a variety of researchers (Andam, Ferraro et al.,2008; Eggers and Hainmueller,2009; Gilligan and Sergenti,2008; Hopkins,2010).

Diamond and Sekhon (2013) and Sekhon and Grieve (2011) propose a matching algorithm, genetic matching (GenMatch), that maximizes the balance of observed covariates between treated and control groups.

4.3 The Genetic Matching Algorithm

One way of generalizing the Mahalanobis metric is to include an additional weight matrix W. Genetic matching is non parametric; variables are chosen according to their weight for minimizing loss with p-value as criteria.

$$d(X_i, X_j) = [(X_i - X_j)^T (S^{-1/2})^T W S^{-1/2} (X_i - X_j)]^{1/2} \quad (4)$$

where W is a k $*$ k positive definite weight matrix and $S^{1/2}$ is the Cholesky decom- position of S which is the variance-covariance matrix of X.

Propensity and mahalanobis matching can be considered special limiting cases of Genetic matching. In fact, if one has a good propensity score model, one should in- clude it as one of the covariates in the genetic matching algorithm. If the propensity score contains all of the relevant information in a given sample, the other variables will be given zero weight. Whereas, if each of k parameters of W are set equal to genetic matching distance is the same as Mahalanobis distance. The algorithm will converge to Mahalanobis distance if that proves to be the appropriate distance measure. (Sekhon, 2011)

Details of the algorithm are provided in Sekhon and Mebane (1998). In short, at the expense of computer time, GenMatch dominates the other matching methods in terms of MSE when assumptions required for EPBR hold and, even more so, when they do not in finite samples. .

5 Descriptive Statistics of the Dataset

5.1 The Spatial Heterogeneity in Farmers' Characteristics and Practices

The sample contains 354 interviewees, which constitutes 209 households because some interviewees are married, widowed, or separated. Table 1 in Appendix B shows that 329 farmers are married, 16 are widowed, and 7 are separated. Farmers also differen- tiate themselves by gender: there are more females than males in the sample, which will help understand how both genders value the impact of soybean on their crop production value.

The number of interviewees vary by region and the sample is quite balanced by region. The northwest region has the most interviewees in the sample (132), followed by the center (119), and then the east (103). Table 1 shows that there is also a difference in terms of farming practices by region. For example, only one (1) farmer interviewed in the northwest irrigates his/her land, while more than 77 farmers irri- gate their lands in the rest of the sample (table 1). This heterogeneity in farmers' characteristics, practices and spatial locations create substantial difference in crop production between farmers.

5.2 The spatial heterogeneity in crop prices

Table 2 in Appendix B shows that prices for the 6 crops planted by Mozambican farmers vary across the regions. Maize has a higher price in the northwest, soybean is more expensive in the northeast, pigeon Pea and beans are more expensive in the center. Whereas, the price of black beans is the same across the regions. The data contained in table 2 are actual average selling prices per region. In fact, the dataset contains information about how much income the farmer received by selling a certain crop quantity. This information was used to recover the average selling price per region, which is the the monetary value per Kg (MT/Kg). Table 2 shows the heterogeneity in crop prices across regions.

From table 1 and table 2 in Appendix B, it is noticeable that there is a lot of variation in the sample in terms of production and prices, which are the determinants of farmers' crop production value. Crop production value is calculated as the the farmer gross revenue if he(she) decides to sell his(her) entire crop production to the market.Let $PROD_i$ be the production for crop i, and P_i the selling price of crop i in a particular region. $VPROD_f$, crop production value for farmer f is written in mathematical form as the following:
Assuming farmer f produces i=1,2,3,...n crops.

$$VPROD_f = \sum_{i=1}^{n} PROD_i * P_i \quad (5)$$

Crop production value is an important measure because farmers will continue or start growing soybean if they realize how much the value of their crop production can increase due to soybean adoption.

It is worth mentioning that it is important to include all the crops planted by the farmers in the analysis, although the interest is on the impact of soybean. In fact, the adoption of soybean can induce some farmers to stop producing their current crops. In the same time, some farmers can decide to produce soybeans jointly with their current crops. This substitution and complementarity patterns affect farmers' crop production value. In fact, according to the USDA, there are crops that are not recommended to be produced together, while some crops give a higher yield when produced jointly with other crops (USDA,2019). Moreover, since the parameter of interest in this study is the causal effect of soybean, it is important to include all the other crops adopted by the farmer to get an unbiased effect of soybean adoption on crop production value.

5.3 The difference between soybean adopters and non adopters households

Table 3 in Appendix B presents a notable distinction between households that em- braced soybean adoption in the last growing season and those that did not. The sample encompasses 77 adopters and 129 non-adopters. Significance is observed in the difference of the logarithm of household crop value at the 1% level, while the mean difference for the non-logged crop production value lacks statistical significance. The utilization of the logarithmic transformation serves to mitigate the influence of out- liers on the analysis.

Furthermore, adopters and non-adopters exhibit disparities in their experience with growing black beans and common beans. Specifically, statistical analysis indi- cates that soybean adopters tend to produce more black beans than non-adopters, highlighting the complementary relationship between crops, as discussed in the pre- ceding section. Additionally, in terms of credit and seed access, soybean adopters demonstrate greater access to informal lending and participation in seed extension programs compared to non-adopters.

Descriptive statistics unveil a notable difference of 4934.56 MT in crop production value between adopters and non-adopters. However, this disparity does not repre- sent the Average Treatment Effect on the Treated (ATT) due to the self-selection of adopters into the treatment (i.e., soybean adoption). Adopters possess characteris- tics distinct from those of non-adopters, necessitating the establishment of a control group akin to the adopters to obtain an unbiased estimate of the impact of soybean adoption on crop production value. This imperative is addressed through the genetic matching algorithm elaborated upon extensively in the third section of this paper.

6 Robustness of the results

The primary assessment conducted is the balancing condition of covariates post- matching. As demonstrated in Figure 2 of Appendix A, the standardized mean dif- ference for all covariates approaches zero more closely after employing the genetic matching algorithm. This indicates that the matching process successfully aligned the characteristics of control groups with those of the treatment group, crucial for validating the results presented in Section 5.

Drawing on insights from Diamond Sekhon (Diamond, 2013), the genetic match- ing algorithm's efficacy can be enhanced by incorporating a propensity score among the covariates. Accordingly, a logit model was developed, regressing the treatment variable (soybean adoption) against all covariates. The results for this scenario are detailed in columns 6 of tables 6 and 7 in Appendix B. The Average Treatment Ef- fect on the Treated (ATT) is estimated at a positive 11,785 MT, with the percent difference in crop production value hovering around 75% and remaining statistically significant at the 99% confidence level.

The covariate balance plot, integrating the propensity score, indicates a mean dif- ference closer to zero after matching, similar to the scenario without the propensity score. This underscores the robustness of the genetic matching algorithm's results, even without the inclusion of the propensity score as implemented in Section 5.

In addition to the covariate balance check, the ATT was disaggregated by gender and region to capture regional and gender-specific effects. As delineated in tables 6 and 7 of Appendix B, all estimates of crop production value ATT are positive across regions. Notably, comparing the Northeast to the Northwest region, soybean adop- tion's impact on household crop production value is higher by 9,450 MT, with the effects remaining statistically significant at the 99% confidence level. Conversely, the results for the central region are positive but not statistically significant due to the limited number of matches obtained in the dataset.

Furthermore, when considering gender separately, soybean adoption is found to increase household crop production value for both males and females. The impact on household crop production value for women is estimated at around 8,000 MT, constituting half the estimate derived from the male population. This suggests that soybean adoption has a comparatively lesser effect on increasing the crop production value of women, with the percent difference in crop production value attributable to soybean adoption by women being lower by 35% compared to the estimate for males.

7 Conclusion

In summary, the adoption of soybean cultivation significantly enhances the crop pro- duction value of Mozambican households. This impact is quantified at 11,000 MT (Mozambican Metical), with an average percent difference in crop production value of 60% observed between non-adopters and adopters. These findings are statistically significant at the 99% confidence level. Notably, in the northeast region, the difference in crop production value between adopters and non-adopters exceeds that of the northwest by 40%. This divergence may stem from natural climatic variations inherent to each region, as elucidated in Section 2 of the paper.

Various scenarios have been explored to ascertain the true estimate of crop pro-duction among married households. Notably, when considering wives' responses as the definitive truth, the resulting Average Treatment Effect on the Treated (ATT) is minimized. Additionally, the impact of soybean adoption on crop production value for women is observed to be half that of their male counterparts. This observation raises questions regarding potential factors influencing women's conservative responses or barriers affecting their crop production value, over which they may lack control. The examination of Mozambican customs and traditions may offer insights into these gen- der disparities, highlighting the importance of further research to understand why women tend to exhibit greater conservatism in agricultural practices compared to men.

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APPENDIX A

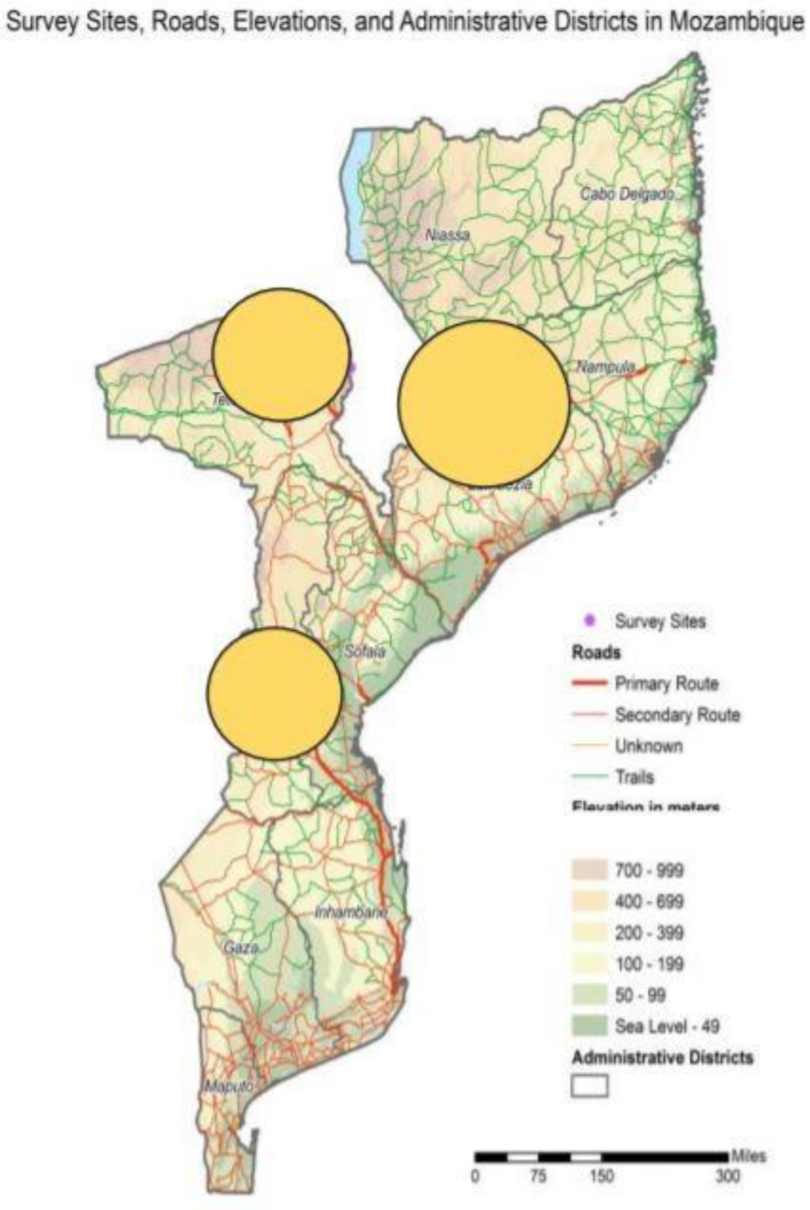

Figure 1: Map with regional locations of village research sites

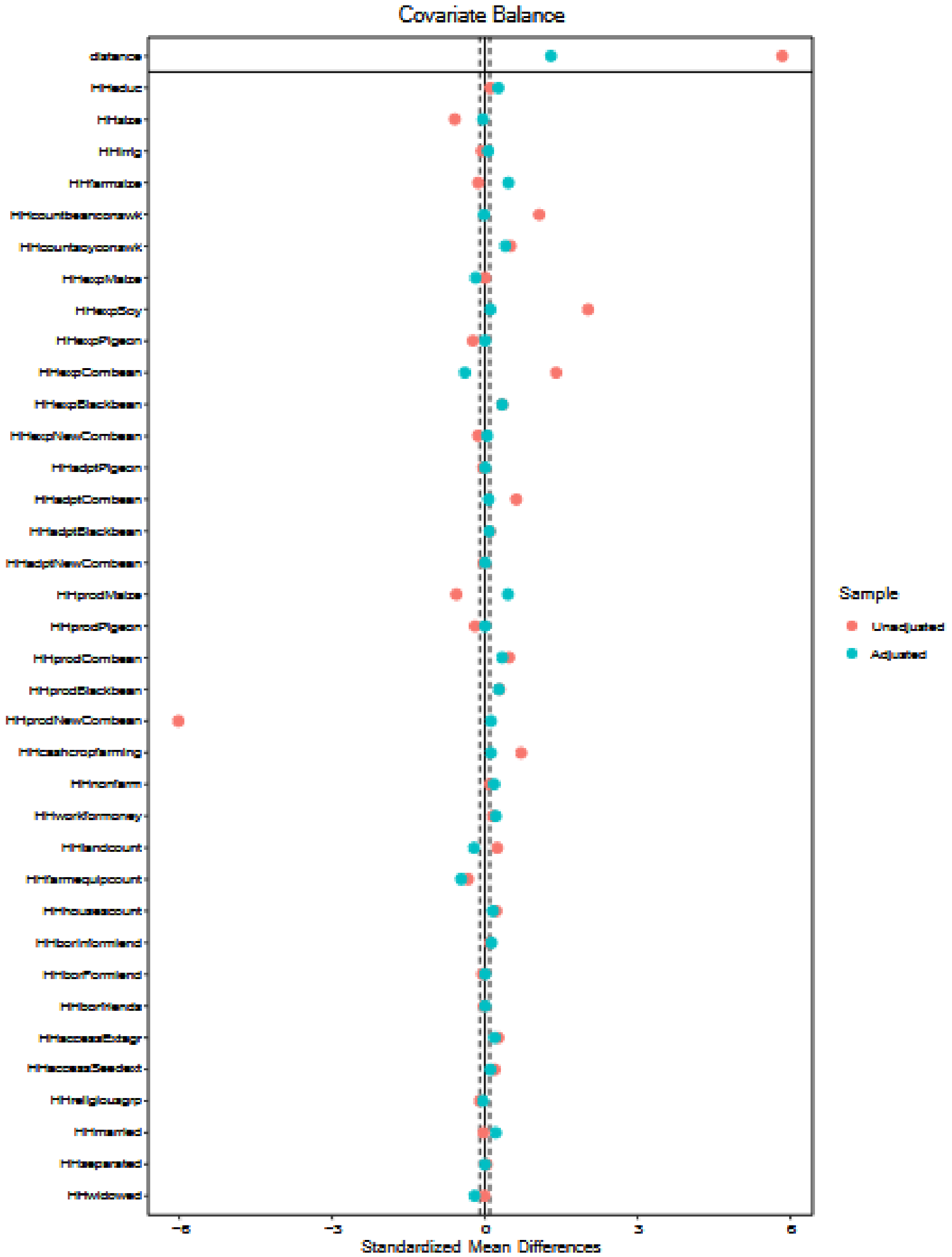

Figure 2: Covariate balance not including pscore

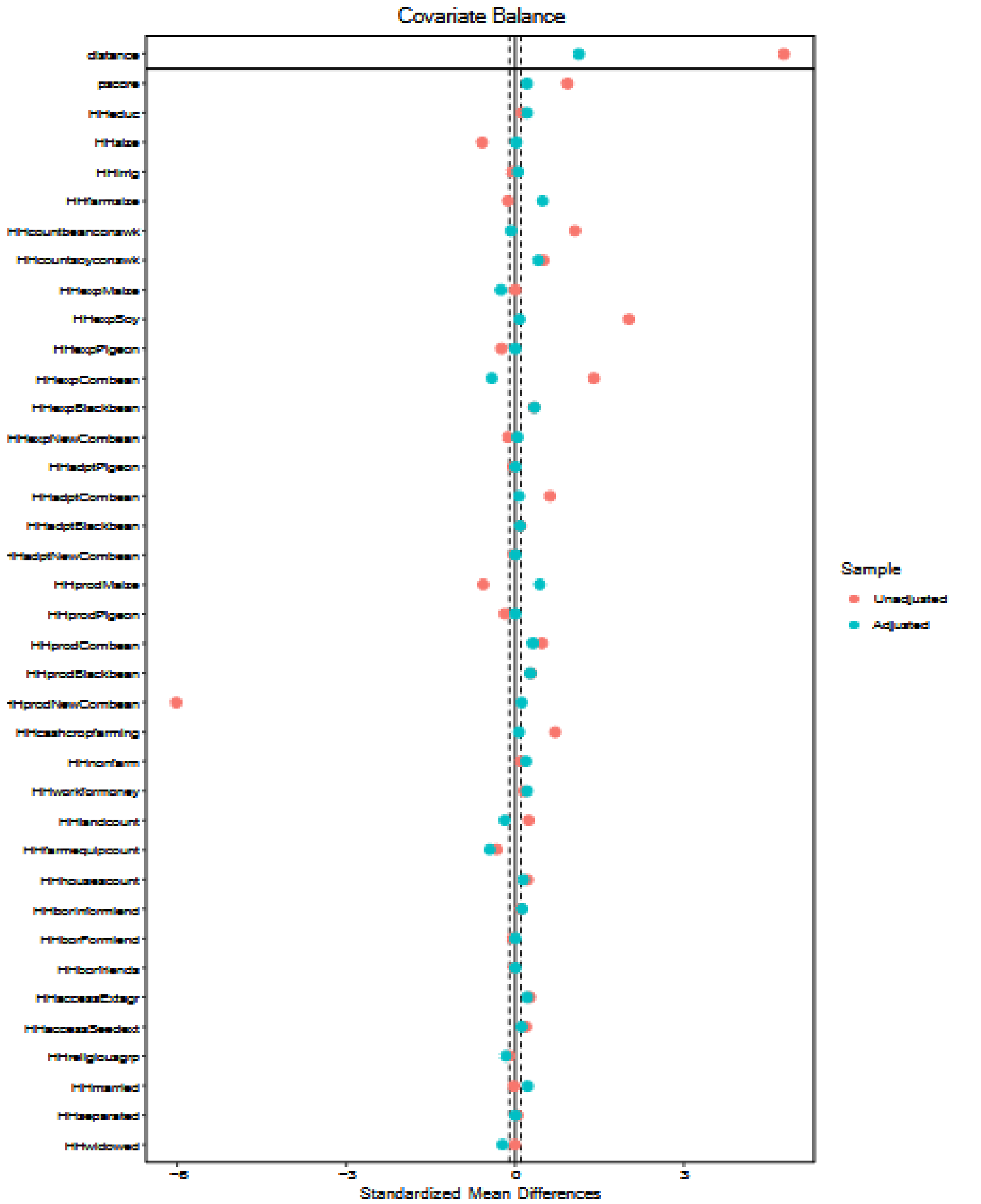

Figure 3: Covariate balance including pscore

Table 1: Statistics on the regional Heterogeneity of Farmer's characteristics and prac- tices

	region	Farmer Total	males	females	married	widowed	separated	irrigation
1	Northwest	132	65	67	124	6	1	1
2	East	103	45	58	90	6	6	13
3	Center	119	60	59	115	4	0	65
4	Combined	354	170	184	329	16	7	79

Table 2: Statistics on the regional Heterogeneity of crop prices

	region	Maize	Soybean	Pigeon Pea	Common beans	Black beans	New com.beans
1	Northwest	10.69	23.14	14.68	41.71	40.00	40.00
2	East	6.19	34.46	7.14	48.31	40.00	41.85
3	Center	9.23	9.58	22.21	54.19	40.00	43.70
4	Combined	8.70	22.50	17.19	48.04	40.00	42.77

Table 3: Sample Descriptive Statistics

	Sample	Variable	Mean Adopters = 1	Mean NonAdopters = 0	p-value	Dif-in-Means	Dif-in-Means (%)
1	full	HHadptSoy	77.00	129.00	0.41	-52.00	-40.31
2	full	HHcropval	20109.01	15174.45	0.21	4934.56	32.52
3	full	HHlogcropval*	9.67	9.13	0.00*	0.54	5.93*
4	full	HHmarried	0.90	0.92	0.53	-0.03	-2.86
5	full	HHseparated	0.05	0.02	0.19	0.04	235.06
6	full	HHwidowed	0.05	0.06	0.76	-0.01	-16.23
7	full	HHeduc	2.90	2.57	0.42	0.32	12.53
8	full	HHsize*	5.21	6.28	0.00*	-1.07	-17.06*
9	full	HHirrig	0.10	0.16	0.22	-0.06	-36.18
10	full	HHfarmsize	2.39	2.49	0.66	-0.10	-3.97
11	full	HHcountbeanconswk*	1.79	0.84	0.00*	0.95	114.07*
12	full	HHcountsoyconswk*	0.86	0.03	0.00*	0.83	2664.29
13	full	HHexpMaize	9.16	9.15	0.97	0.01	0.09
14	full	HHexpSoy*	4.75	0.71	0.00*	4.04	566.49*
15	full	HHexpPigeon	0.00	0.30	0.03	-0.30	-100.00
16	full	HHexpCombean*	7.61	3.91	0.00*	3.70	94.40*
17	full	HHexpBlackbean*	0.69	0.09	0.00*	0.60	639.94*
18	full	HHexpNewCombean	0.05	0.09	0.41	-0.04	-44.16
19	full	HHadptMaize	1.00	1.00	0.41	0.00	0.00
20	full	HHadptPigeon*	0.00	0.04	0.02*	-0.04	-100.00*
21	full	HHadptCombean*	0.81	0.19	0.00*	0.62	332.79*
22	full	HHadptBlackbean*	0.13	0.03	0.02*	0.10	318.83*
23	full	HHadptNewCombean	0.03	0.05	0.30	-0.03	-52.13
24	full	HHprodMaize	1003.79	1418.98	0.12	-415.19	-29.26
25	full	HHprodSoy*	313.43	0.00	0.00*	313.43	Inf*
26	full	HHprodPigeon	0.00	1.51	0.09	-1.51	-100.00
27	full	HHprodCombean	85.69	40.45	0.06	45.24	111.84
28	full	HHprodBlackbean*	4.53	0.19	0.02*	4.34	2238.75*
29	full	HHprodNewCombean	0.52	19.78	0.16	-19.26	-97.37
30	full	HHcashcropfarming*	0.92	0.21	0.00*	0.71	340.55*
31	full	HHnonfarm	0.26	0.16	0.11	0.10	59.55
32	full	HHworkformoney*	0.23	0.08	0.00*	0.16	201.56*
33	full	HHlandcount	2.84	2.48	0.09	0.36	14.66
34	full	HHfarmequipcount	4.38	4.88	0.13	-0.51	-10.38
35	full	HHhousescount	1.73	1.53	0.22	0.19	12.53
36	full	HHborInformlend*	0.13	0.03	0.02*	0.10	318.83*
37	full	HHborFormlend*	0.00	0.05	0.01*	-0.05	-100.00
38	full	HHborfriends	0.00	0.02	0.16	-0.02	-100.00
39	full	HHaccessExtagr*	0.36	0.10	0.00*	0.26	260.84*
40	full	HHaccessSeedext*	0.22	0.03	0.00*	0.19	612.01*
41	full	HHreligiousgrp	0.92	0.95	0.55	-0.03	-3.29

* means significant at least at the 95 % confidence.

Table 4: Genetic Matching results with different truth scenarios regarding the crop production estimates given by married households

	Parameters	HHtruth:mean	HHtruth:female	H truth:male	HHt uth:mostcons	HHtruth:leastcons
1	ATT	10784.34	8129.50	10622.87	8976.77	11387.26
2	se	4773.04	4250.67	6932.19	4171.65	6686.09
3	tstat	2.26	1.91	1.53	2.15	1.70
4	pvalue	0.03	0.06	0.13	0.03	0.09
5	matchobs	77.00	79.00	79.00	77.00	77.00

Table 5: Genetic Matching results with different truth scenarios regarding the crop production estimates provided by married households (log version)

	Parameters	HHtruth:mean	HHtruth:female	HHtruth:male	HHtruth:mostcons	HHtruth:leastcons
1	ATT	0.57	0.56	0.58	0.65	0.60
2	se	0.23	0.18	0.23	0.20	0.21
3	tstat	2.46	3.10	2.54	3.35	2.85
4	pvalue	0.02	0.00	0.01	0.00	0.01
5	matchobs	77.00	79.00	79.00	77.00	77.00

Table 6: Genetic Matching results by region, gender, and including pscore as a co- variate

	Parameters	Northeast	Northwest	Central	O ly females	Only males	Ps ore included
1	ATT	13631.07	4177.38	57783.71	8823.57	16258.12	11785.80
2	se	4776.78	1360.15	45275.70	4335.31	10650.24	5845.77
3	tstat	2.85	3.07	1.28	2.04	1.53	2.02
4	pvalue	0.01	0.00	0.42	0.05	0.13	0.05
5	matchobs	40.00	35.00	2.00	47.00	43.00	77.00

The household dataset used in the robustness section is the dataset where the mean of the wife and husband crop production responses is taken as the true response for the household.

Table 7: Genetic Matching results by region, gender, and including pscore as a co- variate (log version)

	Parameters	Northeast	Northwest	Central	Only females	Only males	Pscore included
1	ATT	0.79	0.38	0.72	0.54	0.89	0.75
2	se	0.20	0.10	0.86	0.21	0.33	0.26
3	tstat	3.92	3.81	0.85	2.61	2.74	2.84
4	pvalue	0.00	0.00	0.55	0.01	0.01	0.01
5	matchobs	40.00	35.00	2.00	47.00	43.00	77.00

The household dataset used in the robustness section is the dataset where the mean of the wife and husband crop production responses is taken as the true response for the household.