ESSAYS IN DEVELOPMENT ECONOMICS AND AGRICULTURAL ECONOMICS

By

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Abstract:

We study the impact of the Kenyan Tea Liberalization program on educational attainment in the Tea growing areas of Kenya. Tea is a major cash crop in Kenya and tea expansion is likely to generate more returns for female labors as females have a comparative advantage in tea cultivation. Following the literature on intra-household allocation we test if this increase in tea production causes improvement in education attainment of children. We compare the tea producing regions with other non-producing regions by applying a simple DID process to estimate an the Treat effect of the of exposure to tea harvesting. The education completion rate shows that the treatment has a positive effect on the treated cohort. However,there is no treatment effect on female labor participation rate for the females. Our results are robust across the specifications and different samples. In Chapter 2,we estimate the effects of increased exposure to agricultural technologies on farmers' adoption and economic well-being in Ghana, Mali, and Senegal using post-implementation data collected in 2019. The program, known as the West Africa Agricultural Productivity Program (WAAPP), aimed at improving agricultural productivity to enhance economic growth, food security and to reduce poverty reduction and ran in two phases. We focus on the second phase of the program, which ran between 2012 and 2019. We use ex-ante matching at the village and household levels to select the estimation sample. We find that households participating in the program have a 32% higher probability of adopting agricultural technologies and are 19% more likely to use improved seeds. The program also increases the productivity and incomes of the treated households by 4% and 29%, respectively. There were no detectable effects on consumption and food security. We provide suggestive evidence indicating that the additional income may have been saved or invested. Taken together, these results suggest that multi-country agricultural programs can be effective at spurring economic transformation. In Chapter 3, we consider the Factories Act 1948 that mandates all recognized manufacturing units need to register their factories and are subject to government regulation, maintain proper work environment and abide by labor regulations. In our paper we use two data sets, for the registered sample we use the Annual Survey of India (ASI) and the National Sample Survey of Un-incorporated Non-agricultural Enterprises. Our estimates show that Registered factories have higher production per worker and have significantly higher salary for the workers.

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CHAPTER I

INTRODUCTION

1.1 Outline

This thesis chapter covers certain important issues in the area of Development Economics and Agricultural Economics. I have attempted to address these economic problems by following the structural route of micro economic theories to introduce robust and acceptable econometric methods to find empirical evidences to support my ideas. It was a conscious choice on my part to keep my work and applications diverse and at the same time use these results to draw out relevant policy implications.

1.2 A brief history

My research area converges between Development Economics and Agricultural Economics. My interest in the areas was stirred during my Ph.D. course work. I find the area of economic development and agricultural economics largely related since most developing and under-developed countries are largely agrarian, hence agricultural policies and economic development share a common ground. As a micro economists most of my work is designed to apply econometric methods to evaluate effectiveness of economic policies and agricultural programs.Keeping my interest in mind, the first chapter of my dissertation titled "Impact of Tea cultivation on Local Economic Outcomes: Evidence from Kenya" studies the effect of Tea expansion following the Liberalization policy undertaken by the government in 2000. This paper is related to the literature of Intrahousehold Allocation problem that shows better bargaining power of females within household can have major impact on household decision on children investment and health. (73) have a similar prelude to study the effects of Tea cultivation on the sex ratio of rural China following a post-Mao agricultural policy. This paper follows the same assumptions as Qian's, that is female workers have a comparative advantage in tea industry and hence it creates an opportunity for exogenous increase in female household income. Therefore, the paper is an attempt to ascertain the effects of the Tea expansion on children educational attainment in Kenya. A simple Difference in Difference estimation method has been applied by exploiting the variation of exposure to the policy across cohort groups and different regions of Kenya.

The next chapter of the dissertation "Impact Assessment of the West Africa Agricultural Productivity Program: Evidence from Ghana, Senegal and Mali" is co-authored with my advisor Dr. Harounan Kazianga and Dr.Yiriyibin Bambio. Western African countries have wide range of geographic, political and economic conditions. But all these countries have a significant percentage of population depending on agriculture, yet these economies face low agricultural productivity and technology adoption. The West African Agricultural Productivity Program (WAAPP) was designed to provide access to technology, deliver training programs and thereby raise productivity. The paper assesses the second phase of the program that was conducted on 3 countries Senegal, Ghana and Mali. This is in line with the issue of technology adoption in rural areas of underdeveloped countries and contributes to the literature by way of it's new method and unique policy design.

Most developing economies have a large proportion of informal/ un-organized sector that generates employment for a significant portion of the population. In India, the unorganized/ informal sector employs close to 50 percent of the population. This important fact has transpired into a major motivation for this paper. Formal and Informal sector definition is based on the Factory Act 1948 that requires manufacturing units employing more than 10 workers to register under the act. Two different data sets were used for the analysis, 1) Annual Survey of Industries (ASI) 2016-17, this covers factories that are registered under the Act and 2) National Sample Survey of Industries 73rd round (2015-16) which surveys industries not registered under the Factories Act. Since the Act is applicable based on a cut off value, a Fuzzy Regression Discontinuity estimation has been applied to obtain the impact of registration. The estimated results indicate that registered entities have significantly higher output per-worker and capital per worker.The results of this paper deliver a major policy implication for developing countries to promote formalization.

CHAPTER II

Influence of Tea plantations on local economic outcomes: Evidence from Kenya

2.1 Introduction

The literature on Gender roles in Household decision making and economic development have long pointed out the importance of the bargaining power of females within a household. How the decision making role is played out between the male and the females within a family can have varied effect on household's members and household's investment decision. (80) have insinuated that that women identify more closely with household interests than men. Understanding the intrahousehold dynamics therefore have an important role to play for policy framework. Effectiveness of public policies can largely be analyzed based on the nature of household dynamics and can help policy makers decide on the policy design and target.The initial studies of intra-household decision making was based on the Unitary model structure and income pooling. In the unitary approach ((15); (77)), the household is treated as a single decision making unit with an aggregated choice set: all income is pooled and the identity of the income recipient does not affect household choices.This simplified model has be contended by several theoretical as well as empirical works. (22) (23)and (17) have emphasized that the most robust model to mold the actual intra-household bargaining process must have minimal assumptions and propose a simpler model to understand the household allocation decisions. Similar results have been forwarded in noncooperative models prepared by (87) and (91) where the household members make separate contributions to household public goods within the format of a standard non-cooperative game where suboptimal public goods provision is a possible outcome. Early works like , (17); (45); (78); (84) have rejected the unitary approach and identify that there is a strong impact of gender identity on labour supply, the health outcomes of children and household expenditure patterns, thereby rejecting income pooling models. These results have established that the gender identity of the household decision maker and spousal bargaining power can influence the household level decision making (see also (39) and (27)). One of the earlier studies that have examined the influence of parent's gender on children's health was (**?**)(See also (32), (74)). This seminal paper provided evidence that maternal education and income have a positive effect on girl child's health. (**?**) have shown that large scale cash transfer to women recipient have a significant impact on the girl child health but not on male child. Also (31) show that in Côte d'Ivoire rainfall shocks affecting female specialized crops have a significant effect on food expenditure. The consequences of female's asset share can improve women's bargaining position in the intra household allocation decision and result in better investment on children has been been true for non-labor income and non-farm income as well. (see(71) ,). (12) points out the endogeneity in the household decision process and finds that increase in female income can lead to lowering of child labor. Improved bargaining power of women is also related to reduction of domestic violence (see (2)). The resource allocation and household decision on spending of public goods (children) can also be influenced by other factors like social and familial norms.(see (55) (56))

Given both the theoretical and empirical findings indicate that the female earnings can have differentiated result on household allocation of resources, (73) shows that increase in female earning in the Tea growing areas of China improves the survival rates of females in the area and thereby improves the gender ratio. This paper considers that females have a comparative advantage in tea cultivation and following a post-Mao reform in the tea industry, it is expected to raise female earnings. Based on the non-unitary model of intra household allocation, she compares the sex ratio of the tea growing counties across different cohorts with the non-tea regions.

Our paper uses a similar set up to examine the impact of increased female earning on children educational attainment. We look at the case of Kenya's tea sector. Kenya is a leading tea exporting country and it is one of the most important cash crops in the country and contributes to 4% of the country's GDP and engages around 10% of the population ((72)). Considering the importance of tea as a cash crop and the fact that women have a comparative advantage in the tea industry, we try to analyze how the tea sector can benefit the local economies and households. Particularly, we consider the Kenyan Tea Liberalization of 2000 that brought about large scale privatization within the Tea industry. This policy allowed the smallholders to sell their produce to private companies and not just the Kenyan Tea Development Association (KTDA). Also following the liberalization, KTDA was converted into a private institution. The basic assuption is that if the liberalization of the tea sector has caused expansion in tea industry, it is likely increase the return to female labor. Under the circumstance following the literature on gender role and development it is likely to improve the household's investment in children. This is to be translated in higher educational attainment among the children who are born or belong to the cohort that is exposed to the program. Our preliminary data shows that the post 2000, there has been a steady rise in tea cultivation in Kenya especially for the smallholders. In our paper we are using two levels of data, 1) The Kenyan Population and Housing Survey of 1989, 1999 and 2009. 2) Tegemeo Agricultural Monitoring and Policy Analysis Project.

The first data is used to ascertain the effect of the policy at a county level. The second data is a household level panel survey which has information about household crop choices, input usage and hence we can identify tea growing households. This also allows us to obtain the Average Treatment on the treated households. We exploit the cohort level variation of treatment exposure and the household crop choice to estimate the treatment effect. Our findings indicate that the Tea liberalization policy has strong positive effects on both the primary and secondary school completion rates for the females and males. There is also no effect of the policy on female labor force participation rates for the treated cohort group indicating that the substitution effect of increase in female earnings is not significant but it does have a positive and significant income effect. Similar studies have been conducted previously to analyze the impact of crop expansions with mixed results (eg see (54)).

The paper is arranged as follows; in Section 1 we discuss the evolution of the Kenyan tea industry and especially KTDA. In Section 2 we discuss the literature that empirically assess similar effects of cash crop plantation on economic outcomes. In Section 3 we discuss the data and identification strategy. Section 4 discusses the results and Section 5 concludes.

2.2 Theoretical Framework

Understanding the general economic set up of an economy carries important economic policy implications. The households and family units are key economic decision makers and these decision process ultimately impacts the market economy. One important aspect of this decision making process is the choice of human capital investment of children. Economists have long used micro-economic models to explain the intra-household decision making process. The foremost of this is the Unitary model, which assumes the household as a collective entity that behave as if they agree on how to pool resources to maximize a joint welfare function. . The model is still popular in Macroeconomic models and carries strong implications for consumption. Unitary model states that the effect of change in income of the demand of a good does not depend on the individual. Because of it's theoretical restrictions this model has been challenged (33; 34; 35; 23; 24; 42; 41; 66).Critics of the unitary model have proposed the households as a collection of individuals with different preferences and the allocation depends on the individual's income (23; 84). Thus this model lays the foundation for several developmental programs that specifically targets women. Our paper is following this non-cooperative model approach to examine the effects of increase in the returns to female labor on children's educational attainment in tea growing areas of Kenya.
The non-cooperative model considers that the household decisions are results of the relative bargaining power between the household decision makers. It applies techniques of game theories to explain this process (See:(87; 91; 49; 53; 52; 62; 63)). Our paper follows closely the framework of (23), as we are looking into cooperative decision making for some goods that are assignable, (education is exclusively consumed by the children within the household).

$$\begin{aligned} \max_{g_1,g_2} \quad & U_1(x_1, G_1) + \mu U_2(x_2, G_2) \\ \text{s.t.} \quad & y_1 + y_2 = x_1 + x_2 + pG \end{aligned} \tag{2.2.1}$$

where μ is the Lagrange multiplier and is interpreted as a collective approach parameter. Here x_i represents the goods consumed by individual i and similarly U_i represents the individual preference and G is the public good (Children specific goods). Based on the optimization process the demand functions for the goods are

$$G = G^e(y_1 + y_2, p, \mu)$$

$$x_j = x_j^e(y_1 + y_2, p, \mu)$$

mu is a function of y_1, y_2 and p and is not observable. It also represents the bargaining power of the individual within the household. If y_1, then individual 1's bargaining power increases and the decision making process gets more skewed. For the sake of simplicity let us assume that y_2 is female's income. Then

This is the income effect of female income on children investment. This will have two channels of impacting household decision, firstly it will increase household's total income and also increase the female's bargaining power. Also, if members disagree over the preference ordering of some goods, this theory suggests that a strong income shock can create an incentive to make some adjustment to purchase more the preferred commodities. This is akin with the anthropological literature women earn cash incomes in order to ensure that certain items are purchased (40). This model also reinforces (79) argument that the ability of individual members to force their preference orderings is a function of their "perceived contribution" to the household. Our paper closely follows this structural idea and uses the Tea liberalization policy introduced by the government of Kenya in 2000 as an exogenous shock to verify the theory of Gender roles in intra-household decision making.

2.3 Policy

Kenya is one of the world's highest tea exporting countries. Unlike other major exporters like India and China, tea in Kenya is an export crop with only 5% of produce used for domestic consumption. Tea is an important cash crop for Kenya and contributes towards 4% of the Gross Domestic Product ((57)). Tea is primarily grown in the western Rift Valley province of Kenya which enjoy adequate rain and are on higher altitude that is required for tea plantations. Out of the 47 counties, it is a major crop in 19 counties [1]. Before Kenya's independence tea was produced mainly by large scale estates. Since independence the Kenyan government have auctioned land to small holders and has allowed for small and marginal scale landholders to enter the market. The government of Kenya established the Kenyan Tea Development Association (KTDA) in 1963 to provide infrastructure and promote tea production. From 1960s till 1990s the KTDA has set up numerous factories in its action areas to help the small scale tea holders. The tea factories are jointly owned by the local smallholders. They elect the board of executives to manage the factories. Apart from the tea factory facilities, the KTDA also extends other facilities like electricity, transportation and water to the local regions. In order to increase efficiency and to open up the tea industry the Kenyan government have allowed for privatization of KTDA and renamed it to Kenyan Tea Development Agency. As per 2017, KTDA has 67 factories in Kenya of which 45 were set up before 2000 and 22 were introduced after 2000. Presently KTDA has around 600,000 smallholder tea growers under it and produce over 60% of the total tea in Kenya. Based on the data from the Tea Board of Kenya, we also see that the policy has had an increase in the tea area cultivation in Kenya after 2000. [2] (See Fig 2, 3 and 4).

Some of the newer factories have been established to support the production in existing factories and the remaining are introduced to promote tea cultivation in newer regions. Since tea production is a delicate procedure, the tea factories are generally located in close proximity to the tea plantations the location of the factories serve as a proxy for clusters of tea production. In our analysis we use the 2000 privatization policy as an exogenous incident

[1] These include Nakuru, Narok, Kericho, Bomet, Nyamira, Kisii, Kakamega, Bungoma, Vihiga, Nandi, Elgeyo Marakwet, Trans-Nzoia, Kiambu, Murang'a, Nyeri, Kirinyaga, Embu, Tharaka-Nithi, and Meru

[2] Also refer to (3)

to explain whether establishment of tea factories lead to improvement in the primary school completion, secondary school completion and the effect on fertility rates in the tea growing region.

2.4 Data

There are two different sets of samples that are used in the analysis. For all the samples, we apply difference in difference identification strategy. We use the three rounds of Kenya Population and Housing Census (KPHC) (1989, 1999 and 2009). In this sample we study the effect of the policy at a county level and compare the households residing in tea growing regions to those in the non-tea growing region. We have two samples for the pre-treatment period (1989 and 1999) and one post-treatment period (2009). This is a census data collected by the Kenya National Bureau of Statistics (KNBS) to gather information about the size, distribution, composition and other social and economic characteristics of the population. The data is collected at district/county level and since the district definitions change over time, they have been mapped to the base period i.e. 1989 level. The KHPC sample is collected at a household level across all the regions in Kenya. Households residing in the tea growing counties are defined as treated and are compared to the households in the non-tea growing areas. This analysis is simple and the estimated results are equivalent to an Intent to Treat (ITT) effect.

Since the KHPC data does not have information on the type of crop grown by the households and hence we approximate the treated units using the district. In order to obtain the Treatment on the treated result we use the panel survey from the Tegemeo Agricultural Monitoring and Policy Analysis Project, a joint project between Tegemeo Institute at Egerton University, Kenya and Michigan State University. This household level panel survey started in 1997 and has been followed by 4 consecutive rounds in 2000, 2004, 2007 and 2010. It studies around 1400 households in rural agricultural areas of Kenya. This survey cover 22 districts of Kenya that spans all the 6 provinces. The data provides extensive information about household's agricultural input, output, productivity, crop, sales and individual level information. Although data are available for the years 1997, 1998, 2000, 2002, and 2004, we only have the access to 4 rounds in 2000, 2004, 2007 and 2010, for the purpose of our analysis we are using the 2000 as the base period and 2010 are the post-intervention period. The policy started in 2000 and tea plantations generally take average 5 years to begin harvesting, so households choosing to expand need to wait for harvest. In this data we are comparing the tea growing households with non-tea growing households. In the 2000 survey, 1510 households were surveyed and in 2010 1309 households were surveyed.

2.5 Results

Based on the specification in equation 2 the DD results in Table 3 and 4. These results show positive effects on both primary and secondary school completion rates for the treated cohort group. We perform the placebo test by considering the samples of 1989 and 1999. The treated time period is taken as the 1999 sample and based on this we see that the placebo results are significant indicating the DD specification is negative and significant for the same age-group. This points that the estimated treatment effect is biased towards zero in the actual sample. Our preferred specification is the DDD results in Table 5 and 6. For the primary education completion rates this result indicate at the county level there is significant effect of the policy on the treated cohort. We do not see any effect on the Secondary Education completion rates of females. These results capture the county level effect of the Tea expansion policy and can be interpreted as an Intent to Treat (ITT) effect and it shows that the policy increases the probability of Primary school completion for both male and female cohorts by 2%. Placebo test results for the DDD estimations however shows that the triple difference corrects for the pre-trend problem. Hence, going by the DDD specification we can state the policy apparently shows a positive impact on the Primary education completion for the treated cohort group. For each of the results we control for household level variables like household size, number of children, migration status and ownership of house. We control for the province fixed effects and the standard errors are clustered at 1989 district level. Since tea expansion is likely to increase labor opportunities for females and hence we also test if for the same exposed cohort group, if there is any effect on their labor force participation. This result is shown in Table 7, for the DD estimates, the female labor force participation is negative but no significant effect for the DDD estimates. The placebo sample shows no effect indicating that the expansion is not directly effecting the labor force participation of the females. This can be interpreted that the substitution effect is not working and the income effect is high. Since children are perceived as normal goods in the intrahousehold set up then then this income effect is possibly causing an improvement in the educational attainment of the treated cohort group.

In case of the TARPA data we estimate the effect of the policy is measured by the effect of the policy based on the change in tea area cultivation. This treatment effect picks up the Average Treatment on the Treated units, the treated cohort includes individuals who are at least 6 years to 17 years of age and the comparison cohort includes individuals aged 18 years to 28 years. The treatment is also measured in terms of the change in tea harvest level between 2000 and 2010. Table 13 shows that program increases the years of schooling for the treated cohort group. The effect is also shown in the restricted sample within the tea growing districts. For this specification, we control for cohort fixed effects, district fixed effects and cluster at Village level. The placebo sample testing shows that there is no effect therefore, the effect is pertaining to the cohort group and not picking up any pre-existing trend.

The strongest and the most robust result is using the KHPC result and this specification is probably more reliable. Hence our preferred specification is the DDD method. Overall, there appears to have a positive effect on education levels which is consistent across all specification.

2.6 Conclusion

The effect on education completion is consistently significant. There is no discernible effect on female labor force participation. This is in sync with the literature that states that investment in child good is more income elastic than the males. The secondary education system for female is not showing any impact and can be attributed to the fact that we only have 10 years of post intervention time frame and a longer run effect may show the effects on secondary education. Also the secondary education enrollment for females in Kenya is lower than males. For the TARPA panel data, the specification is more specific and we see the similar effects on educational attainments. The results from this analysis signifies that the education levels of the exposed cohort have increased and can be attributed to the policy. Also the return to Secondary education can be perceived to be low in the rural areas and hence the substitution effect might dominate the income effect. Findings of the paper also provide evidence for the rejection of unitary model of the Intrahousehold allocation.

2.7 Figures

2.8 Tables

Table 1: Summary Statistics based on Kenyan Housing and Population Census

	Tea county/Pre	Tea county/Post	Non-Tea County/Pre	Non Tea county/Post
primary_comp	0.448	0.508	0.396	0.408
	(0.497)	(0.500)	(0.489)	(0.491)
secondary_comp	0.108	0.148	0.108	0.131
	(0.311)	(0.355)	(0.310)	(0.337)
age_sec	0.305	0.271	0.310	0.281
	(0.460)	(0.444)	(0.463)	(0.450)
age_pri	0.318	0.269	0.316	0.283
	(0.466)	(0.443)	(0.465)	(0.450)
Number of own family members in household	5.745	5.262	5.819	5.955
	(2.894)	(2.626)	(3.401)	(3.133)
Relationship to household head [detailed version]	2701.486	2649.892	2769.233	2740.288
	(1308.972)	(1266.767)	(1373.620)	(1275.043)
Number of own children in household	0.981	0.901	0.918	0.939
	(1.740)	(1.577)	(1.701)	(1.783)
Activity status (employment status) [general version]	1.690	1.763	1.729	1.747
	(0.922)	(1.009)	(0.925)	(1.003)
migrant	0.036	0.019	0.054	0.026
	(0.186)	(0.136)	(0.226)	(0.159)
Ownership of dwelling [general version]	1.173	1.180	1.234	1.239
	(0.399)	(0.411)	(0.447)	(0.442)
Urban-rural status	1.155	1.261	1.311	1.353
	(0.362)	(0.439)	(0.463)	(0.478)
Observations	500343	1412256	679574	2080893

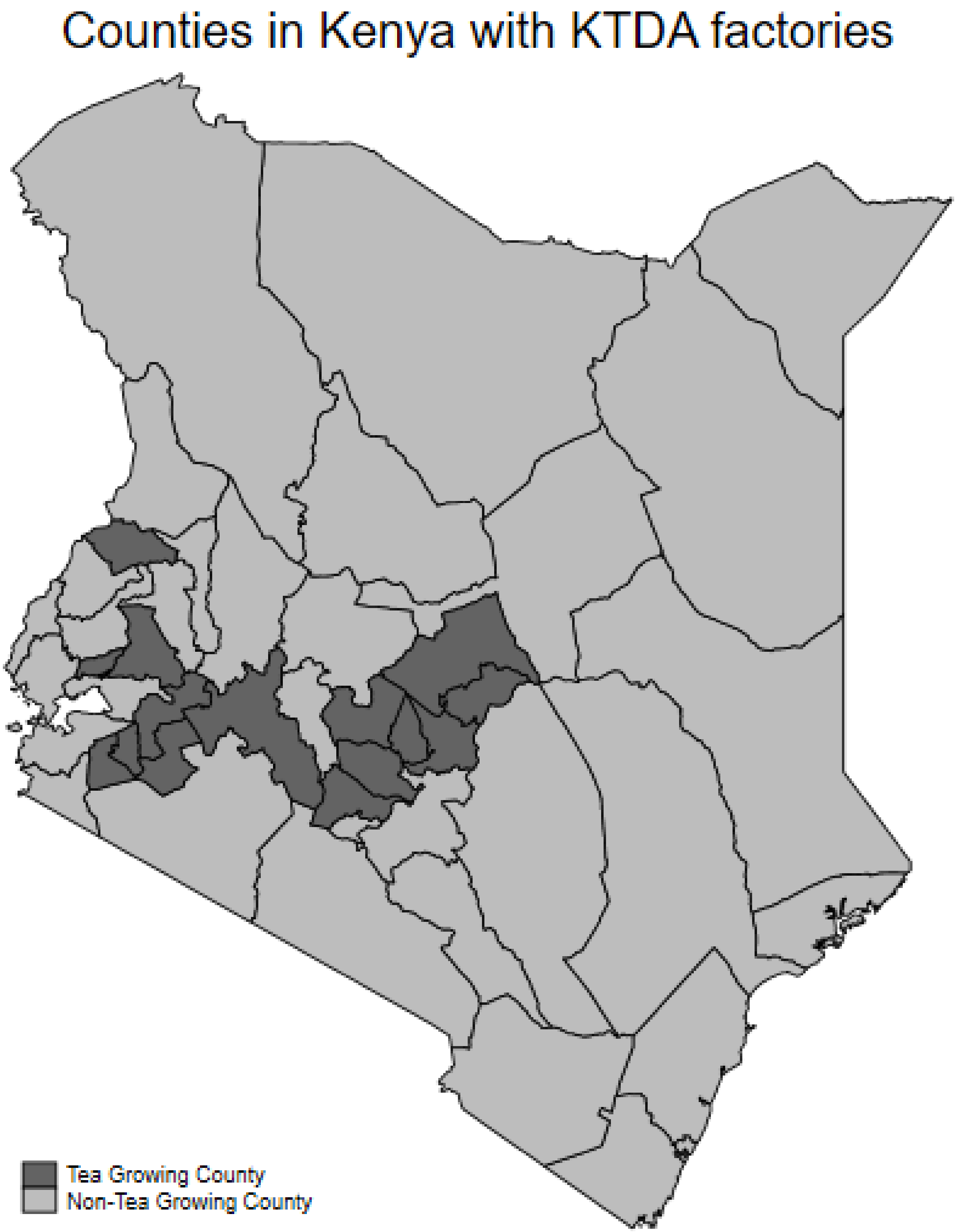


Figure 1: Areas where Tea is grown or can be grown in Kenya

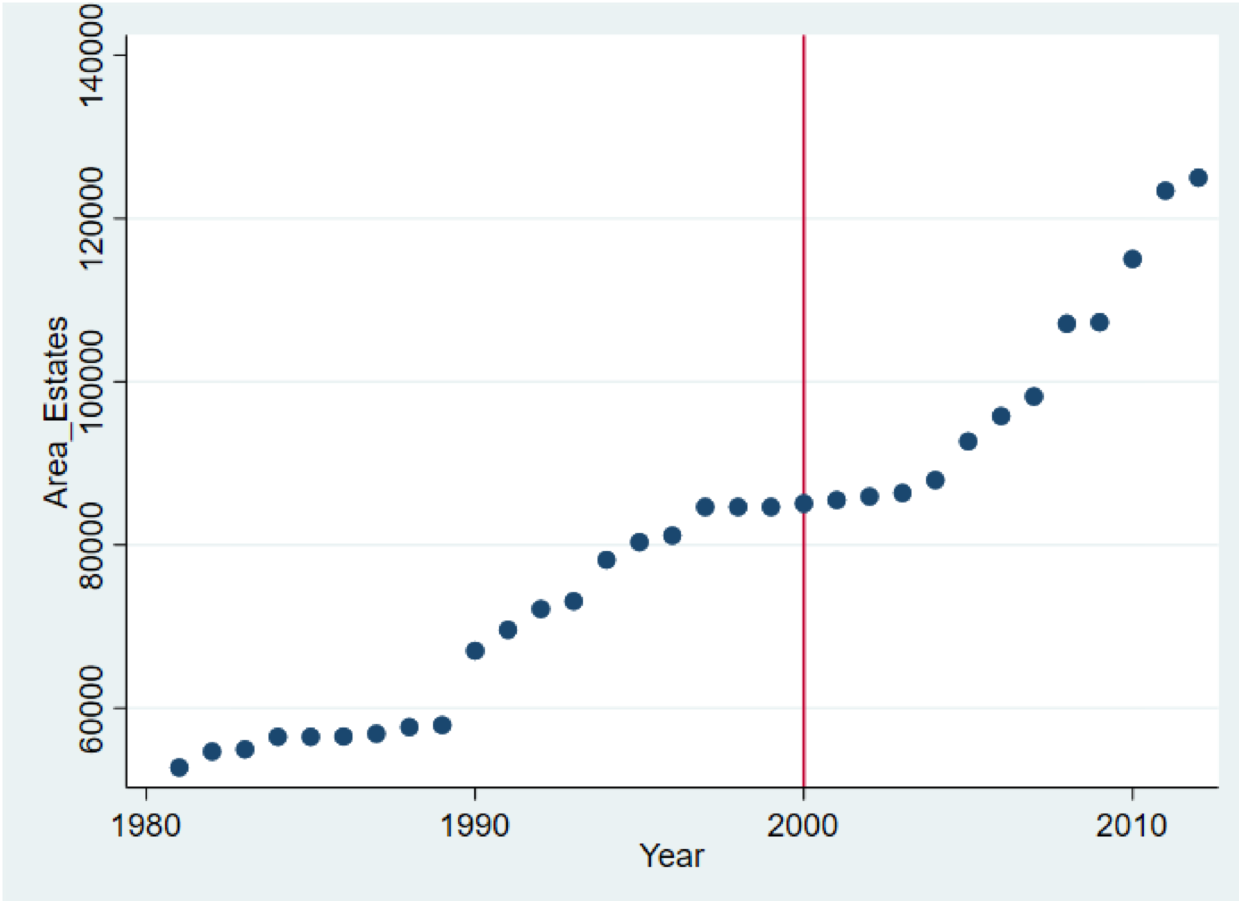


Figure 2: Expansion of Tea cultivation for the estate owners before and after the Liberalization

Table 2: Summary Statistics based on Kenyan Housing and Population Census

	Tea Household/Pre	Tea Household/Post	Non-Tea Household/Pre	Non-Tea Household/Post
Years of schooling	6.632	8.054	5.449	7.447
	(4.423)	(4.301)	(4.257)	(4.243)
Currently in school	0.328	1.636	0.348	1.600
	(0.470)	(0.481)	(0.476)	(0.490)
Household size	9.250	8.073	9.591	9.311
	(3.397)	(3.284)	(3.485)	(4.153)
Relationship to head	2.633	4.488	2.668	4.625
	(1.324)	(3.653)	(1.309)	(3.327)
Household Member total Salaried income	4691.694	10247.739	3290.780	8767.894
	(24764.222)	(52188.116)	(18616.814)	(46689.004)
Household Member Net total income from Non-farm business activities	4966.235	6720.964	3080.033	6480.662
	(40370.319)	(40957.910)	(21473.771)	(55400.158)
Number of children in household	0.804	0.561	1.039	0.804
	(0.981)	(0.787)	(1.225)	(1.063)
ln_hh_asset	11.385	12.063	10.827	11.654
	(1.321)	(1.221)	(1.410)	(1.274)
Number of crops grown by the Household	17.522	18.333	15.728	15.312
	(5.442)	(4.561)	(7.470)	(5.366)
hh_wage_rate	74.377	125.759	71.676	124.342
	(30.682)	(50.603)	(28.820)	(41.908)
Observations	1635	1380	10789	8506

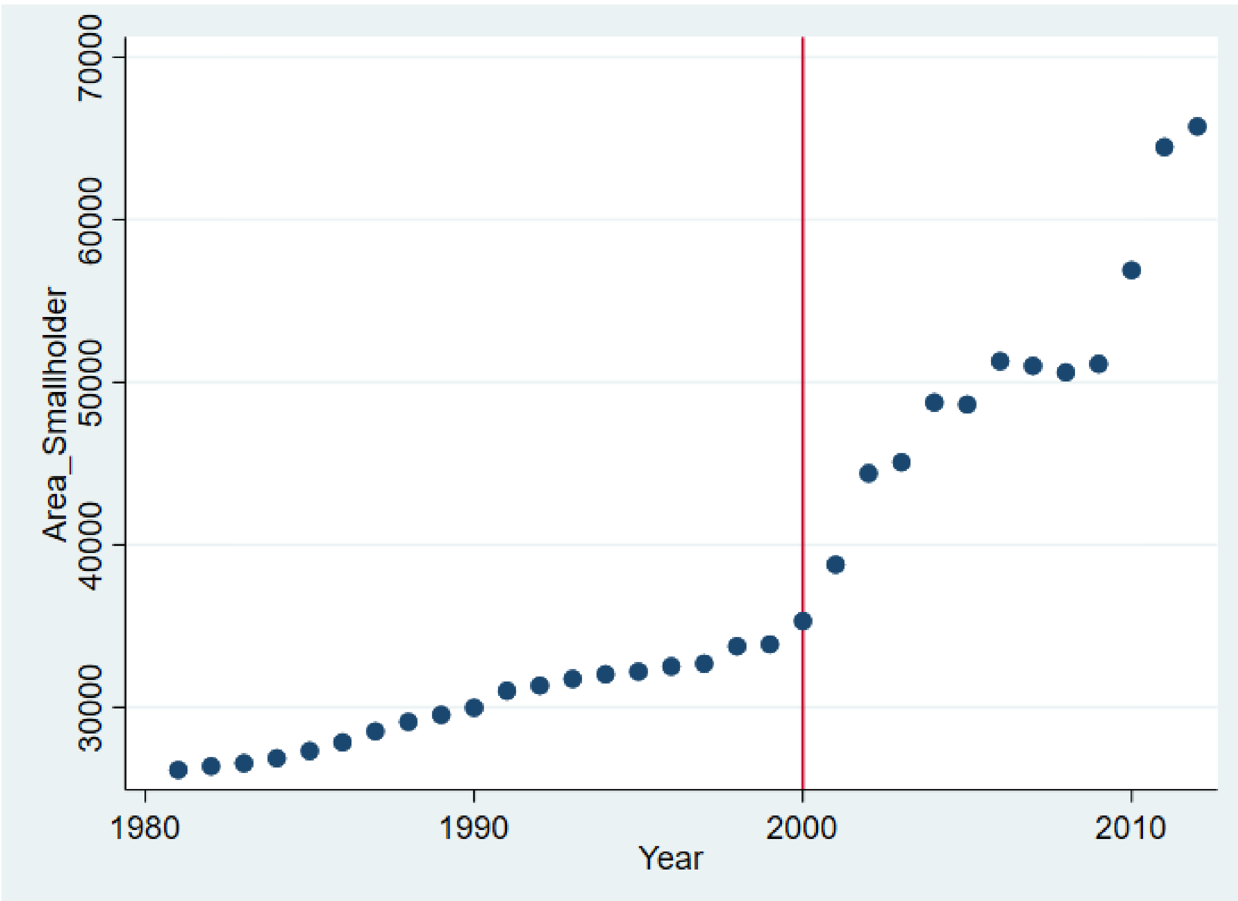


Figure 3: Expansion of Tea cultivation for the smallholders before and after the Liberalization

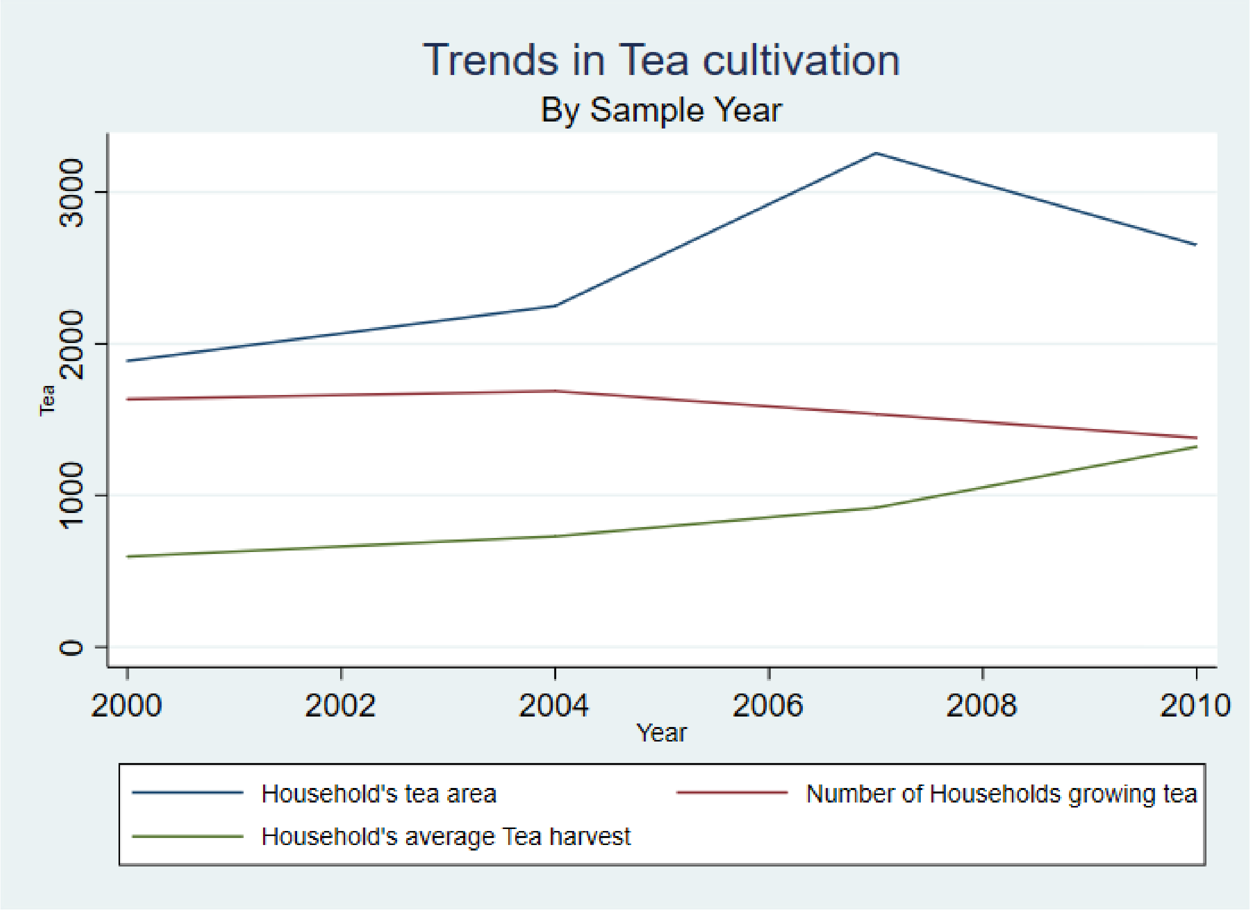


Figure 4: Trends in Tea cultivation; Source:Tegmeo Agricultural Policy Research Aanalysis (TAPRA) Project, Household Survey 2000, 2004, 2007, 2010

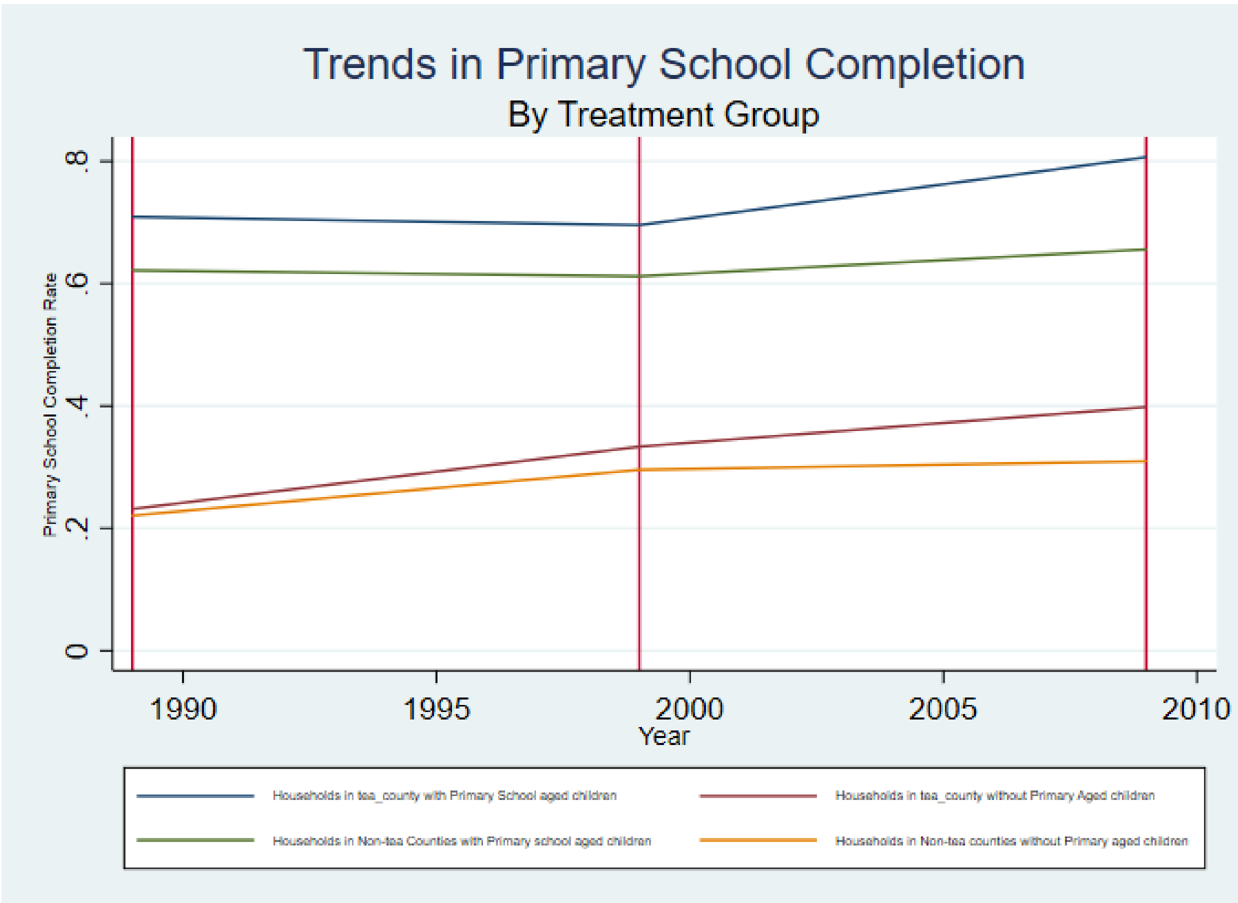


Figure 5: Trends in Primary Education Completion rates; Source:KHPC Data

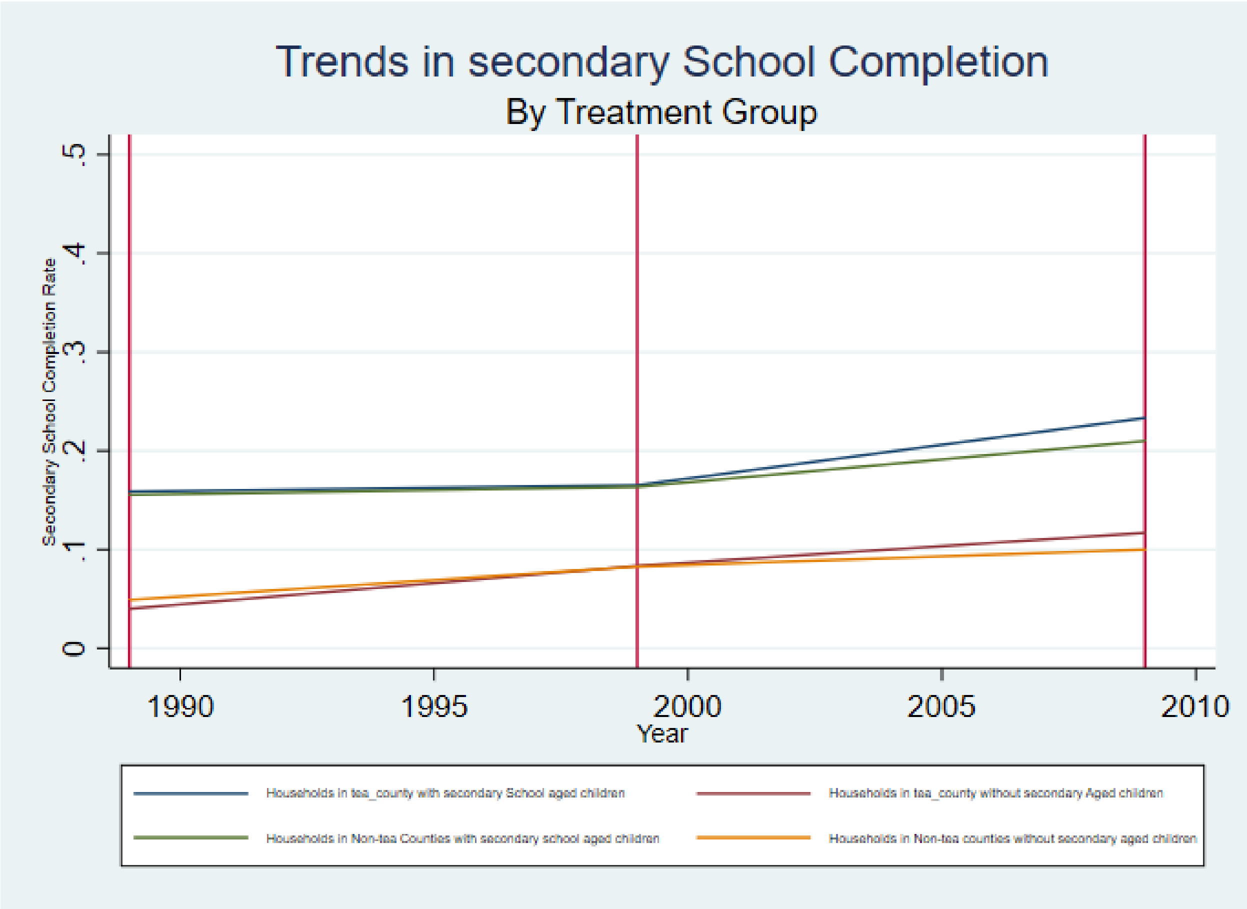


Figure 6: Trends in Secondary Education Completion rates; Source:KHPC Data

Table 3: Double difference estimates of Primary Education Completion

VARIABLES	(1) Female	(2) Male	(3) Overall
age_pri	-0.0713***	-0.134***	-0.0935***
	(0.0131)	(0.0139)	(0.0103)
post_dt	0.0519***	-0.00995	0.0232**
	(0.0132)	(0.00819)	(0.0102)
age_pri X post_dt	0.0529***	0.115***	0.0813***
	(0.00825)	(0.0106)	(0.00788)
Constant	0.786***	0.725***	0.739***
	(0.0165)	(0.0174)	(0.0168)
Household Characteristics	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes
Observations	332,142	305,230	637,372
R-squared	0.051	0.065	0.056

Robust standard errors in parentheses and clustered at District level

*** p<0.01, ** p<0.05, * p<0.1

The treated age cohort (age_pri) is defined as individuals aged between 14 and 25, post variable is 1 for 2009 sample and 0 for 1999 sample, we control for household level characteristics and province fixed effects

Table 4: Double difference estimates of Secondary Education Completion

VARIABLES	(1) Female	(2) Male	(3) Overall
age_sec	-0.116***	-0.150***	-0.130***
	(0.00637)	(0.00522)	(0.00494)
post_dt	0.0331***	-0.0204**	0.00843
	(0.00652)	(0.00887)	(0.00712)
age_sec X post_dt	0.0372***	0.0830***	0.0578***
	(0.00842)	(0.00853)	(0.00787)
Constant	0.206***	0.234***	0.213***
	(0.0250)	(0.0209)	(0.0195)
Household Characteristics	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes
Observations	318,988	288,799	607,787
R-squared	0.082	0.078	0.078

Robust standard errors in parentheses and clustered at District level

*** p<0.01, ** p<0.05, * p<0.1

The treated age cohort (age_sec) is defined as individuals aged between 16 and 28, post variable is 1 for 2009 sample and 0 for 1999 sample, we control for household level characteristics and province fixed effects

Table 5: Triple difference estimates of Primary Education Completion

VARIABLES	(1) Female	(2) Male	(3) Overall	(4) Female	(5) Male	(6) Overall
age_pri	-0.0646***	-0.112***	-0.0867***	-0.0308	-0.104***	-0.0649***
	(0.00962)	(0.0169)	(0.00956)	(0.0261)	(0.00823)	(0.0158)
tea_county	0.117**	0.0890*	0.105**	0.313***	0.217**	0.271***
	(0.0517)	(0.0464)	(0.0482)	(0.0969)	(0.0700)	(0.0844)
age_pri X tea_county	-0.0171	-0.0234	-0.0202	-0.0548**	-0.0286	-0.0442**
	(0.0124)	(0.0227)	(0.0147)	(0.0186)	(0.0227)	(0.0183)
post_dt	0.0369***	-0.0215	0.00882	0.0592	-0.0254	0.0217
	(0.0122)	(0.0132)	(0.00994)	(0.0336)	(0.0333)	(0.0315)
age_pri X post_dt	0.0288***	0.0751***	0.0523***	-0.0165*	0.0416***	0.00998*
	(0.00832)	(0.0144)	(0.00865)	(0.00823)	(0.00606)	(0.00458)
tea_county X post_dt	0.00103	-0.00286	0.000416	-0.00652	0.00584	-0.00299
	(0.0185)	(0.0147)	(0.0140)	(0.0401)	(0.0318)	(0.0334)
age_pri X tea_county X post_dt	0.0274**	0.0408**	0.0324***	0.0547***	0.0490***	0.0543***
	(0.0121)	(0.0168)	(0.0111)	(0.0159)	(0.0134)	(0.0121)
Constant	0.494***	0.512***	0.502***	0.296**	0.415***	0.354***
	(0.0650)	(0.0513)	(0.0544)	(0.131)	(0.0968)	(0.109)
Household Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	818,478	768,218	1,586,696	207,290	198,495	405,785
R-squared	0.152	0.142	0.143	0.149	0.136	0.138

Robust standard errors in parentheses and clustered at District level
*** p<0.01, ** p<0.05, * p<0.1
The treated age cohort (age_pri) is defined as individuals aged between 14 and 25, post variable is 1 for 2009 sample and 0 for 1999 sample, we control for household level characteristics and province fixed effects
Column 4- 6 restricts the sample to Ridge Valley province only

Table 6: Triple difference estimates of Secondary Education Completion

VARIABLES	(1) Female	(2) Male	(3) Overall	(4) Female	(5) Male	(6) Overall
age_sec	-0.0970***	-0.115***	-0.106***	-0.0861***	-0.0901***	-0.0906***
	(0.0129)	(0.00801)	(0.0100)	(0.0234)	(0.0196)	(0.0208)
tea_county	0.0482**	0.0721***	0.0586***	0.0471	0.0988**	0.0741*
	(0.0208)	(0.0229)	(0.0205)	(0.0394)	(0.0367)	(0.0373)
age_sec X tea_county	-0.00473	-0.0304***	-0.0159*	-0.0126	-0.0623**	-0.0383*
	(0.0102)	(0.00929)	(0.00896)	(0.0193)	(0.0198)	(0.0189)
post_dt	0.0336***	0.00361	0.0190**	0.0287**	0.00409	0.0188
	(0.00645)	(0.0117)	(0.00767)	(0.0128)	(0.0156)	(0.0125)
age_sec X post_dt	0.0232***	0.0499***	0.0357***	0.0108	0.0215**	0.0147*
	(0.00759)	(0.00621)	(0.00707)	(0.0112)	(0.00731)	(0.00683)
tea_county X post_dt	4.53e-05	-0.0265*	-0.0119	0.0108	-0.0245	-0.00901
	(0.00804)	(0.0136)	(0.00905)	(0.0130)	(0.0155)	(0.0117)
age_sec X tea_county X post_dt	0.0108	0.0315***	0.0203**	0.00864	0.0562***	0.0330**
	(0.00922)	(0.01000)	(0.00923)	(0.0139)	(0.0134)	(0.0120)
Constant	0.132***	0.153***	0.143***	0.0818	0.123**	0.107**
	(0.0376)	(0.0166)	(0.0250)	(0.0544)	(0.0389)	(0.0439)
Household Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	787,263	725,288	1,512,551	196,642	186,223	382,865
R-squared	0.118	0.121	0.119	0.096	0.088	0.096

Robust standard errors in parentheses and clustered at District level

*** p<0.01, ** p<0.05, * p<0.1

The treated age cohort (age_sec) is defined as individuals aged between 16 and 28, post variable is 1 for 2009 sample and 0 for 1999 sample, we control for household level characteristics and province fixed effects

Column 4- 6 restricts the sample to Ridge Valley province only

Table 7: Female Labor force participation for the exposed cohort group

VARIABLES	(1) Double Difference estimate	(2) Triple Difference estimate
age_lab	0.00944	0.0230
	(0.0135)	(0.0280)
tea_county		0.0829***
		(0.0282)
age_lab X tea_county		-0.0739**
		(0.0297)
post_dt	-0.0197*	-0.00565
	(0.0106)	(0.0255)
age_lab X post_dt	-0.116***	-0.114***
	(0.00863)	(0.0133)
tea_county X post_dt		-0.0111
		(0.0270)
age_lab X tea_county X post_dt		-0.00424
		(0.0167)
Constant	0.793***	0.748***
	(0.0334)	(0.0287)
Household Characteristics	Yes	Yes
Province Fixed effects	Yes	Yes
Observations	318,988	849,609
R-squared	0.087	0.060

Robust standard errors in parentheses and clustered at District level
*** $p<0.01$, ** $p<0.05$, * $p<0.1$
The treated age cohort (age_lab) is defined as individuals aged between 14 and 28, post variable is 1 for 2009 sample and 0 for 1999 sample, we control for household level characteristics and province fixed effects

Table 8: Female Labor force participation for the un-exposed older cohort group

VARIABLES	(1) Double Difference estimate	(2) Triple Difference estimate
age_lab_force1	-0.00809*	-0.00368
	(0.00378)	(0.00586)
tea_county		0.0786***
		(0.0265)
age_lab_force1 X tea_county		-0.00812
		(0.00596)
post_dt	-0.0160*	0.00420
	(0.00879)	(0.0252)
age_lab_force1 X post_dt	-0.00347	0.000650
	(0.00541)	(0.00606)
tea_county X post_dt		-0.0211
		(0.0263)
age_lab_force1 X tea_county X post_dt		-0.00405
		(0.00853)
Constant	0.964***	0.841***
	(0.0278)	(0.0281)
Household Characteristics	Yes	Yes
Province Fixed effects	Yes	Yes
Observations	233,496	547,388
R-squared	0.022	0.048

Robust standard errors in parentheses and clustered at District level

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

The treated age cohort (age_lab_force1) is defined as individuals aged between 25 and 40, post variable is 1 for 2009 sample and 0 for 1999 sample, we control for household level characteristics and province fixed effects

Table 9: Double difference estimates of Primary Education Completion in the Placebo sample

VARIABLES	(1) Female	(2) Male	(3) Overall
age_pri	0.0709***	-0.0243***	0.0262**
	(0.0184)	(0.00618)	(0.00879)
post_dt_plcb	0.144***	0.0440***	0.0960***
	(0.0243)	(0.0120)	(0.0174)
age_pri X post_dt_plcb	-0.147***	-0.0944***	-0.122***
	(0.0215)	(0.0112)	(0.0164)
Constant	0.608***	0.642***	0.627***
	(0.0355)	(0.0187)	(0.0240)
Household characteristics	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes
Observations	170,282	156,127	326,409
R-squared	0.038	0.053	0.041

Robust standard errors in parentheses and clustered at District level

*** p<0.01, ** p<0.05, * p<0.1

The treated age cohort (age_pri) is defined as individuals aged between 14 and 25, post variable is 1 for 1999 sample and 0 for 1989 sample, we control for household level characteristics and province fixed effects

Table 10: Double difference estimates of Secondary Education Completion in the Placebo sample

VARIABLES	(1) Female	(2) Male	(3) Overall
age_sec	-0.0288***	-0.0863***	-0.0621***
	(0.00680)	(0.00645)	(0.00394)
post_dt_plcb	0.0558***	0.0266*	0.0392***
	(0.00926)	(0.0130)	(0.00808)
age_sec X post_dt_plcb	-0.0625***	-0.0561***	-0.0577***
	(0.00904)	(0.0115)	(0.00735)
Constant	0.0836***	0.172***	0.142***
	(0.0236)	(0.0128)	(0.0142)
Household characteristics	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes
Observations	158,575	142,941	301,516
R-squared	0.052	0.061	0.057

Robust standard errors in parentheses and clustered at District level

*** p<0.01, ** p<0.05, * p<0.1

The treated age cohort (age_sec) is defined as individuals aged between 16 and 28, post variable is 1 for 2009 sample and 0 for 1999 sample, we control for household level characteristics and province fixed effects

Table 11: Triple difference estimates of Primary Education Completion in the Placebo sample

VARIABLES	(1) Female	(2) Male	(3) Overall	(4) Female	(5) Male	(6) Overall
age_pri	0.0848***	-0.00578	0.0359***	0.0969***	0.0249	0.0542**
	(0.0196)	(0.00954)	(0.0114)	(0.0277)	(0.0144)	(0.0218)
tea_county	0.117**	0.0739**	0.0989**	0.228**	0.194***	0.218***
	(0.0447)	(0.0348)	(0.0383)	(0.0750)	(0.0518)	(0.0652)
age_pri X tea_county	-0.0123	-0.0175	-0.0164	0.0175	-0.0407**	-0.0156
	(0.0223)	(0.0131)	(0.0130)	(0.0244)	(0.0183)	(0.0195)
post_dt_plcb	0.159***	0.0451***	0.103***	0.131***	0.0637**	0.0968***
	(0.0221)	(0.0109)	(0.0184)	(0.0285)	(0.0216)	(0.0227)
age_pri X post_dt_plcb	-0.143***	-0.0919***	-0.119***	-0.128***	-0.128***	-0.129***
	(0.0177)	(0.0120)	(0.0170)	(0.0258)	(0.0138)	(0.0182)
tea_county X post_dt_plcb	-0.0120	0.00459	-0.00505	0.0796**	0.0170	0.0451
	(0.0306)	(0.0166)	(0.0246)	(0.0347)	(0.0286)	(0.0289)
age_pri X tea_county X post_dt_plcb	-0.00345	-0.00390	-0.00267	-0.0694	0.0185	-0.0228
	(0.0256)	(0.0166)	(0.0229)	(0.1239)	(0.0175)	(0.0179)
Constant	0.316***	0.460***	0.400***	0.141	0.309***	0.244**
	(0.0639)	(0.0474)	(0.0508)	(0.103)	(0.0778)	(0.0898)
Household characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	385,941	358,497	744,438	89,784	85,368	175,152
R-squared	0.108	0.100	0.099	0.108	0.095	0.096

Robust standard errors in parentheses and clustered at District level

*** p<0.01, ** p<0.05, * p<0.1

The treated age cohort (age_pri) is defined as individuals aged between 14 and 25, post variable is 1 for 1999 sample and 0 for 1989 sample, we control for household level characteristics and province fixed effects

Column 4- 6 restricts the sample to Ridge Valley province only

Table 12: Triple difference estimates of Secondary Education Completion in the Placebo sample

VARIABLES	(1) Female	(2) Male	(3) Overall	(4) Female	(5) Male	(6) Overall
age_sec	-0.0295***	-0.0538***	-0.0481***	-0.0253	-0.0254**	-0.0327**
	(0.00745)	(0.00923)	(0.00496)	(0.0143)	(0.00943)	(0.0108)
tea_county	0.0303***	0.0637***	0.0470***	0.0336	0.0801***	0.0589***
	(0.0105)	(0.0209)	(0.0138)	(0.0197)	(0.0190)	(0.0184)
age_sec X tea_county	0.0110	-0.0287**	-0.00836	-0.000385	-0.0368***	-0.0200*
	(0.00760)	(0.0117)	(0.00524)	(0.0115)	(0.0115)	(0.0100)
post_dt_plcb	0.0474***	0.0394***	0.0409***	0.0474**	0.0578**	0.0493**
	(0.00701)	(0.0140)	(0.00887)	(0.0167)	(0.0198)	(0.0169)
age_sec X post_dt_plcb	-0.0476***	-0.0592***	-0.0519***	-0.0389**	-0.0613***	-0.0480***
	(0.00691)	(0.0136)	(0.00893)	(0.0135)	(0.0189)	(0.0150)
tea_county X post_dt_plcb	0.0139	-0.00880	0.00229	0.0165	0.0145	0.0156
	(0.0144)	(0.0194)	(0.0137)	(0.0220)	(0.0295)	(0.0233)
age_sec X tea_county X post_dt_plcb	-0.0173	0.00270	-0.00709	-0.0145	-0.0244	-0.0198
	(0.0123)	(0.0171)	(0.0116)	(0.0179)	(0.0256)	(0.0195)
Constant	0.0360	0.0867***	0.0771***	-0.0142	0.0238	0.0241
	(0.0252)	(0.0197)	(0.0160)	(0.0336)	(0.0219)	(0.0239)
Household characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	364,201	332,737	696,938	84,139	78,918	163,057
R-squared	0.086	0.094	0.092	0.070	0.069	0.071

Robust standard errors in parentheses and clustered at District level
*** p<0.01, ** p<0.05, * p<0.1
The treated age cohort (age_sec) is defined as individuals aged between 16 and 28, post variable is 1 for 1999 sample and 0 for 1989 sample, we control for household level characteristics and province fixed effects
Column 4- 6 restricts the sample to Ridge Valley province only

Table 13: Effect of the Tea Liberalization on Tea cultivation

VARIABLES	(1) Percentage of Land used for Tea	(2) Log of Harvest
1.post_dt	-0.0191	-0.235
	(0.0145)	(0.303)
1.tea_county	0.0594***	1.689***
	(0.0201)	(0.496)
post_dt X tea_county	0.0220*	0.350**
	(0.0130)	(0.140)
Constant	-0.108**	-2.225**
	(0.0508)	(0.954)
Observations	21,477	21,477
R-squared	0.174	0.232

Robust standard errors in parentheses and clustered at Village level
*** p<0.01, ** p<0.05, * p<0.1
tea_county represents the counties where tea is grown and $post_d t$ stands for 2010 years sample.
We control for household level characteristics.
The Column (4) to (6) restricts the sample for the Tea counties

Table 14: Primary Education Completion using TARPA data and DDD specification

VARIABLES	(1) Female	(2) Male	(3) Overall
age_pri	-0.0350	-0.193***	-0.108***
	(0.0343)	(0.0279)	(0.0258)
post_dt	0.0673	0.0157	0.0560*
	(0.0458)	(0.0395)	(0.0324)
age_pri X post_dt	-0.0583	0.0387	-0.0187
	(0.0533)	(0.0448)	(0.0333)
tea_county	0.0243	-0.0398	-0.00300
	(0.0441)	(0.0373)	(0.0322)
age_pri X tea_county	0.0393	0.107**	0.0689**
	(0.0473)	(0.0445)	(0.0343)
post_dt X tea_county	-0.0218	0.0221	-0.0163
	(0.0552)	(0.0447)	(0.0389)
age_pri X post_dt X tea_county	-0.0383	-0.0394	-0.0208
	(0.0646)	(0.0566)	(0.0436)
Constant	-0.156*	0.229***	0.0499
	(0.0867)	(0.0704)	(0.0679)
Observations	4,305	4,761	9,066
R-squared	0.100	0.085	0.084

Robust standard errors in parentheses and clustered at District level
*** p<0.01, ** p<0.05, * p<0.1
The treated age cohort (age_sec) is defined as individuals aged between 14 and 24, post variable is 1 for 2010 sample and 0 for 2000 sample, we control for household level characteristics and province fixed effects

Table 15: Secondary Education Completion using TARPA data and DDD specification

VARIABLES	(1) Female	(2) Male	(3) Overall
age_sec	0.0458	-0.0847**	-0.0169
	(0.0401)	(0.0381)	(0.0323)
post_dt	0.0764	-0.0660	0.0125
	(0.0583)	(0.0616)	(0.0483)
age_sec X post_dt	-0.00116	0.132**	0.0674
	(0.0585)	(0.0582)	(0.0447)
tea_county	0.0905*	0.0442	0.0677
	(0.0501)	(0.0540)	(0.0435)
age_sec X tea_county	-0.0527	-0.00972	-0.0294
	(0.0514)	(0.0524)	(0.0422)
post_dt X tea_county	-0.105	0.0136	-0.0449
	(0.0784)	(0.0757)	(0.0611)
age_sec X post_dt X tea_county	0.102	-0.0582	0.0115
	(0.0821)	(0.0756)	(0.0598)
Constant	-0.773***	-0.583***	-0.677***
	(0.0889)	(0.0831)	(0.0696)
Observations	3,952	4,324	8,276
R-squared	0.145	0.134	0.130

Robust standard errors in parentheses and clustered at District level

*** p<0.01, ** p<0.05, * p<0.1

The treated age cohort (age_sec) is defined as individuals aged between 16 and 26, post variable is 1 for 2010 sample and 0 for 2000 sample, we control for household level characteristics and province fixed effects

Table 16: Years of Schooling completed

VARIABLES	(1) Female	(2) Male	(3) Overall	(4) Female	(5) Male	(6) Overall
age_schl	-3.999***	-4.137***	-4.023***	-3.939***	-3.778***	-3.791***
	(0.171)	(0.158)	(0.133)	(0.267)	(0.258)	(0.206)
hh_tea_acre_change	-0.0501***	-0.0153	-0.0255**	-0.0444***	-0.00370	-0.0154
	(0.0124)	(0.0244)	(0.0112)	(0.0125)	(0.0247)	(0.0111)
age_schl X hh_tea_acre_change	0.0338**	0.0546***	0.0343***	0.0303*	0.0424**	0.0251*
	(0.0170)	(0.0207)	(0.0122)	(0.0176)	(0.0212)	(0.0132)
Constant	2.108***	4.508***	3.302***	2.278***	4.046***	3.257***
	(0.467)	(0.476)	(0.379)	(0.670)	(0.706)	(0.565)
Household and Individual level characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Year of Birth Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,559	5,890	11,449	2,821	3,058	5,879
R-squared	0.600	0.553	0.564	0.608	0.537	0.560

Robust standard errors in parentheses and clustered at Village level
*** p<0.01, ** p<0.05, * p<0.1
The treated age cohort (age_schl) is defined as individuals aged between 6 and 18, The variable hh
measures the change in the acreage of tea plot introduced by the household between 2000 and 2010.
We control for household level characteristics, cohort fixed effects and county fixed effects.
The Column (4) to (6) restricts the sample for the Tea counties

Table 17: School attendance

VARIABLES	(1) Female	(2) Male	(3) Overall	(4) Female	(5) Male	(6) Overall
age_schl_attnd	0.455***	0.395***	0.428***	0.503***	0.431***	0.468***
	(0.0217)	(0.0222)	(0.0172)	(0.0298)	(0.0315)	(0.0232)
hh_tea_acre_change	-0.00583*	0.00734	-0.000108	-0.00532	0.00704	-0.000121
	(0.00348)	(0.00458)	(0.00233)	(0.00356)	(0.00439)	(0.00242)
age_schl_attnd X c.hh_tea_acre_change	0.000333	-0.00963**	-0.00409*	-0.000985	-0.0105**	-0.00510**
	(0.00282)	(0.00455)	(0.00212)	(0.00295)	(0.00441)	(0.00220)
Constant	-0.138**	-0.0363	-0.0917*	-0.270***	-0.168**	-0.224***
	(0.0630)	(0.0678)	(0.0516)	(0.0915)	(0.0827)	(0.0644)
Household and Individual level characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Year of Birth Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,287	5,492	10,779	2,654	2,770	5,424
R-squared	0.451	0.412	0.423	0.463	0.438	0.440

Robust standard errors in parentheses and clustered at Village level
*** p<0.01, ** p<0.05, * p<0.1
The treated age cohort (age_schl_attnd) is defined as individuals aged between 6 and 16, The variable hh_tea_acre_change measures the change in the acreage of tea plot introduced by the household between 2000 and 2010.
We control for household level characteristics, cohort fixed effects and county fixed effects.
The Column (4) to (6) restricts the sample for the Tea counties

Table 18: Years of Schooling completed

VARIABLES	(1) Female	(2) Male	(3) Overall	(4) Female	(5) Male	(6) Overall
age_schl	-3.999***	-4.137***	-4.023***	-3.939***	-3.778***	-3.791***
	(0.171)	(0.158)	(0.133)	(0.267)	(0.258)	(0.206)
hh_tea_harv_change	-0.0501***	-0.0153	-0.0255**	-0.0444***	-0.00370	-0.0154
	(0.0124)	(0.0244)	(0.0112)	(0.0125)	(0.0247)	(0.0111)
age_schl X hh_tea_harv_change	0.0338**	0.0546***	0.0343***	0.0303*	0.0424**	0.0251*
	(0.0170)	(0.0207)	(0.0122)	(0.0176)	(0.0212)	(0.0132)
Constant	2.108***	4.508***	3.302***	2.278***	4.046***	3.257***
	(0.467)	(0.476)	(0.379)	(0.670)	(0.706)	(0.565)
Household and Individual level characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Year of Birth Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,559	5,890	11,449	2,821	3,058	5,879
R-squared	0.600	0.553	0.564	0.608	0.537	0.560

Robust standard errors in parentheses and clustered at Village level
*** p<0.01, ** p<0.05, * p<0.1
The treated age cohort (age_schl) is defined as individuals aged between 6 and 18, The variable hh_tea_harv_change measures the change in the tea harvest reported by the household between 2000 and 2010.
We control for household level characteristics, cohort fixed effects and county fixed effects.
The Column (4) to (6) restricts the sample for the Tea counties

Table 19: School attendance

VARIABLES	(1) Female	(2) Male	(3) Overall	(4) Female	(5) Male	(6) Overall
age_schl_attnd	0.455***	0.395***	0.428***	0.503***	0.431***	0.468***
	(0.0217)	(0.0222)	(0.0172)	(0.0298)	(0.0315)	(0.0232)
hh_tea_harv_change	-0.00583*	0.00734	-0.000108	-0.00532	0.00704	-0.000121
	(0.00348)	(0.00458)	(0.00233)	(0.00356)	(0.00439)	(0.00242)
age_schl_attnd X hh_tea_harv_change	0.000333	-0.00963**	-0.00409*	-0.000985	-0.0105**	-0.00510**
	(0.00282)	(0.00455)	(0.00212)	(0.00295)	(0.00441)	(0.00220)
Constant	-0.138**	-0.0363	-0.0917*	-0.270***	-0.168**	-0.224***
	(0.0630)	(0.0678)	(0.0516)	(0.0915)	(0.0827)	(0.0644)
Household and Individual level characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Year of Birth Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,287	5,492	10,779	2,654	2,770	5,424
R-squared	0.451	0.412	0.423	0.463	0.438	0.440

Robust standard errors in parentheses and clustered at Village level
*** p<0.01, ** p<0.05, * p<0.1
The treated age cohort (age_schl_attnd) is defined as individuals aged between 6 and 16, The variable hh_tea_acre_change measures the change in the acreage of tea plot introduced by the household between 2000 and 2010.
We control for household level characteristics, cohort fixed effects and county fixed effects.
The Column (4) to (6) restricts the sample for the Tea counties

Table 20: Years of Schooling completed (Placebo test)

VARIABLES	(1) Female	(2) Male	(3) Overall	(4) Female	(5) Male	(6) Overall
age_schl_plcb	-0.462	-1.555***	-1.146***	-0.536	-1.302***	-1.050**
	(0.327)	(0.338)	(0.265)	(0.523)	(0.492)	(0.408)
hh_tea_acre_change	0.467	-0.00730	-0.0178	0.393	0.00124	-0.00671
	(0.627)	(0.0128)	(0.0132)	(0.605)	(0.0146)	(0.0140)
age_schl_plcb X hh_tea_acre_change	-0.525	-0.0123	-0.0125	-0.448	-0.0156	-0.0175
	(0.630)	(0.0225)	(0.0121)	(0.609)	(0.0217)	(0.0121)
Constant	0.744	2.286***	1.607**	1.853*	2.602**	2.313**
	(0.850)	(0.803)	(0.695)	(1.072)	(1.186)	(0.931)
Household and Individual level characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Year of Birth Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,743	3,166	5,909	1,422	1,760	3,182
R-squared	0.290	0.206	0.217	0.271	0.217	0.214

Robust standard errors in parentheses and clustered at Village level
*** p<0.01, ** p<0.05, * p<0.1
The treated age cohort (age_schl_plcb) is defined as individuals aged between 18 and 28, The variable hh_tea_acre_change measures the change in the acreage of tea plot introduced by the household between 2000 and 2010.
We control for household level characteristics, cohort fixed effects and county fixed effects.
The Column (4) to (6) restricts the sample for the Tea counties

Table 21: Years of Schooling completed

VARIABLES	(1) Female	(2) Male	(3) Overall	(4) Female	(5) Male	(6) Overall
age_schl_plcb	-0.462	-1.555***	-1.146***	-0.536	-1.302***	-1.050**
	(0.327)	(0.338)	(0.265)	(0.523)	(0.492)	(0.408)
hh_tea_harv_change	0.467	-0.00730	-0.0178	0.393	0.00124	-0.00671
	(0.627)	(0.0128)	(0.0132)	(0.605)	(0.0146)	(0.0140)
age_schl_plcb X c.hh_tea_harv_change	-0.525	-0.0123	-0.0125	-0.448	-0.0156	-0.0175
	(0.630)	(0.0225)	(0.0121)	(0.609)	(0.0217)	(0.0121)
Constant	0.744	2.286***	1.607**	1.853*	2.602**	2.313**
	(0.850)	(0.803)	(0.695)	(1.072)	(1.186)	(0.931)
Household and Individual level characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Year of Birth Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,743	3,166	5,909	1,422	1,760	3,182
R-squared	0.290	0.206	0.217	0.271	0.217	0.214

Robust standard errors in parentheses and clustered at Village level
*** p<0.01, ** p<0.05, * p<0.1
The treated age cohort (age_schl_plcb) is defined as individuals aged between 18 and 28 years, The variable hh_tea_harv_change measures the change in the tea harvest reported by the household between 2000 and 2010.
We control for household level characteristics, cohort fixed effects and county fixed effects.
The Column (4) to (6) restricts the sample for the Tea counties

CHAPTER III

Impact Assessment of the West Africa Agricultural Productivity Program: Evidence from Ghana, Senegal and Mali

3.1 Introduction

The role of technology in agricultural transformation, food security and poverty alleviation in the developing world is well documented (18; 37; 38; 4). Therefore, providing access to agricultural technology and the resulting productivity gains are perceived as crucial to the long-run development goals. In Sub-Saharan Africa, where smallholding agriculture is predominant, technology adoption rates have remained stubbornly low (6; 48; 88) despite some recorded progress. While there is a broad consensus that providing access to technology for these smallholders is vital for agricultural and economic growth, the empirical evidence indicates that potentially promising technologies even available are seldom adopted widely (86). This slow pace of agricultural technology adoption in Sub-Saharan Africa, in particular, has resulted in persistent low agricultural productivity (92), leading to lower household income and food security. Important explanations for the low adoption rates include supply-side constraints (e.g., access and exposure to technologies and farming practices) and demand-side factors such as risk aversion and behavioral biases, for instance. The West African Agricultural Productivity Program (WAAPP) was designed primarily to alleviate some of the supply side constraints by increasing farmers' exposure to new technologies and making these technologies readily available (82).

This paper uses purposefully collected data in rural Ghana, Mali and Senegal to assess the impact of the WAAPP on technology adoption, input usage, income and food security. The WAAPP was an extensive multi-country agricultural development program that ran in two phases between 2007 and 2011, and 2012 and 2018[1]. The program was designed to enhance sustainable agricultural productivity with the goal of ensuring food security and achieving economic growth and poverty reduction. The project also aimed at supporting inter-regional integration in technology dissemination and coordination. We focus on three participating countries of Phase 2 of the program, i.e., Ghana, Mali and Senegal.

Phase 1 of the program began in 2007, focusing on enhancing agricultural productivity of root and tubers crops in Ghana, drought-resistance cereals in Senegal, and rice in Mali. This phase of the program supported an institutional framework for (i) sharing of technology, (ii) supporting technological specialization centers, and (iii) financing the creation, dissemination and adoption of improved agricultural technologies. The program eventually

[1]Phase 1 of this program had three components, corresponding to three sets of countries over the time: WAAPP1A (Ghana, Mali, Senegal) started in 2007, WAAPP1B (Burkina Faso, Côte d'Ivoire, Nigeria) in 2010, and WAAPP1C (Benin, Côte d'Ivoire, Guinea, Liberia, Niger, Sierra Leone, Gambia, Togo) in 2011.

expanded to cover most countries in West Africa. Starting in 2012, a second phase aimed at deepening, expanding and consolidating was initiated in the three countries[2]. The second phase continued to support the center of specialization on roots and tubers in Ghana, on rice by Mali and cereals in Senegal. As in the first phase, the program continued to provide the institutional infrastructure and the financial resources for disseminating the technologies across all countries.

We estimate the impact of WAAPP in 2019 in three countries after the program has run for seven years, using a retrospective quasi-experimental evaluation design. We used a two-step propensity score matching method to select the study sample in each of the three countries. In the first step, we used administrative and national census data to match treated and comparison villages within each randomly selected WAAPP district. In the second, we use recall variables to match households in selected villages based on village-level census data. In practice, we started by enumerating all households in sampled villages. The census data were used to match treated and comparison households in treated villages first. Second, we matched treated households (in treated villages) with comparison households in comparison villages. The household survey was administered only to the matched households. In summary, the survey sample consisted of the following (i) two pairs of matched villages (treated and comparison) within each district, (ii) matched treated and comparison households in each treated village, and (iii) matched comparison households in each comparison village. We then apply OLS to the resulting sample to estimate the impact of the program. We show that our results are robust to using propensity score matching and a larger set of variables on the resulting sample. Moreover, our research design built in the possibility of falsification tests to assess the robustness of our main findings.

Our study contributes to the ever-expanding literature on technology expansion and agricultural growth in developing countries by providing a multi-country assessment of the impact of increasing exposure and access to agricultural technologies. Indeed, researchers have sought to identify the barriers to technology adoption in general and in Sub-Saharan Africa in particular. Researchers have offered several explanations including markets frictions, lack of exposure, risk aversion, time inconsistent preferences, and incomplete learning ((50),(60),(7),(28)(30)(64)).

Most of the extension programs act as a conduit to reach out to the producers. Farmers are only the end users of these technologies. The effectiveness of such "trickle down" process of diffusion has been questioned in the context of sub-Saharan African countries, which has most subsistence level and small-scale farmers (61; 59). Recent studies have emphasized on the importance of cooperative learning and network generation for successful and sustainable use of technologies(e.g., (8; 25)). Some academic work have shown that traditional and indirect means of promoting agricultural innovations are not useful or consistently fruitful in the context of small-scale farmers ((29; 28; 30; 83)).

Recent studies in the literature, evidence rely on a more indirect approach to intensify technology adoption rates through facilitating training and access to credit markets. These have found to have sustainable impacts along with notable spillover effects within geographies ((11; 14; 47)). Field experiments have also used indirect and intuitive methods of promotion of technology adoptions by designing randomized experiments and have found

[2]For security reasons, the second phase was delayed in Mali and started in 2014.

to have persistent short run increase in adoption rates and substantial spillover gains (20). These studies have carried out extension programs in collaboration with regional administration and support from international bodies by targeting a specific section of farmers or crops.

A broad group of studies identifies the presence of strong informational frictions between the farmers and the program stakeholders. Since participation in the programs are not random, the creation of agricultural cooperatives has been found to be successful in enhancing a network among the farmers and coordinating the smallholder farmers in Sub-Saharan Africa. (See: (70), (65), (1)). It is being documented that, if the technology is appropriate and expected profits are sufficiently high, farmers can overcome obstacles to adoption, including bad institutions and poor roads. Farmer decisions identify the information about profitability that arrives between the take-up and follow-through stages ((69)). Other studies have targeted specific gender within households for technology adoption and to serve as a mean to alleviating gender discrimination and improving household member welfare in the long run. (See: (68), (51))

Although, diverse in their approach, the existing literature does not undermine the importance of technology as a tool for productivity growth and poverty alleviation in sub-Saharan Africa. In theme, the WAAPP is similar to many of the extension programs, but by its design it overcomes some issues in the existing literature. Firstly, it's diverse outreach in the three countries with varied sociopolitical climate marks an important diversion from the specific nature of most of the policies studied in the previous works. WAAPP targets a variety of crops in the three countries that have different climatic and environmental requirements, and thereby the findings carry a wider policy implication. By structure, the program also provides multiple layers of facilities by giving access to technologies, training, credit and formation of a cooperative association, all of which are cited in the literature as instrumental in technology dispersion.

With few exceptions, each of these studies focuses on a single country or few regions in a given country; thus, whether the findings are generalizable to other contexts can be ambiguous. By using an identical research design to evaluate the same program in three countries, we can shed some light on the extent to which the results hold across various environments (See(10)). We also demonstrate that a careful research design, at post-implementation, can generate valuable insights. This can be particularly useful in instances where stakeholders become interested in the program's effects after implementation has started or even ended.

Using our preferred specifications, we find that exposure to the program increased WAAPP-related technology adoption by 34.9% and improved seeds by 24.6%. Agricultural productivity increased by 10%. While we did not detect any significant effect on consumption, we found that the program improved food security, raising the index we use by 0.7 or a 4.9% increase relative to the comparison group. Because of the large number of outcomes we investigate and to avoid overemphasizing any single significant result, we follow (58) and create an index for each family of outcomes and then aggregate all individual outcomes in that family together. We then estimate the standardized effects from exposure to WAAPP on these outcome indexes (9). We find that the program consistently raised the index of outcomes across all families of outcomes we considered.

3.2 Theoretical Structure

A farmer's decision of Technology adoption is primarily a joint decision of using multiple inputs subject to spatially as well as serially correlated exogenous factors. The logic of this paper is very much similar to learning model proposed by (25), which explores farmer's decision making process under a profit maximization framework. At a given point in time t, a risk neutral single plot farmer's output is represented by the following function;

$$y_{it} = w_{it}(f(x_{i,t} + \epsilon_{it}) \tag{3.2.1}$$

Here y_{it} is farmer's output, w_{it} is an exogenous shock that influences the marginal productivity of input $x_{i,t}$ and ϵ_{it} is an iid unobserved factor. f is subject to exposure to a program, farmer's decision is based on the expected profit function as follows;

$$E_{it}(\pi_{it}(x_{i,t})) = w_{it}(f(x_{i,t} + \epsilon_{it}) - x_{i,t} \tag{3.2.2}$$

Farmers update their beliefs about f in response to lagged observations of inputs, growing conditions, and outputs. According to (25) w_{it} is known to the farmers, then the expected profit is subject to change due to f or changes in ϵ_{it}), this will ultimately impact the marginal productivity of $x_{i,t}$ and drive the farmer's decision. WAAPP by it's design introduces multiple forms of technologies and allows farmers a channel to learn and expose themselves to the new technologies. The dissemination method followed by the WAAPP approach is also considering the regional characteristics and thereby it is more specific to farmer's needs and requirements. Our objective, therefore is to test through our specification how this program is able to promote farmer's to adopt the technologies by influencing the function f.

3.3 Program description

The West Africa Agricultural Productivity (WAAPP) was promoted by the Economic Community of West African States (ECOWAS). The program was implemented through the West and Central African Council for Agricultural Research and Development (CORAF) and this program covered 13 ECOWAS countries. This was designed to address the two-phase 10-year Adaptable Program Lending (APL) agenda championed by the World Bank to support the The Comprehensive Africa Agriculture Development Program's (CAADP) Research and development goals. The program was designed to fulfill the dual economic goals of (i) improved sustainable agricultural productivity to enhance economic growth, food security and poverty reduction, and (ii) strengthening the integration regional. The main activities consisted in the generation and diffusion of new agricultural technologies and innovations. The implementation of this program in a logic of regional integration made it possible to rationalize the scarce human and financial resources, also minimize waste by duplication, and lastly create economies of scale and regional externalities to mitigate the negative cross-border effects.

The program consisted of four major components,

1. *Regional cooperation in technology generation and dissemination:* This was achieved through common regulations related to genetic materials, pesticides, and other crop

protection products. It led to increased regional coordination in research and more technology sharing across countries.

2. *Intra-regional consolidation:* Within the participating countries, the program supported greater consolidation of regional agricultural needs while taking national objectives in account. This required establishing more Regional Centers of Excellence and upgrading the National Centers of Specialization (CNS), capacity building for researchers and supporting exchange program for technology and development for the participating countries.

3. *Funding for technology generation and adoption:* This component aimed at increasing funding for technology development and research within the countries.

4. *Program management and evaluation:* The program also incorporated tools and measures for coordinating, monitoring, management, and evaluation of the policy.

Under each of the components the WAAPP interventions includes

1. WAAPP technology development: The program improved access to high-yielding variety seeds, pest and drought tolerant seeds, better farm management, training on fertilizer application, farming practices and, and disease and pest management. It also provided support in mechanization; equipment usage and post-harvest processing and storage.

2. WAAPP farmer field schools and demonstrations: The WAAPP agencies along with their program partners have organized farmer field schools, to demonstrate and train the farmers and producers.

3. WAAPP training/capacity building programs: The policy also includes mechanisms for strengthening the implementation partner's capacity and beneficiaries by organizing events like workshops, exchange program for researchers, livestock vaccinations, e-agricultural programs, and technology exchange among the participating countries

3.4 Research design and sample selection

We used the propensity score matching (PSM) method to select the study samples. The PSM is a non-experimental counterfactual method which makes it possible to control the biases (in particular of selection) linked to the observable factors. The method consists in approximating the counterfactual by pairing. The aim is to identify the comparison group made up of individuals with a likelihood of participation in the program similar to that of the beneficiaries based on observable characteristics linked to the selection criteria of these beneficiaries. These characteristics should not be affected by participation in the program, especially in a post-matching situation. This probability is represented by scores $(P(X) = Pr(T = 1|X))$.

In each country, we randomly selected 25 districts from the population of WAAPP participating districts. In practice, we sampled from the entire population of districts since WAAPP was a national program as illustrated in figure **??** which shows the study sample in each country. After sampling the districts, we proceeded in two steps. First, in each sampled district, the program villages were matched with comparison villages. The goal was to minimize the systematic differences that could have existed between treated and comparison villages. This stage generated two treated and two comparison villages which were similar in terms of some observed characteristics that could be collected at the administrative level, usually at the district capital. The variables used at this stage differ across the three countries because of data availability. In Ghana, we had access to population data only. In Mali and Senegal, the population data were supplemented by data on selected public infrastructures[3]. Table 22 summarizes the differences in these variables between treated and comparison villages. Panel A shows before the matching exercise, and panel B shows the differences for the matched sample. The exercise succeeded in reducing the differences between treated and comparison villages, but did not eliminate these differences entirely.

After selecting the study villages, the second step consisted in sampling the households. In each sampled village, we started by enumerating all households. A short survey was used to collect the following variables:

- Age of household head
- Head of household gender
- Education of the head of household
- Number of agricultural workers in 2012 (household members aged 15 to 65 and engaged in agricultural production)
- Area of agricultural land owned by the household in hectares in 2012
- Means of locomotion in 2012 (means of transport owned by the household)
- Crops cultivated in 2012
- Type of farm technology used in 2012 (none, animal, or mechanical)

These variables were used for matching between households as follows. In each treated village, households who participated in the program were matched with those did not participate. In each WAAPP village, the best 10 matches (treated and comparison households) were all selected. Among the following 10 matches (from the 11th to the 20th pair of households), only the treated households were retained. Finally, the 20 WAAPP households in the treated village were matched with 20 (non-WAAPP) households in the control village. When fewer than 20 households that participated in the program in a village, all treated households were included in the sample and then were matched with comparison households. In case there are no more than 10 non-WAAPP households in a WAAPP village, we have selected them all. Likewise, when there were no more than 20 households in a non-WAAPP village, all were surveyed. A full household survey was then administered to the matched sample of households.

[3]Ideally, these variables should be (or at least include) the factors used to allocate WAAPP to villages. Unfortunately, we could not establish unambiguously that those are the variables that were used for allocating the program. However, these variables are correlated with the placement of the program.

The two-step PSM exercise generated three sub-samples of households. For exposition ease, we denote treated and comparisons village by v_1 and v_0, treated and comparison households by h_1 and h_0. Thus, we can use the following sub-samples of households:

- Sub-sample g_1 which consists of all households (h_1 and h_0) living in program villages (v_1).
- Sub-sample g_2 made of households (h_1), i.e., households residing in a WAAPP village and who received the treatment.
- Sub-sample g_3 of comparison households (h_0) from comparison villages, v_0

Our empirical exercise uses various combinations of these sub-samples to identify the program effect. We consider four specifications. First, we consider only treated villages (v_1 and compare h_1 and h_0 to estimate the impact of the program on households who have benefited from the program. This estimate is biased towards zero if there are significant spillover effects within treated villages. This is the strictest specification and is also our preferred one. Second, we consider a version of the first specification which compares treated households (h_1 in g_1) with households in g_0. Third, we can estimate the impact of WAAPP on households living in treated villages, regardless of whether the households benefited from the interventions by comparing treated villages (g_1) and comparison villages (g_0). Fourth, we can run placebo tests by using comparison households (h_0) in treated villages (v_1) and comparison households from comparison households (v_0). This estimate should be zero if there were no externalities in treated villages. In particular, a zero effect would increase our confidence in any significant effect we detect in specifications 1-3.

3.4.1 Descriptive statistics

This section summarizes the variables used in the analysis using the sample of matched households. In table 24 , we show the means for the three categories of households in columns 1-3, and the differences in columns 4 and 5. Column 1 of the table shows the mean and standard error (parenthesis) for the treated households within the treated villages. Column 2 reports the statistics for the non-treated households in the treated villages. Column 3 shows the descriptive statistics for the control households belonging to the non-treated villages in the same district. In Column 4 we report the mean difference between the treated households in the WAAPP villages and the comparison households within the WAAPP villages. In Column 5 we calculate the mean difference between the treated households in the WAAPP villages and all the comparison households in the comparison villages.

Panel A shows the statistics for the outcome variables. Unsurprisingly, there are significant differences between the treated households and the control households. The figures indicate that treated households outperform comparison households for almost all outcome variables. The only noticeable exception is fertilizer, which is used more by comparison households (21 kg/ha) than treated ones (14 kg/ha). Notice, however, that on average households in WAAPP villages used more fertilizers than households in comparison villages. The mean difference for the intermediate outcome variables is significant and insinuates an average difference of 2 percentage points between the treatment units and the control units within the treated villages. One of the main objective of the policy was to increment technology adoption rates and improve agricultural productivity levels, and the descriptive results indicate success in the desired direction. For the column 5, the results reflect a similar picture as Column 4. The program also aims to improve the income and food security conditions in the participating countries, and for this, we analyze the Income and Consumption levels for the households. Income level is stated in terms of Agricultural income and Non-Agricultural income, we see that the participating households are showing significantly higher Agricultural income than the control units both within the same village and for the control villages. No significant difference is observed for Non-agricultural income level. For consumption variables, the difference results are not as expected and not conclusive, but there is a significant improvement in the food security measures for the treated households compared to the control units in both Column 4 and 5.

In the next section, we highlight the difference in the household and village level characteristics that are likely to influence the outcome variables. Ideally, these variables should not be affected by the program even at the enumeration stage but may influence the participation. The household level variables include, age, gender and educational level of the household head and the household wealth index in terms of assets. According to the table, the age of the household head for the participating households is higher than the non-participating units and within the same WAAPP village, the participating household heads are more likely to have female head. The treated units are also showing higher Wealth and it most likely is explained through the higher income for the treatment units post matching.

In our analysis, we also account for village level differences and thus report the village level characteristics. In this case, we only show the difference between the treated units in the WAAPP village and control units in the non-WAAPP village. Based on the results, we see that the treated villages are having significantly higher wage rates than the comparison villages and the treated households in the treated villages have lower infrastructural access than the comparison units. These variables are likely to impact the program participation and hence are controlled for in our analysis.

In Table 23 we show the difference in the Household characteristics for the unmatched sample, these household level variables are used in the matching process. Hence, these variables are not likely to be affected by the program and since these variables are collected at the census stage and date back to 2012. The motivation behind matching is to create a comparison group similar to the treated units based on these observed characteristics. The first 3 columns are similar to Table 24, but Column(4) reports the Probability of WAAPP participation based on our preferred specification and Column (5) reports the same but considers the treated households in the WAAPP village and compared with the control units in the non-WAAPP villages. The results in both Column (4) and (5) shows that the pre-intervention, matching variables are not impacting the WAAPP participation. However, we see that the awareness about the program and education level of the Household head increases the probability of program participation significantly.

3.5 Empirical Strategy and Identification

The objective is to estimate the causal relationship between the outcome variable y and the effect of the treatment, i.e. the WAAPP. Since the allocation of treatment was not done randomly, our next best option is to establish a conditional causal relationship, i.e. by conditioning on certain variables. The structural form in the sense of (90) can be formally described as follows:

$$y_{ihv} = \beta_0 + \beta_1 Treatment + X_{ihv}\alpha_1 + X_{hv}\alpha_2 + X_v\alpha_3 + \delta_{ihv} + \delta_{hv} + \delta_v + \varepsilon_{ihv} \tag{3.5.1}$$

In this equation, y is the outcome of interest, Treatment is a binary variable which designates the status of WAAPP beneficiary, the vectors X_{ihv}, X_{hv} and X_v contain individual, household and village levels variables. We represent individual-level unobserved factors by δ_{ihv}, household-level unobserved by δ_{hv} and village-level unobserved by δ_v. In this structural form, ε_{ihv} is a white noise, independent with the 'Treatment' variable, and the estimate of β_1 by ordinary least squares (OLS) identifies the effect of Treatment on the outcome of interest y. In particular, the unobserved factors are correlated with the Treatment variable since the allocation of interventions was not random at the village, household or individual level. The error term ε_{ihv} is not, however, correlated with the 'Treatment' variable. Thus, if could observe all the variables described in equation 3.5.1, we could recover an unbiased estimate of β_1.

The advantage of starting with equation 3.5.1 is to make the sources of the bias more transparent. In particular, the estimable form is:

$$y_{ihv} = \beta_0 + \beta_1 Treatment + X_{ihv}\alpha_1 + X_{hv}\alpha_2 + X_v\alpha_3 + \mu_{ihv} \tag{3.5.2}$$

Where $\mu_{ihv} = \delta_{ihv} + \delta_{hv} + \delta_v + \varepsilon_{ihv}$ is the effective error term, and all other variables are as defined before. It is now apparent that effective error term is correlated with the variable "Treatment", making the ordinary least squares (OLS) estimator of β_1 biased.

With our cross-sectional data, the bias cannot be eliminated entirely but the research design allows us to at least partially control for some of the unobserved factors which cause the bias. In particular, we can control for the village-level unobserved factors in two ways. First, we use village fixed effects to effectively eliminate time-invariant unobserved factors at the village level, i.e. δ_v. Second, the village-level propensity sore matching (before the census) increases the similarities between treated and comparison villages in their observables, and possibly in their unobserved factors thereby reducing how δ_v varies between treated and comparison villages. Finally, the post-census propensity score matching between treated and comparison households reduces the bias due to the household-level unobservables (δ_{hv}).

Our preferred specification is the one controlling for the village fixed effects, and we use the other specifications for robustness checks. The presentation of the results follows the diagram of the logic of change discussed in section 1. We successively analyze the immediate results, the intermediate results and the final results. We report the estimates for which we control for village fixed effects and use the other specifications to check the robustness of the results.

3.6 Results

We present the program impacts on the immediate outcomes, the intermediate outcomes and the final outcomes in that order.

3.6.1 Impact of technology adoption

In Table 26 we show the program impact on the immediate outcomes, which include adoption of technologies disseminated by WAAPP, adoption of improved seeds, technologies disseminated by other programs and fertilizer usage per hectare. In columns 1-3, the dependent variable is one if the household adopted one of the technologies or the improved seeds, and zero otherwise. In column 4, the dependent variable is the quantity of fertilizer used per household per hectare. Column shows the program effect on an adoption index which aggregates all the outcomes in columns 1-3 following (58).

In column 1, the program had a positive and significant impact on the adoption of the technologies it disseminated. In fact, the adoption rate of technologies disseminated by WAAPP increased by 32.2%. This technology adoption was accompanied by an increase in improved seeds of 19.7% relative to the control villages. In column 3, we show that WAAPP had a positive effect on the adoption of technologies disseminated by other programs. It is plausible that the technologies disseminated by WAAPP and other programs are complementary, which would increase the likelihood of adopting both categories of technologies at the same time. Fertilizer usage per hectare increased by 8.3 kg or 26.8% relative to the control group, although WAAPP did not support fertilizer usage directly. This results suggests that the technologies disseminated by WAAPP and other technologies may be indeed complements[4]. Finally, in column 4, we present the effect of WAAPP on an index ((58)) that aggregates these three variables. This index is calculated so that the average of the control villages is zero. So we can look at the impact of WAAPP on immediate outcomes taken together. The point estimate is large and is statistically significant at the 1% level. It can therefore be concluded without ambiguity that the WAAPP had a considerable impact on the immediate outcomes, which, based the theory of change, is a necessary condition to detect any impact on downstream outcomes.

3.6.2 WAAPP impact on intermediate outcomes

In Table 27, we investigate the effect of WAAPP on intermediate outcomes. This category includes agricultural production, area cultivated, productivity per hectare and agricultural sales. We show the individual outcomes in columns 1-4, and the aggregate KLK index of this family of outcomes in column 5.

We measure agricultural production by harvest value netted of explicit production costs (in US Dollars). We then follow the common practice in the literature and divide net harvest value by cultivated area to get a measure of productivity (e.g. (16); (55),(56),(26) , (36), (85) among others).

In column 1, we show that WAAPP had a substantial effect on household agricultural production. The point estimate is 0.436 and statistically significant at the 1% level. For perspective, this point estimate corresponds to a gain of USD 436 per household or an increase of 20.3% relative to the control villages. While we do not detect any significant effect on area cultivated[5], we find that productivity per hectare increased by 10% (USD 42)

[4]We cannot, however, rule out a reverse causality, i.e. farmers who adopted other technologies and fertilizers are also more likely to adopt the technological packages disseminated by WAAPP.

[5]In column 2, the point estimate is imprecise and does not allow a definitive interpretation of the effect

and the point estimate is statistically significant at the 5 percent level.

This increase in production and productivity was accompanied by an increase in marketing as shown in the estimate in column 4. Sales of agricultural production increased by USD 348, an increase of 52%. compared to controls, and the point estimate is significant at the 1% level. Finally, in column 5, we explore the effect of WAAPP on an index aggregating the four variables. The point estimate is 0.15 and statistically significant at the 1% level, indicating that the WAAPP has a positive and significant impact on all of these variables. In particular, the estimates show gains in production, productivity and a noticeable increase in sales, suggesting that the program was effective throughout the value chain.

3.6.3 Downstream outcomes

We report the program impacts on income, and consumption and food security in table 28 and table 27. In table 28, the estimated impacts on total income and non-farm income are shown in columns 1 and 2 (in thousands of US Dollars). The aggregate KLK index is reported in column 3. Table 29 shows the effects on consumption in columns 1-3, on food security in column 4 and on the aggregate index in column 5.

The estimates show that within treated villages, households who participated in the program enjoyed significant increases in their income. In column 1, we note that WAAPP increased household income by USD 295, which is equivalent to an increase of 16.6% over the average of the control villages. All these effects are tightly estimated, being all statistically significant at the 1% level.

While the program raised income level, we do not detect any significant effect on consumption and on food security. The point estimates in table 29 are all relatively small and statistically not different from zero. In summary, using this specification, we do not detect any effect of WAAPP on consumption, or on food security. We provide two potential explanations to reconcile the concomitant large positive effects on income and the absence of impact on consumption (See table Table 28). First in appendix A, we provide some suggestive evidence indicating that the program raised saving. [Second,]

3.6.4 Aggregating all outcome variables

Although we estimate a positive and significant impact for most of the outcome variables, there are cases where the estimates are not statistically significant. We complement the analysis above with the KLK index calculated using all the outcomes analyzed above. The index is then used to determine whether the overall impact of the treatment on a group of outcome variables is different from zero (e.g. 9).

The estimations are shown in table 31. The results unambiguously indicate that WAAPP had a positive and statistically significant impact on all of the outcomes taken together. It is reassuring to note that there is some internal consistency in the magnitude of the effects estimated according to the specifications. Thus, the magnitude of the estimated effect is the largest when we compare the households that participated in the WAAPP and the control households in the WAAPP villages (column 1). Then, in descending order, we have the specification that compares WAAPP households in WAAPP villages and all households in

of WAAPP on the cultivated area.

control villages (column 2), and the specification that compares households (having or not participated in WAAPP) in villages WAAPP and all households in control villages (column 3). Finally, as expected, there is no detectable effect when comparing households that did not participate in WAAPP in treated villages and households in control villages (columns 4) which serves as a placebo. These results therefore demonstrate that the WAAPP had a positive impact on all of our outcome variables, and that this impact is entirely due to the household's participation in at least one WAAPP activity, and not simply to the presence of the WAAPP.

3.7 Robustness checks

We have already shown in Table 31 that the estimate of the overall effect of WAAPP is stable and exhibits some internal consistency across alternative specifications. In this section, we use the PSM on the study sample[6] to investigate how sensitive our results are to the estimation method used. Broadly similar estimates across alternative methods would increase our confidence in the results. In contrast, substantial differences would make the results questionable.

Tables 1 to 5 in Appendix A, reproduce Tables 5.1 to 5.5 in section 3.6. As can be seen, the estimates are almost identical in all tables. It is remarkable that both in size and statistical precision, the point estimates are similar. The only notable difference is the food security index which is statistically significant at the 5% level in Table D5.4 in the appendix while the OLS estimate in is not. Overall, our main estimates using OLS or PSM are essentially the same. These two estimation methods are based on different assumptions of the conditional orthogonality of unobserved confounding factors **(author?)** (e.g. 5). It is therefore reassuring to note that our estimates are stable under different assumptions.

We consider a second series of robustness checks which consist in re-matching the control households. Figure XXX illustrates the composition of sampled households in a treated village after the census level matching. In each of these villages, we can use the extend set of variables we have access to after the household survey to form three groups of households: (i) the treated households (TH), (ii) comparison households that have matches with treated households (MH), and (iii) c unmatched comparison households (NMH). The identification strategy we use attributes the relationship between households TH and MH (the solid line in figure FXXX) to the program. Suppose instead that the relationship between TH-households and NMH-households is a data artefact or attributable to some unobserved factors (other than the WAAPP). Then, it would be likely that a similar relationship would exist between the comparison households MH abd NMH represented by the dotted line in figure 4.

Table 45 in the appendix summarizes the estimates on the relationship between AMs and UAMs. As can be seen, all the coefficients are very small and none is statistically significant. These results provide further supporting evidence that the relationship we uncovered by comparing treated and comparison households within the same village likely identifies the program effect.

[6] As opposed to using the census.

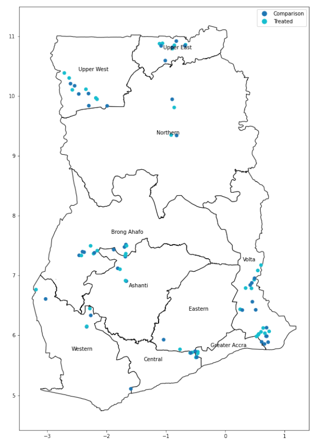
3.8 Conclusion

In this paper, we estimated the impact of The main objectives of the second phase of WAAPP for Ghana, Mali and Senegal include increasing agricultural productivity and household income through the creation and dissemination and adoption of appropriate agricultural technologies. This study has identified the impacts of these activities. Using robust tools, the analysis shows that the WAAPP had a positive overall impact on all the result variables, that this impact is relatively greater for households whose head or member who participated in the WAAPP is female, and for households where the head or member who participated in the WAAPP was young, that is, 35 years of age or younger at the time of the surveys. The magnitude of this impact differs depending on the indicators targeted. WAAPP has had a positive and significant impact on most production and income indicators. The impact of WAAPP participation on the adoption of agricultural technologies is positive. This impact is significant, both for technologies popularized by WAAPP and by other agricultural programs. Moreover, most adopters of technologies have not needed to adapt them. WAAPP has contributed to the improvement of food security (which we detect only with the analysis by the pairing method). Finally, the results show an overall positive impact of WAAPP on farmers' incomes, agricultural incomes and food security. The study also showed a positive impact of WAAPP on the outcome variables taken together.

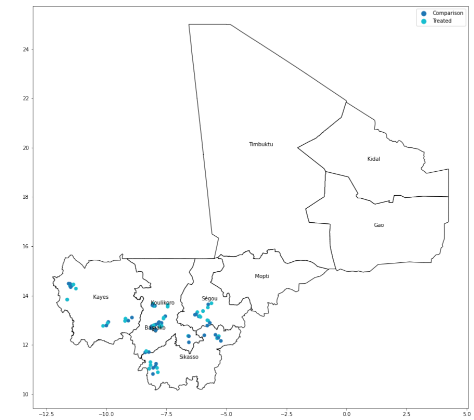
Moreover, the examination of the estimates indicates that the effects are more important on the immediate results and decrease all along the logical chain of change (eg (13)), so that the effects on the final results are attenuated. . The effects on the intermediate outcomes are significant, which suggests that such a program can generate a significant impact on the final results in the medium and long term (e.g. (20)).

3.9 Figures

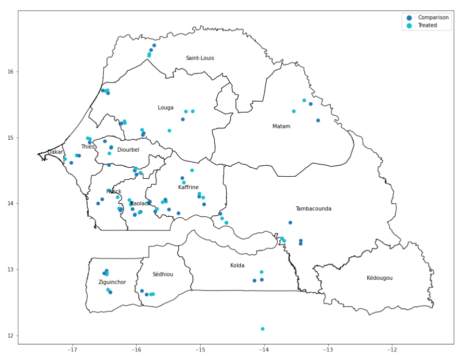
Figure 7: Sampled villages in each country



(a) Sampled villages in Ghana



(b) Sampled villages in Mali



(c) Sampled villages in Senegal

3.10 Tables

Table 22: Descriptive Statistics for all the Villages and the Matched Villages in the sample

	(1)	(2)	(3)	(4)	(5)	(6)
		Ghana			Mali	
Variables	WAAPP	Non-WAAPP	(1)-(2)	WAAPP	Non-WAAPP	(4)-(5)
				Panel A: All villages		
Population	1333.792	1500.052	-166.259	3396.257	778.606	2617.651**
	(167.334)	(79.481)	(185.251)	(945.694)	(38.428)	(946.475
Men	NA	NA	NA	1687.571	384.465	1303.107*
	NA	NA	NA	(466.196)	(18.725)	(466.572
Women	NA	NA	NA	1708.686	394.142	1314.544*
	NA	NA	NA	(479.592)	(19.759)	(479.998
Nber. households	NA	NA	NA	537.857	118.437	419.420**
	NA	NA	NA	(149.467)	(5.839)	(149.581
Road	NA	NA	NA	NA	NA	NA
	NA	NA	NA	NA	NA	NA
Road 2012	NA	NA	NA	NA	NA	NA
	NA	NA	NA	NA	NA	NA
Dam	NA	NA	NA	NA	NA	NA
	NA	NA	NA	NA	NA	NA
Dam 2012	NA	NA	NA	NA	NA	NA
				NA	NA	NA
				Panel B: Matched villages		
Population	1357.912	1440.22	-82.308	3055.957	1064.276	1991.681
	(175.730)	(191.891)	(260.199)	(1140.217)	(162.978)	(1151.806
Men	NA	NA	NA	1521.304	526.759	994.546*
	NA	NA	NA	(561.079)	(79.932)	(566.744
Women	NA	NA	NA	1534.652	537.517	997.135*
	NA	NA	NA	(579.282)	(83.266)	(585.236
Nber. households	NA	NA	NA	480.391	157.069	323.322*
	NA	NA	NA	(179.582)	(25.113)	(181.329
Road	NA	NA	NA	NA	NA	NA
	NA	NA	NA	NA	NA	NA
Road 2012	NA	NA	NA	NA	NA	NA
	NA	NA	NA	NA	NA	NA
Dam	NA	NA	NA	NA	NA	NA
	NA	NA	NA	NA	NA	NA
Dam 2012	NA	NA	NA	NA	NA	NA

Table 23: Descriptive Statistics for all the Households in the Sample before Matching

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	Treated villages (WAAPP)		Comparison Villages (Non-WAAPP)	p value of (1)=(2)	p-value of (1)=(3)	p value of (2)=(3)
	Treated Household	Comparison household	Comparison household			
Panel A (Census Data)						
Post-intervention Variables						
WAAPP awareness	0.988	0.318	0.191	0.000	0.000	0.000
HH member participating in WAAPP	0.677	0.001	0.014	0.000	0.000	0.000
Land endowment in 2019	4.983	5.214	4.533	0.467	0.103	0.600
Ag workers in 2019	4.396	4.403	4.174	0.488	0.0185	0.382
F-Statistics				2924	477.7	10.14
P-value				0.000	0.000	0.000
Pre-intervention Variables						
Male Head	0.874	0.815	0.851	0.353	0.311	0.0149
Female Head	0.126	0.185	0.148	0.353	0.311	0.0149
Age of HH head	53.481	51.636	50.796	0.384	0.229	0.213
Literacy of the HH head	0.406	0.414	0.404	0.00543	0.551	0.406
HH head has Primary education	0.337	0.381	0.354	0.410	0.130	0.0661
HH head has above Primary education	0.339	0.381	0.349	0.175	0.383	0.314
Same HH head in 2012	0.91	0.879	0.887	0.101	0.0102	0.0245
Ag workers in 2012	4.218	3.942	3.892	0.676	0.0123	0.112
HH size	11.807	9.785	10.524	0.296	0.0350	0.279
Land endowment in 2012	4.726	4.731	4.287	0.551	0.0641	0.599
F-Statistics				4.588	5.993	1.538
P-value				0.000	0.000	0.145
Panel B (Sample data)						
Post-intervention Variables						
WAAPP awareness	0.995	0.285	0.213	0.000	0.000	0.000
HH member participating in WAAPP	0.52	0.001	0.016	0.000	0.000	0.000
Land endowment in 2019	6.859	6.933	5.351	0.00312	0.0103	0.00688
Ag workers in 2019	5.895	5.718	4.819	0.00585	0.000557	0.000
F-Statistics				362.7	199.2	20.01
P-value				0.000	0.000	0.000
Pre-intervention Variables						
Male Head	0.967	0.961	0.875	0.613	0.00683	0.000
Female Head	0.033	0.039	0.097	0.613	0.0377	0.000
Age of HH head	53.418	52.621	51.505	0.176	0.167	0.193
Literacy of the HH head	0.322	0.36	0.358	0.156	0.449	0.0927
HH head has Primary education	0.276	0.292	0.306	0.851	0.827	0.163
HH head has above Primary education	0.173	0.226	0.281	0.782	0.161	0.000
Same HH head in 2012	0.908	0.875	0.88	0.332	0.135	0.183
Ag workers in 2012	5.555	5.294	4.453	0.00702	0.000331	0.000
HH size	16.769	15.03	12.467	0.00252	0.00764	0.000
Land endowment in 2012	6.358	6.568	5.05	0.00824	0.00973	0.000486
F-Statistics				1.661	2.666	0.922
P-value				0.115	0.00819	0.509

Table 24: Descriptive Statistics for the Matched sample

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	Treated villages (WAAPP)		Comparison Villages (Non-WAAPP)	p value of (1)=(2)	p-value of (1)=(3)	p value of (2)=(3)
	Treated Household	Comparison household	Comparison household			
Outcome Variables						
WAAPP Tech	0.447	0.000	0.032	0.000	0.000	0.000
Seed	0.231	0.014	0.026	0.000	0.000	0.000
Other_Tech	0.077	0.027	0.026	0.004	0.001	0.003
Fertilizer	14.47	21.511	11.039	0.429	0.0375	0.00900
Production	0.895	0.667	0.779	0.000296	0.0596	0.0631
Area(ha)	2.362	1.911	1.949	0.00138	0.00187	0.0170
Productivity	0.36	0.386	0.394	0.409	0.498	0.858
Sales	0.681	0.469	0.609	0.0310	0.348	0.220
Household Income	0.87	0.688	0.775	0.000428	0.0465	0.0365
Non-Ag Income	0.072	0.044	0.046	0.319	0.205	0.504
Consumption	0.222	0.26	0.217	0.367	0.511	0.0775
Food consumption	0.085	0.095	0.086	0.379	0.771	0.378
Non-food consumption	0.136	0.163	0.129	0.429	0.447	0.0289
Food Security Index	17.006	16.386	16.288	0.0268	0.00102	0.00147
F-Statistics				42.18	16.76	3.097
P-value				0.000	0.000	0.001
Control: Household level						
Age of Head	49.921	48.603	49.194	0.362	0.171	0.0499
Sex of Head	0.832	0.739	0.792	0.00148	0.227	0.0414
HH head has no formal education	0.439	0.385	0.417	0.0896	0.395	0.533
HH head is literate	0.006	0.005	0.001	0.853	0.0892	0.134
HH head has Primary education	0.385	0.405	0.419	0.568	0.774	0.731
HH head has at least Secondary education	0.17	0.204	0.162	0.0996	0.101	0.233
Wealth	0.316	0.075	-0.226	0.00154	0.00274	0.00419
F-Statistics				2.894	3.353	2.584
P-value				0.013	0.005	0.023
Control variables:Village level						
Wage rate 2012	13.403		10.577		0.144	0.188
Distance to raod in 2012	2.175		7.75		0.0561	0.0285
Means of locomotion in 2012	4.156		7.09		0.255	0.378
Distance to MFI in 2012	14.361		15.76		1.399	0.454

Table 25: Composition of the study sample

	Regions	Communes	Villages	[rgb] .02, .388, .757Households[7]		
				WAAPP Villages		Non-WAAPP Villa
				Treatment [8]	Control	
Ghana	10	24	100	303	1098	915
Mali	4	19	98	119	963	1294
Senegal	12	25	96	77	1000	854
Total	**26**	**68**	**294**	**499**	**3061**	**3063**

Source : CORAF, 2019 [9]

Table 26: : Impact of WAAPP on the probability of adoption technologies/ Immediate Outcomes

VARIABLES	(1) WAAPP Tech	(2) Seed	(3) Other Tech	(4) Fertilizer	(5) klk_index_adopt
Treated Household	0.322***	0.197***	0.063***	8.348***	1.466***
	(0.027)	(0.026)	(0.016)	(2.497)	(0.121)
Constant	0.027	0.038	-0.076	-3.742	-0.453
	(0.070)	(0.082)	(0.082)	(11.393)	(0.294)
Observations	3,159	3,159	3,159	3,071	3,159
R-squared	0.350	0.216	0.102	0.371	0.316
Relative change	1570.972	560.594	77.489	26.764	
Comparison villages mean	0.021	0.035	0.082	31.192	
Fixed Effects	Villages	Villages	Villages	Villages	Villages
Household characteristics	Yes	Yes	Yes	Yes	Yes

Standard errors are clustered at the village level
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 27: Impact of WAAPP on Intermediate results

VARIABLES	(1) Production	(2) Area(ha)	(3) Productivity	(4) Sales	(5) klk_index_prod
Treated Household	0.436***	0.262	0.042**	0.348***	0.149***
	(0.162)	(0.204)	(0.017)	(0.103)	(0.042)
Constant	-0.210	1.127	0.446***	-0.338	-0.607***
	(0.561)	(1.614)	(0.149)	(0.384)	(0.197)
Observations	3,159	3,159	3,159	3,143	3,159
R-squared	0.332	0.437	0.221	0.166	0.368
Relative change	20.263	5.357	10.001	52.530	
Comparison villages mean	2.151	4.899	0.424	0.662	
Fixed Effects	Villages	Villages	Villages	Villages	Villages
Household characteristics	Yes	Yes	Yes	Yes	Yes

Standard errors are clustered at the village level
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 28: Impact of WAAPP on household income

VARIABLES	(1) Household Income	(2) Non_Ag Income	(3) klk_index_income
Treated Household	0.295***	0.079**	0.161***
	(0.107)	(0.038)	(0.057)
Constant	-0.436	-0.365***	-1.152***
	(0.451)	(0.110)	(0.185)
Observations	3,159	3,159	3,159
R-squared	0.357	0.071	0.243
Changement relatif			
Moyenne Villages Controles			
Effets fixes			
Caracteristiques des menages			
Relative change	16.619	45.515	
Comparison villages mean	1.776	0.174	
Fixed Effects	Villages	Villages	Villages
Household characteristics	Yes	Yes	Yes

Standard errors are clustered at the village level
*** p < 0.01, ** p < 0.05, * p <0.1.

Table 29: Impact of WAAPP on household Food consumption and security, with Village fixed effects

VARIABLES	(1) Consumption	(2) Food Consumption	(3) Non-food consumption	(4) Food Security Index	(5) klk_index_cons
Treated Household	0.008	0.014	-0.005	0.142	0.017
	(0.030)	(0.028)	(0.007)	(0.115)	(0.053)
Constant	0.097	-0.029	0.124***	14.250***	-0.859***
	(0.172)	(0.166)	(0.031)	(1.064)	(0.278)
Observations	3,148	3,158	3,158	3,143	3,159
R-squared	0.525	0.568	0.268	0.283	0.377
Relative change	1.564	3.301	-4.543	0.834	
Comparison villages mean	0.540	0.435	0.104	17.042	
Fixed Effects	Villages	Villages	Villages	Villages	Villages
Household characteristics	Yes	Yes	Yes	Yes	Yes

Standard errors are clustered at the village level
*** p < 0.01, ** p < 0.05, * p <0.1.

Table 30: Impact of WAAPP on household food consumption and security, with alternate specification and District level fixed effects

VARIABLES	(1) Consumpton	(2) Food Consumption	(3) Non-food consumption	(4) Food Security Index	(5) klk_index_cons
Treated Village	0.040	0.035	0.006	0.565***	0.140**
	(0.037)	(0.032)	(0.008)	(0.170)	(0.067)
Constant	0.037	-0.064	0.100***	15.386***	-0.834***
	(0.094)	(0.088)	(0.022)	(0.935)	(0.203)
Observations	3,117	3,125	3,125	3,074	3,126
R-squared	0.419	0.479	0.137	0.237	0.269
Relative change	7.333	8.039	5.386	3.313	
Comparison villages mean	0.540	0.435	0.104	17.042	
Fixed Effects	Districts	Districts	Districts	Districts	Districts
Household characteristics	Yes	Yes	Yes	Yes	Yes
Village characteristics	Yes	Yes	Yes	Yes	Yes

Standard errors are clustered at the village level

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

Table 31: Overall impact of WAAPP

VARIABLES	(1)	(2)	(3)	(4)
	klk_index			
Treated Household	0.670***			
	(0.063)			
Treated Village		0.538***	0.170***	0.016
		(0.059)	(0.034)	(0.032)
Constant	-1.053***	-0.915***	-0.675***	-0.576***
	(0.216)	(0.325)	(0.182)	(0.181)
Observations	3,159	3,129	5,352	4,416
R-squared	0.351	0.420	0.381	0.429
Fixed Effects	Villages	Districts	Districts	Districts
Household characteristics	Yes	Yes	Yes	Yes

Notes: Standard errors are clustered at the village level.
*** p <0.01, ** p <0.05, * p <0.1
Column 1 includes case and control households in WAAPP villages. Column 2 includes all households in control villages and only case households in WAAPP villages. Column 3 includes the entire sample. Finally, column 4 includes all households in control villages (non-WAAPP) and control households in WAAPP villages

Table 32: Impact of WAAPP on Household's Savings

VARIABLES	(1) Saving	(2) Saving
Treated Household	0.285**	0.397***
	(0.110)	(0.125)
Treated Hh. X distance to MFI 2012		-0.007**
		(0.003)
Constant	-0.527	-0.565
	(0.430)	(0.435)
Observations	3,148	3,148
R-squared	0.375	0.375
Relative change	23.007	
Comparison villages mean	1.238	
Fixed Effects	Villages	Villages
Household characteristics	Yes	Yes

Standard errors are clustered at the village/ District level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 33: Impact of WAAPP based on the Gender of the Beneficiary participant

	(1)	(2)	(3)	(4)	(5)
	Global Index: KLK Index				
	Immediate Impact	Intermediate Impact	Final Impact		Overll Impact
VARIABLES	Adoption	Production	Income	Consumption	KLK Index
Treated Household	1.294***	0.147***	0.162**	0.007	0.599***
	(0.128)	(0.054)	(0.071)	(0.060)	(0.075)
Woman X Treated Household	1.663***	0.022	-0.010	0.090	0.682***
	(0.180)	(0.063)	(0.061)	(0.080)	(0.091)
Constant	-0.568**	-0.608***	-1.152***	-0.865***	-1.100***
	(0.282)	(0.213)	(0.201)	(0.287)	(0.222)
Observations	3,159	3,159	3,159	3,159	3,159
R-squared	0.358	0.368	0.243	0.377	0.365
Gender Effect	2.957	0.169	0.152	0.097	1.281
P-value of the F-test	0.000	0.021	0.037	0.522	0.000
Fixed effects	Villages	Villages	Villages	Villages	Villages
Household characteristics	Yes	Yes	Yes	Yes	Yes

Standard errors are clustered at the Village level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 34: Placebo test by comparing the Control households in WAAPP villages to the Control households in the Non-WAAPP villages

	(1)	(2)	(3)	(4)	(5)
	Global Index: KLK Index				
	Immediate Outcome	Intermediate Outcome	Final Outcome		Overall
VARIABLES	Adoption	Production	Income	Consumption	KLK Index
Treated Village	-0.003	0.005	0.008	0.090***	0.040
	(0.032)	(0.028)	(0.032)	(0.034)	(0.031)
Constant	-0.681***	-0.547***	-0.766***	-0.495*	-0.899***
	(0.175)	(0.177)	(0.292)	(0.291)	(0.217)
Observations	4,416	4,416	4,416	4,413	4,416
R-squared	0.281	0.549	0.355	0.454	0.547
Fixed Effects	Villages	Villages	Villages	Villages	Villages
Household characteristics	Yes	Yes	Yes	Yes	Yes

Standard errors are clustered at the Village level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

CHAPTER IV

Impact of Formalization in the Manufacturing sector: Case study of India

4.1 Introduction

After gaining independence in 1947, the Indian government announced the Factory Act 1948. This act was intended to set out rules and regulations for the manufacturing industries to maintain proper working environment and ensure safety and good health of the factory workers. The Act lays out some rules for registration of factories. The article 2m and 85 of the act lays down criteria for factory registration.

1. Section 2m(i) states any factory whereon 10 or more workers are working, or were working, on any day of the preceding 12 months, and in any part of which a manufacturing process is being carried on with the aid of power qualify

   es to be a registered factory

2. Section 2m(ii) states any factory twenty or more workers are working, or working on any day of the preceding 12 months and in any part of which a manufacturing process is being carried on without the aid of power qualifies for registration

3. The section 85 of the act also stipulates factory registration requirement that gives states and Union Territories to designate any manufacturing unit to be a factory required for registration that does not comply the section 2m.

Factories, registered under this act is required to abide multiple regulations in terms payments to workers, maintaining proper work environment, ensuring adequate safety measures for workers and are also subject to regular inspection and surveys from government agencies.

The objective of this paper is to investigate if there is any systematic distinction between the registered and un-registered factories. As the Act is implemented based on the threshold value of number of workers it gives us an opportunity to use Regression Discontinuity technique to estimate the impact of formal registration on the manufacturing sector of India. The rest of the paper is arranged as follows, Section 2 discusses the literature and motivation of the paper, Section 3 describes the data and Section 4 shows the methodology and results and Section 5 concludes.

4.2 Literature Review and Objective

(81) uses a non-parametric Propensity Score Matching technique and finds that registration

leads to significant increase in sales and output per employee for micro-entrprises in India. Other papers like (67) shows that Brazilian retail firms increased investments in long-run projects, as a result of increase in licensing due to the SIMPLES program. Similarly (76) shows that becoming officially registered leads to an increase in firm profits, investments and access to credit for Vietnamese small and medium enterprises. Also 89 show that delay in registration has positive effect on firm's profit and sales than firms that start as registered on the onset. These papers have all shown the effect of registration on firm's performance and our objective is also to show the impact of factory registration on the firms. (21) shown that large portion of the firms in India who are eligible to be registered under the Factories Act are not complying with the regulation.

The purpose of this paper is to establish the impact of registration under the Factory Act on the Manufacturing sector in India. Given the registration rule of Factory Act section 2m(i) and 2m(ii) which stipulates a cut-off requirement for firms to register is an interesting premise to apply a regression discontinuity analysis. Applying this method will enable us to capture the localized effect of registration around the cutoff. This also marks the use of Regression Discontinuity estimation in evaluating the effect of the Factories Act on India's manufacturing sector.

4.3 Data and methodology

Data has been extracted from two different sources. For the entities, registered under the Factory Act, the Annual Survey of Industries (ASI) 2016-17 data has been used. For the entities that are not registered under the act, we utilize the National Sample Survey (NSS) 2015-2016 survey of Un-incorporated Non-Agricultural Enterprises. This data constitutes the 73rd round of National Sample Survey (NSS). Both the data are collected by the National Sample Survey Office (NSSO) under the Ministry of Statistics and Programme Implementation of the Government of India.

ASI sample comprises of two parts – Central Sample and State Sample. The Central Sample consists of two schemes: Census and Sample. Under Census scheme, all the units are surveyed. All the remaining units in the frame are considered under Sample Scheme. For all the states, strata are formed for each State x District x Sector x 3-digit NIC-2008 factories. The survey on Unincorporated Non-Agricultural Enterprises (Excluding Construction) of NSS 73rd round (July 2015- June 2016) was conducted as a repeat survey of NSS 67th round (July 2010 –June 2011) survey on the same subject.

The same data has been used in multiple papers which compared the Registered and Un-registered sector in India. (See (44) (75)).

4.4 Methodology and Results

The first step in the Regression Discontinuity is to establish the change in the probability of treatment assignment around the cut off. Based on the requirement of the act, the forcing variable is based on the number of workers in the factory. Using in Fig 1, we see that there is a gap in the probability of being registered, around the cut off value. The forcing variable has been calculated using the Number of workers and subtracting the cut off of 10. Based on the scatter plot, the probability of the treatment around the threshold shows substantial discontinuity. Following (19) and (46) method of binning the forcing variable and computing the average outcome around the threshold we see the discontinuity in the average registered entities around the threshold. The distribution of the firms around the cut off are provided in Table 2.

we try to estimate the impact of the Factories Act, using a Fuzzy Regression Discontinuity design. Fuzzy Design exploits the discontinuities in the probability or expected value of treatment conditional on a covariate. Fuzzy RD estimation uses a 2SLS estimation strategy. We use the following identification strategy stipulated by (43).

$$y = \alpha_{0c} + \tau_c w + \beta_0(x - c) + \delta I[x \geq c].(x - c) + e \tag{4.4.1}$$

Here x is the forcing variable and w is the treatment indicator. By assumption, w is endogenous and is instrumented using $z = 1[x \geq c]$.

In our estimation, we consider four explanatory variables to determine the treatment effect around the cut-off. These include, capital per worker, where capital is defined as the total asset owned by the entity. We also consider the average salary per worker, gross value added per worker and the output per employee. We also consider the logarithm transformation of the same. We also control for other co-variates like the Year of establishment of the factory, type of organization and Industry level fixed effects.

The estimated results indicate that the registration status does have an impact on the average salary of the workers and the production per worker. The 2SLS estimates for the Fuzzy estimation considers the entire sample. Since ASI data is sampled at State level and the NSS data is sampled at district level, we chose the standard error clustering at state level. There are not much factory owner level information in the ASI data compared to the NSS dataset. We have only two covariates that determine the factory level characteristics.

4.5 Conclusion

The preliminary results show that the registration has a positive effect on the Capital Labor ratio and output per worker. These results point out that the choice of registering firms can lead to higher investment and greater labor productivity. The results hold significance for a developing country like India whose manufacturing sector is largely un-registered and where small scale industries contribute significant share of the industrial production.

Table 35: Distribution of the Registered and Un-registered Factories

regist_st	Freq	Percent	Cum
Un-registered	290113	80.99	80.99
Registered	68105	19.01	100
Total	358,218	100	

Table 36: Distribution of the Registered and Un-registered Factories considering sampling weights

regist_st	Freq.	Percent	Cum.
Un-registered	357,521.38	99.81	99.81
Registered	670.622065	0.19	100
Total	358,192	100	

Table 37: RD plot Bin distribution

Cut off c=0	Left of c	Right of c
Number of observations	289586	15846
Percentage of observations	0.94812	0.051881
Polynomial of order	4	4
Chosen scale	1.000	1.000
Selected Bins	54	13

Table 38: Regression results without State fixed effects

	Capital Labor ratio	Salary per employee	Value added per employee	Output per emp
regist_st	743096.5***	135827.0***	232588.7***	69806.7
	(251237.0)	(14278.2)	(37457.4)	(107423.0)
score	4145.8	544.0***	506.5***	5209.1***
	(2623.2)	(53.44)	(107.8)	(856.4)
inst_score_int	-4094.3	-517.0***	-494.1***	-5178.4***
	(2588.3)	(55.56)	(107.3)	(826.4)
Observations	342448	190484	338375	320532
r2	0.00253	0.435	0.000942	0.000846
F	95.02	401.5	166.6	159.5
First Stage F	55.79	51.14	56.39	57.09

Robust Standard Errors in parenthesis and clustered at State level

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 39: Regression results without State fixed effects for Log transformation

	Capital Labor ratio	Salary per employee	Value added per employee	Output per emp
regist_st	-2.316	-1.893**	4.626*	2.129
	(1.859)	(0.774)	(2.322)	(2.130)
score	0.0172	0.161***	0.0478**	0.0832***
	(0.0152)	(0.00965)	(0.0176)	(0.0160)
inst_score_int	-0.0167	-0.160***	-0.0481***	-0.0834***
	(0.0150)	(0.00959)	(0.0172)	(0.0157)
Observations	342448	190484	328938	316260
r2	0.0191	0.0371	0.0280	0.0283
F	107.9	328.5	234.1	50.65
First Stage F	55.79	51.14	51.70	56.08

Robust Standard Errors in parenthesis and clustered at State level.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 40: Regression results with State fixed effects

	Capital Labor ratio	Salary per employee	Value added per employee	Output per emp
regist_st	805614.4***	136188.3***	235406.7***	67526.3
	(249446.2)	(14419.7)	(39096.8)	(112235.6)
score	2392.6	534.6***	436.7***	5119.0***
	(2252.6)	(58.97)	(115.5)	(933.4)
inst_score_int	-2354.9	-507.6***	-425.0***	-5087.8***
	(2210.7)	(61.18)	(112.1)	(902.6)
Observations	342448	190484	338375	320532
r2	0.00321	0.437	0.000965	0.00109
F	23125304.2	45264645.7	699117611.7	2910982.7
First Stage F	56.06	52.23	56.65	57.35

Robust Standard Errors in parenthesis and clustered at State level

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 41: Regression results with State fixed effects for Log transformation

	Capital Labor ratio	Salary per employee	Value added per employee	Output per emp
regist_st	-1.957	-1.446**	4.906**	2.188
	(2.090)	(0.621)	(2.389)	(2.202)
score	0.00448	0.154***	0.0406**	0.0770***
	(0.0144)	(0.00760)	(0.0156)	(0.0150)
inst_score_int	-0.00407	-0.153***	-0.0411**	-0.0772***
Observations	342448	190484	328938	316260
r2	0.0777	0.166	0.102	0.0882
F	24622069.5	6903208.4	537809052.1	149427382.
First Stage F	56.06	52.23	51.88	56.29

Robust Standard Errors in parenthesis and clustered at State level

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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APPENDICES

Appendix Chapter

Table 42: Impacts of WAAPP on immediate results and gender

	(1)	(2)	(3)	(4)
	Immediate impacts: Adoption			**Global immediate impact**
VARIABLES	Tech. WAAPP	Seeds	Other Tech	KLK Index
Household Treated	0.272***	0.180***	0.063***	1.407***
	(0.027)	(0.028)	(0.016)	(0.141)
Woman X Household Treated	0.487***	0.158***	-0.001	1.928***
	(0.057)	(0.046)	(0.025)	(0.213)
Constant	-0.006	0.027	-0.076	-0.364
	(0.070)	(0.082)	(0.084)	(0.324)
Observations	3,159	3,159	3,159	3,159
R-square	0.425	0.226	0.102	0.371
Gender effect	0.759	0.339	0.063	3.335
P-value of the F-test	0.000	0.000	0.000	0.000
Relative change			77.092	
Average Control Villages	0.003	0.018	0.081	
Fixed effects	Villages	Villages	Villages	Villages
Household characteristics	Yes	Yes	Yes	Yes

Standard errors have been adjusted for grouping at the Village level.
*** p < 0.01, ** p < 0.05, * p <0.1.

Table 43: Impacts of WAAPP on intermediate outcomes and gender

VARIABLES	(1) Production	(2) Area(ha)	(3) Productivity	(4) Sales	(5) klk_index_prod
Treated Household	0.427**	0.246	0.044**	0.339**	0.147***
	(0.208)	(0.248)	(0.021)	(0.136)	(0.054)
Woman X Treated Household	0.087	0.163	-0.013	0.086	0.022
	(0.231)	(0.300)	(0.025)	(0.121)	(0.063)
Constant	-0.216	1.116	0.447***	-0.344	-0.608***
	(0.618)	(1.704)	(0.149)	(0.427)	(0.213)
Observations	3,159	3,159	3,159	3,143	3,159
R-squared	0.332	0.437	0.221	0.166	0.368
Gender Effect	0.514	0.409	0.030	0.425	0.169
P-value of the F-test	0.083	0.393	0.113	0.020	0.021
Relative change	22.781	7.575	6.743	71.573	
Average Control Villages	2.255	5.395	0.452	0.594	
Fixed effects	Villages	Villages	Villages	Villages	Villages
Household characteristics	Yes	Yes	Yes	Yes	Yes

Standard errors have been adjusted for grouping at the Village level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 44: Impacts of WAAPP on income and gender

VARIABLES	(1) Household Income	(2) Non_Ag Income	(3) klk_index_income
Treated Household	0.283**	0.083*	0.162**
	(0.133)	(0.045)	(0.071)
Woman X Treated Household	0.114	-0.040	-0.010
	(0.154)	(0.032)	(0.061)
Constant	-0.444	-0.362***	-1.152***
	(0.495)	(0.110)	(0.201)
Observations	3,159	3,159	3,159
R-squared	0.357	0.071	0.243
Gender Effect	0.398	0.043	0.152
P-value of the F-test	0.048	0.177	0.037
Relative change	19.576	25.933	
Average Control Villages	2.031	0.167	
Fixed effects	Villages	Villages	Villages
Household characteristics	Yes	Yes	Yes

Standard errors have been adjusted for grouping at the Village level.
*** p < 0.01, ** p < 0.05, * p <0.1.

Table 45: Impacts of WAAPP on consumption and gender

VARIABLES	(1) Consumpton	(2) Food Consumption	(3) Non-food consumption	(4) Food Security Index	(5) klk_index_cons
Treated Household	0.003	0.009	-0.004	0.106	0.007
	(0.033)	(0.030)	(0.008)	(0.131)	(0.060)
Woman X Treated Household	0.048	0.054*	-0.005	0.347	0.090
	(0.035)	(0.031)	(0.012)	(0.266)	(0.080)
Constant	0.093	-0.032	0.125***	14.227***	-0.865***
	(0.178)	(0.171)	(0.031)	(1.086)	(0.287)
Observations	3,148	3,158	3,158	3,143	3,159
R-squared	0.526	0.568	0.268	0.284	0.377
Gender Effect	0.052	0.063	-0.009	0.453	0.097
P-value of the F-test	0.377	0.220	0.767	0.313	0.522
Relative change	7.895	11.500	-8.549	2.602	
Average Control Villages	0.655	0.548	0.106	17.413	
Fixed effects	Villages	Villages	Villages	Villages	Villages
Household characteristics	Yes	Yes	Yes	Yes	Yes

Standard errors have been adjusted for grouping at the Village level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 46: Overall impact of WAAPP and gender

	(1)	(2)	(3)	(4)
VARIABLES		klk_index		
Treated Household	0.599***			
	(0.075)			
Woman X Treated Household	0.682***			
	(0.091)			
Woman X Treated Village		-0.162	-0.096	0.073
		(0.122)	(0.105)	(0.095)
Woman Household		-0.008	0.029	-0.011
		(0.043)	(0.058)	(0.051)
Treated Village		0.896***	0.274***	-0.066
		(0.128)	(0.101)	(0.075)
Constant	-1.100***	-0.911***	-0.835***	-0.797***
	(0.222)	(0.199)	(0.164)	(0.177)
Observations	3,159	3,129	5,352	4,416
R-squared	0.365	0.322	0.237	0.281
Gender effect	1.281	0.734	0.178	0.007
P-value of the F-test	0.000	0.000	0.020	0.624
Fixed Effects	Villages	District	District	District
Household characteristics	Yes	Yes	Yes	Yes

Notes: Standard errors have been adjusted for grouping at the Village/District level.
*** p <0.01, ** p <0.05, * p <0.1
Column 1 includes case and control households in WAAPP villages. Column 2 includes all households in control villages and only case households in WAAPP villages. Column 3 includes the entire sample. Finally, column 4 includes all households in control villages (non-WAAPP) and control households in WAAPP villages

Table 47: . Impact of WAAPP on the adoption of technologies by households

VARIABLES	(1) WAAPP Tech	(2) Seed	(3) Other Tech	(4) Fertilizer	(5) klk_index_adopt
Treated Household_Ghana	0.417***	0.196***	0.068***	4.723	1.695***
	(0.046)	(0.042)	(0.019)	(3.640)	(0.198)
Treated Household_Mali	0.249***	0.236***	0.005	18.719***	1.344***
	(0.055)	(0.063)	(0.028)	(6.000)	(0.269)
Treated Household_Senegal	0.248***	0.140***	0.141***	-0.554	1.203***
	(0.043)	(0.027)	(0.033)	(3.987)	(0.173)
Constant	-0.027	0.029	-0.043	10.954	-0.465
	(0.075)	(0.085)	(0.081)	(13.774)	(0.304)
Observations	3,159	3,159	3,159	3,071	3,159
R-squared	0.361	0.218	0.107	0.374	0.320
Relative change Ghana	2029.833	558.647	83.549	15.143	
Relative change Mali	1214.337	672.376	5.903	60.011	
Relative change Senegal	1209.042	398.154	172.158	-1.777	
Average Control Villages	0.021	0.035	0.082	31.192	
Fixed Effects	Villages	Villages	Villages	Villages	Villages
Household characteristics	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors have been adjusted for grouping at the Village level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 48: Impact of WAAPP on household agricultural production

VARIABLES	(1) Production	(2) Area(ha)	(3) Productivity	(4) Sales	(5) klk_index_prod
Treated Household_Ghana	0.403*	0.316	0.036	0.285**	0.134**
	(0.216)	(0.331)	(0.025)	(0.136)	(0.063)
Treated Household_Mali	0.654	0.077	0.040	0.500**	0.176*
	(0.438)	(0.498)	(0.029)	(0.211)	(0.098)
Treated Household_Senegal	0.175	0.434	0.060	0.245	0.138
	(0.165)	(0.505)	(0.038)	(0.278)	(0.084)
Constant	1.099*	4.280**	0.506***	-0.151	-0.197
	(0.570)	(1.691)	(0.156)	(0.405)	(0.196)
Observations	3,159	3,159	3,159	3,143	3,159
R-squared	0.332	0.437	0.221	0.166	0.368
Relative change Ghana	18.752	6.449	8.390	42.968	
Relative change Mali	30.398	1.570	9.389	75.558	
Relative change Senegal	8.128	8.866	14.042	37.012	
Average Control Villages	2.151	4.899	0.424	0.662	
Fixed Effects	Villages	Villages	Villages	Villages	Villages
Household characteristics	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors have been adjusted for grouping at the Village level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 49: Impact of WAAPP on household income

VARIABLES	(1) Household Income	(2) Non_Ag Income	(3) klk_index_income
Treated Household_Ghana	0.317*	0.030	0.116*
	(0.165)	(0.034)	(0.063)
Treated Household_Mali	0.192	0.185	0.243
	(0.239)	(0.117)	(0.162)
Treated Household_Senegal	0.406*	0.017	0.127
	(0.241)	(0.043)	(0.095)
Constant	0.924**	-0.239**	-0.655***
	(0.447)	(0.115)	(0.194)
Observations	3,159	3,159	3,159
R-squared	0.358	0.073	0.244
Relative change Ghana	17.844	17.143	
Relative change Mali	10.826	106.562	
Relative change Senegal	22.853	9.906	
Average Control Villages	1.776	0.174	0.000
Fixed Effects	Villages	Villages	Villages
Household characteristics	Yes	Yes	Yes

Notes: Standard errors have been adjusted for grouping at the Village level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 50: Impact of WAAPP on household food consumption and security

VARIABLES	(1) Consumpton	(2) Food Consumption	(3) Non-food consumption	(4) Food Security Index	(5) klk_index_cons
Treated Household_Ghana	-0.021	-0.004	-0.015	0.183	-0.041
	(0.029)	(0.024)	(0.012)	(0.256)	(0.078)
Treated Household_Mali	0.069	0.054	0.015	0.108	0.137
	(0.079)	(0.076)	(0.014)	(0.189)	(0.125)
Treated Household_Senegal	-0.024	-0.009	-0.014*	0.113	-0.051
	(0.062)	(0.057)	(0.008)	(0.194)	(0.101)
Constant	0.975***	0.915***	0.062*	15.321***	0.197
	(0.173)	(0.168)	(0.034)	(1.021)	(0.273)
Observations	3,148	3,158	3,158	3,143	3,159
R-squared	0.526	0.568	0.270	0.283	0.378
Relative change Ghana	-3.919	-0.884	-14.111	1.072	
Relative change Mali	12.722	12.446	14.090	0.636	
Relative change Senegal	-4.404	-2.170	-13.666	0.663	
Average Control Villages	0.540	0.435	0.104	17.042	0.000
Fixed Effects	Villages	Villages	Villages	Villages	Villages
Household characteristics	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors have been adjusted for grouping at the Village level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 51: Overall impact of WAAPP and gender

VARIABLES	(1)	(2)	(3)	(4)
		klk_index		
Treated Household_Ghana	0.721***			
	(0.102)			
Treated Household_Mali	0.703***			
	(0.147)			
Treated Household_Senegal	0.523***			
	(0.087)			
Treated Village_Ghana		0.891***	0.338***	-0.008
		(0.162)	(0.126)	(0.107)
Treated Village_Mali		0.675**	0.022	-0.194
		(0.262)	(0.188)	(0.176)
Treated Village_Senegal		0.680***	0.193	0.159
		(0.232)	(0.163)	(0.165)
Constant	-0.338	-0.319*	-0.348**	-0.322*
	(0.220)	(0.184)	(0.175)	(0.182)
Observations	3,159	3,129	5,352	4,416
R-squared	0.352	0.321	0.239	0.285
Fixed Effects	Villages	Districts	Districts	Districts
Household characteristics	Yes	Yes	Yes	Yes
Relative change		23.007	23.007	23.007

Notes: Standard errors have been adjusted for grouping at the Village/District level.
*** p <0.01, ** p <0.05, * p <0.1
Column 1 includes case and control households in WAAPP villages. Column 2 includes all households in control villages and only case households in WAAPP villages. Column 3 includes the entire sample. Finally, column 4 includes all households in control villages (non-WAAPP) and control households in WAAPP villages

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