EXPLORING THE ADVANTAGES AND DRIVERS OF SUSTAINABLE AGRICULTURAL PRACTICES IN CENTRAL ASIA

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DEDICATION

This dissertation is dedicated to the cherished memory of my grandfathers, **TADJIEV ABDURAHMONKHON** and **AKBAROV UZBEKHON**, and my grandmothers, **AMIROVA ROBIYAKHON** and **TURSUNOVA ZULFIYAKHON**.

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SUMMARY

Improving soil productivity and agricultural outputs pose significant challenges in developing countries, including Central Asia. Inadequate land use during the Soviet times, coupled with the absence of a structured land management system during the period, engendered numerous issues including cropland degradation that exerts a substantial impact on agricultural productivity in the Central Asian countries. The adoption of sustainable agricultural practices stands as a crucial remedy to address these issues. Despite the comprehensive coverage within global literature regarding the benefits of sustainable agricultural practices, there persists a marked discrepancy in their adoption levels by farmers. Furthermore, there is a scarcity of empirical investigations explaining the primary drivers and the impacts associated with the adoption of sustainable agricultural practices in Central Asia. From this perspective, the overarching aim of this doctoral dissertation is to gain deeper insights into the factors that facilitate the adoption of selected sustainable agricultural practices among farmers in various settings of Central Asia.

The thesis comprises five chapters, incorporating three empirical sections. The initial chapter introduces to the general problem background pertaining to the issue of sustainable agricultural development in Central Asia and the key research questions of the PhD dissertation. Empirical findings are presented in the second, third and fourth chapters. A general conclusion is given in Chapter 5.

The second chapter investigates the drivers of farmers' decision to adopt crop rotation and how its adoption impacts farmers' cotton yields and net returns in two contrasting settings of Central Asia by applying an endogenous switching regression model to cross-sectional survey data collected from 592 cotton growers in 2019 in Kazakhstan and Uzbekistan. Cotton monoculture inherited from the former Soviet cultivation system led to the decline of soil fertility and reduced cotton yields in irrigated areas of Central Asia. Adopting a diversified crop rotation approach is a viable solution to maintain soil quality and long-term economic benefits. The chapter findings

highlight these two countries' differing institutional contexts surrounding cotton farming. Kazakhstani farmers' decision to adopt crop rotation is positively related to age, participation in farm training, the farmer's opinion about the quality of the irrigation canal, and the share of adopters in a village. In Uzbekistan, farmers who perceive greater land tenure security are more inclined to adopt crop rotation. In Uzbekistan, employing crop rotation leads to higher cotton yields compared to traditional crop cultivation methods. In Kazakhstan, cotton farmers experience a contrasting outcome.

Employing an endogenous switching regression model on the plot-level panel data of 878 of Kyrgyzstan's smallholders, the third chapter investigates the determinants of the decision to adopt zero tillage and its effect on smallholders' production costs. The chapter finds that the probability of zero tillage adoption is associated with employment in agriculture, assets, agricultural shocks, fertilizer use, number of plots and average distances from the dwelling to household fields and to the main road. Furthermore, the chapter indicates that zero tillage adoption decreases land preparation costs by 23%, but increases hired labor and herbicide costs by 13% and 15%, respectively compared to the conventional tillage method. Nevertheless, zero tillage can reduce total production costs by 15%. The third chapter confirms that zero tillage can be promoted as an option for resource-scarce smallholders, especially those in remote areas with poor access to inputs and machinery services. Promoting zero tillage adoption as a labor-saving or herbicide reducing practice can create false expectations among smallholders.

The fourth chapter investigates the question of how participation in informal cooperation in water management influences the intensity of the adoption of sustainable agricultural practices by using two-years of 2019 and 2022 farm survey data of Uzbekistan and employing a marginal treatment effects model. The results show that farmers who are likely to participate in informal cooperation in water management tend to benefit more from the participation in terms of higher adoption intensity of sustainable agricultural practices.

Finally, the fifth chapter synthesizes the research findings, summarizes the policy implications along with research limitations and provides ideas for future research.

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ABBREVIATIONS

ATE:	The Average Treatment Effect
ATT:	The Average Treatment Effect on the Treated
ATU:	The Average Treatment Effect on the Untreated
BH:	Base Heterogeneity
CI:	Confidence Intervals
Coeff:	Coefficient
ESR:	Endogenous Switching Regression
FAO:	Food and Agriculture Organization of the United Nations
GDP:	Gross Domestic Products
IMR:	Inverse Mills Ratio
IV:	Instrumental Variables
KGS:	Kyrgyz Som
LATE:	Local Average Treatment Effect
LiK:	Life in Kyrgyzstan
LU:	Livestock Unit
MTE:	Marginal Treatment Effect
OLS:	Ordinary Least Square
PCA:	Principal Component Analysis
PSM:	Propensity Score Matching
SAPs:	Sustainable Agricultural Practices
TH:	Transitional Heterogeneity
WUA:	Water Users Association
ZT:	Zero Tillage

1 GENERAL INTRODUCTION

1.1 Challenges for sustainable agricultural development in Central Asia

The literature on land degradation in Central Asia highlights the significant negative impact of extensive and intensive land utilization practices (Mirzabaev et al., 2016). Several key factors have been identified as contributing to the process of land degradation in the region, including extensive cotton cultivation, unregulated irrigation practices, and insufficient crop diversification options (Nurbekov et al., 2016). The Soviet agricultural policies for several decades prioritized monoculture, particularly of cotton, under the state-planned economy (Rumer, 1989). This approach, while aiming for high output targets, overlooked the ecological sustainability of such practices (Robinson, 2016). The heavy reliance on a single crop not only reduced biodiversity but also led to the depletion of soil nutrients, increasing susceptibility to erosion and land degradation (Mueller et al., 2014). Unregulated irrigation practices, especially for cotton cultivation, resulted in the manifestation of salinization and waterlogging of cropland diminished soil fertility and decreased cotton yields across irrigated regions in Central Asia (Pender et al., 2009). Furthermore, the centralized irrigation systems were often inefficient, leading to salinization and waterlogging of arable lands (Qadir et al., 2014). This was compounded by the lack of local governance structures or incentives for sustainable land management among the collective and state farms (Rumer, 1989).

The degradation of land and water resources degrades crop yields and agricultural income. Furthermore, insufficient crop diversification options, challenges associated with old-established machinery, the expansion of cotton cultivation under the paradigm of 'conventional cotton' monoculture, inadequate adoption of crop rotation management, the scarcity of high-yield varieties, and incomplete land preparation jointly contribute to declining land productivity in Central Asia (Hornidge et al., 2016; Kienzler et al., 2012; Rumer, 1989).

Although the intensive fertilizer application has lessened the visible impact and masked the problem's full extent, irrigated croplands in Central Asia—especially in cotton-producing areas—have become focal points for land degradation. This degradation resulted in the loss of US$ 6 billion in 2001-2009, with desertification and agricultural abandonment costing US$ 1 billion each (Mirzabaev et al., 2016).

Enhancing soil productivity and mitigating land degradation stand as pivotal challenges in Central Asia. Yet, the post-independence transition to market economies in these countries presented new challenges for mitigating land degradation (Pomfret, 2019). Land reforms, aimed at redistributing state-owned lands to private individuals, often lacked the necessary support mechanisms to foster sustainable land management practices (Kienzler et al., 2012). Farm fragmentation hindered the efficient use of resources and adoption of modern agricultural technologies, further contributing to land degradation and lower agricultural productivity (Lerman and Sedik, 2018). Access to knowledge, technology, financial resources, and infrastructure necessary for implementation of sustainable land management by newly-emerged agricultural producers was lacking (Hornidge et al., 2016; Kienzler et al., 2012).

1.2 Sustainable agricultural practices

The adoption of sustainable agricultural practices (SAPs) present a promising solution to these challenges by improving soil fertility, capturing carbon to address climate change, and boosting both crop yields and financial returns (Manda et al., 2016). The adoption of SAPs stands as a principal strategy directed towards enhancing farm productivity, improving agricultural profitability, and reducing production expenses (e.g., Lee, 2005; Manda et al., 2016; Tadjiev et al., 2023a; Zhao et al., 2020). Scholars argue that sustainable agricultural development embodies five primary characteristics: (1) resource conservation, (2) environmental preservation, (3) technological suitability, (4) economic viability, and (5) social acceptability (FAO, 1989; Teklewold et al., 2013). Accordingly, sustainable agricultural practices are characterized by their inherent capacity to yield positive externalities in crucial domains such as biodiversity, water conservation, soil health, landscape preservation, and climate change mitigation. This distinguishing feature sets them apart from conventional practices (Dessart et al., 2019).

SAPs encompass a spectrum of farming practices that include environmental, societal, and economic aspects. These practices include crop rotation, intercropping, conservation tillage, biological methods for pest control, residue retention, improved crop varieties, animal manure, soil and water conservation (e.g., Lee, 2005; Manda et al., 2016; Teklewold et al., 2013; Zeweld et al., 2017). Insufficiency of financial, physical, and human resources stands as a predominant issue faced by rural households and individual farms within the Central Asian region (Wolfgramm et al., 2010; Djanibekov et al., 2012). Moreover, the rising expenses associated with production inputs pose significant challenges for farms in Central Asia (Djanibekov et al., 2012). Hence, it is imperative to advocate for the adoption of resource-saving practices that entail lower financial resources among farms. For example, crop rotation, zero tillage, intercropping is an approach to soil management that involves minimal input, and preferably less off-farm sources (Baker and Saxton, 2007; Tanveer et al., 2019). In various empirical chapters of my dissertation, I thus focus on studying the adoption of crop rotation, zero tillage, low-tillage, biological methods for pest control, and intercropping practices in the context of Central Asia. The utilization of these selected practices offers economic, social, and environmental advantages to farmers (e.g., Abdollahzadeh et al., 2015; Baker and Saxton, 2007; Glaze-Corcoran et al., 2020; Ogieriakhi and Woodward, 2022; Yigezu and El-Shater, 2021; Zhao et al., 2020). The adoption of these practices provides potential for mitigating challenges of sustainable agricultural development in Central Asia (FAO, 2013; Kienzler et al., 2012; Nurbekov et al., 2016; Pender et al., 2009). Furthermore, the above-listed SAPs have been successfully tested for feasibility in Central Asia (Nurbekov et al., 2016; Pender et al., 2009).

Biological pest control refers to the environmentally conscious approach of managing pests by harnessing natural adversaries (Kumari et al., 2022; Nigam and Mukerji, 2023). Biological pest controls reduce the dependency of modern agriculture on pesticide applications and maintain high crop yields (Schneider et al., 2015). Biological control is a component of an integrated pest management strategy and the adoption of integrated pest management will be introduced to manage pest populations and crop producers' net returns will be improved (Hoffmann and Frodsham, 1993; McNamara et al., 1991).

Crop rotation is a method of cultivating crops in a systematic sequence on the same piece of land, with the goal of preserving soil fertility and ensuring that farmers maintain or increase their land-related profits (Sumner, 1982; Tanveer et al., 2019). Crop rotation, particularly with leguminous crops, has been shown to sustain and enhance farm productivity and income (FAO, 2015). Studies like Manda et al. (2016) demonstrated that maize-legume rotation, combined with improved varieties and residue retention, boosts maize yields and household income. In China, cotton-legume rotation increases cotton yields by nearly a quarter (Zhao et al., 2020). Implementing crop rotation, especially with alfalfa, sorghum, or mung beans as cover crops, within an organic-based agricultural framework in Uzbekistan enhances net present value and reduces expenses (Franz et al., 2009). Farmers who practiced crop rotation had higher welfare compared to non-adopters (Ghimire et al., 2012; Mohammad et al., 2012; Zeweld et al., 2020).

Conservation agriculture means no or minimum mechanical soil disturbance, seeding or planting directly into untilled soil, and using crop residues and cover crops to protect and feed soil life and this can help to improve soil quality, and increase soil organic matter (FAO, 2023; Nurbekov et al., 2016). The study investigates the adoption of zero tillage as a form of conservation agriculture. *Zero tillage*, namely when crops are planted directly into a seedbed not tilled after harvesting the previous crop accumulates soil carbon and increases soil nitrogen, thus promoting soil, moisture and nutrients conservation for increasing crop productivity (Baker and Saxton, 2007; FAO, 2023; Ofstehage and Nehring, 2021). Zero tillage is also proved to be a solution to target low financial and resource capacity of smallholders in developing countries (Jaleta et al., 2016; Jaleta et al., 2019; Montt and Luu, 2020; Musafiri et al., 2022).

Intercropping is the simultaneous cultivation of two or more crop species in the same field at a given time (Stomph et al., 2020; Wang et al., 2014). Intercropping minimizes the use of chemical inputs such as pesticides and herbicides, as well as enhances soil fertility and yields (Brooker et al., 2015; Ha et al., 2023; Stomph et al., 2020).

1.3 Problem statement, research objectives and structure of the thesis

As earlier mentioned, the global scholarly discourse extensively examines the issue on the adoption of sustainable agricultural practices and its impact on farm performance. To combat the land degradation, in the mid-1990s, the concept of conservation agriculture was presented by international agencies (Wolfgramm et al., 2015) and several practices have been successfully tested in Central Asia (Nurbekov et al., 2016; Pender et al., 2009; Kienzler et al., 2012). Nevertheless, the adoption of sustainable agricultural practices is still low in Central Asia and most farmers are reluctant to adopt them. The conversion to sustainable practices of crop cultivation in Central Asia, is challenged by the lack of agronomic knowledge about sustainable agricultural methods, inadequate supply of extension services, lack of seed varieties and machinery suitable for sustainable crop cultivation, as well as the absence of government incentives for adopting such practices (Kienzler et al., 2012; Nurbekov et al., 2016).

Although much of the literature emphasizes the main drivers of the adoption of SAPs and their impact on farm performance (e.g., Knowler and Bradshaw, 2007; Ruzzante et al., 2021; Takahashi et al., 2020), there is a lack of empirical studies that thoroughly examine the determinants and impact of sustainable agricultural practices in the context of Central Asia. So, the issue of how the adoption of sustainable agricultural practices can be promoted among farmers in Central Asia remains an understudied research question. This dissertation addresses this existing research gap and aims to provide a more comprehensive and refined understanding of the subject matter by answering the research question “What factors determine adoption of selected SAPs and how this affects farm performance?”. By doing so, the dissertation also contributes to the global discussion on adoption and impact of SAPs in a developing country farming system.

This study encompasses three objectives aimed at comprehending the essential drivers for promoting the adoption of sustainable agricultural practices by farmers and their effects on farm performance in Central Asia:

1. *to understand the main determinants of farmer's decision to adopt SAP and its impacts on farm outcomes;*
2. *to investigate whether the adoption of SAP offers economic benefits to farmers by reducing production costs;*
3. *to explore determinants of farmers' participation in informal cooperation in water management and its impact on the intensity of SAPs adoption.*

To achieve the research goal, I study commercial farms and rural households of three Central Asian countries, namely Kazakhstan, Kyrgyzstan and Uzbekistan. I utilize empirical models as methodological tools to accomplish the objectives of the study. As the sample is not truly random, but based on preselection of study regions, I follow up on the p-value warnings when specific sampling designs are ignored (Hirschauer et al., 2020). Instead of reporting the model results with p-value, I use confidence intervals (CI). As the p-value or the measure of statistical significance is not the relevant output from an analysis, it is argued that reporting the estimation results with CIs is more preferable (Imbens, 2021). CIs also provide a convenient way of summarizing the hypothesis test results for effect sizes (Greenland et al., 2016).

This first objective is addressed in Chapter 2 where I used crop rotation in irrigated cotton farming systems as an example of SAP. Crop rotation, or sequentially growing cotton with leguminous crops on the same plot, can contribute to sustainability of cotton cultivation by improving soil fertility, reducing land degradation, and preventing nutrient loss in the long run (Ball et al., 2005) and affecting soil microbiology and phytotoxins (Tanveer et al., 2019). Existing research on Central Asia's crop rotation relies on agronomic experiments (Takata et al., 2008) or employs remote sensing tools (Conrad et al., 2017; Löw et al., 2017) rather than employing economic rigor to assess the advantages of this SAP. While the documented agronomic advantages of crop rotation in cotton cultivation schemes are well-established (Takata et al., 2008; Zhao et al., 2020), farmers are interested in monoculture for reaching short-term profit maximization goals. This raises questions about factors defining the adoption of crop rotation, and whether crop rotation improves cotton growers' revenues and yields. Hence, I hypothesize that farmers who adopt crop rotation achieve higher cotton yields and net revenues compared to non-adopters. It is the first empirical research delving into the factors influencing the adoption of crop rotation among Central Asian farmers. Here, I examine two historically cotton-dominated irrigated areas in the region, namely, Turkistan province in Kazakhstan and Samarkand province in Uzbekistan by using a farm survey data collected in the framework of the AGRICHANGE[1] research project in March-April 2019. The distinctive approach, examining multiple countries instead of single-country research focusing solely on the productivity and income impacts of adopting soil-improvement practices, presents additional insights on the heterogeneity in institutional responses and policy effectiveness across contrasting national settings. This part of the study is one of the few studies globally to empirically analyze crop rotation's effect on cotton producers' performance. To better understand the impact of crop rotation on farmer's cotton yield and cotton net returns I employ an endogenous switching regression (ESR) model and measure average treatment effects. The empirical results show implications of two countries' contrasting institutional settings of cotton cultivation on adoption of crop rotation. Compared to conventional crop cultivation, crop rotation in Uzbekistan increases cotton yields and revenues. However, an opposite effect is observed among cotton growers in Kazakhstan.

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[1] Institutional Change in Land and Labour Relations of Central Asia's Irrigated Agriculture (AGRICHANGE), www.iamo.de/en/agrichange.

The second objective is addressed in Chapter 3 where zero tillage is used as an example of an SAP offering socio-economic benefits for smallholders through lower production costs (Chatterjee and Acharya, 2021). However, there is an ongoing debate whether zero tillage only reduces smallholders' production costs or whether it alters the production cost structure. A summary of findings from nine empirical studies on the impact of conservation tillage methods, including zero tillage, is presented in Table A3 in the Appendix. For instance, some findings suggest that zero tillage can increase monetary herbicide expenditure and total labor costs (Teklewold et al., 2013). While arguing that zero tillage reduces fuel and labor cost, Yigezu and El-Shater (2021) found that its effect on the labor requirement and expenses are not necessarily straightforward as zero tillage can increase manual work requirements for weeding. Furthermore, while lowering female and male labor requirements, reduced and zero-tillage methods lead to higher application doses of chemical fertilizers and herbicides (Tessema et al., 2018). This empirical study contributes to this debate on whether zero tillage saves or increases production costs in smallholder settings. To achieve the research objective, I utilized plot-level panel data from the "Life in Kyrgyzstan (LiK) survey, which provides detailed longitudinal information on smallholder farmers in Kyrgyzstan. My investigation shows that zero tillage adoption increases hired labor and herbicide costs, but decreases land preparation and total production costs compared to the conventional tillage method among households in Kyrgyzstan.

The third objective is addressed in Chapter 4. Farmers' participation in informal cooperation in water management allows them to overcome water distribution disputes and to share maintenance costs. In addition, farmers' cooperation in water management provides a platform for knowledge exchange among participants, such as about SAPs use. Participation in collective initiatives can improve soil conservation by facilitating the exchange of planting materials, information, and labor among farmers, overcoming household labor constraints, and thereby enhancing the implementation of labor-intensive soil conservation practices (Willy and Holm-Müller, 2013). Additionally, community-based collective action initiatives contribute to soil conservation through collective learning and knowledge exchange. The participation in informal cooperation is expected to enhance the information sharing among farmers, leading to an improved intensity of SAPs adoption. Over the last four decades, globally, a significant number of studies have been investigating SAPs adoption determinants including farm and farmer characteristics, institutional and behavioral factors (e g., Dessart et al., 2019; D'Emden et al., 2008; Feder et al., 1985; Ruzzante et al., 2021). Despite this voluminous literature on SAPs adoption, there is a lack of empirical research of how informal cooperation among water users affects their SAPs adoption (Willy and Holm-Müller, 2013; Xue et al., 2022). Willy and Holm-Müller (2013) offer a perspective on the effects of various collaborative efforts, such as mutual support initiatives within a community, the upkeep of rural access roads, and water management, on soil conservation efforts of rural smallholders. Xue et al. (2022) investigate the impact of participation in collective action on smallholders' decisions to adopt no-tillage technology. Several studies investigated the impact of formal cooperative membership on farmers' SAPs adoption decisions (e.g., Wu et al., 2023; Zhang et al., 2020). In Chapter 4 of my thesis, I thus explore both the determinants and effects of informal cooperation on the intensity of SAPs adoption. For doing so, I use two waves of farm survey data of Uzbekistan collected within the framework of the AGRICHANGE and SUSADICA[2] projects in 2019 and 2022, and employ marginal treatment effects (MTEs) model. The analysis of the marginal returns associated with participation in informal cooperation contributes to the empirical knowledge on SAP adoption in developing countries. The results show that farmers who are likely to participate in informal cooperation tend to benefit more from participation in terms of intensity of SAP adoption.

[2] Structured doctoral programme on Sustainable Agricultural Development in Central Asia (SUSADICA), https://www.iamo.de/en/research/research-projects/

The final chapter of the dissertation presents conclusions and provides policy recommendations aimed at enhancing the adoption of SAPs in Central Asia. Furthermore, this concluding chapter addresses limitations, as well as proposes ideas for future research.

2 DETERMINANTS AND IMPACTS OF CROP ROTATION ADOPTION AMONG COTTON GROWERS IN IRRIGATED AREAS OF KAZAKHSTAN AND UZBEKISTAN

2.1 Reforms in the cotton sector and the adoption of crop rotation practices in Kazakhstan and Uzbekistan

Cotton farming in irrigated areas like South Kazakhstan and Uzbekistan makes significant contributions to rural livelihoods (Shtaltovna and Hornidge, 2014), and in addition to farm employment, creates jobs in the ginning and textile sectors (Baffes, 2005). Thus, cotton production is directly linked to rural incomes and employment. During the Soviet era cotton cultivation system in Central Asia, based on production plans and state regulation of procurement prices and value chain actors (Rumer, 1989), combined six-year sequences of cotton followed by three years of leguminous crops (mainly alfalfa) and fallow land (Toderich et al., 2007). As the Soviet planners demanded the fulfilment of cotton production plans, disregarding environmental consequences, crop rotation was often abandoned, and farmers relied on the intensive use of fertilizers and machinery (Rumer, 1989). The continuous practice of cotton monoculture resulted in cropland degradation. Along with this, pests and water shortages have stagnated cotton yields since the 2000s (OECD/FAO, 2022). Available sustainable agronomic practices can improve cotton yields (OECD/FAO, 2022). One example is crop rotation, an alternative to monoculture, which involves growing cotton sequentially with leguminous crops on the same plot, contributing to soil fertility, reducing land degradation, and preventing nutrient loss (Ball et al., 2005). Diversifying crop cultivation, such as with sorghum, instead of monoculture, offers a solution to the environmental challenge of soil salinity in Central Asia (Bobojonov et al., 2013).

Following the dissolution of the Soviet Union, Kazakh and Uzbek governments took contrasting approaches to reform their cotton sectors (Pomfret, 2019). In Kazakhstan, an upper middle-income economy and the richest country in Central Asia thanks to its oil exports, the government rapidly reformed the cotton sector in the 1990s (Pomfret, 2019). The cotton sector in

Kazakhstan, initially insignificant on a national scale but vital in the Turkistan region, experienced significant growth following the removal of Soviet cotton policies. The introduction of private investors and competition led to the widespread adoption of contract farming, with private ginneries supplying inputs to farmers (Petrick et al., 2017). Cotton is cultivated only in one administrative province, Turkistan, and in 2018 it occupied about 132 thousand hectares.

In Uzbekistan, which has the largest population in the region, the government took a gradual transition keeping control over the cotton sector (Pomfret, 2019). In fact, Uzbekistan's cotton is currently produced on almost one million hectares, of which 82.3 thousand hectares are in the study region of Samarkand. Until recently, the Uzbek cotton sector resembled the Soviet central planning system comprising production targets and procurement prices, and the sectoral monopoly of parastatal ginneries, input suppliers and cotton exporters (Asfaw, 2021; Pomfret, 2019). To ensure cotton outputs, the government supplied farmers, particularly adopters of 'conventional cotton' monoculture, with subsidized seeds, fertilizers, irrigation water, machinery services and credit. In 2020, to promote domestic textile production and exports, the government announced cotton sector liberalization by privatizing the cotton-textile sector (Asfaw, 2021). Similar to Kazakhstan's cotton sector, contract farming replaced the state procurement contracts and cotton prices were liberalized. The new private clusters took over the state's role in supplying inputs to farmers.

It is notable that in the implementation of cotton sector reforms in Kazakhstan and recently in Uzbekistan, economic and social considerations such as rural income and employment, cotton yields and deeper value addition have outweighed environmental considerations, such as sustaining soil quality. For instance, both governments keep supporting cotton productivity by subsidizing inputs and machinery services (Asfaw, 2021; OECD, 2020). Investment subsidies are primarily directed to machinery and technologies for import-substitution and export promotion (Asfaw, 2021; OECD, 2020). To overcome the lack of expertise, both governments along with the international development community implement agricultural training programs to improve the agronomic knowledge of farmers. Because cotton plays a strategic role in Uzbekistan's gross agricultural output, cotton growers remain under close government attention. In Kazakhstan where cotton production is not on the national but on the local agenda cotton growers are left on their own (Shtaltovna and Hornidge, 2014). The agricultural ministries in both countries operate specialized research institutes, for instance, on cotton agronomy and irrigation, and organizations such as associations of water user and farmers providing partial agricultural extension services (Shtaltovna and Hornidge, 2014). At the same time, international development projects which train farmers on sustainable land management serve a relatively small number of farmers and have short-lived effects without a wider adoption of sustainable practices. As a result, sustainable land management, including crop rotation schemes, are abandoned in many places and farmers apply 'conventional cotton' monoculture through intensive use of inputs and machinery services (Kienzler et al., 2012).

2.2 Data and descriptive analysis

For this empirical investigation, I used data from a farm survey conducted in the AGRICHANGE research project in Turkistan and Samarkand provinces in March-April 2019. A multistage random sampling procedure was used to select farmers for interviews. For this, Turkistan (formerly South Kazakhstan) and Samarkand provinces were selected based on their long-lasting experience in cotton cultivation and the post-Soviet paths of agricultural reforms. Next, two types of districts based on their crop specialization were selected. Maktaaral and Shardara districts in Turkistan and Pastdargom and Payarik districts in Samarkand are more specialized in cotton cultivation. Farmers in the Sariagash district in Turkistan and the Jomboy district in Samarkand have diversified from cotton to other high-value crops such as vegetables and melons. Identified farmers answered a detailed questionnaire on individual socio-demographic data, individual perceptions, farm, field, and location characteristics, and the type and level of adopted SAPs.

The farm survey dataset covers 963 farmers, with 503 farmers located in the Turkistan province of Kazakhstan and 460 farmers in the Samarkand province of Uzbekistan. The dataset consists of 592 cotton-growing farmers of whom 285 farmers are in Turkistan province of Kazakhstan and 307 farmers are in Samarkand province of Uzbekistan. The sample is not truly random, preventing extrapolation to all farms in South Kazakhstan or Uzbekistan. In Kazakhstan, only one region produces cotton, namely Turkistan. In Uzbekistan, the Samarkand region was selected due to the location of the project partner organization in Uzbekistan. Next, two districts in each province were randomly selected based on cotton specialization, namely Maktaaral and Shardara districts in Turkistan and Pastdargom and Payarik districts in Samarkand. For Kazakhstan, three villages were sampled in each district, and 50 farm managers were randomly chosen from farm lists for each selected village. In Samarkand, farm managers were randomly chosen from a farm list at the district level. Figure 2.1 demonstrates the map of the study areas.

Figure 2.1: The map of the study area
Note: The map is prepared based on database of Global Administrative Areas (2012) (GADM database of Global Administrative Areas, version 2.0. [online] URL: www.gadm.org).

The interviewed farmers answered a detailed questionnaire on individual characteristics and behavioral perception, as well as farm, field, and location attributes. In the section on adoption of sustainable agricultural practices, the interviewed farmers were asked if they use "crop rotation to improve land fertility”. Based on their answers, the respondents were divided into two groups, i.e. into adopters and non-adopters of crop rotation. An adopter is a farmer who responded “yes” to the use of crop rotation. In total, the sample includes 66 cotton growers in Turkistan province and 64 cotton growers in Samarkand province who responded positively to using crop rotation.

Table 2.1 presents descriptive statistics for adopters and non-adopters. Kazakh farmers allocate approximately 80% of their sown area, about 12 hectares, to cotton cultivation. Uzbek farmers, on the other hand, allocate around 50% of their sown area, approximately 25 hectares, to cotton. In Kazakhstan, most farmers receive information on new technologies and agronomy through TV, radio, and the internet. In Uzbekistan, this percentage is lower due to a lack of media providing practical information to farmers. Additionally, Kazakh farmers rely more on peers and neighbors for information about new technologies compared to their Uzbek counterparts.

Over 20% of interviewed Kazakh farmers mentioned participating in contract farming with a ginnery which supplies inputs and machinery services. The state control of the Uzbek cotton sector guarantees cotton growers access to subsidized fertilizers. This explains the statistically significant difference in fertilizer costs between crop rotation adopters and non-adopters in Samarkand. Until recently, in Uzbekistan, the parastatal ginneries procured the entire cotton harvest, and contract farming schemes were absent. In Kazakhstan’s sample, each village includes 50 cotton growers. In Samarkand, only a few farms were surveyed at the village level. Compared to Uzbekistan, 95% of adopters in Kazakhstan perceive land tenure as secure. Therefore, the variables of “contract farming” and “village share of adopters” are excluded from the models for Uzbekistan, and “tenure security” is excluded for Kazakhstan.

Table 2.1: Descriptive statistics of farm-level variables by adopters and non-adopters of crop rotation

Variables	Kazakhstan			Uzbekistan		
	Adopters (N=66)	Non-adopters (N=219)	Mean diff	Adopters (N=64)	Non-adopters (N=243)	Mean diff
Outcome variables						
Cotton net returns (US$/ha)	795.638 (375.541)	919.745 (419.976)	-124.100	792.684 (249.970)	661.124 (284.775)	131.600
Cotton yield (kg/ha)	2025.455 (710.374)	2262.283 (836.891)	-236.800	2517.344 (562.535)	2313.086 (577.708)	204.300
Explanatory variables						
Total cotton fertilizer cost (US$/ha)	78.333 (63.408)	76.487 (75.421)	1.845	139.820 (27.956)	123.926 (27.093)	15.890
Total labor in a farm (persons/ha)	2.458 (2.327)	2.331 (2.561)	0.127	0.941 (0.561)	1.229 (1.093)	-0.259
Share of cotton in total sown area (%)	0.821 (0.226)	0.854 (0.207)	-0.033	0.522 (0.096)	0.503 (0.115)	0.019
Cotton area (ha)	11.947 (20.988)	11.961 (14.505)	-0.014	26.003 (13.922)	24.090 (14.235)	1.993
Farmer’s age (year)	48.955 (12.196)	45.845 (13.407)	3.110	44.344 (10.201)	44.173 (9.771)	0.171
Farmer has education in agriculture (1/0)	0.333 (0.475)	0.361 (0.481)	-0.027	0.391 (0.492)	0.407 (0.492)	-0.017
Farmer perceives canal condition as good (1/0)	0.485 (0.504)	0.416 (0.494)	0.069	0.281 (0.453)	0.296 (0.458)	-0.015
Farm fields located irrigation canal head (1/0)	0.273 (0.449)	0.228 (0.421)	0.044	0.172 (0.380)	0.263 (0.441)	-0.091
Farmer participates in contract farming (1/0)	0.212 (0.412)	0.237 (0.426)	-0.025	0.016 (0.125)	0.012 (0.111)	0.004
Farmer participates in farm trainings (1/0)	0.409 (0.495)	0.100 (0.301)	0.309	0.781 (0.417)	0.790 (0.408)	-0.009
Credit-rationed farmer (1/0)	0.212 (0.412)	0.297 (0.458)	-0.085	0.500 (0.504)	0.329 (0.471)	0.171
Farmer perceives land tenure as secure (1/0)	0.955 (0.210)	0.854 (0.354)	0.101	0.844 (0.366)	0.477 (0.501)	0.366
Share of land with good soil quality (0-1)	0.374 (0.450)	0.407 (0.450)	-0.033	0.613 (0.328)	0.596 (0.443)	0.016
Distance to the district center (km)	44.379 (29.540)	43.451 (27.774)	0.928	13.141 (5.374)	15.728 (6.800)	-2.588

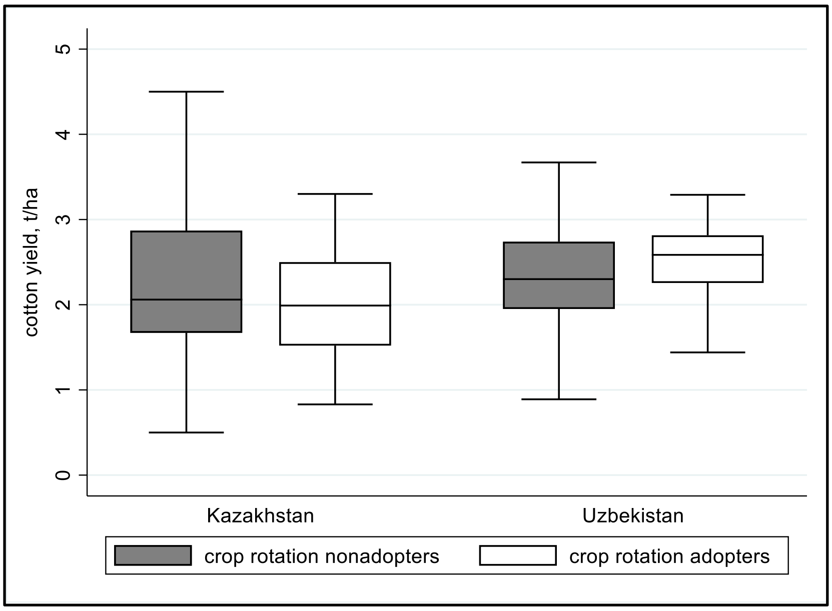
Table 2.1 cont.

Variables	Kazakhstan			Uzbekistan		
	Adopters (N=66)	Non-adopters (N=219)	Mean diff	Adopters (N=64)	Non-adopters (N=243)	Mean diff
Farmer receives information about new technologies and agronomy from other farms and community (1/0)	0.470 (0.503)	0.616 (0.487)	-0.146	0.516 (0.504)	0.407 (0.492)	0.108
Farmer receives information about new technologies and agronomy from media, internet or radio (1/0)	0.833 (0.376)	0.767 (0.424)	0.066	0.281 (0.453)	0.547 (0.499)	-0.266
Village share of adopters of crop rotation (Kazakhstan) (%)	0.241 (0.063)	0.226 (0.056)	0.015	x	x	x
Farmer located in Maktaaral (1/0)	0.530 (0.503)	0.516 (0.501)	0.014	x	x	x
Farmer located in Shardara (1/0)	0.470 (0.503)	0.484 (0.501)	-0.014	x	x	x
Farmer located in Payarik (1/0)	x	x	x	0.578 (0.498)	0.486 (0.501)	0.093
Farmer located in Pastdargom (1/0)	x	x	x	0.422 (0.498)	0.514 (0.501)	-0.093

Note: Standard deviation in parenthesis.
Source: Based on the AGRICHANGE 2019 farm survey data.

The survey data revealed further contrasting differences between Kazakh and Uzbek farmers. Uzbek adopters of crop rotation had statistically higher cotton yields compared to non-adopters (Figure 2.2 (a) and (b)). This picture is different in Kazakhstan, where non-adopters had statistically higher yields than adopters. This, in turn, resulted in differences in net revenues between adopters and non-adopters across two countries. The mean differences, however, do not account for the effects of other characteristics affecting farmers' adoption decisions, on the basis of which they can self-select into adopters and non-adopters.

a)



b)

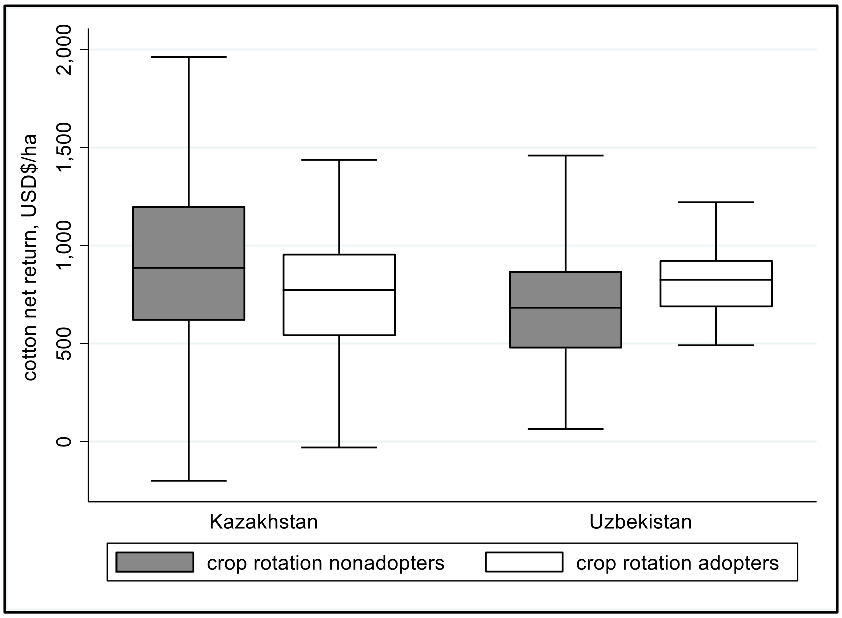


Figure 2.2: Cotton yields (a) and net revenues (b) among crop rotation adopters and non-adopters in Kazakhstan and Uzbekistan
Source: Based on the AGRICHANGE 2019 farm survey data.

2.3 Methodological approach

The assessment of the technology adoption impact based on non-experimental cross-sectional data requires the correction of self-selection bias, identification of proper counterfactuals, and controlling for non-observable farm characteristics (Asfaw et al., 2012; Jaleta et al., 2016). I explain the empirical models in the following subsections and motivate the selection of the methodology for this section.

2.3.1 Crop rotation adoption decision and farm outcome

The identification of farmers' decision to adopt crop rotation is based on the measurement of profitability and yield-increasing effects. To estimate the impact of crop rotation on farm outcomes, I followed existing literature such as Abdulai and Huffman (2014), Amadu et al. (2020), Jaleta et al. (2016), and Issahaku and Abdulai (2020), and employed a two-stage estimation approach. Farmers will adopt crop rotation (${C_1}^*$) if they expect to achieve higher yields and net returns from crop rotation compared to a decision with not to adopt (${C_0}^*$). Here, expected yields and net returns are not observed, but adoption decision is observed. In this perspective, adoption decision (C_i) is treated as a dichotomous choice, namely $C_i = 1$ if ${C_1}^* > {C_0}^*$ and $C_i = 0$ if ${C_0}^* > {C_1}^*$. Thus, farmers' adoption decision is related to their perception of whether adoption maximizes net returns or not. Based on given latent variable model, in the first stage, determinants of adoption were analyzed by the following probit model:

$$C_i^* = \delta K_i + \varepsilon_i \quad (2.1)$$

here, C_i is a dummy variable indicating whether farmer i adopts crop rotation or not. K_i is a vector of determinants of adoption decision ($n \times m$). δ is a vector of parameters to be estimated $m \times 1$, ε_i is a vector of error term ($n \times 1$) normally and independently distributed with mean 0 and variance σ^2.

To connect the relationship between adoption of crop rotation scheme and farm outcomes, it is assumed that farmers maximize expected net returns from cotton production, and the function is expressed following Dubbert (2019), and Zheng et al. (2021):

$$max\, \pi_i = P_i Q_i(R_i, Z_i) - I_i R_i \quad (2.2)$$

where π is the maximum net returns of farmer i gained from cotton production, P is cotton price per kg, and Q is cotton yield in kg. R represents input quantities such as fertilizer, seeds, and labor. Z represents the vector of explanatory variables, i.e. farm/farmer characteristics. I is a vector of input prices. Net returns (π_i) are expressed as a function of input and output prices, farm/farmer characteristics, and adoption of crop rotation scheme as follows:

$$\pi_i = \pi(P_i, I_i, Z_i, C_i) \quad (2.3)$$

Applying Hoteling's lemma to Equation (2.2) yields a reduced form of the cotton output supply function as follows:

$$Q_i = Q(P_i, I_i, Z_i, C_i) \quad (2.4)$$

Given the challenges in measuring production costs, it is assumed that farmers aim to maximize both yield and net returns. For larger farms in Samarkand, knowledge about yields, prices, and revenues is available, but input use data is fragmented among various experts, including agronomists, machinery engineers, and irrigation experts, making measurement complex. In this study, net returns from cotton production are calculated by deducting fertilizer costs (nitrogen, phosphorus, and potassium), cotton seed costs, and labor costs (payments for land preparation and cotton cultivation) from cotton revenue (yield multiplied by cotton price). Since manual cotton-picking wages are linked to the amount of harvested crop rather than actual labor effort, this cost component is not included. Equations (2.3) and (2.4) determine net returns and cotton yield based on input and output prices, farm/farmer characteristics, and the adoption of crop rotation.

In the second stage, to better understand the impact of adoption, I applied a simple model of farmers' outcomes. Cotton yield and net returns are determined by several factors, including land, labor, and fertilizer. A Cobb-Douglas production function was used, connecting farm outputs with inputs and other factors:

$$Y_i = F(A, L, N) \quad (2.5)$$

where Y_i is a vector of outcome variables of farmer i, A stands for farm size (in this case, cotton area in ha), L stands for labor quantity (in persons per ha), and N stands for fertilizer use (US$ per ha). As mentioned above, family labor dominates among Kazakh cotton-growers, and thus labor quantity in persons is used in the model.

Taking the logarithm of outcome variables and production inputs, I derived cotton yield (or cotton net returns) function as linearly separable (Amadu et al., 2020). Additionally, I accounted for other dummy or non-logarithmic variables. Thus, the effect of crop rotation adoption on cotton yield and net returns was modelled through a $\ln(Y)$ functional form related to production inputs and other factors such as farm/farmer characteristics and institutional settings as follows:

$$LnY_i = \alpha_0 + \beta lnA + \mu lnL + \kappa lnN + \psi Z_i + \varsigma C_i + u_i \quad (2.6)$$

It is assumed that the outcome variable (Y_i) is associated with production inputs (A, L and N), a vector of other explanatory variables (Z_i), and rotation adoption (C_i) take a value of 1 if a farm adopts crop rotation and 0 otherwise. α_0 is a constant, β, μ, κ, ψ and ς are vectors of estimated parameters, and u_i is an error term. The impact of the adoption of crop rotation on cotton yield and net returns is computed by the estimation of the parameter ς. This approach might create biased estimates because it assumes that adoption is exogenously determined, while it is potentially endogenous (Di Falco et al., 2011). Farmers' decision to adopt or not to adopt may be based on individual self-selection. Farmers who adopt crop rotation can have different characteristics compared to non-adopters. Furthermore, farmers can decide to adopt based on expected benefits but structurally differ in their expectations (Asfaw et al., 2012; Di Falco et al., 2011). Considering that the interviewed farmers might have self-selected into adopting crop rotation schemes, selection bias can occur because of observable and unobservable attributes affecting adoption and outcome variables at the same time. Hence, an Ordinary Least Squares (OLS) estimator might generate biased and inconsistent estimates (Di Falco et al., 2011; Dubbert, 2019). Following the arguments expressed in recent existing studies by Asfaw et al. (2012), Di

Falco et al. (2011), and Jaleta et al. (2016), I employed an endogenous switching regression (ESR) model that accounts for both endogeneity and sample selection bias.

2.3.2 Endogenous switching regression

To examine the influence of crop rotation on farm outcomes, I applied the Average Treatment Effect on the Treated (ATT). The ATT estimates average differences in outcome variables between adopters who actually adopted crop rotation (observed) and those who would not have adopted it (counterfactual). Although the Propensity Score Matching (PSM) method can also calculate ATT, it does not account for unobservable factors that simultaneously influence farmers' adoption decisions and outcome variables (Jaleta et al. 2016). For instance, Abdulai and Huffman (2014), Asfaw et al. (2012), Jaleta et al. (2016) and Issahaku and Abdulai (2020) applied the ESR model approach to analyze the impact of sustainable agricultural practices on outcome variables in the binary regime of adopters and non-adopters. Following these studies, in the second stage, the relationship between outcome variables and adoption decisions including other explanatory variables, can be formulated in two regimes with an OLS regression model. Consequently, Equation 2.6 is expressed as follows:

Regime 1 (crop rotation adopters): $y_{1i} = X_{i1}\beta_1 + \omega_{1i}$ if $C = 1$ (2.7a)

Regime 2 (crop rotation non-adopters): $y_{2i} = X_{i2}\beta_2 + \omega_{2i}$ if $C = 0$ (2.7b)

where y_{1i} and y_{2i} are outcome variables for adopters and non-adopters. X_{i1} and X_{i2} are vectors of determinants of the outcome variables. β_1 and β_2 are vectors of parameters to be estimated. ω_{1i} and ω_{2i} are error terms.

The probit model in Equation 1 supplies essential information to examine and correct the potentially resulting bias (Maddala, (1983, 223); Petrick, (2004, 151)). To test selection bias, according to Heckman (1979) the Inverse Mills Ratio (IMR) can be calculated from the results of a probit estimation as follows:

$$\lambda_{1i} = \frac{\varphi(\delta K_i)}{\Phi(\delta K_i)} \qquad \lambda_{2i} = \frac{-\varphi(\delta K_i)}{1-\Phi(\delta K_i)} \quad (2.8)$$

where $\varphi(.)$ and $\Phi(.)$ indicate probability density function and cumulative density function of the standard normal distribution, respectively. λ_{1i} and λ_{2i} represent IMR. Equations 2.7a and 2.7b are used to correct selection bias. Thus, the outcome equations in two regimes stand for:

Regime 1 (crop rotation adopters): $y_{1i} = X_{i1}\beta_1 + \sigma_{1\varepsilon}\lambda_{1i} + \eta_{1i}$ if $C = 1$ (2.9a)

Regime 2 (crop rotation non-adopters): $y_{2i} = X_{i2}\beta_2 + \sigma_{2\varepsilon}\lambda_{2i} + \eta_{2i}$ if $C = 0$ (2.9b)

where $\sigma_{1\varepsilon}$ and $\sigma_{2\varepsilon}$ are parameters to be estimated, η_{1i} and η_{2i} are normally distributed error terms with mean zero and constant variance.

Existing studies explain that for a more robust identification, it is important to select instrumental variables (IV) that affect C_i in Equation 2.1 and do not appear in explanatory variables of outcome equation. Technology adoption studies employ information sources, such as other farmers, neighbors, and relatives, as valid IVs (Asfaw et al., 2012; Di Falco et al., 2011; Manda et al., 2016). Previous findings show that adopters of maize-legume rotation or improved technologies have better access to relevant information on application and associated benefits (Manda et al., 2016). Based on these arguments, I used variables "information from other farmers and neighbors", and "information from media, internet and radio about technologies and agronomy" as IVs for measuring the impact of crop rotation in both study regions. For Kazakhstan, I also used "village share of crop rotation adopters" as an IV. Thus, these variables were excluded from Equations 2.9a and 2.9b.

I explored acceptability of instruments through a simple falsification test to determine whether the selected variables were reasonable and thus affect farmer's adoption decision, but not outcome variables (Di Falco et al., 2011; Jaleta et al., 2016). The results of the falsification test show that selected instruments are jointly statistically significant in the adoption decision (for adoption decision $\chi2$=7.81, p-value=0.05 for Kazakhstan; $\chi2$=6.93, p-value=0.03 for Uzbekistan), but statistically insignificant in the outcome equation of non-adopters (for net returns and cotton yield respectively F-stat=0.55 and 0.78, p value=0.65 and 0.51 for Kazakhstan; F-stat=0.22 and 0.18, p value=0.80 and 0.83 for Uzbekistan) (See Table A1 in Appendix A). Consequently, the selected instruments can be considered as plausible.

2.3.3 Average treatment effects

The impact of crop rotation on farmers' outcome can be tested through the comparison of expected outcomes of adopters and non-adopters in actual and counterfactual situations. For this, the Average Treatment Effect on the Treated (ATT) and the Treatment Effect on the Untreated (ATU) were computed within the ESR model. To do this, I calculated the expected outcome for adopters and non-adopters in actual and counterfactual scenarios based on Equations 2.9a and 2.9b as follows:

$E(y_{1i}|X,\ C_i = 1) = X_{1i}\beta_1 + \sigma_{1\varepsilon}\lambda_{1i}$ (2.10a)

$E(y_{2i}|X, C_i = 0) = X_{2i}\beta_2 + \sigma_{2\varepsilon}\lambda_{2i}$ (2.10b)

$E(y_{2i}|X,\ C_i = 1) = X_{1i}\beta_2 + \sigma_{2\varepsilon}\lambda_{1i}$ (2.10c)

$E(y_{1i}|X.\ C_i = 0) = X_{2i}\beta_1 + \sigma_{1\varepsilon}\lambda_{2i}$ (2.10d)

Here, Equation 2.10a is for adopters ($C = 1$) , and Equation 2.10b is for non-adopters ($C = 0$), both observed in the sample. In contrast, two other equations consider counterfactuals, such as Equation 2.10c is for adopters who would have decided not to adopt, and Equation 2.10d is for non-adopters who would have decided to adopt. The differences between Equations 2.10a and 2.10c can be formulated as Equation 2.11 which explains the comparisons of the expected outcomes (net returns in US$/ha, and cotton yield in t/ha), and allows for the calculation of the average treatment effect on the treated (ATT) as follows:

$ATT = (2.10a) - (2.10c) = E(y_{1i}|X, C_i = 1) - E(y_{2i}|X,\ C_i = 1) = X_{1i}\,(\beta_1 - \beta_2) + \lambda_{1i}(\sigma_{1\varepsilon} - \sigma_{2\varepsilon})$ (2.11)

The differences between Equations 2.10b and 2.10d can be formulated as Equation 2.12 which is the average treatment effect on the untreated (ATU):

$$ATU = (2.10b) - (2.10d) = E(y_{2i}|X,\ C_i = 0) - E(y_{1i}|X,\ C_i = 0) = X_{2i}\,(\beta_1 - \beta_2) + \lambda_{2i}(\sigma_{1\varepsilon} - \sigma_{2\varepsilon}) \quad (2.12)$$

Thus, the heterogeneity effect is measured by utilizing Equations 2.11 and 2.12. According to Asfaw et al. (2012), Di Falco et al. (2011), and Jaleta et al. (2016) the effect of base heterogeneity (BH) for adopters can be calculated as the difference between Equations 2.10a and 2.10d, and for non-adopters as the difference between Equations 2.10c and 2.10b (see Table 2.2). Additionally, the outcomes for two groups (crop rotation adopters and non-adopters) may differ because of unobserved factors, as each group may react differently to changing conditions over time. This variation is referred to as "transitional heterogeneity" (TH), indicating that the effects of adopting crop rotation can vary across groups.

Table 2.2: Expected conditional, average treatment and heterogeneity effects

Subsamples	Decision stage		Treatment effects
	To adopt CR	Not to adopt CR	
Adopters	(a) $E(y_{1i}|X,\ C_i = 1)$	(c) $E(y_{2i}|X,\ C_i = 1)$	ATT
Non-adopters	(d) $E(y_{1i}|X,\ C_i = 0)$	(b) $E(y_{2i}|X,\ C_i = 0)$	ATU
Heterogeneity effects	BH_1	BH_2	TH

Notes: (a) and (b) represent observed expected farm outcome (cotton net returns (US$/ha), and crop yield (t/ha)). (c) and (d) represent counterfactual expected farm outcome (cotton net returns (US$/ha), and crop yield (t/ha)).
C = 1 if farmer i adopted crop rotation. C = 0 if farmer i did not adopt crop rotation.
y_{1i} = farm outcome if farmers treated with crop rotation adoption; y_{2i} = farm outcome if farmers treated with crop rotation non-adoption.
ATT = average treatment effect on treated.
ATU = average treatment effect on untreated.
BH_1 = the effect of base heterogeneity for crop rotation adopters.
BH_2 = the effect of base heterogeneity for crop rotation non-adopters.
TH = transitional heterogeneity (ATT-ATU).
Source: Authors based on Jaleta et al. (2016).

2.4 Results and discussion

2.4.1 Determinants of farmers' decision to adopt crop rotation

This section presents and discusses the results from the probit model. Figure 2.3 shows the estimated average marginal effect coefficients and 90% CIs of each explanatory variable. Table A2 in Appendix A provides more details to the model results. The econometric models were estimated in STATA 17 software.

A cross-country comparison of the model results highlights the influence of divergent institutional settings in the cotton sectors of the two countries. Kazakhstan's approach involved distributing land to former members of state and collective farms who were actively involved in crop cultivation (Petrick et al., 2017). In contrast, Uzbekistan allocated land through auctions to residents, both rural and urban, with strong entrepreneurial skills and capital, sometimes with limited agricultural experience (Djanibekov et al., 2012). The estimation results reveal that in Kazakhstan, farmers' age positively correlates with the likelihood of adopting crop rotation, indicating that older farmers with more experience are more likely to adopt this practice. However, this is not the case for cotton growers in Uzbekistan.

Furthermore, farm restructuring implied contrasting levels of land tenure security in two countries. In Kazakhstan, individuals received farmland for private use (Petrick et al., 2017). In Uzbekistan, farmland remained state-owned and could be revoked at any time, as it has been done through several farm consolidation campaigns (Djanibekov et al. 2012). Scholars continuously note that Uzbek land tenure insecurity hinders the wider adoption of sustainable agricultural practices requiring a longer lifespan for generating farm benefits (Hamidov et al., 2022; Kienzler et al., 2012). The model results confirm the effect of land tenure security for Uzbekistan, where cotton growers perceiving higher land tenure security are more likely to adopt crop rotation. This relationship is not observed for Kazakhstan, where respondents generally felt more optimistic about their land tenure security.

Another contrasting result is related to the organization of agricultural credits for cotton growers. In Kazakhstan, private ginneries provide financing through contract farming, or farmers seek commercial or subsidized credits (Petrick et al., 2017). Conversely, Uzbekistan's tightly controlled cotton sector relies on parastatal agricultural banks for short-term credits. The model results reflect this difference. In Kazakhstan, credit rationing does not impact crop rotation adoption, as farmers obtain finance and inputs through ginneries in contract farming arrangements. In Uzbekistan, farmers facing credit rationing are more likely to adopt crop rotation, which makes sense since crop rotation with legumes or alfalfa requires fewer financial resources and inputs. This aligns with Montt and Luu's (2020) findings of a positive relationship between credit rationing and the adoption of cost-effective crop management practices. Credit-constrained farmers opt for more affordable rotation with legumes and alfalfa instead of costly high-value crops. Consequently, the results suggest that access to agricultural finance makes Uzbek cotton growers less inclined to employ crop rotation.

Both study areas rely on irrigation, impacting farmers' crop choices through variables like proximity to the main irrigation canal and farmers' perception of its condition. Inherited Soviet irrigation systems favor farmers at the canal's head, leading to decreased cotton crop rotation near canals due to the lower water requirements of legumes compared to high-value crops like rice, potatoes, vegetables, and melons. Farmers with better water access are more likely to rotate cotton with water-intensive crops. This effect is more pronounced in Uzbekistan, where limited water supply pressures cotton cultivation and crop rotation becomes a strategy. Additionally, farmers' opinions about canal conditions influence their choices, with improved conditions encouraging sustainable crop rotation and defining investment risks in multi-year land-improving practices (Hamidov et al., 2022).

Farm training and knowledge delivery methods vary between Kazakhstan and Uzbekistan. In Kazakhstan, farm training participation is voluntary and based on farmers' requests (Shtaltovna and Hornidge, 2014), whereas in Uzbekistan, the government mandates cotton-focused training to meet production targets, with less emphasis on soil quality, and cotton growers are obligated to attend (Shtaltovna and Hornidge, 2014). The model results highlight this difference, with the positive effect of training being more significant in Kazakhstan. In other words, Kazakh cotton growers who attended training are more likely to adopt crop rotation. This aligns with Zheng et al. (2021), who found that farm training participation increases the adoption of sustainable agricultural technologies. However, in Uzbekistan, farmers' participation in training does not correlate with crop rotation adoption. This divergence between the two countries underscores the importance of the farm training approach for promoting wider crop rotation adoption.

The organization of farm training and information delivery in Kazakhstan and Uzbekistan is linked to certain independent variables. In Uzbekistan, there is a negative correlation between information sources and crop rotation adoption, implying that farmers who acquire knowledge from media sources like radio and the internet are less inclined to use crop rotation. This suggests that Uzbekistan's state-controlled media does not promote the benefits of crop rotation, focusing instead on conventional cotton monoculture to meet production targets rather than soil quality maintenance (Shtaltovna and Hornidge, 2014). Uzbek farmers primarily receive agricultural information from government-organized field days and training events conducted through public universities and research institutes. In Central Asia, cotton growers prioritize commercial issues and cotton monoculture when exchanging information with peers, such as sourcing cost-effective inputs and marketing products, as well as determining fertilizer and pesticide application rates. This helps explain the findings that Kazakh farmers who obtain agronomic knowledge from peers and neighbors are less likely to adopt crop rotation.

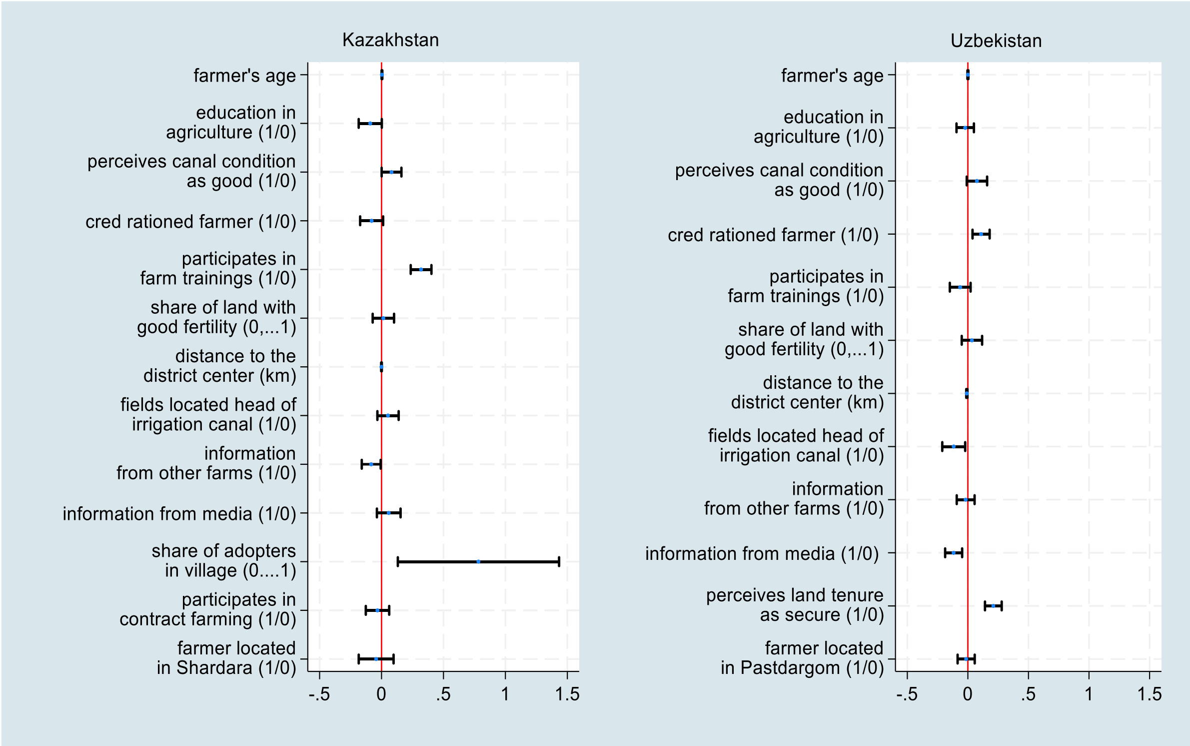


Figure 2.3: Determinants of farmers' crop rotation adoption decision
Source: Based on the AGRICHANGE 2019 farm survey data.

In Kazakhstan, the share of adopters in neighboring villages strongly influences the probability of crop rotation adoption, indicating that observing the benefits of adoption in one's community is a key factor for Kazakh cotton growers. This, combined with the influence of obtaining information from peers and neighbors, highlights that farmers are more likely to adopt crop rotation when they see its advantages demonstrated by local adopters.

2.4.2 Determinants of cotton yields and net returns of cotton growers

Tables 2.3 and 2.4 present the estimation results of the determinants of cotton yield and net returns for adopters and non-adopters calculated by employing Equations 2.9a and 2.9b. In Table 2.3 and 2.4, the coefficient of IMR suggests the presence of selection bias arising from unobservable factors, and that a negative selection bias is important in the adoption decision (e.g., Amadu et al., 2020; Zheng et al., 2021). In other words, farmers with above-average yields and net returns were unable to adopt crop rotation. This finding supports the choice to apply the ESR model.

Similar to the results described above, the determinants of outcome variables depend on the country context. For instance, fertilizer costs are positively related to cotton yields of non-adopters in Kazakhstan and Uzbekistan. This shows that "conventional cotton" monoculture has a stronger responsiveness to fertilizer application than rotation-based cotton cultivation. In fact, cotton cultivation in post-Soviet Central Asia strongly depends on fertilizer application. Karimov (2014) found a significant effect of nitrogen fertilizer on yields of Uzbek cotton varieties. The observed fertilizer effect among adopters and non-adopters is consistent with the findings of Jaleta et al. (2016) that increasing fertilizer use intensity improves maize yields among conventional tillage adopters. Furthermore, the area of cotton cultivation has a positive effect on both outcome variables for adopters in Kazakhstan, and on net returns among non-adopters in Uzbekistan. The results further suggest that in Kazakhstan, farm performance improves with farm size under crop rotation, whereas in Uzbekistan, it declines.

The farm restructuring approach also determines the contrasting effect of age on both outcome variables. Older adopters in Kazakhstan are likely to have higher cotton yields and net revenues, while this relationship is the opposite among non-adopters. The negative impact of age on net return and cotton yield among non-adopters indicates that younger farmers are likely to have higher economic benefits from 'conventional cotton' monoculture than older farmers. This result is supported, for instance, by Manda et al. (2016) who found a negative relationship between a farmer's age and maize yield in Zambia. Furthermore, specialized agricultural education increases net returns and cotton yields among non-adopters in Uzbekistan suggesting that agricultural education has an effect in "conventional cotton" farming. According to Karimov (2014) educational background in agriculture improves the efficiency of Uzbek cotton growers. However, agricultural education facilitates gains particularly among non-adopters because its content traditionally emphasizes productivity aspects rather than sustainable agriculture.

As expected, the condition of irrigation infrastructure is positively related to outcome variables. In other words, farmers with a positive opinion about irrigation canal condition are likely to obtain higher net returns and cotton yields. In Kazakhstan, this relationship holds both for adopters and non-adopters, while in Uzbekistan it holds only for “conventional cotton” growers. Figure 1 suggested that the high quality of irrigation infrastructure is important for the adoption of crop rotation. Furthermore, according to Löw et al. (2017) widespread access to irrigation water at main canals can increase cotton yields by 280 kg/ha in Uzbekistan.

Uzbekistan's subsidized inputs and loans for “conventional cotton” monoculture prevent farmers from practicing sustainable crop rotation and accessing inputs and machinery services. Credit-rationed Uzbek adopters usually lack access to inputs and machinery services required for sustainable crop rotation. The model results show that cotton net returns and yields of credit-rationed adopters can be penalized by the lack of access to fertilizers and machinery services. In “conventional cotton” monoculture, farmers’ lack of access to credit is offset by the centralized provision of subsidized fertilizers and machinery services. In Kazakhstan, credit-rationing does not necessarily penalize cotton growers, since their contracts with ginneries guarantee inputs and machinery services. Participation in contract farming can positively affect crop yields and net revenues through better input access (Dubbert, 2019).

The priority setting by parastatal ginneries in Uzbekistan for ‘conventional cotton’ monoculture is visible also in the relationship between soil quality and cotton yields. In Kazakhstan, where farmers have land allocation freedom, soil fertility is linked to higher cotton yields for both adopters and non-adopters. In contrast, in Uzbekistan, cotton growers' performance is not linked to land quality, as the government until recently allocated land without considering its quality (Djanibekov et al., 2012). Along with the Uzbek policy of subsidized inputs and machinery services, the centralized land allocation reduces the relationship between soil quality and cotton yields (Shtaltovna and Hornidge, 2014).

In Kazakhstan, contract farming emphasizes ‘conventional cotton’ monoculture, leading to higher net returns and cotton yields for non-adopters. Conversely, adopters of crop rotation in contract farming tend to have lower cotton yields. The contracts with private ginneries typically stipulate repeated cotton cultivation as ‘conventional cotton’ monoculture. Transitioning to perennial crops to maintain land quality poses challenges for farmers reliant on ginneries for inputs and financing. (Petrick et al., 2017).

In both Uzbekistan and Kazakhstan, the distance to a district center negatively impacts the net returns and cotton yields of both adopters and non-adopters. This implies that cotton growers' performance tends to worsen as they move farther from district centers. This is due to increased transportation costs for accessing input and output markets. Interestingly, in Uzbekistan, adopters of crop rotation located further from a district center may have higher cotton yields. This suggests that remote crop rotation practitioners enjoy more decision-making autonomy compared to those closer to district centers, where government supervision is easier due to the proximity of cotton fields to administrative hubs (Shtaltovna and Hornidge, 2014).

For adopters and non-adopters in both countries, the farm fields’ location along an irrigation canal is positively related to net returns and cotton yields. In fact, the proximity of farm fields to the irrigation canal ensures adequate, timely and more secure water access for cotton cultivation. Similarly, Löw et al. (2017) found that in Uzbekistan less productive cotton fields are located further away from main irrigation canals. However, the benefit is higher for adopters, suggesting that crop rotation allows farmers to better utilize their advantage in irrigation water access. The lower effect of irrigation water access on non-adopters’ cotton yields can come from the government policy of subsidized inputs and machinery to cotton growers, which favors ‘conventional cotton’ monoculture.

The regional dummy variable has a positive effect on net returns and cotton yield for adopters and non-adopters in Kazakhstan. This suggests that compared to cotton growers in Maktaaral district (reference group), adopters and non-adopters of crop rotation in Shardara district are likely to have higher net returns and cotton yields. In the case of Uzbekistan, non-adopters in Pastdargom district have lower cotton yields than non-adopters in Payarik district (reference group). The 2018 official agricultural statistical data confirms that cotton yields in Shardara district (2.74 ton/ha) were higher than in Maktaaral district (2.53 ton/ha). Similarly, according to Uzbekistan's 2018 official statistical data, cotton yields in Payarik district (1.53 ton/ha) were higher than in Pastdargom district (1.12 ton/ha).

Table 2.3: Second stage endogenous switching regression estimates for net returns from cotton

	Kazakhstan						Uzbekistan					
	Adopters			Non-adopters			Adopters			Non-adopters		
	Coeff.	[90% confidence interval]		Coeff.	[90% confidence interval]		Coeff.	[90% confidence interval]		Coeff.	[90% confidence interval]	
Log of total cotton fertilizer cost (US$/ha)	-0.132 (0.085)	-0.275	0.011	-0.025 (0.059)	-0.123	0.073	-0.330 (0.448)	-1.082	0.421	0.020 (0.142)	-0.214	0.254
Log of total labor in a farm (persons /ha)	0.012 (0.062)	-0.091	0.116	0.024 (0.035)	-0.034	0.081	0.021 (0.123)	-0.186	0.228	0.083 (0.056)	-0.010	0.176
Log of cotton area (ha)	0.238 (0.080)	0.103	0.371	-0.014 (0.048)	-0.093	0.065	-0.012 (0.118)	-0.210	0.186	0.168 (0.082)	0.033	0.304
Farmer’s age (year)	0.001 (0.007)	-0.010	0.013	-0.008 (0.003)	-0.012	-0.003	-0.006 (0.006)	-0.015	0.004	-0.003 (0.004)	-0.009	0.004
Farmer has education in agriculture (1/0)	-0.070 (0.173)	-0.361	0.221	-0.052 (0.098)	-0.214	0.110	0.148 (0.153)	-0.109	0.405	0.251 (0.067)	0.140	0.362
Farmer perceives canal condition as good (1/0)	0.242 (0.130)	0.024	0.461	0.219 (0.090)	0.070	0.369	-0.036 (0.144)	-0.278	0.206	0.248 (0.097)	0.088	0.409
Credit-rationed farmer (1/0)	0.017 (0.144)	-0.224	0.259	0.068 (0.079)	-0.063	0.199	-0.545 (0.275)	-1.005	-0.084	0.036 (0.096)	-0.124	0.195
Farmer participates in farm trainings (1/0)	0.228 (0.374)	-0.399	0.855	0.091 (0.263)	-0.343	0.525	0.155 (0.158)	-0.109	0.420	-0.020 (0.101)	-0.187	0.148
Share of land with good fertility (0-1)	0.187 (0.114)	-0.004	0.378	0.080 (0.075)	-0.044	0.204	0.065 (0.248)	-0.351	0.482	-0.016 (0.098)	-0.179	0.146
Distance to the district center (km)	-0.021 (0.006)	-0.030	-0.011	-0.006 (0.003)	-0.011	-0.001	0.014 (0.014)	-0.010	0.038	-0.011 (0.006)	-0.021	-0.001
Farm fields located at irrigation canal head (1/0)	0.303 (0.136)	0.074	0.532	0.098 (0.089)	-0.049	0.245	0.543 (0.287)	0.061	1.025	0.043 (0.104)	-0.129	0.215
Farmer perceives land tenure as secure (1/0)	x	x	x	x	x	x	-0.721 (0.464)	-1.498	0.057	0.168 (0.126)	-0.040	0.376

Table 2.3 cont.

	Kazakhstan						Uzbekistan					
	Adopters			Non-adopters			Adopters			Non-adopters		
	Coeff.	[90% confidence interval]		Coeff.	[90% confidence interval]		Coeff.	[90% confidence interval]		Coeff.	[90% confidence interval]	
Farmer participates in contract farming (1/0)	-0.243 (0.154)	-0.501	0.015	0.215 (0.080)	0.083	0.348	x	x	x	x	x	x
Farm located in Shardara (1/0)	1.375 (0.390)	0.720	2.029	0.327 (0.157)	0.068	0.586	x	x	x	x	x	x
Farm located in Pastdargom (1/0)	x	x	x	x	x	x	0.191 (0.173)	-0.100	0.481	-0.121 (0.067)	-0.231	-0.010
mills1	0.204 (0.364)	-0.406	0.814	x	x	x	-1.616	-2.624	-0.609	x	x	x
mills2	x	x	x	-0.101	-0.737	0.535	x	x	x	0.183	-0.388	0.754
_cons	6.332 (0.999)	4.658	8.007	7.057 (0.324)	6.521	7.593	10.658 (3.165)	5.352	15.964	5.924 (0.713)	4.747	7.102
N	64			214			64			243		
R-squared	0.423			0.163			0.419			0.163		

Note: Standard error in parenthesis. Net returns from cotton is given in US$/ha (ln).

Source: Based on the AGRICHANGE 2019 farm survey data.

Table 2.4: Second stage endogenous switching regression estimates for cotton yield

	Kazakhstan						Uzbekistan					
	Adopters			Non-adopters			Adopters			Non-adopters		
	Coeff.	[90% confidence interval]		Coeff.	[90% confidence interval]		Coeff.	[90% confidence interval]		Coeff.	[90% confidence interval]	
Log of total cotton fertilizer cost (US$/ha)	0.050 (0.057)	-0.046	0.147	0.104 (0.039)	0.039	0.169	0.096 (0.205)	-0.247	0.440	0.159 (0.078)	0.031	0.288
Log of total labor in a farm (persons /ha)	0.049 (0.040)	-0.019	0.116	0.042 (0.026)	-0.001	0.085	0.051 (0.061)	-0.052	0.153	-0.007 (0.030)	-0.056	0.043
Log of cotton area (ha)	0.184 (0.055)	0.093	0.276	-0.009 (0.036)	-0.069	0.050	-0.044 (0.061)	-0.146	0.057	-0.002 (0.036)	-0.061	0.057
Farmer's age (year)	0.001 (0.004)	-0.006	0.009	-0.004 (0.002)	-0.008	0.000	-0.001 (0.003)	-0.006	0.004	-0.002 (0.002)	-0.005	0.001
Farmer has education in agriculture (1/0)	-0.127 (0.111)	-0.312	0.059	0.001 (0.069)	-0.113	0.115	0.005 (0.074)	-0.121	0.130	0.077 (0.036)	0.018	0.135
Farmer perceives canal condition as good (1/0)	0.118 (0.095)	-0.041	0.278	0.120 (0.064)	0.014	0.225	-0.007 (0.079)	-0.139	0.126	0.037 (0.059)	-0.048	0.120
Credit-rationed farmer (1/0)	-0.010 (0.97)	-0.173	0.153	0.014 (0.066)	-0.095	0.122	-0.279 (0.127)	-0.491	-0.066	0.019 (0.048)	-0.060	0.099
Farmer participates in farm trainings (1/0)	0.160 (0.239)	-0.241	0.560	0.033 (0.181)	-0.267	0.332	0.001 (0.077)	-0.129	0.131	0.001 (0.048)	-0.077	0.080
Share of land with good fertility (0-1)	0.185 (0.083)	0.045	0.324	0.096 (0.053)	0.009	0.183	0.066 (0.117)	-0.131	0.262	0.062 (0.043)	-0.010	0.133
Distance to the district center (km)	-0.012 (0.004)	-0.018	-0.005	-0.004 (0.002)	-0.007	-0.001	0.012 (0.007)	0.001	0.024	-0.0004 (0.003)	-0.006	0.005
Farm fields located at irrigation canal head (1/0)	0.164 (0.105)	-0.012	0.339	0.055 (0.063)	-0.049	0.159	0.246 (0.141)	0.009	0.483	0.046 (0.051)	-0.038	0.131
Farmer perceives land tenure as secure (1/0)	x	x	x	x	x	x	-0.333 (0.208)	-0.682	0.016	0.037 (0.059)	-0.061	0.135

Table 2.4 cont.

	Kazakhstan						Uzbekistan					
	Adopters			Non-adopters			Adopters			Non-adopters		
	Coeff.	[90% confidence interval]		Coeff.	[90% confidence interval]		Coeff.	[90% confidence interval]		Coeff.	[90% confidence interval]	
Farmer participates in contract farming (1/0)	-0.240 (0.114)	-0.430	-0.049	0.115 (0.058)	0.020	0.211	x	x	x	x	x	x
Farm located in Shardara (1/0)	0.835 (0.272)	0.378	1.291	0.233 (0.095)	0.076	0.390	x	x	x	x	x	x
Farm located in Pastdargom (1/0)	x	x	x	x	x	x	0.018 (0.075)	-0.107	0.143	-0.128 (0.032)	-0.181	-0.075
mills1	0.156 (0.224)	-0.219	0.531	x	x	x	-0.832 (0.267)	-1.279	-0.384	x	x	x
mills2	x	x	x	-0.065 (0.286)	-0.538	0.407	x	x	x	0.001 (0.161)	-0.265	0.266
_cons	6.697 (0.636)	5.631	7.763	7.325 (0.230)	6.945	7.706	8.630 (1.458)	6.186	11.075	7.006 (0.369)	6.396	7.616
N	64			214			64			243		
R-squared	0.425			0.177			0.475			0.151		

Note: Standard error in parenthesis. Cotton yield is given in kg/ha (ln).
Source: Based on the AGRICHANGE 2019 farm survey data.

2.4.3 *Cotton yield and net returns impacts of the adoption of crop rotation*

As described earlier, the impact of the adoption of crop rotation on farmers' expected outcomes under actual and counterfactual conditions is measured by the average treatment effect on the treated (ATT) and the average treatment effect on the untreated (ATU) estimated by the ESR model. Table 2.5 presents the results from the ESR treatment effect model for Kazakhstan and Uzbekistan. The fifth column of Table 2.5 provides the treatment effects of the adoption of crop rotation. The obtained results reveal that the impact of the adoption of crop rotation on net returns and cotton yields differs between Kazakh and Uzbek farmers.

The adoption of crop rotation has a negative impact on the outcomes of Kazakh farmers. This means that in Kazakhstan, the treatment effect of the adoption of crop rotation on net returns and cotton yield per ha is -0.168 and -0.139, respectively. In other words, interviewed Kazakh adopters of crop rotation would have received 15% higher net returns and 12% higher cotton yields had they not adopted crop rotation. Based on a meta-regression analysis, Ogundari and Bolarinwa (2018) show that crop rotation among other natural resource management strategies has a substantial effect on production and social measures but not on economic outcomes. Such an unexpected impact of crop rotation on the performance of cotton growers in Kazakhstan can be explained by the fact that the existing institutional environment and infrastructure in Kazakhstan after the cotton sector reform actually provide an advantage to farmers who practice "conventional cotton" monoculture. In the sample of Kazakh respondents, cotton is cultivated on 85% of farmers' sown area (Table 2.1). This can be explained by conditions imposed by contract farming arrangements with private ginneries, favoring cotton monoculture practices to ensure a supply of raw cotton (Petrick et al., 2017). Thus, Kazakh farmers who choose sustainable crop rotation are likely to lose timely access to the ginnery's provision of inputs like seeds, fertilizers, pesticides, and machinery services. This suggests that to promote sustainable agricultural practices in Kazakhstan's cotton growing areas, economic incentives for both sides of the contractual arrangement should be considered, not only for cotton growers but also for processors.

In contrast, the adoption of crop rotation has a positive impact on both outcome variables of Uzbek cotton growers. The estimation results reveal that the adoption of crop rotation increases cotton yields and net revenues by 19% and 5% respectively. In other words, interviewed Uzbek farmers who actually adopted crop rotation would have obtained 19% less net returns or 5% less cotton yield had they not adopted crop rotation. These findings are confirmed by other studies. For instance, Zhao et al. (2020) found that in China crop rotation increased cotton yields on average by 20% compared with "conventional cotton" monoculture. Löw et al. (2017) found that higher cotton yields in Uzbekistan are likely to be areas with higher share of crop rotation area.

For both countries, the model results show that cotton growers who actually did not adopt crop rotation would have lower net returns and cotton yields if they had adopted this practice. Although, the ATU on the outcome variable is negative, the result presents positive TH effects for net returns and cotton yields among Uzbek cotton growers indicating that net returns and cotton yields are higher among adopters of crop rotation. However, negative TH effects are observed for Kazakh cotton growers revealing that cotton yields and net returns are lower among adopters of crop rotation.

Furthermore, counterfactual adopters of crop rotation have higher cotton yield and net returns than actual non-adopters in both countries (Table 2.5). The result shows that there are several important sources of heterogeneity that make adopters of crop rotation better cotton producers than non-adopters.

Table 2.5: Average expected net returns and cotton yield for adopters and non-adopters of crop rotation in Kazakhstan and Uzbekistan

	Category	To adopt	Not to adopt	Treatment effect		
1	2	3	4	5	6	
Cotton net returns (US$/ha) (ln)		Decisions in Kazakhstan			[90% confidence interval]	
	ATT	(a) 6.587 (0.039)	(c) 6.755 (0.025)	-0.168 (0.048)	-0.247	-0.088
	ATU	(d) 6.639 (0.031)	(b) 6.723 (0.015)	-0.084 (0.034)	-0.140	-0.027
	HE	BH_1= -0.052	BH_2= 0.03	TH = -0.084		
		Decisions in Uzbekistan				
	ATT	(a) 6.591 (0.042)	(c) 6.415 (0.028)	0.176 (0.051)	0.091	0.260
	ATU	(d) 6.263 (0.031)	(b) 6.363 (0.015)	-0.100 (0.034)	-0.156	-0.043
	HE	BH_1= 0.328	BH_2= 0.052	TH = 0.276		
Cotton yield (kg/ha) (ln)		Decisions in Kazakhstan				
	ATT	(a) 7.561 (0.028)	(c) 7.700 (0.017)	-0.139 (0.032)	-0.193	-0.084
	ATU	(d) 7.578 (0.021)	(b) 7.668 (0.011)	- 0.090 (0.024)	-0.129	-0.051
	HE	BH_1= -0.017	BH_2= 0.032	TH =-0.049		
		Decisions in Uzbekistan				
	ATT	(a) 7.802 (0.022)	(c) 7.757 (0.012)	0.045 (0.025)	0.002	0.086
	ATU	(d) 7.594 (0.018)	(b) 7.712 (0.007)	-0.118 (0.019)	-0.150	-0.086
	HE	BH_1=0.208	BH_2=0.045	TH =0.163		

Note: Standard errors are in parenthesis. For calculation of the percent differences of treatment effect, 100*(e^{ATT} -1) equation is used following Asfaw et al. (2012).

Source: Based on the AGRICHANGE 2019 farm survey data.

3 DOES ZERO TILLAGE SAVE OR INCREASE PRODUCTION COSTS OF SMALLHOLDERS IN KYRGYZSTAN?[3]

3.1 Smallholders' challenges in the adoption of conservation agriculture in Kyrgyzstan

Kyrgyzstan is a land-locked low-income food-deficit country with a population of about 6 million, of which almost two-thirds live in rural areas (FAO, 2020). In 2021, GDP per capita was US$ 1,123 (in constant 2015 US$). Despite the progress in poverty reduction, one-fourth of the population lives below the poverty line (World Bank, 2023). Rural areas, where two-thirds of the population live in poverty, are still lagging behind these figures (FAO, 2020). Although agriculture's contribution to the country's gross domestic product (GDP) has been steadily declining, it still plays a central role in the rural economy. In 2021, agriculture accounted for almost 15% of GDP (World Bank, 2023). As of 2019, about 20% of employment was in agriculture (World Bank, 2023).

Kyrgyzstan's late-1990s land reform drove the switch from planned socialist agriculture to smallholder market-oriented agriculture (Lerman and Sedik, 2018). Through the recognition of private land ownership in 1996-1999 the government redistributed over 80% of arable land among rural families, creating a smallholder-based farming system (FAO, 2020). The majority of smallholders are characterized by intercropped and mixed crop-livestock systems with production mostly for their own consumption (Jalilova et al., 2019). In 2016, the official statistics reported about 1,150,000 rural households and peasant farms with an average size of about 0.87 ha (FAO, 2020). This includes 727,000 rural households with an average land size of about 0.1 ha, and 415,000 peasant farms with an average size of 2.2 ha (FAO, 2020).

Although the smallholders have been important in food security and poverty alleviation, the fragmented nature of the farming system is prone to the problems of 'smallness'. For instance,

[3] Chapter 3 was published following open-access article: Tadjiev, A., Djanibekov, N., Herzfeld, T. (2023) Does zero tillage save or increase production costs? Evidence from smallholders in Kyrgyzstan. *International Journal of Agricultural Sustainability* 21 (1), 2270191. https://doi.org/10.1080/14735903.2023.2270191. This chapter builds upon that article.

in fragmented agricultural settings of Kyrgyzstan, limited physical, financial, and human resources raise concerns about the future of agricultural food production and the sustainability of arable lands (Wolfgramm et al., 2010). Among the reasons is that rural households have to cope with the increasing costs of agricultural inputs. Most public finance and agricultural subsidies do not reach rural households and are captured by large commercial farms (Lerman and Sedik, 2018). The government does not have a sufficient budget to provide adequate support to smallholders to cover field operation costs. The scarcity of agricultural machinery has been imposing high machinery service costs for land preparation among smallholders, making it 55% more expensive than in neighboring southern Kazakhstan, and has hindered agricultural productivity in Kyrgyzstan (Guadagni and Fileccia, 2009). Farmers might be facing a mix of price, risk and quantity rationing as the number of credits at affordable rates is limited (Kuhn and Bobojonov 2021). The high rates and transaction costs of commercial credits may be unacceptable for smallholders the majority of whom cannot access limited subsidized credits.

The lack of access to new technologies and to knowledge of conservation tillage practices limits the wider adoption of zero tillage among smallholders in Kyrgyzstan. Kyrgyzstan's irrigated agriculture is among the most vulnerable in Eastern Europe and Central Asia to climate change (Fay et al., 2010). A modeling study by Bobojonov and Aw-Hasan (2014) suggests that under a water shortage scenario, predicted farm incomes in the semiarid parts of Kyrgyzstan might decline by 15% harming smallholders' profits and long-term sustainability. In light of the importance of agriculture in rural incomes and food security, the intensity and spread of land degradation and increasing pressure from water scarcity will affect agricultural productivity and threaten agricultural livelihoods.

Cost-saving practices like zero tillage can be an option for smallholders that suffer from low credit access, underinvestment and are prone to water stress. In 2016, the full technical potential adoption level of conservation agriculture in Kyrgyzstan, including reduced and zero-tillage and crop rotation, was estimated at 1.2 million ha of cultivated area under cereals, oil and leguminous crops (Polo et al., 2022). The results of the financial analysis presented by Polo et al. (2022) show that conservation agriculture scores moderately with an investment return rate of 13% and a payback period of seven years. It was estimated that conservation agriculture can increase agricultural production via long-term improved soil nutrient management and water retention. For instance, raised-bed and no-tillage planting can increase wheat yield by 25–38% compared to the conventional cultivation method (Nurbekov et al., 2016). The economic value of the annual additional production due to the adoption of conservation agriculture in Kyrgyzstan was estimated at over US$ 35 million or 9% of gross agricultural value (Polo et al., 2022). However, despite these advantages, the gap between present and potential uptake has remained substantial with little change (Polo et al., 2022).

3.2 Conceptual framework

Numerous studies have noted three paradigms such as "the innovation-diffusion", "the adoption perception" and "economic constraints" to define farmers' adoption of conservation practices (Chatterjee and Acharya, 2021; Ruzzante et al., 2021). Each paradigm assumes several factors influencing the adoption decision (Figure 3.1). For example, to illustrate adoption behavior, the economic paradigm assumes the maximization of the farmer's profit and considers economic constraints such as access to natural resources, access to capital, investment costs and risk attitude. The innovation-diffusion paradigm assumes that access to information is the main parameter to improve adoption decisions. The adoption perception paradigm postulates that a farmer's adoption behavior depends on perceived attributes of innovation, access to information, and individual factors such as the farmer's experience and education, as well as institutional factors that can affect their perceptions (Ruzzante et al., 2021).

I conceptualize that a household faces the decision to adopt zero tillage on a specific plot versus conventional tillage methods in crop cultivation. From this perspective, the economic paradigm stipulates that the adoption decision occurs under the farmer's objective of profit maximization.

Thus, it can be assumed that a farmer will adopt zero tillage method if the expected net returns from the adoption are maximized given crop yields and output prices. In this regard, the adoption decision is related to the farmer's perception whether adoption reduces production costs or not, i.e. production costs under adoption (C_a) are lower than the ones under nonadoption (C_{na}), thus, $(C_{na} - C_a > 0)$

The adoption of zero tillage can, thus, be considered as a farmer's binary choice that is influenced by various factors related to individual characteristics of the household head, household farm characteristics, institutional and location settings. Along with the adoption of zero tillage, these factors can change the structure of production costs and reduce the total production costs. Household head and farm characteristics include gender, ethnicity, education, experience, occupation, and age of the household head, as well as household size, wealth, number and size of operated plots and livestock.

Farmers with a higher level of education, or with longer schooling years, are more likely to adopt zero tillage as education increases comprehension about application methods and about benefits of sustainable agricultural practices (El-Shater et al., 2020; Jaleta et al., 2016; Yigezu et al., 2021). The age of the household head is negatively related to the likelihood of minimum tillage adoption (Ngoma, 2018). One common explanation for this is that older farmers are more risk-averse than younger farmers and, thus, are less likely to adopt new technologies. The adoption of minimum tillage can also be associated with the occupation of the household head in farming and agriculture (Musafiri et al., 2022). Household heads working in agriculture are more likely to be exposed to training and practical application of new methods. Furthermore, the adoption decision can vary with respect to the household head's gender. Female farmers can have difficulties in accessing productive resources such as machinery services, agricultural credits and have lower non-farm opportunities (Wainaina et al., 2016). As a result of resource access problems, they are more likely to adopt resource-saving agricultural practices rather than input-intensive ones (Rola-Rubzen et al., 2020). Moreover, the decision to adopt agricultural practices can vary across household ethnicity. Atamanov and Van den Berg (2012) found that Kyrgyz households are more likely to narrowly focus on farming activities rather than other rural nonfarm activities and are less likely to mix farm and nonfarm activities.

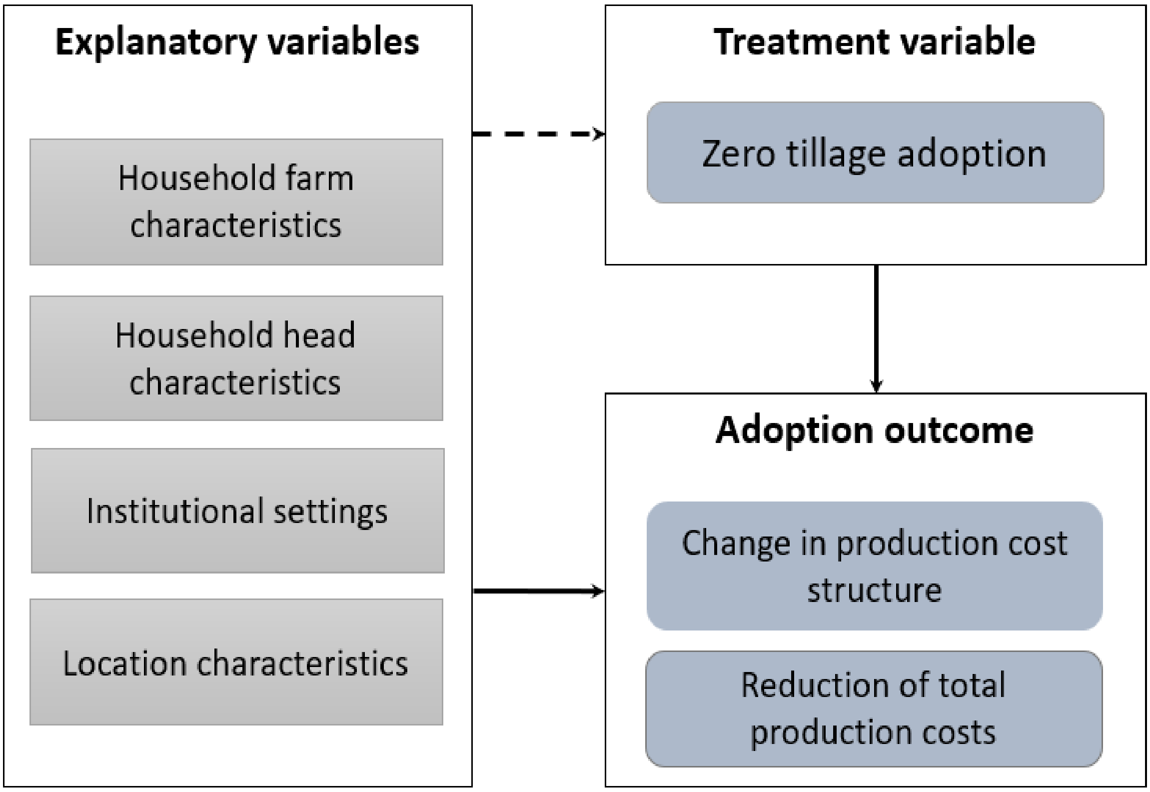


Figure 3.1: Conceptual framework displaying hypothesized determinants of zero tillage adoption and its economic effects on production costs

Source: Tadjiev et al. (2023a).

The adoption of minimum tillage can be determined by the number of household members. For instance, empirical evidence shows that the likelihood of adopting minimum tillage decreases with the increase in household size (Montt and Luu, 2020). Tambo and Mockshell (2018) found a negative and statistically significant relationship between minimum soil disturbance and household size, thus pointing out that households with fewer family members are likely to adopt minimum tillage. The size of household plots can also explain the decision to adopt agricultural practices. According to Teklewold et al. (2013) households with larger arable plots are more likely to adopt conservation tillage practices. Similarly, Jaleta et al. (2016) found that households with larger plots tend to adopt minimum tillage. Furthermore, a greater distance of household plots from the homestead increases the likelihood of adopting minimum tillage (Jaleta et al., 2016).

The adoption of resource-saving practices is likely to be lower among households who own agricultural machinery and equipment because these tools allow households to receive better control over the application of conventional tillage methods (Jansen et al., 2006). Furthermore, Ngoma (2018) found that an increase in household assets reduces the likelihood of minimum tillage adoption. The adoption of minimum tillage can be negatively associated with a household's ownership of livestock because such households rely on the harvesting of crop residues for animal feeding (Jaleta et al., 2016). Finally, institutional settings are important in supporting the adoption decisions of smallholders. They can improve a farmer's financial capacity and either promote the adoption of costly tillage practices or improve the farmer's ability to take up resource-saving practices. For instance, according to Musafiri et al. (2022) the adoption of minimum tillage is positively associated with a household's access to credit.

3.3 Data and descriptive analysis

For this empirical investigation, I used the dataset from the "Life in Kyrgyzstan" (LiK) survey. The LiK collects data from all provinces of Kyrgyzstan and two major cities. The LiK is an open access, longitudinal survey and is representative at the national and regional levels (East, West, North, South), as well as for urban and rural areas (Brück et al., 2014). The LiK contains six waves conducted in 2010, 2011, 2012, 2013, 2016, and 2019. Initially, the first wave covered 3000 households and 8160 individuals from these households (Brück et al., 2014). The households for the study were drawn using stratified two-stage random sampling (Brück et al., 2014). As a multi-purpose, socio-economic survey it covers a wide range of topics for economic and sociological research (Brück et al., 2014). An agricultural module that covers plot-level data about crop cultivation and tillage methods was introduced in the 2016 wave and repeated in 2019. These two waves cover 2529 and 2316 households, respectively.

I applied several conditions to narrow the dataset to fit my research objectives. Since the study focuses on rural households, I excluded observations in the cities of Bishkek and Osh as these cover urban households without or with limited agricultural activities. As the agricultural module comprises questions across household plots, all variables are listed at the plot level. The plot-level specification of the dataset also allows for an increase in the number of observations in the sample. Furthermore, I kept only observations of rural households that operated plots for crop cultivation. Therefore, the sample does not include households that did not cultivate land or that focused only on livestock keeping without land operations.

I assumed that household heads were the main decision-maker in agriculture in households and thus accounted for their responses. In the sample, 82% of respondents in 2016 and 75% of respondents in 2019 wave were household heads. I kept rural households that participated in both 2016 and 2019 waves. In the end, the total sample covers 2788 plot-level observations that belong to 878 rural households. I pooled two-year panel data to take advantage of the variability in the dataset. Since some households used a different number of plots across the two years, the panel data is an unbalanced one.

The average size of household lands in the sample is about 1.6 ha, which is close to the national average size of rural households in Kyrgyzstan. The average size of a household plot in the sample is about 0.8 ha. Each household has on average 2 plots. In the 2019 data out of 878 interviewed households, 149 households were commercial, i.e. cultivating crops for sale. 531 households were subsistence, i.e. cultivating crops purely for home consumption. 101 households were a mix of commercial and subsistence. The remaining 97 respondents were either cultivating fodder crops or could not answer the question.

The questionnaire addresses a question to household heads that is “What types of tillage methods were used in this field?”. This question lists eight answers with an option to choose up to two main tillage methods applied in a particular plot. I treated the responses “zero tillage” and “did not till – broadcast seed” as zero tillage method. The other six tillage methods which include hand tillage, ploughing with tractor, ploughing with horses, ridging (before planting), mounding and other tillage methods, I aggregated into a non-zero tillage method. By doing so, a binary choice variable was generated with two expressions such as 0 standing for non-zero tillage and 1 for zero tillage use. The full sample of 2016 and 2019 of 878 interviewed households has 297 households, or about one-third of respondents, who applied zero tillage on one of the plots.

The survey provides plot-level information on payments for hired labor, machinery costs for land preparation and seeding, weeding, and herbicide costs. I used these responses for outcome variables to estimate the economic effect of zero tillage adoption on production costs. The outcome variables are given in the national currency, Kyrgyz Som (KGS), which were converted to US dollars[4]. If households responded that they did not report about input costs, their values were reported as zero. Households provided information on costs for land preparation, seeding, and weeding for each crop at a plot level. These variables include costs for own and hired machinery services. The machinery cost variable in the model comprises two outcome variables, namely “Machinery costs for land preparation and seeding” and “Machinery costs for weeding”. About 73% of interviewed household heads, i.e. 640 households out of 878, in the sample reported incurring machinery costs for land preparation and seeding on at least one plot. About 34% of interviewed household heads in the sample reported machinery costs for weeding. I aggregated land preparation and seeding costs for all crops and generated total land preparation costs at a plot level. Similarly, I generated a variable of total weeding costs at a plot level. Finally, all mentioned input costs were added to total production costs.

To understand the use of zero tillage by smallholders in Kyrgyzstan, I conducted field research in September 2021 with open-ended interviews of key experts such as farmers, staff of crop

[4] According to the National Bank of Kyrgyzstan, an average exchange rate in 2016 was 1$=69.90 KGS and in 2019 1 US$=69.79 KGS.

research institutes, university researchers and experts from the Bishkek office of the UN Food and Agricultural Organization (FAO). These interviews provided additional information to interpret the estimation results.

Table 3.1 provides information about several control variables used in this chapter. The variables are divided into “outcome variables” which are production costs, “treatment variable” which is a dummy variable of plots with or without zero tillage, and “explanatory variables”. Explanatory variables comprise “household characteristics” and “plot characteristics”. To account for heterogeneity, I used household and plot characteristics such as age, education, gender, ethnicity of the household head, number of household members, number of assets, tractor ownership, receiving remittance, plot size, plot distance from dwelling, fertilizer use etc. The summary statistics across the treatment variable are also presented in Table A4 in the Appendix.

Table 3.1: Summary statistics of variables by survey year

Variables	2016		2019		Full sample	
	Mean	Sd	Mean	Sd	Mean	Sd
Outcome variables						
Total payment for hired labor (US$/ha)	10.217	52.284	6.747	37.924	8.443	45.539
Machinery costs for land preparation and seeding (US$/ha)	35.149	61.600	37.769	81.693	36.488	72.567
Machinery costs for weeding (US$/ha)	7.144	36.072	10.736	48.454	8.980	42.880
Herbicide costs (US$/ha)	7.262	34.853	21.942	77.896	14.690	61.015
Total machinery, labor and herbicide costs (US$/ha)	59.539	121.217	74.960	152.445	67.342	138.095
Treatment variable						
Plots under zero tillage (1/0)	0.068	0.252	0.204	0.403	0.137	0.344
Household head characteristics						
Age of household head (year)	55.794	12.450	56.189	11.958	55.996	12.201
Education level of household head (categorical, 1=illiterate…7=university degree)	4.333	1.275	4.217	1.185	4.274	1.231
Female household head (1/0)	0.199	0.399	0.253	0.435	0.226	0.419
Household head employment in agriculture (1/0)	0.340	0.474	0.337	0.473	0.339	0.473
Household head’s ethnicity (1/0, 1 = Kyrgyz)	0.785	0.411	0.769	0.422	0.777	0.416

Table 3.1 cont.

Variables	2016		2019		Full sample	
	Mean	Sd	Mean	Sd	Mean	Sd
Household farm characteristics						
Number of household members that can work in agriculture (above 10 and under 65 years old)	4.407	1.781	4.570	1.927	4.490	1.859
Asset index	0.400	0.139	0.354	0.168	0.376	0.156
Household owns a tractor (1/0)	0.051	0.226	0.035	0.188	0.043	0.207
Number of livestock units owned by household	3.364	4.260	2.377	4.268	2.859	4.292
Household received remittances last year (1/0)	0.145	0.353	0.226	0.418	0.187	0.390
Household applied chemical fertilizers last year (1/0)	0.252	0.434	0.246	0.431	0.249	0.432
Household experienced a weather shock last year (1/0)	0.629	0.483	0.161	0.367	0.390	0.488
Household experienced an agricultural shock last year (1/0)	0.364	0.481	0.088	0.283	0.223	0.416
Plot under grains and legumes (1/0)	0.318	0.466	0.353	0.478	0.336	0.472
Plot under vegetables (1/0)	0.400	0.490	0.270	0.444	0.334	0.472
Plot under a mix of crops (grain, legumes and vegetables) (1/0)	0.073	0.260	0.022	0.146	0.047	0.211
Location characteristics						
Distance to main road from dwelling (km)	0.521	0.738	0.777	0.891	0.652	0.830
Distance from dwelling to plot (km)	1.470	2.840	1.174	2.536	1.319	2.693
Number of land plots owned by household	1.966	0.627	1.980	0.702	1.973	0.666
Plot size (ha)	0.694	1.340	0.794	1.898	0.745	1.649
Institutional settings						
Amount of credit received by household last year (US$)	210.154	775.394	339.183	1387.313	276.103	1131.974
Provinces						
Issyk Kul (1/0)	0.160	0.367	0.179	0.383	0.170	0.375
Djalal Abad (1/0)	0.213	0.409	0.201	0.401	0.207	0.405
Naryn (1/0)	0.073	0.260	0.048	0.213	0.060	0.237
Batken (1/0)	0.125	0.331	0.122	0.328	0.123	0.329
Osh (1/0)	0.260	0.439	0.293	0.455	0.277	0.448
Talas (1/0)	0.079	0.270	0.070	0.256	0.075	0.263
Chuy (1/0)	0.160	0.367	0.179	0.383	0.170	0.375

Note: N=1363 for 2016, N=1425 for 2019 and N=2788 for the full sample. Because of missing values of herbicide costs, the number of observations for 2016, 2019 and the full sample are 1342, 1396 and 2738, respectively.
Source: Tadjiev et al. (2023a).

As a proxy for household wealth, I calculated the asset index using the principal component analysis (PCA) as suggested in Filmer and Pritchett (2001). I used binary information regarding ownership of 35 assets based on the standardized PCA scores, and the min-max normalization (feature scaling) method was used to convert the scaled data to a range (0–1).

The number of total livestock units (TLU) is an additional household wealth indicator. I calculated TLU based on livestock unit coefficients[5]. First, I multiplied each type of livestock by LU coefficients, and then summarized the result by households. The summary statistics suggest that the number of livestock units owned by a household was on average 3 in 2016 and 2 in 2019.

In the study, I also considered the number of plots owned by households. Table 3.1 indicates that households have on average 2 plots in both years. Remittances and migration have been among the main income sources in rural areas of many developing countries and particularly of Kyrgyzstan where remittances affect households' decisions in agriculture (Atamanov and Van den Berg, 2012). Following the argument by Montt and Luu (2020) that successful conservation agriculture practice requires appropriate management of external inputs such as fertilizers, I added a household's application of fertilizers as an explanatory dummy variable in the models.

Furthermore, I considered the opinion of household heads about whether their households experienced agricultural shocks over the last year such as pest infestations, crop and livestock diseases, insufficient irrigation water supply, theft of livestock, or inability to sell agricultural products as well as weather shocks such as drought, flood, heavy rain or extremely cold winter temperatures. I assumed that such agricultural and weather shocks can affect a household's decision to adopt zero tillage practices by harming the household's agricultural outputs and assets.

[5] Total livestock units (TLU) is calculated based on livestock unit (LU) coefficients according to the following sources:
(1) https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:Livestock_unit_(LSU) and (2) http://adlib.everysite.co.uk/adlib/defra/content.aspx?id=000il3890w.198awldohj69f3#nix .

Smallholders often cultivate a mix of crops on a single plot. I aggregated all costs for various crop types to control their effect on zero tillage adoption decision. I generated three dummy variables which explain that the plot was cultivated (1) purely by grain and legume crops, (2) by vegetables, and (3) by a mix of grains, legumes and vegetables.

3.4 Methodological approach

The following subsections explain the empirical models and motivate the selection of the estimation strategy. The assessment of the economic effects of technology adoption from non-experimental survey data requires the correction of self-selection bias, identification of proper counterfactuals and control for non-observable farm characteristics (Asfaw et al., 2012; Jaleta et al., 2016). I based the identification of a farmer's decision to adopt zero tillage on the measurement of profitability through its production cost reducing effects. To estimate the impact of zero tillage on production costs, I followed the existing literature such as Abdulai and Huffman (2014), Jaleta et al. (2016), Keil et al. (2020), Khonje et al. (2018), and Montt and Luu (2020) and employed a two-stage estimation approach. I assessed different models to investigate the relationships between zero tillage adoption and payments for hired labor, machinery costs for land preparation and seeding, weeding, and herbicide costs as well as total costs. The Mundlak device (Mundlak, 1978) was employed to estimate time-invariant endogeneity. Furthermore, I used the endogenous switching regression (ESR) model to account for selection bias. To estimate the association between zero tillage adoption and each production cost considered above, I used the counterfactual framework that measures average treatment effects on the treated (ATT).

3.4.1 Zero tillage adoption decision and production costs

The decision to adopt zero tillage and the selection of plots under this method are made by a household head and other household members, and thus are not random. Such a self-selection problem implies a potential bias in the effect of zero-tillage adoption on production costs. In reality, households might apply zero tillage on plots with higher production costs. As a result, the effect of zero tillage on production costs can be overestimated. As commonly done in other studies (e.g., Jaleta et al., 2016; Khonje et al., 2018; Keil et al., 2020; Montt and Luu, 2020), to correct for selection bias, I employed a two stage ESR model. In the first stage, I estimated the main determinants of zero tillage adoption. The probability of zero tillage adoption for an individual can be written as follows:

$$Pr(zt_{jit}) = f(X_{jit}) \quad (3.1)$$

where, $Pr(zt_{jit})$ is the probability of zero tillage adoption of i's household in j's plot at time t. X is a vector of explanatory variables describing household and plot characteristics, personal characteristics, location settings, etc.

I used the Mundlak approach where the means of observable time-variant variables were added to the model. The Mundlak approach is applied to panel fixed-effects in cases of variation within units over time and when time-invariant observables affect both adoption decision and outcomes (Khonje et al., 2018; Montt and Luu, 2020; Mundlak, 1978). This approach also reduces the problem of unobserved heterogeneity. The fundamental assumption of using the Mundlak approach is to consider unobserved time-invariant components by calculating and employing the mean of time-variant variables as a proxy (Montt and Luu, 2020; Mundlak, 1978). I computed the means of all time-variant variables ($\bar{x}_i$) and added them to a probit regression model to measure the probability of zero tillage adoption. Furthermore, I included province dummies (R_p, here, Issyk Kul is the reference province) and a time dummy (Y_t, here, 2016 is the reference year) for all models to account for the province-level and year differences. The regional dummies allow for accounting for other cross-regional differences that can be associated with adoption decisions such as costs of machinery, labor and other inputs. Thus, from Equation (3.1), a household i's likelihood of adopting zero tillage in their j's plot at time t can be formulated as:

$$Pr(zt_{jit} = 1|X_i, R_p, \overline{X_i}, Y_t) = \Phi(a_i + \beta' x_{jit} + \delta' x_{it} + R_p + Y_t) \quad (3.2)$$

where, β, δ and γ are the parameters to be estimated. x_{jit} contains observables at the plot level. x_{it} contains observables at the household level. $\bar{x}_i$ is the mean of time-varying variables that follow the Mundlak approach.

In the second stage, an OLS model was applied under two regimes, namely, under non-adoption and adoption of zero tillage. Here, the model estimates the relationship of outcome variables for zero tillage adopters and non-adopters as follows:

$$\begin{cases} y_{1jit} = K_{jit1}\beta_1 + \bar{k}_{i1}\nu_1 + R_p + Y_t + \eta_{1jit}, & \text{if } ZT = 1 \\ y_{0jit} = K_{jit0}\beta_0 + \bar{k}_{i0}\nu_0 + R_p + Y_t + \eta_{0jit}, & \text{if } ZT = 0 \end{cases} \quad (3.3)$$

where y_{jit} is an outcome variables such as machinery costs for land preparation, machinery costs for weeding, payment for hired labor, and herbicide costs, on plot j of i's household at time t. K_{jit} is a set of explanatory variables that relate to the outcomes. $\bar{k}_i$ is the mean of time-varying variables. As mentioned before, R_p and Y_t are the province and time dummies. Some households reported relatively high costs per plot and high amounts of credit. Therefore, the natural logarithm was used for these variables. However, there are some observations with "0" values. Hence, to avoid missing values, I added "+1" for these variables before transforming to the natural logarithm.

The probit model supplies essential information to examine and correct the potentially resulting bias (Maddala, 1983: 223; Petrick, 2004: 151). To test selection bias, I followed Heckman (1979) and used the Inverse Mills Ratio (IMR) calculated from the results of a probit estimation as follows:

$$\lambda_{1jit} = \varphi(\delta x_{jit})/\phi(\delta x_{jit}); \lambda_{0jit} = -\varphi(\delta x_{jit})/[1 - \phi(\delta x_{jit})] \quad (3.4)$$

where $\varphi(.)$ and $\Phi(.)$ indicate the density and cumulative density function of the standard normal distribution, respectively. λ_{0itj} and λ_{1itj} represent the IMR. The calculated IMR was added to the second stage model to correct selection bias and resulted in the following equation:

$$\begin{cases} y_{1jit} = K_{jit1}\beta_1 + \bar{k}_{i1}\nu_1 + R_p + Y_t + \lambda_{1jit}\sigma_1 + \ Y_t * \lambda_{1jit}\tau_1 + \eta_{1jit} & \text{, if } ZT = 1 \\ y_{0jit} = K_{jit0}\beta_0 + \bar{k}_{i0}\nu_0 + R_p + Y_t + \lambda_{0jit}\sigma_0 + \ Y_t * \lambda_{0jit}\tau_0 + \eta_{0jit} & \text{, if } ZT = 0 \end{cases} \quad (3.5)$$

Furthermore, to consider changes in the selection effect over time, the IMR was interacted with the time dummy ($Y_t * \lambda_{jit}$) following Montt and Luu (2020).

Several studies emphasize the selection of valid instruments that influence adoption decisions but do not affect outcome variables. I assume households near the main road will have more convenience in using conventional tillage methods due to easy access to machinery services and, thus, thus, are less likely to adopt zero tillage than households located further away from the road. A falsification test shows that "distance to the main road" relates to zero tillage adoption decision but does not affect the outcome variables (see Table A5 in the Appendix).

3.4.2 Estimation of average treatment effect on the treated

The average treatment effect was estimated within the ESR framework method to test the impact of zero tillage adoption on outcome variables. First, the expected outcomes of zero tillage adopters and non-adopters were compared in actual and counterfactual situations. The expected (actual) outcome for zero-tillage adopters can be expressed as follows:

$$E\left(y_{1jit} \middle| zero\ tillage = 1\right) = K_{jit1}\beta_1 + \bar{k}_{i1}\nu_1 + R_p + Y_t + \lambda_{1jit}\sigma_1 + \ Y_t * \lambda_{1jit}\tau_1 \quad (3.6)$$

The expected outcome for adopters had they not adopted zero tillage (counterfactual) can, thus, be expressed as follows:

$$E\left(y_{0jit} \middle| zero\ tillage = 1\right) = K_{jit1}\beta_0 + \bar{k}_{i1}\nu_0 + R_p + Y_t + \lambda_{1jit}\sigma_0 + \ Y_t * \lambda_{1jit}\tau_0 \quad (3.7)$$

Second, the differences between the actual and counterfactual expected outcomes, which explain the ATT are estimated as follows:

$$ATT = E\left(y_{1jit} \middle| zero\ tillage = 1\right) - E\left(y_{0jit} \middle| zero\ tillage = 1\right) \quad (3.8)$$

3.5 Results and discussion

3.5.1 Determinants of zero tillage adoption

This section briefly discusses the results from a probit adoption model since the primary interest of this chapter is to study the resource-saving impact of zero tillage. The average marginal effects are assessed from the probit model (Equation 3.2). The model results are given in the first column of Table 3.2. The statistical significance of the Wald test shows that all coefficients for explanatory variables are not simultaneously equal to zero. The falsification test shows a significant correlation between the instrumental variable and zero tillage adoption decision, but not with production costs (Table A5 in the Appendix). Hence, the selected instrument is plausible. The econometric models were estimated in STATA 17 software.

In summary, the results show that zero tillage is favored by poorer households whose heads are employed in agriculture, have fewer plots, are located in remote areas and do not apply chemical fertilizers. More specifically, household heads with agricultural employment are more likely to use zero tillage because they are exposed to knowledge about sustainable practices. Secondly, agricultural wages are lower than in other sectors (Atamanov and Van den Berg, 2012) and thus such households are more likely to opt for zero tillage rather than apply conventional tillage.

The relationship between the asset index of households and the adoption of zero tillage practices is negative. This indicates that households with more assets, i.e., wealthier households, are likely to adopt conventional agricultural practices that depend on mechanized tractor services. This result is consistent with Ngoma (2018), who found that household assets reduce the likelihood of minimum tillage adoption. Furthermore, the model results show that households with more plots are less likely to adopt zero tillage. Applying chemical fertilizer can also be related to smallholders' wealth status, where poor smallholders have more challenges accessing this input and often cannot afford it. The model result shows that households who apply chemical fertilizers are less likely to adopt zero tillage.

Households located further away from their land plots and main roads are likely to adopt zero tillage. This is not surprising since it is expected that households located further away from their lands and road are likely to have higher costs for accessing production inputs and machinery services and, thus, likely to switch to input-saving zero tillage. This result is in line with the findings of Jaleta et al. (2016) and Tessema et al. (2018), who found a positive relationship between plot distance and minimum tillage adoption. A remote location in a rural area can be associated with lower wealth status.

Households that experienced agricultural shocks are less likely to adopt zero tillage. Other studies that considered agricultural shocks, e.g., waterlogging stress by Teklewold et al. (2013), droughts and floods frequencies by Wainaina et al. (2016), did not find an association with the adoption of conservation tillage.

Finally, the estimation results show that the dummy variable of “grain and legume production” is positive but statistically insignificant in relation to zero-tillage adoption. In contrast, there is a negative and statistically significant relationship between vegetable production and zero tillage adoption decision. It can be explained that some vegetable crops may not be planted using zero-tillage method.

The negative values of regional dummy variables show that the adoption of zero tillage among smallholders in Djalal Abad, Osh and Talas regions is less likely than among smallholders in the Issyk Kul province. At the same time, there is no significant difference in likelihood of zero-tillage adoption between smallholders in the Issyk Kul province and in its neighboring Naryn and Chuy regions and the Batken province. Various unobserved region-specific characteristics can explain these cross-regional differences in the adoption of zero-tillage. For instance, higher population density and limited availability of land in Osh and Djalal-Abad provinces (Zhunusova and

Herrmann, 2018) can reduce smallholders' costs for hired labor in tillage operations and as a result lower the adoption rate of zero-tillage in these two provinces. Furthermore, agro-ecological zoning of the regions of Kyrgyzstan can account for differences in crop portfolio, production specialization and tillage methods (Jalilova et al., 2019). Chuy, Talas and Issyk Kul regions are closer agro-ecologically to each other representing the northern regions. Djalal Abad, Osh and Batken represent southern agro-ecological regions encompassing the Fergana valley. Naryn region represents the central zone with vast alpine areas of mountains and valleys suitable for winter grazing and crop cultivation.

Table 3.2: Determinants of zero tillage adoption decision

	Marginal effect	Standard error	[90% confidence interval]	
Age of household head (years)	0.0003	0.002	-0.002	0.003
Education level of household head (categorical, 1=illiterate…7=university)	0.002	0.005	-0.007	0.011
Female household head (1/0)	-0.008	0.016	-0.033	0.018
Household head employed in agriculture (1/0)	0.048	0.025	0.007	0.089
Number of household members that can work in agriculture (above 10 and under 65 years old)	-0.003	0.009	-0.018	0.011
Household head's ethnicity (1/0)	0.022	0.017	-0.005	0.050
Asset index	-0.245	0.068	-0.357	-0.132
Household owns a tractor (1/0)	0.089	0.051	-0.001	0.167
Household received remittances last year (1/0)	-0.042	0.028	-0.088	0.003
Household experienced a weather shock last year (1/0)	0.034	0.022	-0.002	0.069
Household experienced an agricultural shock last year (1/0)	-0.043	0.024	-0.082	-0.004
Amount of credits received by household last year (logarithm, US$)	0.002	0.003	-0.004	0.008
Number of land plots owned by household	-0.021	0.010	-0.038	-0.004
Number of livestock units owned by households	0.002	0.003	-0.002	0.007
Distance from dwelling to plot (km)	0.004	0.002	0.001	0.008
Household applied chemical fertilizers last year (1/0)	-0.051	0.019	-0.083	-0.020
Plot size (ha)	0.001	0.004	-0.005	0.006
Plot under grains and legumes (1/0)	0.009	0.017	-0.018	0.036
Plot under vegetables (1/0)	-0.062	0.017	-0.089	-0.035
Plot under a mix of crops (grain, legumes and vegetables) (1/0)	-0.026	0.034	-0.082	0.030
Djalal Abad (1/0)	-0.096	0.022	-0.131	-0.061
Naryn (1/0)	-0.042	0.028	-0.088	0.005
Batken (1/0)	0.012	0.022	-0.024	0.048
Osh (1/0)	-0.127	0.024	-0.166	-0.088
Talas (1/0)	-0.221	0.040	-0.286	-0.155
Chuy (1/0)	0.048	0.023	0.009	0.086
Survey year (2019=1)	0.133	0.015	0.108	0.158
Distance from dwelling to the main road (km)	0.019	0.007	0.008	0.031
Pseudo R2		0.168		
N		**2788**		

Source: Tadjiev et al. (2023a).

3.5.2 *Resource-saving effects of zero tillage*

Table 3.3 and Figure 3.2 present ESR-based average treatment effects of the adoption of zero tillage on the costs of labor, machinery and herbicide under actual and counterfactual conditions. The second-stage regression estimates (Equation 3.5) are not discussed due to space limitations (Table A6 in the Appendix).

The result of the average treatment effect shows that per-hectare costs of machinery land preparation and seeding are lower for plots under zero tillage. According to Figure 3.2, adopting zero tillage decreases land preparation and seeding costs by almost 23%. In other words, if households who applied zero tillage method would have decided not to use it, their per hectare land preparation cost would be higher by 23%. This result is in line with the findings of Erenstein et al. (2008) who found a negative effect of zero tillage on land preparation costs. Montt and Luu (2020) showed that the adoption of zero tillage reduces per-hectare costs for land preparation and threshing. Although, the per-hectare cost for mechanized weeding is higher for zero tillage plots, this difference is not statistically significant.

The adoption of zero tillage increases hired labor requirements. This is visible in the estimation results which show that payment for hired labor is higher for zero tillage plots than for plots under conventional tillage. The treatment effect of the adoption of zero tillage on the hired labor costs per ha is 0.125. This means that households who used zero tillage spent 13% more for hired labor than their counterfactual. This result is consistent with findings by Montt and Luu (2019) and Teklewold et al. (2013) who found that conservation tillage increases household labor demand and associated labor costs.

The results of the average treatment effect show a positive effect of zero tillage adoption on herbicide costs (Figure 3.2). Households spent 15% more on herbicides under zero tillage than under conventional tillage. This is in line with findings by Teklewold et al. (2013) who found that zero tillage adopters use more chemical pesticides and herbicides than nonadopters.

Furthermore, Polo et al. (2022) showed that during the first years, conservation practices in Kyrgyzstan can reduce fuel consumption and field operations, but can increase herbicide costs.

The above-mentioned positive effects of zero tillage adoption on labor and herbicide costs are related to the fact that zero tillage demands more labor resources and herbicides for weed management in the short term. This finding can be a sign that smallholders are lacking access to technologies specialized for conservation tillage and thus have to rely on family and hired labor. Merely implementing zero tillage practices is insufficient to reduce production costs. Its wider adoption requires a whole set of adjustments and specialized equipment such as seeding equipment modified to local conditions to manage and cut through crop residues, planting and weed control (Jaleta et al., 2019). Often adapting existing equipment for zero tillage purposes can be unfeasible and small size of farms impedes smallholders' investment in a specialized machine. The absence or high cost of adequate machines poses a significant obstacle to the widespread adoption of zero tillage practices among smallholders, hence limiting its future diffusion in Central Asia. Yigezu et al. (2018) showed that the provision of new technologies to smallholders via free trials and field days increases the speed and rate of adoption. Brazil's "zero-tillage revolution" is an example showing that a variety of relatively low-cost zero tillage equipment can be made available for resource-poor farmers (Ofstehage and Nehring, 2021). Furthermore, weeds are problematic particularly in the initial years after switching from conventional to zero tillage (Nichols et al., 2015). In fact, weed infestation and associated management costs are among the major constraints for the widespread adoption of conservation tillage (Lee and Thierfelder, 2017).

In summary, zero tillage changes the agricultural practices on household plots by reducing demand for mechanized services for land preparation, seeding and weeding, but increasing demand for labor and herbicides. Despite the labor cost requirements not being distinguishable across season and field operations, the increased demand in herbicide use indicates the increasing demand for labor for weed control (e.g. for manual weeding or herbicide application), as well as for the sowing period as a response to the decline on machinery costs.

Finally, when considering the three cost components, the adoption of zero tillage has a negative and statistically significant effect on the aggregate input costs. The treatment effect of zero tillage adoption on the input costs is -0.168, which suggests that adopting zero tillage reduces households' production costs by almost 15% (Figure 3.2). Thus, the additional resource-saving benefits under zero tillage can compensate the increase in labor and herbicide costs.

Table 3.3: Impact of zero tillage adoption on production costs

Outcome variable	Zero tillage (actual)	Conventional (counterfactual)	ATT (average treatment effect on the treated)		
			Coeff.	[90% confidence interval]	
Total payment for hired labor (US$/ha) (ln)	0.380 (0.030)	0.255 (0.020)	0.125	0.0649	0.184
Machinery costs for land preparation and seeding (US$/ha) (ln)	1.264 (0.061)	1.524 (0.065)	-0.260	-0.407	-0.114
Machinery costs for weeding (US$/ha) (ln)	0.542 (0.035)	0.529 (0.025)	0.013	-0.058	0.084
Herbicide costs (US$/ha) (ln)	0.898 (0.051)	0.760 (0.032)	0.138	0.038	0.238
Total cost (US$/ha) (ln)	2.049 (0.071)	2.217 (0.066)	-0.168	-0.329	-0.008

Note: Standard errors are in parenthesis.

Source: Tadjiev et al. (2023a).

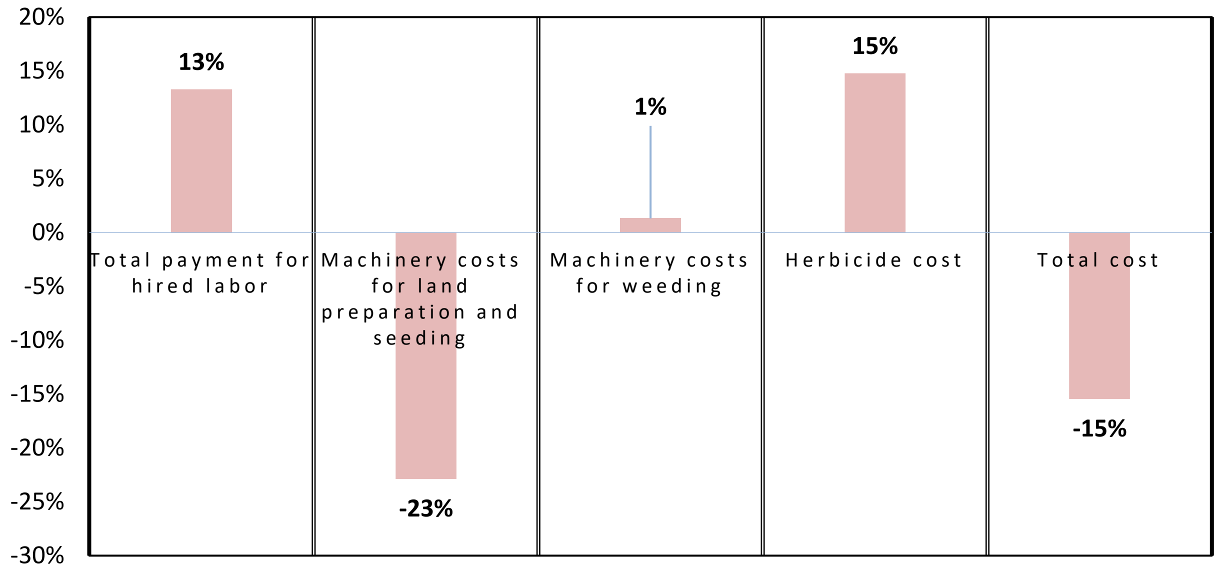


Figure 3.2: Average treatment effect on the treated of zero tillage adoption on production costs
Note: The effect of zero tillage on weeding costs is insignificant. The percentage difference of treatment effects from Table 3.3 were calculated according to Asfaw et al. (2012) and used $100*(e^{ATT} -1)$ equation.
Source: Tadjiev et al. (2023a).

A Propensity score matching (PSM) approach was performed as a robustness check of the estimated average treatment effect results from the ESR model. Table A7 in the Appendix shows the results of treatment effects based on the PSM approach. The PSM approach shows that the impact of zero tillage on labor cost is positive, and for land preparation and for total costs are negative and statistically significant, as well as positive and statistically insignificant for weeding cost. Hence, the PSM results are consistent with the results discussed above in Table 3.3 and Figure 3.2. Compared to the ESR approach, the PSM estimator showed positive but statistically not significant effect of zero tillage adoption on herbicide costs. This difference can be due to better control of unobserved factors by the ESR estimation than by the PSM approach (Abdulai and Huffman, 2014; Khonje et al., 2018).

4 PARTICIPATION IN INFORMAL COOPERATION AND ADOPTION OF SUSTAINABLE AGRICULTURAL PRACTICES. EMPIRICAL EVIDENCE FROM UZBEKISTAN[6]

4.1 Informal cooperation in water management in Central Asia

As a consequence of reorganizing collective and state farms, inspired by an international donor-driven discourse on integrated water resources management, the Central Asian governments introduced water users associations (WUAs) to oversee irrigation water management and operate and maintain irrigation and drainage infrastructure (Abdullaev et al., 2010). Farmers were expected to work together as WUA members to contribute to irrigation infrastructure maintenance and reach agreements on water distribution. Although WUAs have officially registered as non-governmental and non-commercial organizations, their establishment has been orchestrated through top-down directives from local public administration (Abdullaev et al., 2010). The top-down manner in which the WUAs were introduced hindered the establishment of institutional arrangements that promote farmers' ownership and participation in their WUAs (Djanibekov et al., 2012b). Due to the poor functioning of WUAs, the discipline among water users stagnated, resulting in "water theft" and wasteful water application, causing widespread disruption of irrigation water delivery and the functioning of irrigation infrastructure (Oberkircher, 2011).

In response to the inadequacies of formal institutions, local communities have taken the initiative by establishing their own regulations and engaging in mutual aid for water resource management (Hamidov et al., 2020). In response to these unfavorable conditions in setting up formal organizations of water management, there has been a notable emergence of informal

[6] Chapter 4 was published following open-access article: Tadjiev, A., Djanibekov, N., Soviadan, M. K., & Herzfeld, T. (2025) Participation in informal cooperation in water management and adoption of sustainable agricultural practices: Empirical evidence from Uzbekistan. *Australian Journal of Agricultural and Resource Economics.* DOI: 10.1111/1467-8489.70036. This chapter builds upon that article.

cooperation within the farming community in Uzbekistan. This collaborative effort has encompassed various forms of mutual assistance towards a common goal, particularly in water management, such as the maintenance of irrigation pumps and canals, and the distribution of water, particularly among narrow social groups such as friends, relatives, and neighbors (Veldwisch and Spoor, 2008; Shtaltovna, 2013). The organization of rural life in Uzbekistan revolves around networks of social connections that establish a sense of "community" through a series of events at the settlement level involving all members, or at the provincial level where local elites and farm managers are included (Trevisani, 2007). This organization of the rural community has strong historical roots and means that a farm manager is placed in a specific set of social expectations from its neighbors, including other farmers (Amirova et al., 2019). These are related to certain obligations toward neighbors and other village residents, such as in expected efforts for maintaining irrigation infrastructure or following agreed schedules of water use (Liu, 2017). This platform of the rural community also facilitates communication among farmers, enabling them to coordinate their activities in a cooperative manner (Oberkircher, 2011).

A prime example of informal cooperation grounded in social norms is “hashar” (Sievers, 2002), a practice entailing voluntary, uncompensated labor contributions to the community, aimed at addressing pressing local issues. This tradition of self-help in agriculture, such as the maintenance of irrigation canals and pumps, significantly contributes to solidarity and social order within the community, thus fostering voluntary cooperation (Troschke, 2011). Liu (2017) lists honor, shame, and the spirit of local community and belonging as the drivers of hashar in Uzbekistan. In addition, participation in hashar strengthens social ties and can be considered as an investment in the community’s support in the future. Throughout history, hashar, serving as a pivotal event within village governance, held a position of utmost significance, and individuals who chose not to participate faced repercussions, including monetary fines or deprivation of access to land and water distribution (O’Hara, 2000).

In Uzbekistan, cooperation occurs within narrow social groups already in frequent interaction, such as neighboring farmers (Radnitz et al., 2009). In this regard, informal cooperation helps participating farmers to overcome organizational problems caused by resource shortages and reduce transaction costs (Djanibekov et al., 2015). For instance, when irrigation water service provision becomes unreliable, farmers extend their reliance on mutual self-help by contributing labor or financial means to repair a commonly owned irrigation pump or canal (O'Hara, 2000).

Beyond managing water resources, cooperation plays a crucial role in knowledge sharing among Uzbekistan's farming community. The primary challenges lie in the absence of extension services facilitating knowledge exchange or information sharing in agriculture (Kazbekov and Qureshi, 2011). Due to the poor extension system, farmers often seek other sources of information, such as exchanging knowledge with their peers (Kurbanov et al., 2022), for example, through the participation in informal cooperation activities, like irrigation canal cleaning and the repair of common irrigation pump. Furthermore, farmers participating in informal cooperation actively engage in social media groups, facilitating the dissemination of information and the exchange of knowledge (Tadjiev et al., 2023b).

4.2 Conceptual framework

I conceptualize that farmers who participate in informal cooperation in irrigation water management are more predisposed to adopting SAPs. This assertion derives from the notion that participation in informal cooperation facilitates the dissemination of knowledge and the exchange of information related to SAPs among participants, thereby fostering higher awareness and comprehension of these practices (Olawuyi and Mushunje, 2020; Willy and Holm-Müller, 2013). Thus, I assume that participation in informal cooperation can serve as a catalyst for greater SAPs adoption among farmers, potentially leading to a broader implementation of such practices within the agricultural community. Moreover, the adoption of new agricultural practices introduces uncertainty, wherein farmers may possess inadequate knowledge concerning the attributes of SAPs (Chavas and Nauges, 2020; Rogers, 2003). This includes understanding the suitability of new SAPs under specific soil conditions, as well as understanding how best to use the SAPs especially when combined with other production factors such as fertilizers (Chavas and Nauges, 2020). Hence, gathering information from early adopter-farmers through participation in informal cooperation in water management may reduce farmers' resistance to the adoption of SAPs.

Several factors exhibit associations with both participation in informal cooperation and the decision to adopt SAPs (figure 4.1). They can be divided into farm and farmer characteristics, farm biophysical characteristics, institutional factors, and locational settings (e g., Dessart et al., 2019; D'Emden et al., 2008; Feder et al., 1985; Ruzzante et al., 2021). The diverse array of factors exhibits varying effects on both the intensity of SAP adoption and farmers' decision to participate in informal cooperation. Figure 4.1 shows hypothesized signs of the relationship between explanatory variables and dependent variables.

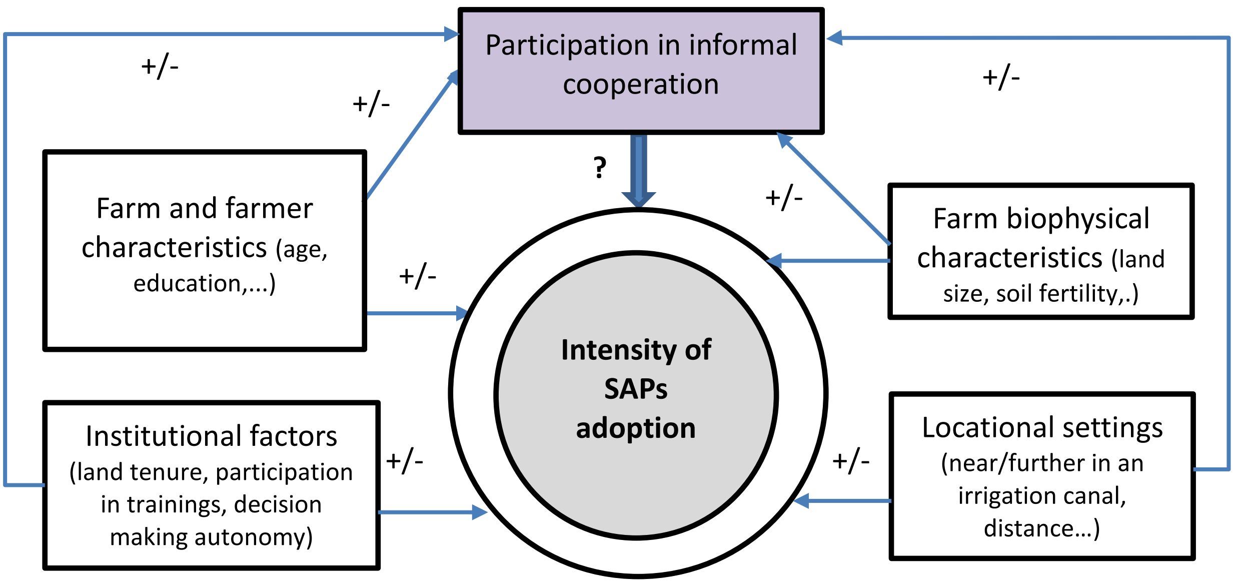


Figure 4.1 Conceptual relationship between SAP adoption and informal cooperation, and explanatory variables

I test whether participation in informal cooperation in water management increases or decreases the intensity of SAP adoption. Social learning refers to the process through which farmers acquire new knowledge, skills, attitudes, or behaviors by interacting with others in their social environment. It involves the sharing and exchange of information, experiences, and practices among farmers to improve farming methods, and enhance productivity and revenues. Through this process, participation in informal cooperation is anticipated to influence the extent of SAP adoption. This model relies on peer-to-peer learning and shared experiences to overcome barriers to adopting new agricultural technologies (Foster and Rosenzweig, 1995). On one hand, informal cooperation among farmers, facilitated by shared water management and knowledge exchange, is seen as a way to enhance SAP adoption, particularly where formal extension services are weak. In contrast, in contexts where low-level awareness regarding SAPs is high in the farming community, this very informal interaction might reinforce traditional, input-intensive cultivation practices, reducing the adoption intensity of SAPs (Bakker et al., 2021; Wagner et al., 2016).

Facilitating access to agricultural technology information among farmers enhances cooperation and significantly reduces the transaction costs linked to technology adoption decisions (Ugochukwu and Phillips, 2018). During communal activities, such as hashar or water infrastructure maintenance, farmers engage in open discussions about agronomy, technology processes, and the economic implications of adopting new agricultural practices. This cooperative environment fosters a robust platform for capacity building and the exchange of critical information related to SAPs within the rural agricultural setting (Olawuyi and Mushunje, 2020). Moreover, the influence of neighborhood social dynamics plays a crucial role in fostering social learning, thereby accelerating the uptake of innovative crop cultivation methods (Willy and Holm-Müller, 2013). The interplay between information sharing, social learning, and social capital is identified as instrumental in the adoption of agricultural technologies among local farming communities (Dessart et al., 2019; Marra et al., 2003).

4.3 Data and descriptive analysis

The present study utilizes farm survey data derived from two distinct waves conducted within the framework of the AGRICHANGE and SUSADICA[7] projects from the Turkistan (Kazakhstan) and Samarkand (Uzbekistan) provinces. In the study, I focus on Uzbekistan, hence Kazakhstan subsample is excluded. The initial wave of the survey was collected in 2019, followed by a subsequent wave in 2022. In the first wave of 2019, 460 farmers actively participated from the Samarkand province. In the 2022 survey, 450 farmers were surveyed in the Samarkand province. A total of 309 farmers participated in both survey waves, thereby facilitating a longitudinal analysis of agricultural dynamics.

A multistage random sampling procedure was used to select farmers for interviews. For this, I selected three districts according to their crop specialization. Pastdargom and Payarik districts in Samarkand are more specialized in cotton cultivation, while farmers in Jomboy district in Samarkand have diversified from cotton to other high-value crops such as vegetables and melons. Identified farmers answered a detailed questionnaire on individual socio-demographic data, individual behavioral perception, as well as farm, field, and location characteristics, and the adoption of SAPs.

I applied several conditions to the dataset to fit the research objectives. I pooled the years 2019 and 2022, because more than 30% of farmers participated in only one wave. Additionally, variations among farm management were noted between the two years, where farm business was run by different family members in 2019 and 2022, further justifying the decision to aggregate the datasets for a comprehensive and representative analysis.

Following the definition by Piñeiro et al. (2020), several farming practices were covered in the surveys, such as crop rotation, biological pest control methods, laser levelling of fields, low

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[7] Structured doctoral programme on Sustainable Agricultural Development in Central Asia (SUSADICA), https://www.iamo.de/en/research/research-projects/

tillage of land, direct planting without tillage, intercropping, drip and sprinkler irrigation. For each type of practice, farmers had the option to choose one of the following three answers, thus, (1) “yes and still use it”, (2) “yes, but I stopped using it” and (3) “no, never used it”. I treated the responses “yes and still use it” as adoption, and the other two responses were aggregated into a non-adoption. By doing so, a binary variable was generated for each type of SAP. Figure 4.2 presents the adoption level of each practice.

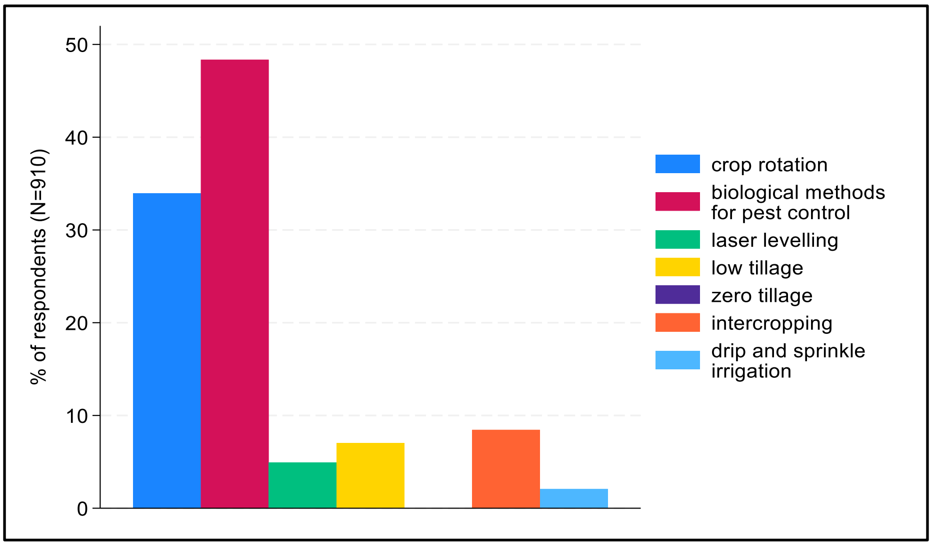

Figure 4 2: SAPs adoption level in Samarkand region in 2018 and 2021 (pooled)
Source: Authors.

The primary objective of this study is to scrutinize the adoption patterns of low-cost agricultural practices. Consequently, I excluded the assessment of adoption pertaining to laser leveling, drip irrigation, and sprinkler irrigation practices. The methodology involves the consolidation of the utilized SAPs by individual farmers, which is subsequently normalized by Simpson’s (Simpson, 1949) diversity index (e.g., Conrad et al., 2017; Lyson and Welsh, 1993). Therefore, I use the following formula to calculate the intensity of adoption of different SAPs relative to farm size as presented in equation 4.1:

$$S = \frac{\sum a^2}{A^2} \quad (4.1)$$

where, S is the intensity of SAP adoption, a is the area under a particular SAP out of total land area, A is a farm’s total land area. This index expresses the intensity of SAP adoption for each farmer and ranges from zero to 2.4. An index value of 0 signifies the absence of SAP application, while a higher numerical value indicates a greater implementation of diversified SAPs across a larger share of the farmer's land. In the analysis, it is shown that a farmer adopts maximum three SAPs out of five. The theoretically observable maximum value of S=2.4 would imply that more SAPs will be used on a farm's total area. This index of SAP serves as the principal outcome variable in the following analysis.

The survey provides information on which formal and informal form of cooperation farmers participated in regarding irrigation water management. A binary dummy variable was created, representing the treatment variable in the research, thereby categorizing farmers into two distinct groups: "participants in informal cooperation" and "non-participants in informal cooperation". I use this binary variable measuring farmers' engagement in informal cooperation in "irrigation of fields and control of water distribution", "repair and cleaning of irrigation and drainage canals", and "joint maintenance, utilization, construction and repair of irrigation equipment and infrastructure". If farmers responded that they participated in informal cooperation in irrigation water management - that is, if farmers made informal agreements with other farmers or if they participated in hashar for irrigation activities the values of the variable of interest were coded as one. The dataset of 909 observations included 51 respondents who disclosed participation in water management cooperation purely based on formal agreements. Given the relatively small number of respondents involved exclusively in formal cooperation, I excluded these cases from the estimation model to maintain focus on informal cooperation's impact. Farmers not participating in any form of cooperation, i.e. 351 responses, were assigned a value of zero. Interestingly, Table 4.1 reveals that 32 farmers were involved in both formal and informal cooperation. These individuals, alongside another 475 who were engaged exclusively in informal cooperation, were coded as one in the analysis, highlighting the predominant role of informal mechanisms in irrigation water management. Thus, I used 858 observations in the estimations, including 507 farmers participating in informal cooperation.

Table 4.1: Cross tabulation of forms of cooperation in water management

Type of cooperation		Informal	
		participant	non-participant
Formal	participant	32	**51**
	non-participant	475	351
Total		**507**	**402**

Source: Authors.

Table 4.2 provides information about the summary statistics of variables across the treatment variable used in the study. The variables are divided into "outcome variable", which is the intensity of SAP adoption, and "explanatory variables".

Table 4.2: Descriptive statistics of variables across farmers that participated and non-participated in informal cooperation (pooled 2019 and 2022)

Variables	**Description**	**Participant (N=507)**	**Non-participant (N=351)**	**Mean diff**
		Mean	**Mean**	
Outcome variable				
Intensity of SAPs adoption	Intensity of SAP adoption to farm size (0-a farm does not use any SAPs, a higher index value denotes the adoption of at least one SAP)	0.340 (0.490)	0.386 (0.480)	-0.046
Explanatory variables				
Age	Age of farm manager (years)	44.846 (10.224)	44.934 (10.252)	-0.088
Education	1 if farmer has special education in agriculture, 0 otherwise	0.444 (0.497)	0.387 (0.488)	0.056
Farm size	Total available land of farm (ha)	74.198 (53.805)	79.998 (49.413)	-5.800
Agronomy	1 if farmer has own knowledge on agronomy, 0 otherwise	0.462 (0.499)	0.416 (0.494)	0.046
Tractor	1 if farmer owns a tractor, 0 otherwise	0.844 (0.363)	0.823 (0.382)	0.021
Caring opinion	A farmer cares about opinion of neighbors, relatives, and other farmers (index of 1-5, where 1- doesn't care and 5 =very much cares)	3.274 (0.753)	3.198 (0.768)	0.076
Training	1 if farmer participates in trainings related to SAPs, 0 otherwise	0.359 (0.480)	0.262 (0.440)	0.097***
Free decision	A farmer is free to decide what crop to cultivate and where to sell harvest (index of 1-5, where 1-not free and 5=fully free)	2.398 (1.165)	1.870 (1.200)	0.528***

Table 4.2 cont.

Variables	Description	Participant (N=507)	Non-participant (N=351)	Mean diff
		Mean	Mean	
Land tenure	1 if farmer perceives not losing land rights in the next 3 years, 0 otherwise	0.469 (0.499)	0.595 (0.492)	-0.126***
Soil fertility	Index of perceived soil fertility (0-low fertility … 1-high fertility)	0.669 (0.406)	0.615 (0.382)	0.054*
WUA supplies water	1 if irrigation water to farm field supplied mostly by local water user association, 0 otherwise	0.712 (0.453)	0.442 (0.497)	0.270***
Canal condition	1 if farmer satisfied about condition of irrigation and drainage canals, 0 otherwise	0.921 (0.270)	0.806 (0.396)	0.115***
Plot location	1 if farm field is located at the head of the water source, 0 otherwise	0.233 (0.423)	0.182 (0.387)	0.050*
Distance to house	Distance to the house from farm field (km)	4.403 (5.041)	4.098 (5.014)	0.305
Distance to local market	Distance to the local market from farm field (km)	12.301 (6.183)	14.610 (6.791)	-2.309***
Year	1 if observations belong to 2022, 0 otherwise	0.562 (0.497)	0.330 (0.471)	0.232***

Note: Standard deviation are reported in parentheses; ***, ** and * are significant at p<0.01, p<0.05 and p<0.1 level, respectively.

Source: Authors.

In the questionnaire, farmers were asked about the significance they attribute to the opinions of neighbors, relatives, and farm colleagues. Respondents were required to select responses on a categorical scale ranging from 1 to 5, where "1" denoted "not at all" and "5" signified "very much". The two categorical questions, namely "how much they care about the opinion of neighbors and relatives" and "how much they care about the opinion of farm colleagues," were used to compute the average, thereby generating a new control variable called "farmers' caring opinion of neighbors, relatives, and farm colleagues".

In addition, the questionnaire also provides information on "to what extent farmers are free in crop cultivation and crop rotation to use" and "how free farmers are in deciding where to sell their main harvested crops.". The responses to these categorical questions ranged from "1= I cannot decide myself" to "5= It is fully my decision." The control variable "freedom to decide crop cultivation and selling" represents the arithmetic average of farmers' responses to each of these questions.

As indicated before, in the study, main outcome variable is the intensity of SAP use, calculated as in Equation 4.1. The summary statistics show that the intensity of SAP use is slightly higher for non-participant farmers than participants, but the difference is relatively small. The data presented in Table 4.2 also show significant differences in participation in trainings, free decision to crop cultivation and selling, land tenure security, soil fertility, condition of irrigation and drainage, farm field location relative to water resources and distance to the local market from farm field between participant and nonparticipant farmers. Nevertheless, a simplistic comparison of mean differences between participant and nonparticipant farmers fails to consider potential confounding factors contributing to these disparities. Consequently, I employ a state-of-the-art econometric method, namely the marginal treatment effect model, to disentangle biases stemming from self-selection into participation in informal cooperation, and, in turn, to analyze its influence on the intensity of SAP adoption.

4.4 Methodological approach

4.4.1 Methodological approach for the determinants of participation in informal cooperation

Following existing literature such as Addai et al. (2023), Andresen (2018), Dubbert et al. (2023), this study employs the marginal treatment effect (MTE) approach. Thus, I assume that participation in the informal cooperation of a farm i is a binary variable indicated by G_i. The assumption is that a farmer participates in informal cooperation in water management with other farmers, where they share agricultural knowledge and information that improves the SAP adoption level. Participation in informal cooperation can be expressed as a function of observable and unobservable elements in the following latent variable model:

$$G_i^* = \beta_G(Z) - V_i \quad (4.2)$$

with $G_i = 1$ if $G_i^* \geq 0$ and $G_i = 0$ otherwise, where G_i is a binary indicator that equals 1 if a farm participates in informal cooperation, and zero otherwise. $Z = (X_i, \tilde{Z}_i)$ stand for a vector of observable variables given in figure 4.1 as X_i that influence the outcome equation of the intensity of SAP adoption, and an instrument for identification, $\tilde{Z}_i$, excluded from the outcome equation. In our case, $\tilde{Z}_i$, is the distance to a local market from farm field. β_G is a vector of parameters to be estimated. V_i is the unobserved resistance to treatment or participation in informal cooperation, i.e., the error term. The negative sign associated with the error term in the selection equation signifies the unobserved characteristics that might decrease the likelihood of an individual farmer engaging in informal cooperation. In the MTE literature, it is commonly known as the “unobserved resistance" to the treatment (Andresen, 2018; Dubbert et al., 2023). Farmers with high values of V are less likely to participate (high resistance to participate) in informal cooperation, compared to farmers with low V values who are more likely to participate (low resistance to participate) in informal cooperation.

4.4.2 Methodological approach for the impact of participation in informal cooperation on adoption level of sustainable agricultural practices

I set out the model of the relationship between participation in informal cooperation and SAP adoption level by following an approach presented by Dubbert et al. (2023). S_{1i} denotes the intensity of SAP adoption of farmer i under the assumed condition where the farmer is treated, that is, participates in informal cooperation. S_{0i} represents the intensity of SAP adoption under the assumption that the farmer i is not treated, and does not participate in informal cooperation. This relationship between SAP adoption intensity S_{ji} and participation in informal cooperation can be modelled as follows:

$$S_{ji} = \beta_j X_i + U_{ji} \; j = 0,1 \quad (4.3)$$

where X_i stands for a vector of observable variables as in Equation 4.2. β_j vector of parameters to be estimated. U_{ji} is the error term representing unobserved characteristics that affect SAP adoption level. The subscript j indicates the participation status, where $j = 1$ when farmer participates in informal cooperation, and $j = 0$ stands for non-participation.

I focus on the individual treatment effect, which refers to the difference in SAP adoption between farmers who participate in informal cooperation and those who do not, as given by $S_{1i} - S_{0i} = X_i(\beta_1 - \beta_0) + U_{1i} - U_{0i}$. Treatment effect heterogeneity thus results from observed $X_i(\beta_1 - \beta_0)$ and unobserved $(U_{1i} - U_{0i})$ characteristics. The key feature of the MTE approach is that it allows the unobserved gains from treatment $(U_{1i} - U_{0i})$ to be correlated with unobserved characteristics that affect selection V_i. Following Addai et al. (2023), Andresen (2018), Cornelissen et al. (2018) and Dubbert et al. (2023), the MTE for an individual farmer with observed characteristics $X = x$ who is in the u_g-th quantile of the V distribution will have a propensity score (a farmer's probability of participating in informal cooperation) $P(Z) = U_g$. Building upon prior studies, I assume that the MTE is additively separable into observed and unobserved components:

$$MTE(x, u_g) = E(S_1 - S_0 \mid X_i = x, U_G = u_g) = x(\beta_1 - \beta_0) + E(U_1 - U_0 \mid U_G = u_g) \quad (4.4)$$

where $x(\beta_1 - \beta_0)$ represent the heterogeneity in observables and $E(U_1 - U_0 \mid U_G = u_g)$ is assumed to capture the heterogeneity in unobservables, g means informal cooperation, that is, the above-mentioned dummy variable.

Equation 4.4 measures average gains in outcomes for people with particular values of X and the unobserved resistance to treatment U_g. Alternatively, the MTE can be interpreted as the mean return to treatment for individuals at a particular margin of indifference. The above expression illustrates how the separability assumption enables the division of the treatment effect into a component that changes based on observable factors and another component that varies due to unobserved resistance to treatment (Andresen, 2018).

For the estimation of the MTE, I followed Dubbert et al. (2023) and modeled the expected value of the intensity of SAPs adoption (S_i) conditional on the observed characteristics (X_i) and the propensity score $P(Z)$:

$$E(S_i \mid X_i = x, P(Z) = p) = X_i\beta_0 + X_i(\beta_1 - \beta_0)p + K(p) \quad (4.5)$$

where $X_i\beta_0$ is the effects of the observed characteristics in the nonparticipation state, $X_i(\beta_1 - \beta_0)$ is the treatment effects due to observed characteristics, p is the propensity score, and $K(p) = pE(U_1 - U_0 \mid U_G \leq p)$ is a nonlinear function of the propensity score. I estimated the model using parametric normal MTE model with local IV approach as proposed by Andresen (2018) and Brinch et al. (2017).

The MTE can be aggregated over U_G to estimate the ATE (average treatment effect), ATT (effect of treatment on the treated), and ATUT (effect of treatment on the untreated) as weighted averages of the MTE (Heckman and Vytlacil, 2005; Cornelissen et al., 2018; Dubbert et al., 2023).

4.5 Results and discussion

This section puts forward the estimates from the analysis. Firstly, I set out the determinants of participation in informal cooperation. Following this, I describe the heterogeneity in treatment effects based on observed characteristics on the intensity of sustainable agricultural practices adoption. The final part of this section presents the average treatment effect of participation in informal cooperation. The estimation was implemented in STATA 17 using the *mtefe* command introduced by Andresen (2018).

4.5.1 Determinants of participation in informal cooperation

The MTE's identification relies on the common support of the propensity score, demanding a substantial similarity in the attributes of farmers who participate in informal cooperation and those who do not, for proper comparison. Figure 4.3 depicts this shared range, spanning roughly from 0.1 to 0.9, highlighting a significant overlap between these two farmer groups.

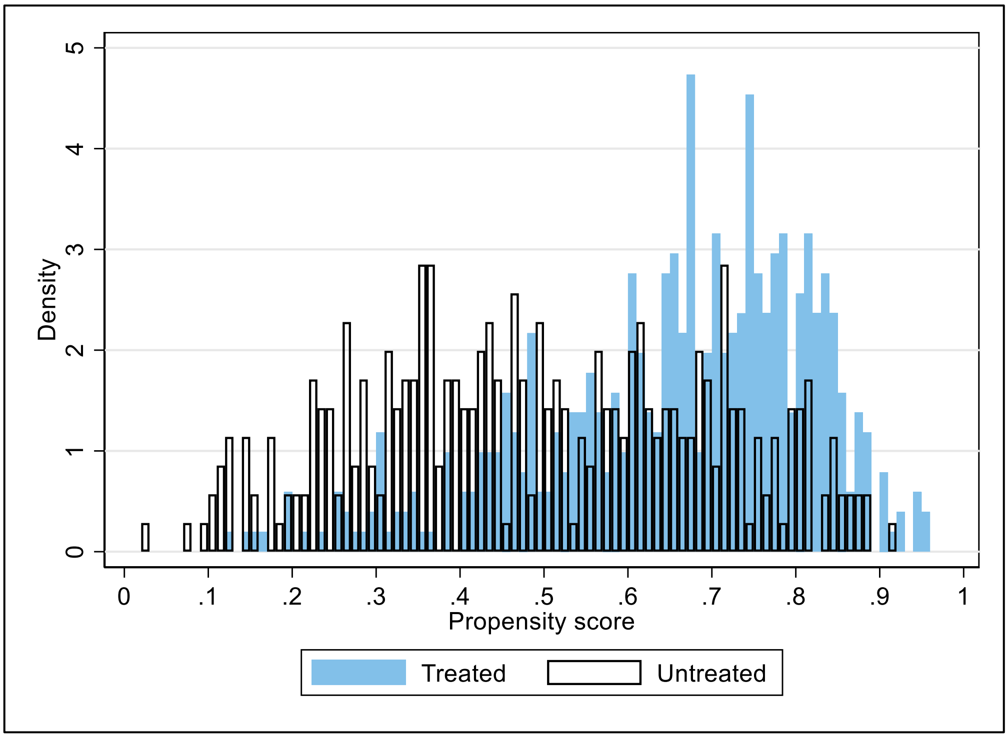

Figure 4 3: Common support of the propensity scores
Note: Propensity scores $\boldsymbol{P(X_i, Z_i)}$ for $\boldsymbol{G = 1}$ (treated/participant farmers) and $\boldsymbol{G = 0}$ (untreated/nonparticipant farmers) on the intensity of SAPs adoption.
Source: Authors.

Table 4.3 presents the determinants of farmers' participation in informal cooperation. As previously indicated, the distance to the local market from the farm field is used as an instrument for the estimation. To check the validity of the instrument, I utilized a falsification test introduced by Di Falco et al. (2011). Such falsification test requires that the selected instrument affects the participation in informal cooperation decision, but does not significantly affect the intensity of SAP adoption among farmers not participating in informal cooperation. The result shows that the identifying instrument significantly affects participation in informal cooperation (in selection equation: Chi^2 = 22.23; p-value = 0.000) but does not affect the intensity of SAP adoption of non-participant farmers (in outcome equation: F-stat = 1.46; p-value = 0.23) (See Table A8 in the Appendix).

Table 4 3: Factors influencing participation in informal cooperation in irrigation activities

Variables	Marginal effect	Std.err	[90% confidence interval]	
Age	-0.002	0.002	-0.004	0.001
Education	0.014	0.033	-0.039	0.068
Farm size	<-0.001	<0.001	-0.001	0.0002
Agronomy	0.079	0.032	0.025	0.132
Tractor	0.077	0.044	0.005	0.149
Caring opinion	0.031	0.021	-0.003	0.065
Training	0.064	0.038	0.001	0.127
Free decision	0.051	0.017	0.023	0.079
Land tenure	-0.135	0.032	-0.188	-0.082
Soil fertility	0.054	0.040	-0.013	0.120
WUA supplies water	0.154	0.041	0.086	0.222
Canal condition	0.144	0.047	0.066	0.221
Plot location	0.062	0.040	-0.003	0.127
Distance to house	0.004	0.003	-0.002	0.009
Distance to local market	-0.012	0.003	-0.016	-0.008
Year	0.009	0.049	-0.071	0.089
Pseudo R2	*0.126*			
N	858			

Source: Authors.

Probit model results in Table 4.3 show that farmers' own knowledge on agronomy positively influences participation in informal cooperation, indicating that a farmer with knowledge of agronomy is more likely to participate in informal cooperation. This is consistent with the result of Cardenas et al. (2011) who found that the more educated people are more likely to contribute to the cooperation in water management. Furthermore, the result indicates that participation in training courses about sustainable agricultural practices also improves participation in informal cooperation in water management.

The coefficient of owning a tractor is positive, suggesting that an increase in tractor ownership is associated with an increase in participation in informal cooperation. Owning a tractor expresses the wealth of a farmer, and reflects higher ability to invest in innovations and inputs (Fischer and Qaim, 2012), as well as the ability to invest in irrigation drainage and to participate in informal cooperation in water management.

The result also shows that a farmer with more freedom in crop cultivation and crop selling will more likely participate in informal cooperation. Surprisingly, the variable representing land tenure security tends to be a negative determinant for participation in informal cooperation. In other words, farmers who perceive their land tenure less secure are more likely to take part in informal cooperation in water management. This result can tell that in Uzbekistan, land tenure insecurity may lead farmers to seek ways to lower costs by engaging in informal cooperation - pooling resources to maintain common canal and irrigation pump - rather than making costly investments individually.

The variables representing water supply tends to be a positive determinant for participation in informal cooperation, indicating that farmers who receive irrigation water primarily from water user associations are more likely to participate in informal cooperation. This result can be explained by the fact that local WUAs are based on principles of informal cooperation among farmers and social mobilization of water users for water management via voluntary communal contributions in the form of hashar (Abdullaev et al., 2010; Zinzani, 2016).

The obtained results show that participation in informal cooperation increases if a farmer is satisfied with the condition of irrigation and drainage canals. Scholars state that farmers are more willing to participate in self-management of water resources when supply infrastructure is of higher quality (Uphoff et al., 1990). This is particularly true for WUAs in Uzbekistan, which are mostly operated through funds issued from the public budget and do not depend on the water users' fees (Amirova et al., 2019).

The variable representing the distance to the local market from farm field is a negative and significant determinant of participation in informal cooperation. This finding is consistent with Takayama et al. (2018) who found negative effect of distance to the market on collective action for irrigation management. Farmers located in distant locations may have difficulties accessing markets and thus have fewer chances for commercial prospects to make irrigation profitable (Meinzen-Dick et al., 2002; Takayama et al., 2018). Farmers who are situated farther from the local market may experience a reduced opportunity for social interaction with neighboring farms. This distance limits their chance to meet fellow farmers in public places like the local market, potentially decreasing their engagement in informal cooperation.

4.5.2 *Heterogeneity in treatment effects in observed characteristics (the intensity of SAPs adoption)*

Table 4 shows the estimates for the effect of informal cooperation on the intensity of SAP adoption in the non-participation (untreated) (β_0) (column 1) and participation (treated) ($\beta_1 - \beta_0$) (column 2) stages. The estimates reveal negative and significant relationship between farm size and SAP adoption scale for the non-participation state, indicating that an increase of nonparticipant farmers' land area by 1 ha is associated with a decrease in SAP adoption intensity by 0.4 percentage points. But the result is positive and significantly different from zero in the participation state, showing that farmers with larger farm size tend to higher SAP adoption. The adverse impact of farm size on the intensity of SAP adoption of non-participant farmers can be elucidated by the knowledge asymmetry concerning SAPs. Larger farmers, owing to their resources and access, tend to employ traditional farming technologies more extensively, potentially due to the limited awareness among non-participant farmers about the benefits and application of SAPs. In contrast, farmers participating in informal cooperation tend to possess greater awareness regarding the benefits associated with SAPs, and those with larger land areas are more inclined to adopt SAPs due to their capacity to accommodate and implement these practices more effectively. Dubbert et al. (2023) corroborate these observations, noting a negative yet statistically insignificant impact of farm size on the adoption of sustainable farming practices among non-participant farmers in contract farming arrangements. Within the cohort of participating farmers, Dubbert et al. (2023) found that farm size exhibits a positive yet statistically insignificant influence on the adoption of sustainable farming practices.

Ownership of a tractor tends to have differential effects on participants and nonparticipants in informal cooperation in water management. In the non-participation state, the result shows that if a farmer owns a tractor, the intensity of SAP adoption will be improved by 22.3 percentage points. In contrast, in the participation state farmers' ownership of a tractor decreases SAP adoption intensity by 37.3 percentage points. Scholars emphasize that adoption of SAPs, such as conservation agriculture, or any new technology require sufficient financial well-being (e.g., Knowler and Bradshaw, 2007). Farmers with their own tractor are considered wealthier and may be more likely adopt SAPs. Such farmers have also greater access to credit as they are able to use their tractors as collateral (Ruzzante et al., 2021). However, in the participation state farmers may cooperate with their peers on sharing tractors and less likely to adopt technologies such as zero tillage (Ngoma, 2018; Tadjiev et al., 2023a).

Soil fertility also tends to produce differential effects on treated and untreated farmers. The estimated results demonstrate that SAP adoption intensity may decrease by 21 percentage points for farmers with better soil fertility in the non-participation state. This phenomenon may be attributed to cases where farms with fertile soil might neglect the implementation of soil management methods, such as crop rotation or intercropping. Knowler and Bradshaw (2007) showed an inverse correlation between highly productive soil and the adoption of conservation agricultural practices. However, when farmers with better soil fertility participate in informal cooperation their intensity of SAP adoption increases by 36.2 percentage points.

In the untreated state, if a local WUA is primary supplier of irrigation water to farmers, intensity of SAP adoption will decrease by 68.5 percentage points. However, if farmers participate in informal cooperation their intensity of SAP adoption will increase by 64.7 percentage points when the irrigation water is mainly supplied by a local WUA. This highlights the importance of a WUA in encouraging farmers to participate in informal cooperation that can increase the intensity of SAPs adoption

The coefficient of land tenure secure in Table 4.4 is positive in the non-participation state, indicating that farmers with more land tenure security will have more intensity of SAP adoption. However, the result is negative but not statistically significant in the participation state.

Moreover, in the non-participation state, the intensity of SAP adoption will decrease by 1.6 percentage points for farmers who have farm fields in distance from home dwellings.

In our model, we also control year dummy (here 2019 is the reference year) variable to better understand year differences of the intensity of SAP adoption in both the non-participation and participation state. The result shows that in the non-participation state, the intensity of SAP adoption is higher by 113 percentage points in 2022 comparing to 2019, in contrast, in the participation state, the intensity of SAP adoption is lower by 83.3 percentage points in 2022 comparing to 2019.

Table 4.4: Outcome equations

Variables	(1)				(2)			
	Outcome (β_0)				Outcome $(\beta_1 - \beta_0)$			
	Coeff.	Std.err	[90% confidence interval]		Coeff.	Std.err	[90% confidence interval]	
Age	-0.001	0.005	-0.009	0.006	0.004	0.008	-0.009	0.016
Education	0.024	0.108			-0.004	0.169	-0.282	0.275
			-0.153	0.201				
Farm size	-0.004	0.001	-0.006	-0.002	0.008	0.002	0.004	0.011
Agronomy	-0.021	0.088	-0.166	0.125	0.056	0.148	-0.188	0.299
Tractor	0.223	0.118	0.028	0.418	-0.373	0.200	-0.702	-0.044
Caring opinion	-0.027	0.059	-0.124	0.070	-0.076	0.095	-0.233	0.080
Training	0.021	0.106	-0.153	0.196	0.274	0.162	0.008	0.540
Free decision	-0.097	0.072	-0.215	0.021	0.080	0.112	-0.103	0.264
Land tenure	0.250	0.114	0.063	0.437	-0.222	0.208	-0.565	0.121
Soil fertility	-0.210	0.116	-0.400	-0.019	0.362	0.193	0.044	0.680
WUA supplies water	-0.685	0.179	-0.979	-0.390	0.647	0.315	0.128	1.167
Canal condition	-0.020	0.123	-0.223	0.182	-0.100	0.303	-0.598	0.399
Plot location	0.013	0.118	-0.180	0.207	-0.038	0.180	-0.335	0.259
Distance to house	-0.016	0.008	-0.030	-0.002	0.009	0.013	-0.013	0.031
Year	1.132	0.197	0.808	1.456	-0.833	0.301	-1.329	-0.338
Constant	0.232	0.249	-0.178	0.643	-0.196	0.560	-1.118	0.726
Test of observed heterogeneity, p-value	0.005							
Test of essential heterogeneity, p-value	0.049							
Number of observations				858				

Note: Columns 1 and 2 offer the estimates of the intensity of SAPs adoption equation in the non-participation and not participation in informal cooperation states (the difference between participation and non-participation), respectively. The reported test heterogeneity shows whether the treatment effect $(\beta_1 - \beta_0)$ varies across the observed covariates (Addai et al., 2023; Andresen, 2018; Dubbert et al., 2023).

Source: Authors.

4.5.3 Average and marginal treatment effects estimates

The main goal of this study is to better understand how farmers' participation in informal cooperation in water management tends to impact the intensity of SAP adoption. This section helps in ascertaining whether farmers benefit from participation in informal cooperation and how these effects differ with regard to their unobserved characteristics.

The MTE curve in Figure 4.4 illustrates the distribution of marginal returns to treatment over varying levels of unobserved resistance to treatment (referred to as U_G), specifically the resistance to participation in informal cooperation among farmers. It shows a downward slope, with relatively high treatment effects above 2 at the beginning of U_G distribution and eventually declining to negative effects below -2 at the right end of the distribution, suggesting that the effect of participation in informal cooperation on the intensity of SAP adoption varies with levels of unobserved characteristics.

In Figure 4.4, the ATE line stays at around 0.33, and the downward sloping pattern implies positive selection on unobservable patterns. This finding thus tells us that, given the unobserved characteristics, farmers who are more likely to participate in informal cooperation in water management have higher intensity of SAP adoption from participation. This pattern of unobserved heterogeneity in returns to participation is statistically significant at the 5% level (the p-values for the test of unobserved heterogeneity is given in Table 4.4) for the intensity of SAP adoption. Consequently, a lower level of unobserved resistance to participation (high propensity to participate in informal cooperation) is linked with a higher intensity of SAP adoption, but the intensity of SAP adoption tends to decrease as the unobserved resistance to participation increases.

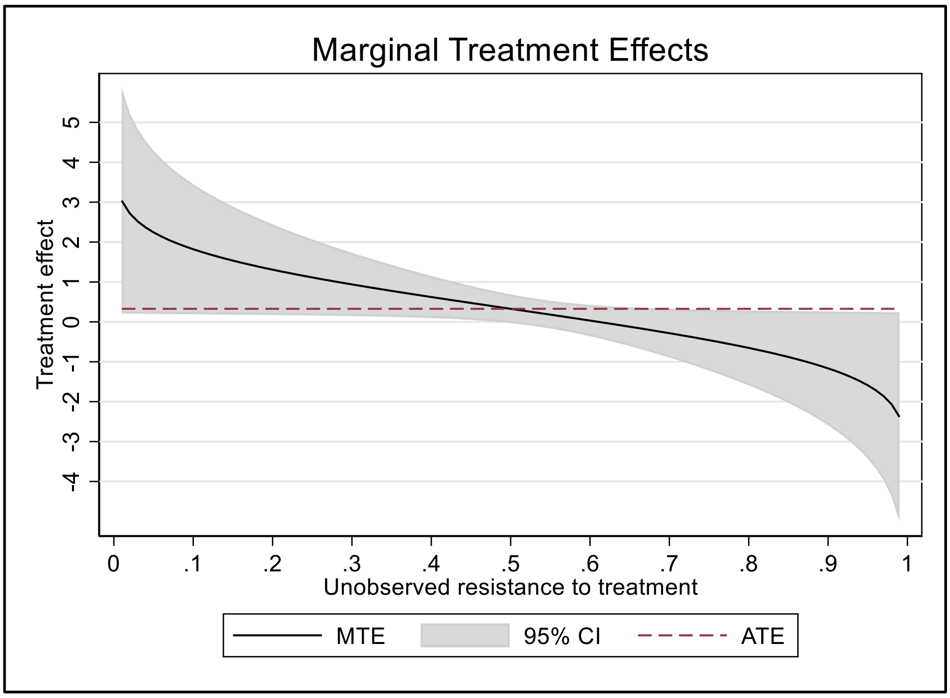

Figure 4.4: MTE curve for the intensity of SAPs adoption
Source: Authors.

Table 4.5 puts forward a summary of the treatment effects in terms of SAP adoption from the participation in informal cooperation. The result of the ATE shows that participation in informal cooperation significantly increases the intensity of SAPs adoption for the average farmer. The ATE estimation for SAPs adoption is 0.328, which indicates that randomly selecting farmers from the population and having them participate in informal cooperation increases the intensity of SAP adoption by 32.8 percentage points.

The findings of the ATT, which put more weight on farmers with high propensity scores for participation, suggest that participation in informal cooperation significantly – in this case, by 98.3 percentage points - increases SAPs adoption intensity for the average farmer who participates in informal cooperation. On the other hand, the ATUT estimates presents that participation in informal cooperation would decrease the intensity of SAP adoption for the average untreated farmer, but the hypothesis that ATUT equal to zero cannot be rejected.

A general picture of the estimates shows that the coefficient of ATT is greater than the ATE, which is also greater than the ATUT: $\mathrm{ATT}\ (0.983) > \mathrm{ATE}\ (0.328) > \mathrm{ATUT}\ (-0.616)$. This ranking of three effect measurements indicates positive selection on gains, where farmers who are probable to participate in informal cooperation tend to benefit more from participation in terms of the intensity of SAP adoption. The finding confirms the study by Willy and Holm-Müller (2013), who found that participation in collective action enhances soil conservation efforts.

Table 4.5 also provides the result of an estimation of the local average treatment effect (LATE). The LATE estimate for SAP adoption is 0.664. This indicates that farmers who participate in informal cooperation due to closer location to the local market increase the intensity of SAP adoption by 66.4 percentage points.

Table 4.5: Average treatment effects

	The intensity of SAP adoption			
	Coeff.	Std.err.	[90% confidence interval]	
ATE	0.328	0.183	0.026	0.629
ATT	0.983	0.466	0.216	1.750
ATUT	-0.616	0.514	-1.462	0.230
LATE	0.664	0.170	0.383	0.944
Test of essential heterogeneity, p-value	0.049			

Source: Authors.

5 GENERAL CONCLUSIONS AND POLICY IMPLICATIONS

The present section starts by summarizing the research findings of three empirical chapters of the dissertation. Following this, it derives important policy messages based on the research findings. Finally, it presents research limitations and outlook for further research.

5.1 Synthesis of research findings

Overall, the three empirical chapters of the dissertation provide a comprehensive analysis of SAPs in Central Asia and emphasize their diverse and context-specific nature, highlighting the potential of practices like crop rotation and zero tillage in improving farm outcomes, and the importance of informal cooperation in water management for expansion of sustainable agriculture.

Chapter 2 delves into crop rotation in Kazakhstan and Uzbekistan, highlighting its variable impact on cotton yields and net revenues, and how factors such as farmer age, educational training, and perceptions of land tenure security play a role. Chapter 3's focus on zero tillage in Kyrgyzstan sheds light on its economic trade-offs for smallholders, balancing input cost savings against increased labor and herbicide expenses. Chapter 4’s exploration of informal cooperation in water management in Uzbekistan reveals its influence on the adoption of sustainable practices, underscored by variables like farmers’ agronomy knowledge and the quality of agricultural infrastructure. These chapters underscore the diverse and context-specific nature of adoption of sustainable agriculture in Central Asia.

Chapter 2 examined factors influencing the adoption of crop rotation and its impact on cotton yields and net revenues of cotton growers by applying parametric and nonparametric empirical methods on cross-sectional farm survey data from Central Asia’s two cotton-growing areas. The results demonstrated that sample selection bias could have occurred if the impact of crop rotation was estimated without considering observable and unobservable factors in the adoption decision. Thus, to control for the selection bias issues arising from observable and unobservable factors, the ESR model is employed that estimates differential impacts of adoption of crop rotation on continuous outcome variables like cotton yields and net revenues. The model results suggested the presence of selection bias. After controlling for the bias, the estimation results showed that crop rotation increases cotton yields by 5% and net revenue by 19% in Uzbekistan. However, an opposite (negative) impact is revealed for Kazakhstan. Such unexpected impact of crop rotation on performance of cotton growers in Kazakhstan is explained by the fact that the existing institutional environment and infrastructure in Kazakhstan after the cotton sector reform actually provide advantage to farmers who practice conventional cotton monoculture. The large role here can be assigned to contractual arrangements with private gins who favor farmers cultivating cotton each year, i.e. cotton monoculture (Petrick et al., 2017). As a result, Kazakh farmers who opt for the soil-improving crop rotation scheme are most likely to end up outside such contractual arrangements and lose timely access to external inputs like cotton seeds, fertilizer, pesticides and machinery supplied by a private ginnery through contract farming.

Furthermore, the results provided insights into factors affecting farmers' decision to adopt crop rotation as well as its impact on cotton yields and net returns. In Kazakhstan, crop rotation adoption positively associates with farmers' age, participation in farm trainings, perception about irrigation canal condition, and village share of adopters. The results also suggested that Kazakh farmers who learned about new technologies and agronomy from peers and neighbors were less likely to use crop rotation. In Uzbekistan, the probability of adoption of crop rotation is higher among credit-rationed farmers and those who perceive land tenure as secure. Uzbek farmers in remote areas, at irrigation canal heads, and who receive agricultural information from the internet, media, and radio are less likely to adopt crop rotation. The results showed that production inputs were important determinants of cotton cultivation in both study areas. In Kazakhstan, the intensity of fertilizer use affects cotton yields of non-adopters, while size of cotton sown area is an important factor for adopters. In Uzbekistan, cotton sown area is positively related with net returns of non-adopters, and fertilizer use positively affects cotton yields of non-adopters. In Kazakhstan, contract farming with private ginneries raises outcomes in ‘conventional cotton’ monoculture, but puts adopters of crop rotation in disadvantage. Furthermore, in both countries, crop rotation allows better use of the advantage of close location to irrigation canals.

Chapter 3 measured the adoption determinants and resource-saving effects of zero tillage among smallholders in Kyrgyzstan by using parametric and nonparametric empirical methods on two waves of longitudinal data. The findings suggest that zero tillage can be an attractive option for resource-poor smallholders located in remote areas. The probability of zero tillage adoption is positively associated with household head’s employment in agriculture, and distance of household dwellings to household fields and main road. Furthermore, the probability of zero tillage adoption is negatively related to household wealth measured in asset index and number of household plots as well as fertilizer application. The findings suggest that zero tillage can generate tangible benefits to smallholders in terms of reducing input costs by 15%. At the same time, zero tillage adoption affects the structure of production costs. As expected it reduces machinery costs for land preparation and seeding by almost 23%. As a result, of substituting the machinery services with external workers, zero tillage can increase hired labor costs by 13%. Furthermore, zero tillage increases herbicide costs by 15%.

Chapter 4 provides first-time estimation of marginal effects of participation in informal cooperation in water management on the adoption intensity of sustainable agricultural practices in a developing country setting. To do so, it uses two years 2019 and 2022 survey data of farmers in Uzbekistan and employed empirical methods. The MTE model was used to account for selection bias, and observable and unobservable heterogeneity among farmers. Furthermore, I investigate main determinants of farmers’ participation in informal cooperation. The findings showed that the probability of participation in informal cooperation is positively related to farmers’ knowledge on agronomy, tractor ownership, participation in SAP trainings, decision making freedom, sources of irrigation water supply, and quality of irrigation and drainage infrastructure. Furthermore, the probability of participation in informal cooperation is negatively associated with land tenure security and distance to the local market. The findings indicate that participation in informal cooperation emerges as a favorable prospect for farmers who possess educational background in agriculture and have improved condition of irrigation and drainage infrastructure. The empirical results showed significant heterogeneity in the influence of informal cooperation on the intensity of SAP adoption. Notably, the results pertaining to observable characteristics suggest that farmers possessing own tractors tend to more likely participate in informal cooperation. However, its treatment effects reveal that the intensity of SAP adoption level becomes lower compared to nonparticipant farmers. Additionally, participation in informal cooperation exhibits a propensity to positively influence the intensity of SAP adoption, particularly among farmers endowed with larger land holdings and better soil fertility. Finally, the results on treatment effects revealed that farmers who are likely to participate in informal cooperation tend to benefit more from the participation in terms of higher intensity of SAP adoption.

The three empirical chapters underscore the crucial role of SAPs in enhancing farm outcomes as exemplified in different settings of Central Asia. The analyzed practices, including crop rotation and zero tillage, demonstrate significant potential for improving crop yields and farm revenues. Furthermore, the studies highlight the pivotal role of informal cooperation in water management. This cooperation is key to enhancing the adoption intensity of SAP, reflecting the importance of community-level engagement in water resource management for fostering agricultural sustainability in the region.

5.2 Policy recommendations

Empirical findings presented in this dissertation allow to derive policy recommendations related to the promotion of the adoption of sustainable agricultural practices among farmers and smallholders in Central Asia. Firstly, crop rotation has the potential to enhance farm productivity and profits, as can be seen from the sample of cotton growers in Uzbekistan. This indicates that farmers' awareness programs targeting sustainable agriculture can be explicit about the economic benefits of crop rotation. Furthermore, correcting the contractual arrangements between farmers and ginneries can improve the access of crop rotation adopters to inputs and machinery services. Redesigning the contract farming schemes by accounting for crop rotation requires consideration of the incentives of cotton growers and processors. The negative effect of crop rotation for Kazakhstan should raise the attention of the Uzbek government which has recently liberalized the cotton sector and privatized ginneries. Early consideration of destructive contract farming will prevent the liberalized cotton sector in Uzbekistan from falling into cotton monoculture, and will utilize the existing advantages of crop rotation. As peer knowledge sharing decreases crop rotation, additional extension services are required to better inform cotton growers. Investments in irrigation infrastructure and content and information distribution channels will be important for a wider adoption of crop rotation, as well as policies targeting remote cotton growers. Finally, an important (and repeating) message for Uzbekistan is that secure land rights will facilitate sustainable land management.

Secondly, policymakers and the development community should promote zero tillage among smallholders as a cost-reducing option, particularly for machinery services. Zero tillage practice can be attractive for resource-poor smallholders located in remote rural areas and who lack access to inputs and machinery services. However, zero tillage adoption should not be promoted as a labor-saving or herbicide-reducing practice. Doing so will create false expectations among its potential adopters. The observed labor-increasing property of zero tillage is particularly important for Central Asia where an increasing shortage of agricultural labor might have adverse effects if zero tillage comes with higher labor demand. A solution should come by identifying and developing specialized labor-saving machinery and implements suitable for smallholders.

Promoting hiring services of zero tillage machinery and supplying zero tillage implements at subsidized rates through soft loans for smallholders can expedite its adoption in Kyrgyzstan.

The findings show that policymakers should also be aware that zero tillage expansion can increase herbicide use by smallholders, thus producing additional environmental damage and resulting in higher health costs. The trade-off between farm-level suitability and benefits from a societal perspective requires that the government and research organizations take more actions to introduce effective alternatives for weed control. The findings suggest that zero-tillage expansion can be suppressed when labor and herbicides become more expensive or prices for machinery services and fuel go down. Thus, expanding the adoption of zero tillage practices among smallholders in Central Asia will require supporting policy instruments such as greater knowledge dissemination, pilots with lead farmers, demonstrations and free trials, and further tailoring inputs and machines to local conditions.

Thirdly, policymakers and the development community should encourage farmers' cooperation in water management as part of actions for expanding the use of sustainable agricultural practices. Policymakers should keep promoting community-based self-organized initiatives where farmers collectively manage irrigation water resources and infrastructure as part of their broader efforts to promote sustainable agricultural practices. In this regard, the government and international development agencies could further promote initiatives that facilitate interactions among farmers, especially those living closer to local markets. Encouraging communal spaces or platforms that enable knowledge-sharing and face-to-face communication among farmers will boost their participation in informal cooperation and subsequently enhance SAP adoption. Supplying farm training on sustainable agriculture can produce an indirect effect by contributing to farmers' participation in informal cooperation in water management. The finding that irrigation water supply by local organizations increases the intensity of adoption of sustainable agricultural practices among cooperating farmers calls for actions for promoting functional WUAs. The government's effort to improve ownership of agricultural machinery, particularly tractors will not only increase the likelihood of farmers' engagement in informal cooperation but also boost overall implementation of SAPs in communities where informal cooperation is absent.

5.3 Research limitations and outlook for further research.

The limitations of the dissertation stem from its reliance on specific datasets, which constrain the depth and scope of the analysis. The study used cross-sectional data from cotton-growing farmers in Kazakhstan and Uzbekistan and a panel dataset from smallholders in Kyrgyzstan and thus has several limitations related to the datasets. First, since the data does not tell how long farmers have been applying selected SAPs, the estimated determinants should be interpreted as underlying factors for current or short-term adoption rather than for their continuous use. These data limitations hinder the ability to understand the dynamics of SAP adoption, such as the duration of practice and its effects on farm performance or soil quality over a longer time horizon.

Furthermore, the datasets used in the three empirical chapters do not adequately differentiate between various labor types such as household members, permanent farm workers, and hired/seasonal workers, but only record hired labor costs, which is a critical factor in agricultural economics. The aggregation of labor data may mask significant variations in labor use patterns, which are essential for understanding the labor economics of SAPs. Differentiating between household, permanent, and seasonal workers is essential for a nuanced understanding of labor allocation, cost structures, and the socio-economic impacts of SAPs on rural communities.

The limitations in the LiK data used in Chapter 3 regarding the inability to differentiate between various tillage practices and crop species significantly restrict the depth of analysis. The impact of SAPs can vary substantially depending on the type of crop and the specific tillage method employed. This variability is crucial to understand for formulating targeted and effective agricultural policies tailored to the specific needs of different crops and farming practices.

Accurate and detailed data on these aspects are essential for a more comprehensive policy development process, aimed at improving agricultural output while maintaining sustainability and environmental health in the long run.

Finally, the absence of detailed information on the reasons for adoption or non-adoption of SAPs beyond socio-economic factors restricts a comprehensive understanding of farmer decision-making processes, particularly in relation to agronomic and soil quality considerations. These motivations are likely influenced by a complex interplay of cultural, socio-economic, institutional, and behavioral factors, which are not captured or are limited in the current datasets. This highlights the need for future research incorporating qualitative methods, such as expert interviews and focus groups, to capture the broader range of factors influencing SAP adoption decisions. Future research on the adoption of SAPs in Central Asia will thus benefit from integrating environmental impact assessments, social network analysis, and farmer behavioral studies to provide a more comprehensive picture.

These limitations underscore the vital need for a more nuanced approach in future studies on SAPs in Central Asia. To thoroughly comprehend the multifaceted relationship between agricultural practices, environmental sustainability, socio-economic factors, and the policy framework, a longitudinal and multidimensional data collection and analysis approach is essential. This approach would enable a more comprehensive understanding of the complex factors affecting farmers' decisions to adopt sustainable agricultural practices, and contribute to more informed policy-making and practice in Central Asia. These insights, in turn, will be important for designing and implementing agricultural policies that are not only effective in promoting sustainable agriculture but also responsive to the socio-economic and environmental challenges facing the region.

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APPENDIX

Table A1: Falsification test for instrumental variables

	Kazakhstan		Uzbekistan	
	Joint significance test	p-value	Joint significance test	p-value
Crop rotation adoption (probit model regression)	$\chi2$ (3)=7.81	0.05	$\chi2$ (3)= 6.93	0.03
Net returns from cotton for non-adopters	F(3, 197) = 0.55	0.65	F(2, 227) =0.22	0.80
Cotton yield for non-adopters	F(3, 197) = 0.78	0.51	F(2, 227) =0.18	0.83

Note: IV are Information source about new technologies and agronomy (i.e., information from other farms and community, information from media, internet and radio), and the village share of adopters of crop rotation (only for Kazakhstan for estimating the crop rotation impact).
Source: Based on AGRICHANGE 2019 farm survey data.

Table A2 Probit estimation on determinants of adoption decision of crop rotation among cotton growers

	Kazakhstan			Uzbekistan		
	Marginal effect	90% Confidence Interval		Marginal effect	[90% Confidence Interval]	
Farmer's age (year) [age]	0.003 (0.002)	0.001	0.006	0.001 (0.002)	-0.003	0.004
Farmer has education in agriculture (1/0) [aredu]	-0.091 (0.057)	-0.185	0.002	-0.022 (0.044)	-0.094	0.050
Farmer perceives canal condition as good (1/0) [cancon]	0.081 (0.049)	0.001	0.161	0.075 (0.051)	-0.009	0.159
Credit-rationed farmer (1/0) [credrat1]	-0.080 (0.056)	-0.173	0.013	0.109 (0.043)	0.039	0.180
Farmer participates in farm trainings (1/0) [parttraining]	0.319 (0.051)	0.235	0.403	-0.063 (0.052)	-0.149	0.022
Share of land with good fertility (0-1) [goodfert]	0.014 (0.052)	-0.072	0.101	0.033 (0.051)	-0.051	0.117
Distance to the district center (km) [discenter]	-0.001 (0.002)	-0.003	0.002	-0.009 (0.003)	-0.014	-0.004
Farm fields located irrigation canal head (1/0) [locwrt]	0.052 (0.052)	-0.034	0.138	-0.117 (0.057)	-0.212	-0.022
Farmer receives information about new technologies and agronomy from other farms and neighbors (1/0) [infstechagr]	-0.083 (0.046)	-0.160	-0.007	-0.018 (0.045)	-0.092	0.056
Farmer receives information about new technologies and agronomy from media, internet or radio (1/0) [media_1]	0.058 (0.058)	-0.037	0.153	-0.117 (0.043)	-0.188	-0.047
Village share of adopters of crop rotation (Kazakhstan) (%)[crshare_adopt_mah]	0.782 (0.396)	0.132	1.433	x	x	x
Farmer perceives land tenure as secure (1/0) [tnr_secur]	x	x	x	0.210 (0.042)	0.141	0.279
Farmer participates in contract farming (1/0) [contrcfrm]	-0.033 (0.057)	-0.127	0.062	x	x	x
Farmer located in Shardara (1/0)	-0.044 (0.086)	-0.184	0.097	x	x	x
Farmer located in Pastdargom (1/0)	x	x	x	-0.014 (0.043)	-0.085	0.056
N	278			307		
Pseudo R^2	0.153			0.172		
Wald χ^2 (13)/(12)	47.66			46.10		
Log likelihood	-126.98			-130.08		

Note: Standard error in parenthesis.
Source: Based on AGRICHANGE 2019 farm survey data.

Table A3: Review of empirical studies on impact of zero-tillage adoption on crop production costs

Author (s)	Country	Data	Method	Main findings
Teklewold et al. (2013)	Ethiopia	Farm household survey	Multinomial ESR	Adoption of conservation tillage significantly increased pesticide application and labor demands.
El-Shater et al. (2016)	Syria	Farm survey of 621 wheat farmers	PSM and ESR	Negative relationship found between quantity of fertilizer use, quantity of labor use and zero tillage adoption. The major benefits of the adoption of ZT come from tillage and labor cost savings.
Jaleta et al. (2016)	Ethiopia	Survey of 12 peasant associations	Probit and ESR models	Minimum tillage reduces total labor use, and draft power use (oxen-days/ha) for land preparation.
Tessema et al. (2018)	Ethiopia	Households survey	2 step estimation procedure, probit model, OLS	Conservation tillage increases herbicide use but reduces female and male labor requirements.
Keil et al. (2020)	India	Panel dataset from 961 farm households	ESR	Adoption of zero tillage leads to reduction of total variable per-unit production cost
Montt and Luu (2020)	Eastern and Southern Africa	Longitudinal farm data of 3,617 households	Multinomial logit and ERS models	Conservation tillage increases labor requirements in households. However, minimum tillage saves working time during land preparation and weed control.
Yigezu and El-Shater (2021)	Morocco	Survey of 995 households	ESR model	Zero tillage has no effect on the total amount of agricultural labor use.
Erenstein et al. (2008)	India & Pakistan	Survey of 400 households in India and 458 households in Pakistan	Descriptive analysis	Resource-saving effects in diesel, tractor time and cost savings for wheat cultivation. Water savings are less pronounced than expected from on-farm trial data.
Krishna & Veettil (2014)	India	Survey of 180 households	Production function and semi-parametric technical efficiency estimation methods	Wheat productivity increases by 5%, paid-out variable cost reduces by 14%, while the resource use efficiency indirectly increases by 1%

Table A4: Descriptive statistics of variables by adopters and non-adopters of zero tillage methods

Variables	2016 (N=1363)			2019 (N=1425)			Pooled 2016 and 2019 (N=2788)		
	ZT plots (N=93)	non-ZT plots (N=1270)	mean differ	ZT plots (N=290)	non-ZT plots (N=1135)	mean differ	ZT plots (N=383)	non-ZT plots (N=2405)	mean differ
Outcome variables									
Total payment for hired labor (US$/ha)	5.199	10.584	-5.385	8.891	6.199	2.692	7.994	8.514	-0.520
Machinery costs for land preparation and seeding (US$/ha)	11.272	36.898	-25.626***	31.281	39.426	-8.146	26.422	38.091	-11.670***
Machinery costs for weeding (US$/ha)	3.714	7.395	-3.681	13.935	9.919	4.017	11.453	8.586	2.867
Herbicide costs (US$/ha)	7.940	7.213	0.727	31.644	19.497	12.147***	25.750	12.956	12.794***
Total machinery, labor and herbicide costs (US$/ha)	28.124	62.089	-33.955***	84.192	75.283	8.909	70.250	68.257	1.993
Household head characteristics									
Age of household head (years)	54.516	55.887	-1.371	56.928	56.001	0.927	56.342	55.941	0.401
Education level of household head (categorical, 1=illiterate…7=university)	4.677	4.308	0.370***	4.245	4.210	0.035	4.350	4.262	0.088
Female household head (dummy, 1=female)	0.247	0.195	0.052	0.197	0.267	-0.070**	0.209	0.229	-0.020
Household head employment in agriculture (dummy, 1 = occupation in agriculture)	0.559	0.324	0.235***	0.431	0.313	0.118***	0.462	0.319	0.143***
Household head's ethnicity (dummy, 1 = Kyrgyz)	0.893	0.779	0.114***	0.790	0.766	0.024	0.815	0.772	0.042*

Table A4 cont.

Variables	2016 (N=1363)			2019 (N=1425)			Pooled 2016 and 2019 (N=2788)		
	ZT plots (N=93)	non-ZT plots (N=1270)	mean differ	ZT plots (N=290)	non-ZT plots (N=1135)	mean differ	ZT plots (N=383)	non-ZT plots (N=2405)	mean differ
Household farm characteristics									
Number of household members that can work in agriculture (above 10 and under 65 years old)	4.032	4.435	-0.403**	4.766	4.520	0.246*	4.587	4.475	0.113
Asset index	0.425	0.398	0.027*	0.356	0.353	0.003	0.373	0.377	-0.004
Household owns a tractor (dummy, 1=yes)	0.032	0.050	-0.018	0.052	0.030	0.022*	0.047	0.041	0.006
Number of livestock units owned by household	4.750	3.262	1.487***	2.766	2.278	0.488*	3.247	2.798	0.450*
Household received remittance last year (dummy, 1=yes)	0.065	0.151	-0.087**	0.217	0.228	-0.011	0.180	0.188	-0.007
Household applied chemical fertilizer last year (dummy, 1=applied)	0.129	0.261	-0.132***	0.221	0.253	-0.032	0.198	0.257	-0.059**
Household experienced a weather shock last year (dummy, 1=yes)	0.849	0.613	0.237***	0.186	0.154	0.032	0.347	0.396	-0.049*
Household experienced an agricultural shock last year (dummy, 1=yes)	0.204	0.376	-0.171***	0.155	0.070	0.085***	0.167	0.232	-0.065***
Plot under grains and legumes (dummy, 1=yes)	0.538	0.302	0.235***	0.338	0.357	-0.019	0.386	0.328	0.058**
Plot under vegetables (dummy, 1=yes)	0.043	0.426	-0.383***	0.245	0.277	-0.032	0.196	0.356	-0.160***
Plot under a mix of crops (grain, legumes and vegetables) (dummy, 1=yes)	0.097	0.071	0.026	0.007	0.026	-0.019*	0.029	0.050	-0.021

Table A4 cont.

Variables	2016 (N=1363)			2019 (N=1425)			Pooled 2016 and 2019 (N=2788)		
	ZT plots (N=93)	non-ZT plots (N=1270)	mean differ	ZT plots (N=290)	non-ZT plots (N=1135)	mean differ	ZT plots (N=383)	non-ZT plots (N=2405)	mean differ
Location characteristics									
Distance to main road from dwelling (km)	0.381	0.531	-0.150*	0.945	0.734	0.211***	0.808	0.627	0.181***
Distance from dwelling to plot (km)	2.085	1.425	0.660**	1.398	1.117	0.281*	1.565	1.280	0.285*
Number of land plots owned by household	2.323	1.939	0.383***	1.776	2.033	-0.257***	1.909	1.983	-0.075***
Plot size (ha)	1.090	0.665	0.425***	1.007	0.739	0.268**	1.027	0.700	0.327***
Institutional settings									
Amount of credit received by household last year (US$)	441.183	193.236	247.9***	624.287	266.337	357.950***	579.826	227.735	352.091***
Provinces									
Issyk Kul	0.419	0.141	0.278***	0.241	0.163	0.078***	0.285	0.151	0.133***
Djalal Abad	0.118	0.220	-0.101**	0.155	0.212	-0.057**	0.146	0.216	-0.070***
Naryn	0.161	0.066	0.095***	0.041	0.049	-0.008	0.070	0.058	0.012
Batken	0.172	0.121	0.051	0.217	0.098	0.119***	0.206	0.110	0.096***
Osh	0.075	0.274	-0.199***	0.152	0.329	-0.177***	0.133	0.300	-0.167***
Talas	0.011	0.084	-0.073**	0.017	0.084	-0.066***	0.016	0.084	-0.068***
Chuy	0.043	0.094	-0.051	0.176	0.065	0.111***	0.144	0.080	0.063***

Note: ***, ** and * are significant at 1%, 5% and 10% level, respectively.
Source: Based on 2016 and 2019 waves of the LiK data.

Table A5: Falsification test for instrumental variable

Variables	Test	p-value
Zero tillage adoption (probit model regression)	$\chi 2$ (1)=7.68	0.006
Total payment for hired labor (US$/ha) (ln)	F(1, 2376) = 0.23	0.631
Machinery costs for land preparation and seeding (US$/ha) (ln)	F(1, 2376) = 0.53	0.466
Machinery costs for weeding (US$/ha) (ln)	F(1, 2376) = 0.00	0.946
Herbicide costs (US$/ha) (ln)	F(1, 2356) = 0.00	0.966
Total machinery, labor and herbicide costs (US$/ha) (ln)	F(1, 2356) = 0.01	0.934

Note: Here, “distance to the main road” is instrument variable.
Source: Based on 2016 and 2019 waves of the LiK data.

Table A6: Second stage endogenous switching regression estimates for the outcome variables

	Total payment for hired labor (US$/ha) (ln)						Machinery costs for land preparation and seeding (US$/ha) (ln)					
	ZT plots			*nZT plots*			*ZT plots*			*nZT plots*		
	Coeff.	[90% confidence interval]		Coeff.	[90% confidence interval]		Coeff.	[90% confidence interval]		Coeff.	[90% confidence interval]	
Age of household head (years)	0.002	-0.018	0.022	-0.007	-0.014	0.001	0.026	-0.001	0.054	0.001	-0.011	0.013
Education level of household head (categorical, 1=illiterate…7=university)	0.059	-0.015	0.132	0.030	-0.002	0.063	0.052	-0.044	0.147	-0.033	-0.083	0.016
Female household head (dummy, 1=female)	0.078	-0.181	0.338	0.030	-0.063	0.124	-0.304	-0.649	0.040	0.105	-0.047	0.258
Household head employed in agriculture (dummy, 1 = occupation as agriculture)	0.338	-0.168	0.844	0.154	-0.010	0.317	0.684	-0.036	1.404	0.464	0.192	0.736
Number of household members that can work in agriculture (above 10 and under 65 years old)	0.031	-0.133	0.195	-0.013	-0.066	0.039	0.173	-0.073	0.418	0.052	-0.030	0.134
Household head's ethnicity (dummy, 1 = Kyrgyz)	-0.203	-0.532	0.125	-0.162	-0.265	-0.058	0.218	-0.170	0.606	0.272	0.113	0.430
Assets index	-0.725	-2.278	0.829	-0.841	-1.380	-0.301	-0.995	-3.269	1.280	0.301	-0.549	1.150
Household owns a tractor (dummy, 1=yes)	0.010	-1.241	1.261	0.005	-0.261	0.271	0.014	-1.042	1.070	0.287	-0.289	0.863
Plot size, (ha)	0.057	-0.005	0.120	0.057	0.025	0.088	0.011	-0.044	0.066	-0.030	-0.062	0.003
Household received remittances last year (dummy, 1=yes)	-0.399	-0.856	0.059	0.092	-0.058	0.242	-1.079	-1.803	-0.356	0.246	-0.007	0.499
Household experienced a weather shock last year (dummy, 1=yes)	0.026	-0.384	0.437	0.093	-0.050	0.235	0.790	0.191	1.389	0.544	0.324	0.765
Household experienced an agricultural shock last year (dummy, 1=yes)	0.040	-0.498	0.578	-0.241	-0.373	-0.110	0.463	-0.221	1.147	-0.187	-0.440	0.067

Table A6 cont.

	Total payment for hired labor (US$/ha) (ln)						Machinery costs for land preparation and seeding (US$/ha) (ln)					
	ZT plots			*nZT plots*			*ZT plots*			*nZT plots*		
	Coeff.	[90% confidence interval]		Coeff.	[90% confidence interval]		Coeff.	[90% confidence interval]		Coeff.	[90% confidence interval]	
Distance from dwelling to plot (km)	0.070**	0.015	0.125	0.081	0.056	0.106	0.110	0.046	0.175	0.111	0.082	0.140
Household applied chemical fertilizers last year (dummy, 1=applied)	0.379	-0.151	0.908	0.306	0.178	0.435	0.377	-0.373	1.127	0.868	0.657	1.079
Number of land plots owned by household	-0.029	-0.253	0.195	-0.071	-0.135	-0.006	-0.275	-0.585	0.035	0.088	-0.017	0.193
Number of livestock units owned by households	-0.026	-0.079	0.026	0.007	-0.010	0.025	-0.064	-0.142	0.015	-0.014	-0.040	0.012
Amount of credits received by household last year (logarithm, US$)	0.018	-0.044	0.080	0.022	-0.001	0.044	0.023	-0.067	0.113	-0.015	-0.053	0.023
Plot under grains and legumes (dummy, 1=yes)	0.018	-0.237	0.272	0.039	-0.085	0.163	1.261	0.894	1.628	1.774	1.600	1.947
Plot under vegetables (dummy, 1=yes)	-0.362	-0.916	0.192	-0.342	-0.457	-0.227	0.070	-0.753	0.892	0.656	0.468	0.844
Plot under a mix of crops (grain, legumes and vegetables) (dummy, 1=yes)	0.337	-0.581	1.255	-0.431	-0.609	-0.254	2.185	1.198	3.171	2.076	1.779	2.374
Djalal-Abad	-0.271	-0.894	0.352	-0.223	-0.378	-0.067	-1.932	-2.879	-0.985	-0.783	-1.073	-0.492
Naryn	-0.049	-0.500	0.401	0.119	-0.085	0.323	-1.191	-2.026	-0.355	-0.841	-1.164	-0.519
Batken	0.060	-0.307	0.427	-0.014	-0.112	0.084	-0.021	-1.671	0.885	-0.635	-0.874	-0.396
Osh	0.575	-0.451	1.602	-0.226	-0.409	-0.042	-0.393	-0.534	0.492	-0.062	-0.408	0.283
Talas	-0.003	-1.754	1.747	0.413	0.136	0.690	-2.291	-4.841	0.259	-0.523	-0.988	-0.058
Chuy	0.392	-0.160	0.945	0.473	0.290	0.655	-0.607	-1.474	0.260	-0.463	-0.743	-0.183
Survey year (2019=1)	0.447	-0.736	1.630	-0.173	-0.332	-0.014	2.545	0.722	4.369	-0.173	-0.438	0.093
Mean of age of household head	0.002	-0.020	0.024	0.014	0.005	0.022	-0.010	-0.042	0.021	-0.004	-0.017	0.009

Table A6 cont.

	Total payment for hired labor (US$/ha) (ln)						Machinery costs for land preparation and seeding (US$/ha) (ln)					
	ZT plots			*nZT plots*			*ZT plots*			*nZT plots*		
	Coeff.	[90% confidence interval]		Coeff.	[90% confidence interval]		Coeff.	[90% confidence interval]		Coeff.	[90% confidence interval]	
Mean of household head employed in agriculture	-0.330	-0.748	0.089	0.030	-0.156	0.216	-0.012	-0.807	0.783	0.015	-0.298	0.329
Mean number of household members that can work in agriculture	0.003	-0.181	0.186	0.018	-0.039	0.076	0.009	-0.274	0.292	-0.013	-0.103	0.076
Mean of assets index	0.538	-1.322	2.398	0.775	0.117	1.434	1.073	-1.784	3.930	-0.755	-1.824	0.315
Mean of household owns a tractor	-0.293	-1.642	1.056	-0.226	-0.595	0.143	-0.499	-2.089	1.091	0.317	-0.426	1.060
Mean of household received remittances last year	-0.018	-0.740	0.703	0.006	-0.194	0.206	0.831	-0.183	1.845	-0.255	-0.580	0.070
Mean of household experienced a weather shock last year	0.128	-0.442	0.698	-0.069	-0.254	0.115	-0.603	-1.436	0.231	-0.140	-0.440	0.160
Mean of household experienced an agricultural shock last year	0.398	-0.185	0.982	0.311	0.122	0.500	-0.619	-1.343	0.104	0.421	0.081	0.761
Mean of amount of credit received by household last year (ln)	0.003	-0.065	0.070	0.009	-0.020	0.038	0.035	-0.096	0.166	0.053	0.004	0.101
Mean of household applied chemical fertilizers last year	0.587	-0.256	1.430	0.373	0.156	0.591	0.727	-0.391	1.845	0.328	-0.023	0.680
Mean of number of livestock units owned by household	0.034	-0.019	0.088	0.007	-0.017	0.032	0.124	0.034	0.214	0.025	-0.006	0.056
year (2019)*mills1	-0.107	-0.755	0.542	x	x	x	-0.042	-1.072	0.988	x	x	x
mills1	0.628	-0.737	1.993	x	x	x	2.515	0.531	4.498	x	x	x
year (2019)*mills2	x	x	x	-1.354	-2.075	-0.632	x	x	x	-2.702	-3.870	-1.534
mills2	x	x	x	2.486	1.330	3.642	x	x	x	3.803	1.963	5.644
_cons	-1.678	-4.797	1.441	0.191	-0.126	0.508	-6.501	-11.150	-1.852	0.804	0.232	1.377
R2	0.253			0.172			0.395			0.331		
N	383			2405			383			2405		

Source: Based on 2016 and 2019 waves of the LiK data.

Table A6 cont. (for machinery costs for weeding and herbicide cost)

	Machinery costs for weeding (US$/ha) (ln)						Herbicide cost (ln) (US$/ha)					
	ZT plots			*nZT plots*			*ZT plots*			*nZT plots*		
	Coeff.	[90% confidence interval]		Coeff.	[90% confidence interval]		Coeff.	[90% confidence interval]		Coeff.	[90% confidence interval]	
Age of household head (years)	0.021	-0.004	0.045	-0.009	-0.017	-0.0001	-0.009	-0.042	0.025	-0.012	-0.020	-0.004
Education level of household head (categorical, 1=illiterate…7=university)	0.071	-0.007	0.150	0.004	-0.032	0.040	-0.015	-0.127	0.097	0.019	-0.021	0.059
Female household head (dummy, 1=female)	0.109	-0.149	0.367	-0.012	-0.118	0.093	-0.150	-0.545	0.245	0.079	-0.043	0.200
Household head employed in agriculture (dummy, 1 = occupation as agriculture)	-0.151	-0.776	0.474	0.395	0.195	0.594	0.412	-0.330	1.154	0.186	-0.028	0.400
Number of household members that can work in agriculture (above 10 and under 65 years old)	-0.099	-0.302	0.104	0.033	-0.021	0.087	-0.290	-0.505	-0.075	0.051	-0.005	0.107
Household head’s ethnicity (dummy, 1 = Kyrgyz)	-0.016	-0.347	0.315	-0.049	-0.157	0.059	-0.365	-0.901	0.171	-0.061	-0.191	0.069
Assets index	0.071	-1.802	1.944	0.198	-0.411	0.807	-0.596	-3.014	1.822	0.288	-0.333	0.910
Household owns a tractor (dummy, 1=yes)	-0.466	-1.273	0.340	-0.010	-0.435	0.416	1.322	-0.059	2.703	0.218	-0.088	0.524
Plot size, (ha)	0.013	-0.027	0.053	0.070	0.044	0.096	-0.038	-0.089	0.013	-0.020	-0.045	0.006
Household received remittances last year (dummy, 1=yes)	-0.011	-0.554	0.532	-0.058	-0.225	0.110	0.027	-0.678	0.732	-0.166	-0.345	0.012
Household experienced a weather shock last year (dummy, 1=yes)	-0.110	-0.561	0.342	0.084	-0.070	0.239	0.152	-0.412	0.717	0.207	0.033	0.380
Household experienced an agricultural shock last year (dummy, 1=yes)	0.458	-0.097	1.013	0.121	-0.039	0.281	-0.579	-1.205	0.048	-0.072	-0.250	0.106

Table A6 cont. (for machinery costs for weeding and herbicide cost)

	Machinery costs for weeding (US$/ha) (ln)						Herbicide cost (ln) (US$/ha)					
	ZT plots			*nZT plots*			*ZT plots*			*nZT plots*		
	Coeff.	[90% confidence interval]		Coeff.	[90% confidence interval]		Coeff.	[90% confidence interval]		Coeff.	[90% confidence interval]	
Distance from dwelling to plot (km)	0.056	-0.009	0.121	0.074	0.049	0.098	0.002	-0.050	0.054	0.027	0.008	0.047
Household applied chemical fertilizers last year (dummy, 1=applied)	0.876	0.206	1.547	0.259	0.109	0.408	0.531	-0.161	1.223	0.803	0.637	0.970
Number of land plots owned by household	-0.069	-0.332	0.194	0.055	-0.021	0.131	-0.079	-0.406	0.247	-0.063	-0.141	0.014
Number of livestock units owned by households	-0.079	-0.130	-0.027	-0.002	-0.018	0.013	0.096	0.034	0.157	0.032	0.013	0.051
Amount of credits received by household last year (logarithm, US$)	0.008	-0.039	0.055	-0.008	-0.034	0.018	0.056	-0.023	0.135	-0.036	-0.062	-0.009
Plot under grains and legumes (dummy, 1=yes)	0.279	-0.044	0.603	0.367	0.229	0.505	-0.189	-0.547	0.169	-0.135	-0.279	0.010
Plot under vegetables (dummy, 1=yes)	0.050	-0.569	0.669	-0.032	-0.165	0.101	0.625	-0.055	1.305	-0.299	-0.442	-0.156
Plot under a mix of crops (grain, legumes and vegetables) (dummy, 1=yes)	0.554	-0.257	1.365	0.060	-0.147	0.266	-0.931	-1.972	0.111	-0.458	-0.672	-0.244
Djalal-Abad	-0.290	-1.012	0.431	-0.894	-1.116	-0.672	-0.422	-1.308	0.465	-1.444	-1.673	-1.216
Naryn	-0.455	-1.027	0.117	-0.775	-0.988	-0.563	-0.427	-0.995	0.141	-1.035	-1.272	-0.798
Batken	0.092	-0.346	0.531	-0.362	-0.543	-0.182	0.409	-0.246	1.064	-0.696	-0.919	-0.474
Osh	0.271	-0.748	1.289	-1.022	-1.276	-0.769	0.767	-0.536	2.069	-1.174	-1.437	-0.911
Talas	-0.462	-2.438	1.514	-0.638	-0.979	-0.297	-0.725	-2.954	1.504	-1.135	-1.459	-0.810
Chuy	-0.220	-0.848	0.407	-0.166	-0.373	0.042	0.170	-0.639	0.979	-0.699	-0.936	-0.462
Survey year (2019=1)	0.809	-0.427	2.045	0.305	0.134	0.476	-0.995	-2.769	0.779	0.368	0.158	0.577

Table A6 cont. (for machinery costs for weeding and herbicide cost)

	Machinery costs for weeding (US$/ha) (ln)						Herbicide cost (ln) (US$/ha)					
	ZT plots			*nZT plots*			*ZT plots*			*nZT plots*		
	Coeff.	[90% confidence interval]		Coeff.	[90% confidence interval]		Coeff.	[90% confidence interval]		Coeff.	[90% confidence interval]	
Mean of age of household head	-0.016	-0.044	0.012	0.010	0.000	0.019	0.020	-0.018	0.057	0.012	0.003	0.022
Mean of household head employed in agriculture	0.386	-0.284	1.056	-0.187	-0.410	0.035	-0.618	-1.308	0.072	0.071	-0.171	0.312
Mean number of household members that can work in agriculture	0.189	-0.048	0.426	0.009	-0.050	0.068	0.332	0.091	0.573	-0.039	-0.102	0.025
Mean of assets index	0.063	-2.244	2.369	-0.450	-1.232	0.332	0.833	-2.546	4.213	-0.228	-1.029	0.572
Mean of household owns a tractor	-0.489	-1.558	0.580	0.084	-0.480	0.648	-2.032	-3.721	-0.343	-0.341	-0.781	0.099
Mean of household received remittances last year	-0.721	-1.516	0.074	-0.001	-0.216	0.214	-0.136	-1.006	0.735	0.070	-0.170	0.309
Mean of household experienced a weather shock last year	-0.227	-0.895	0.442	0.112	-0.097	0.320	0.049	-0.732	0.830	-0.383	-0.621	-0.146
Mean of household experienced an agricultural shock last year	-1.013	-1.611	-0.415	-0.056	-0.266	0.154	-0.230	-0.989	0.530	-0.211	-0.470	0.047
Mean of amount of credit received by household last year (ln)	-0.042	-0.115	0.031	0.050	0.014	0.085	0.016	-0.083	0.114	0.090	0.053	0.127
Mean of household applied chemical fertilizers last year	0.123	-0.782	1.029	0.414	0.169	0.659	0.652	-0.477	1.781	0.609	0.346	0.872
Mean of number of livestock units owned by household	0.099	0.039	0.158	-0.006	-0.026	0.014	-0.110	-0.179	-0.041	-0.024	-0.043	-0.004
year (2019)*mills1	-0.296	-0.973	0.381	x	x	x	0.872	-0.026	1.770	x	x	x
mills1	0.488	-1.030	2.006	x	x	x	-0.660	-2.648	1.329	x	x	x
year (2019)*mills2	x	x	x	-1.705	-2.515	-0.896	x	x	x	-1.251	-2.006	-0.497
mills2	x	x	x	3.312	2.012	4.611	x	x	x	2.282	1.074	3.490
_cons	-1.378	-5.031	2.275	0.630	0.235	1.025	1.178	-3.730	6.085	1.471	1.000	1.943
R2		0.246			0.128			0.307			0.183	
N		383			2405			373			2365	

Source: Based on 2016 and 2019 waves of the LiK data.

Table A6 cont. (for total cost)

	Total machinery, labor and herbicide costs (US$/ha) (ln)					
	ZT plots			*nZT plots*		
	Coeff.	[90% confidence interval]		Coeff.	[90% confidence interval]	
Age of household head (years)	-0.003	-0.036	0.030	-0.009	-0.022	0.003
Education level of household head (categorical, 1=illiterate…7=university)	0.025	-0.110	0.161	-0.028	-0.086	0.031
Female household head (dummy, 1=female)	-0.388	-0.864	0.089	0.169	-0.007	0.345
Household head employed in agriculture (dummy, 1 = occupation as agriculture)	1.066	0.201	1.931	0.442	0.127	0.756
Number of household members that can work in agriculture (above 10 and under 65 years old)	-0.020	-0.311	0.271	0.044	-0.046	0.135
Household head’s ethnicity (dummy, 1 = Kyrgyz)	-0.026	-0.617	0.565	0.174	-0.012	0.359
Assets index	-0.471	-3.284	2.342	0.408	-0.512	1.328
Household owns a tractor (dummy, 1=yes)	1.059	-0.413	2.531	0.361	-0.262	0.985
Plot size, (ha)	-0.013	-0.095	0.070	-0.020	-0.057	0.018
Household received remittances last year (dummy, 1=yes)	-0.539	-1.375	0.298	0.115	-0.155	0.384
Household experienced a weather shock last year (dummy, 1=yes)	0.734	-0.009	1.478	0.551	0.300	0.803
Household experienced an agricultural shock last year (dummy, 1=yes)	0.239	-0.546	1.024	-0.155	-0.430	0.121
Distance from dwelling to plot (km)	0.066	-0.009	0.140	0.119	0.089	0.149
Household applied chemical fertilizers last year (dummy, 1=applied)	1.059	0.202	1.916	1.233	1.006	1.459
Number of land plots owned by household	-0.363	-0.733	0.008	-0.005	-0.126	0.117
Number of livestock units owned by households	-0.051	-0.146	0.044	0.004	-0.026	0.034
Amount of credits received by household last year (logarithm, US$)	0.071	-0.041	0.184	-0.021	-0.062	0.020
Plot under grains and legumes (dummy, 1=yes)	1.250	0.780	1.719	1.565	1.366	1.764
Plot under vegetables (dummy, 1=yes)	0.511	-0.349	1.371	0.346	0.131	0.561
Plot under a mix of crops (grain, legumes and vegetables) (dummy, 1=yes)	1.301	0.274	2.328	1.489	1.166	1.812

Table A6 cont. (for total cost)

	Total machinery, labor and herbicide costs (US$/ha) (ln)					
	ZT plots			*nZT plots*		
	Coeff.	[90% confidence interval]		Coeff.	[90% confidence interval]	
Djalal-Abad	-1.850	-2.889	-0.810	-1.451	-1.779	-1.122
Naryn	-1.249	-2.159	-0.338	-1.181	-1.536	-0.825
Batken	0.624	-0.094	1.342	-0.974	-1.271	-0.677
Osh	0.236	-1.228	1.699	-0.740	-1.123	-0.358
Talas	-2.240	-5.034	0.553	-0.975	-1.476	-0.473
Chuy	-0.270	-1.290	0.750	-0.776	-1.119	-0.433
Survey year (2019=1)	1.611	-0.604	3.825	-0.022	-0.310	0.265
Mean of age of household head	0.030	-0.008	0.069	0.007	-0.007	0.021
Mean of household head employed in agriculture	-0.562	-1.453	0.329	0.075	-0.280	0.430
Mean number of household members that can work in agriculture	0.188	-0.132	0.507	-0.018	-0.117	0.081
Mean of assets index	1.985	-1.849	5.818	-0.504	-1.705	0.697
Mean of household owns a tractor	-2.306	-4.185	-0.426	-0.090	-0.922	0.742
Mean of household received remittances last year	-0.302	-1.385	0.781	-0.199	-0.550	0.152
Mean of household experienced a weather shock last year	-0.422	-1.459	0.614	-0.412	-0.756	-0.067
Mean of household experienced an agricultural shock last year	-0.712	-1.614	0.191	0.353	-0.033	0.740
Mean of amount of credit received by household last year (ln)	0.028	-0.118	0.175	0.088	0.034	0.141
Mean of household applied chemical fertilizers last year	0.972	-0.332	2.276	0.657	0.283	1.032
Mean of number of livestock units owned by household	0.092	-0.017	0.201	0.019	-0.017	0.054
year (2019)*mills1	0.424	-0.745	1.593	x	x	x
mills1	1.887	-0.380	4.153	x	x	x
year (2019)*mills2	x	x	x	-3.460	-4.762	-2.158
mills2	x	x	x	4.490	2.428	6.553
_cons	-5.434	-10.869	0.002	1.883	1.222	2.544
R2		0.351			0.293	
N		373			2365	

Source: Based on 2016 and 2019 waves of the LiK data.

Table A7: Propensity score matching (PSM) estimation (ATT) results (impact of zero tillage adoption)

Outcome variable	ATT (average treatment effect on the treated)			
	Coefficient	Standard error	[90% confidence Interval]	
Total payment for hired labor (USD $/ha) (ln)	0.170	0.071	0.053	0.287
Machinery costs for land preparation and seeding (USD $/ha) (ln)	-0.292	0.159	-0.554	-0.031
Machinery costs for weeding (USD $/ha) (ln)	0.120	0.110	-0.062	0.301
Herbicide cost (USD $/ha) (ln)	0.128	0.126	-0.080	0.335
Total cost (USD $/ha) (ln)	-0.311	0.167	-0.587	-0.036

Source: Based on 2016 and 2019 waves of the LiK data.

Table A8: Falsification test to check validity of instrument

	First-Stage	Second-Stage
Instrument	Participation in informal cooperation	Intensity of Sustainable Agricultural Practices adoption of Non-participant Farmers
Distance to the local market from farm field (km)	- 0.012 (0.002) χ^2 = 22.23 p-value = 0.000	-0.004 (0.003) F-Stat.=1.46 p-value = 0.228
Sample Size	858	351

Note: Standard errors are reported in parentheses.
Source: Based on AGRICHANGE and SUSADICA farm survey data.

CURRICULUM VITAE

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Present Position

January 2019 – present Doctoral researcher at the Department of External Environment for Agriculture and Policy Analysis, Leibniz Institute of Agricultural Development in Transition Economies (IAMO). Dissertation title: Exploring the advantages and drivers of sustainable agricultural practices in Central Asia

Professional experience

September 2008 – December 2018: Assistant Professor and Researcher at Samarkand Institute of Veterinary Medicine (former Samarkand Agricultural University), Uzbekistan. Responsibilities included undergraduate classes and seminars, agricultural economics research, supervision of bachelor and master students.

Academic Qualifications

January 2019 - September 2024: Ph.D. in Agricultural economics, at Leibniz Institute of Agricultural Development in Transition Economies (IAMO), Halle, Germany. In the framework "SUSADICA" project, I successfully defended my second doctoral thesis entitled "Exploring the advantages and drivers of sustainable agricultural practices in Central Asia" at the faculty of "Natural Sciences III" of the Martin Luther University Halle-Wittenberg. 23rd September, 2024.

January 2019 - September 2020: Ph.D. in Agricultural economics (Candidate of Sciences), at the Tashkent Institute of Irrigation and Agricultural Mechanization Engineers (TIIAME) in Uzbekistan. I successfully defended my first doctoral thesis entitled "Evaluation of land and water reforms and cooperation among farmers: The case of Samarkand province"

September 2006 – July 2008: MSc. in Sectoral Economics, Samarkand Institute of Economics and Service, Uzbekistan

September 2002 – July 2006: BSc. in Agricultural Economics, Samarkand Agricultural University, Uzbekistan

Participation in Research projects

Since 2023 – BMBF-funded project led by IAMO "UzFarmBarometer Better understanding of the adoption of sustainable agricultural practices in Uzbekistan"

2019-2023 – VolkswagenStiftung-funded project led by IAMO "Structured doctoral programme on Sustainable Agricultural Development in Central Asia (SUSADICA)"

2015-2019 – VolkswagenStiftung-funded project led by IAMO “Institutional change in land and labour relations of Central Asia’s irrigated agriculture (AGRICHANGE)”

Relevant Academic Trainings

25/06/2023 – 30/06/2023 – “Panel Data Analysis”, Barcelona School of Economics, Spain

24/10/2018 – 28/10/2018 – “Capacity Building of Young Researchers from Central Asia and Afghanistan in Water for Policy Studies”, Dushanbe office of OECE, Tajikistan

03/06/2018 – 14/06/2018 – “Regional training course on Applied Econometric analysis”, Westminster International University in Tashkent and IFPRI, Tashkent, Uzbekistan

19/02/2017 – 23/03/2017 – “Training course on Agricultural economics”, Leibniz Institute for Agricultural Development in Transition Economies (IAMO), Halle (Saale), Germany

Selected publications

Tadjiev, A., Djanibekov, N., Herzfeld, T. (2023) Does zero tillage save or increase production costs? Evidence from smallholders in Kyrgyzstan. *International Journal of Agricultural Sustainability* 21 (1)

Kurbanov, Z., **Tadjiev, A.**, Djanibekov, N. (2022) Adoption of sustainable agricultural practices and investments in productive assets in irrigated areas of Central Asia: Farm-survey evidence from Kazakhstan and Uzbekistan. IAMO Annual 24, pp. 69-79.

Tadjiev, A., Kurbanov, Z., Djanibekov, N., Govind, A., Akramkhanov, A. (2023) Determinants and impact of farmers' participation in social media groups: Evidence from irrigated areas of Kazakhstan and Uzbekistan. IAMO Discussion Paper No. 201, Halle (Saale), IAMO.

Tadjiev, A., Djanibekov, N., Soviadan, M. K., & Herzfeld, T. (2025) Participation in informal cooperation in water management and adoption of sustainable agricultural practices: Empirical evidence from Uzbekistan. *Australian Journal of Agricultural and Resource Economics*

Networking Activities and Outreach

Science and policy briefs

Djanibekov, N., Kurbanov, Z., **Tadjiev, A.**, Govind, A., Akramkhanov, A. (2023) Farmers' social media groups for better extension and advisory services. IAMO Policy Brief No. 46, Halle (Saale).

Tadjiev, A. (2023) Impacts of crop rotation on the performance of cotton growing farmers in Central Asia. Science Brief 4, SUSADICA project.

Organization of conference session

2021: "Understanding Farmers’ Decisions Towards Sustainable Agriculture in Irrigated Areas of Central Asia" at 31th Virtual International Conference of Agricultural Economists (ICAE).

Selected conference presentations

Tadjiev, A. (2023) Does adoption of zero tillage save or intensify production costs? Evidence from Kyrgyzstan. XVII Congress of EAAE “Agri-food systems in a changing world”, Rennes, France.

Tadjiev, A. (2023) Participation in informal cooperation and adoption of sustainable agricultural practices. SUSADICA final symposium, Tashkent, Uzbekistan.

Tadjiev, A., Djanibekov, N., Sanaev, G. (2021) Adoption of sustainable agricultural practices in irrigated areas of Central Asia. XVI Online Congress of EAAE.

Tadjiev, A. (2021) Impact of sustainable agricultural practices adoption on output of cotton producing farms. 31st Virtual ICAE 2021, Neu Delhi /Online, India.

Tadjiev, A., Djanibekov, N., Sanaev, G. (2020) Determinants of sustainable agricultural practices in Central Asia. 6th Annual 'Life in Kyrgyzstan' Conference, Online, Germany.

Teaching

Ad hoc lectures on An econometric analysis in Stata: Impact evaluation of sustainable agricultural practices, 13–14 March 2023, IAMO, Halle (Saale), Germany.

Ad hoc lectures on "Econometric analysis of farmers' adoption decisions of sustainable agricultural practices" Part II, 7–11 April 2025, Westminster International University in Tashkent (WIUT), Uzbekistan.

Ad hoc lectures on "Econometric analysis of farmers' adoption decisions of sustainable agricultural practices", 7–11 October 2024, Westminster International University in Tashkent (WIUT), Uzbekistan.

Professional Activities and Memberships

International Association of Agricultural Economists (IAAE),
European Association of Agricultural Economists (EAAE)

Halle (Saale), 2025

Eidesstattliche Erklärung / *Declaration under Oath*

Ich erkläre an Eides statt, dass ich die Arbeit selbstständig und ohne fremde Hilfe verfasst, keine anderen als die von mir angegebenen Quellen und Hilfsmittel benutzt und die den benutzten Werken wörtlich oder inhaltlich entnommenen Stellen als solche kenntlich gemacht habe.

I declare under penalty of perjury that this thesis is my own work entirely and has been written without any help from other people. I used only the sources mentioned and included all the citations correctly both in word or content.

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Datum / Date Unterschrift des Antragstellers / *Signature of the applicant*