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Innovation adoption among smallholder farmers in Bangladesh and effects on agricultural production and dietary quality

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Abstract

Securing sufficient and diverse, nutritious food for all is challenging, especially in developing countries, where the economy is often largely dependent on agriculture. Governments are introducing various interventions for smallholder farmers; however, these are not always successful in practice. Even if food production improves, poor dietary quality and malnutrition still persist among rural smallholders. Adoption of different farming techniques, access to information technology, and changes in land-use policies may be helpful in supporting smallholders. In three essays, this dissertation empirically investigates the effects of rice-aquaculture adoption, internet use for information access, and land fragmentation on certain dietary outcomes and time allocation among farm households in rural Bangladesh. Primary survey data were collected from 720 farm households and are analysed using various econometric techniques.

The first essay examines the effect of rice-aquaculture adoption on household diets and nutrition. Results from different econometric analyses suggest that adopting rice-aquaculture is associated with a decrease in household dietary quality, especially during the agricultural lean season. Heterogeneous impact analysis reveals that smallholders with young household heads, low education levels, and small landholdings are over-proportionally affected. The possible mechanisms of these unexpected negative diet effects show that rice-aquaculture adopters spend much more time on farming, leaving less time for off-farm activities, cooking and other domestic tasks. Adopters have lower crop and livestock production diversity, lower income from forest extraction activities, and higher debts than non-adopters.

The second essay explores the effects of internet use on smallholders' agricultural production and food consumption. Employing propensity score matching and instrumental variable methods, the study demonstrates that internet use is positively associated with farm production outcomes, i.e. production diversity, commercialization, and income. Regarding smallholders' consumption outcomes, the study also finds positive effects on dietary diversity, even though the results depend on the specific dietary indicators used. Internet use increases household and women's dietary diversity, whereas the effects on child dietary diversity are not statistically significant. Internet use encourages the production of certain nutritious foods, but the positive effects do not always translate into improved consumption outcomes. Our results highlight the important role of the internet in enhancing farm productivity, income, and potentially diets.

The third essay focuses on the impact of land fragmentation on women's non-farm activities and dietary quality. Our findings demonstrate that land fragmentation significantly increases the time women spend on farming activities, thereby reducing the time available for cooking and food preparation. Among women with low levels of education and young children, land fragmentation is also associated with less time spent in non-farm employment activities. Regarding dietary diversity, we do not find statistically significant effects. These findings imply that land defragmentation should be promoted, as it does not harm household diets, while improving farm productivity, reducing women's farming workloads, and freeing up time for non-farm employment. In addition, policies that enhance women's education could further improve access to profitable non-farm jobs and support better household dietary quality.

Zusammenfassung

Die Sicherstellung einer ausreichenden und vielfältigen Versorgung aller Menschen mit nahrhaften Lebensmitteln ist eine Herausforderung, insbesondere in Entwicklungsländern, deren Wirtschaft von der Landwirtschaft abhängig ist. Die Regierungen führen verschiedene Massnahmen für Kleinbauern ein, die jedoch in der Praxis nicht immer erfolgreich sind. Selbst wenn sich die Lebensmittelproduktion verbessert, leiden Kleinbauern in ländlichen Gebieten weiterhin unter schlechter Ernährungsqualität und Mangelernährung. Die Einführung verschiedener Anbaumethoden, der Zugang zu Informationstechnologie und Änderungen in der Landnutzungspolitik können zur Unterstützung von Kleinbauern beitragen. In drei Aufsätzen untersucht diese Dissertation empirisch die Dynamik der Einführung von Reis-Aquakultur, die Nutzung des Internets für den Zugang zu Informationen und die Fragmentierung von Land auf bestimmte Ernährungsergebnisse und die Zeitverteilung in landwirtschaftlichen Haushalten im ländlichen Bangladesch. Für die quantitative Analyse wurderm Primärdaten von 720 landwirtschaftlichen Haushalten erhoben und mit ökonomerischen Modellen analysiert.

Der erste Aufsatz untersucht die Auswirkungen der Einführung von Reis-Aquakultur auf die Ernährung der Haushalte. Die Ergebnisse verschiedener ökonometrischer Analysen deuten darauf hin, dass die Einführung von Reis-Aquakultur mit einer Verschlechterung der Ernährungsqualität der Haushalte einhergeht, insbesondere während der landwirtschaftlichen Nebensaison. Eine heterogene Wirkungsanalyse zeigt, dass Kleinbauern mit jungen Haushaltsvorständen, niedrigem Bildungsniveau und kleinen Landbesitzen überproportional betroffen sind. Die möglichen Mechanismen dieser unerwarteten negativen Auswirkungen auf die Ernährung zeigen, dass diejenigen, die Reis-Aquakultur betreiben, viel mehr Zeit für die Landwirtschaft aufwenden und weniger Zeit für außerlandwirtschaftliche Beschäftigung, das Kochen und andere häusliche Aufgaben haben. Sie haben eine geringere Vielfalt an Ackerbau- und Viehzuchtprodukten, geringere Einkünfte aus der Waldnutzung und höhere Schulden als diejenigen, die keine Reis-Aquakultur betreiben.

Der zweite Aufsatz untersucht die Auswirkungen der Internetnutzung auf die landwirtschaftliche Produktion und die Nahrungsmittelkonsumgewohnheiten von Kleinbauern. Unter Verwendung von Propensity-Score-Matching- und Instrumentvariablenmethoden zeigt die Studie, dass die Internetnutzung positiv mit landwirtschaftlichen Produktionsindikatoren – wie Produktionsvielfalt, Kommerzialisierung und Einkommen – assoziiert ist. Hinsichtlich des Konsums zeigt sich ebenfalls ein positiver Zusammenhang zwischen Internetnutzung und Ernährungsvielfalt, wenngleich die Ergebnisse von den jeweils verwendeten Ernährungsindikatoren abhängen. Die Internetnutzung verbessert die Ernährungsvielfalt auf Haushaltsebene sowie die Ernährungsvielfalt von Frauen, während die Effekte auf die Ernährungsvielfalt von Kindern statistisch nicht signifikant sind. Darüber hinaus fördert die Internetnutzung die Produktion bestimmter nährstoffreicher Lebensmittel; die positiven Produktionseffekte führen jedoch nicht immer zu entsprechenden Verbesserungen im Konsum. Die Ergebnisse unterstreichen die bedeutende Rolle des Internets bei der Steigerung der landwirtschaftlichen Produktivität, des Einkommens und potenziell auch der Ernährung.

Der dritte Aufsatz analysiert die Auswirkungen von Landfragmentierung auf die ausserlandwirtschaftlichen Aktivitäten von Frauen sowie auf die Ernährungsqualität. Die Ergebnisse zeigen, dass Landfragmentierung signifikant die Zeit erhöht, die Frauen für landwirtschaftliche Tätigkeiten aufwenden, wodurch weniger Zeit für Kochen und Nahrungszubereitung zur Verfügung steht. Bei Frauen mit niedrigem Bildungsniveau und kleinen Kindern ist Landfragmentierung zudem mit einer geringeren Beteiligung an ausserlandwirtschaftlichen Erwerbstätigkeiten verbunden. Hinsichtlich der Ernährungsvielfalt ergeben sich keine statistisch signifikanten Effekte. Diese Befunde deuten darauf hin, dass Massnahmen zur Reduzierung der Landfragmentierung gefördert werden sollten, da sie die Ernährungsqualität der Haushalte nicht beeinträchtigen, gleichzeitig jedoch die landwirtschaftliche Produktivität erhöhen, die Arbeitsbelastung von Frauen in der Landwirtschaft reduzieren und mehr Zeit für ausserlandwirtschaftliche Tätigkeiten schaffen können. Darüber hinaus könnten bildungspolitische Massnahmen, die die Bildung von Frauen fördern, den Zugang zu profitabler ausserlandwirtschaftlicher Beschäftigung verbessern und eine ausgewogenere Ernährungsqualität der Haushalte unterstützen.

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ADB	Asian Development Bank
ATT	Average Treatment Effects on the Treated
BAU	Bangladesh Agricultural University
BBS	Bangladesh Bureau of Statistics
BDT	Bangladeshi Taka (currency)
BFRI	Bangladesh Fisheries Research Institute
BRRI	Bangladesh Rice Research Institute
CEGIS	The Center for Environmental and Geographic Information Services
CFA	Control Function Approach
CGIAR	Consultative Group for International Agricultural Research
CDDS	Child Dietary Diversity Scores
DDS	Dietary Diversity Scores
DOF	Department of Fisheries
FAO	Food and Agriculture Organization
GDP	Gross Domestic Product
GRFC	Global Report on Food Crisis
GOB	Government of Bangladesh
GPRS	General Packet Radio Service
HDDS12	Household Dietary Diversity Score for 12 food groups
HDDS9	Household Dietary Diversity Score for 9 food groups
HIES	Household Income and Expenditure Survey
IV	Instrumental Variable
IRRI	International Rice Research Institute
MDDS	Men Dietary Diversity Score
NGO	Non-government organization
NNM	Nearest Neighbour Matching
OLS	Ordinary Least Squares
PDS12	Production Diversity Score for 12 food groups
PDS9	Production Diversity Score for 9 food groups
PSM	Propensity Score Matching
UN	United Nations
UNDP	United Nations Development Program
WDDS	Women's Dietary Diversity Score
WFP	World Food Programme
ZEF	Center for Development Research

Dedicated to all farmers whose hard work and dedication fill our plates with food every day

\- Fariha Farjana

CHAPTER 1

1 Introduction and motivation

1.1 Introduction

Hunger, malnutrition and poor dietary diversity are major global threats and public health concerns. All over the world, about 828 million and 2284.8 million people are experiencing the risk of severe food insecurity and moderate food insecurity, respectively (FAO, 2025). This situation is also worsening due to increased population (Tanrıvermiş et al., 2024). Smallholders in rural areas of developing countries are more vulnerable to inadequate dietary intake (Niles & Brown, 2017; Touch et al., 2024) due to subsistence farming, climate change, and limited opportunities for non-farm work. Lack of diverse food consumption is a major public health concern as it can cause different forms of malnutrition, i.e. stunting, wasting, unhealthy weight gain etc. (Saxena, 2018). So, it is important to adopt agricultural innovation to increase production (Lidder et al., 2025; Malec at al., 2024) and farm income. The adoption of new farming techniques may also free up time from farm activities and increase the scope for non-farm employment (Liu et al., 2024), resulting in higher household income and improved food consumption. Governments are implementing various interventions and promoting innovative farming practices to support smallholders, which improves farm productivity, farm income, and access to diverse food sources. However, adoption of these interventions is not always translated into benefits due to various challenges. For instance, due to limited access to information, innovation is not always successful (Ayanwale et al., 2023). At the same time, internet access and its rapid use are transforming smallholders' farm production and consumption decisions, and dietary behaviour (Choruma et al., 2024; Cui et al., 2024; Yang et al., 2023). The effects of internet use are ambiguous as different information access may improve income and healthy diets (Chen & Liu, 2022; Luo et al., 2024), while excessive use may reduce productivity and income (Ayran et al., 2021; Duke & Montag, 2017; Vandelanotte et al., 2009). Structural barriers and farm characteristics, i.e. land fragmentation, also pose significant challenges for smallholders to adopt innovative farming practices as they increase production cost and reduce farming efficiency (Manjunatha et al., 2013; Pun et al., 2024). There is also debate about land consolidation, as it may reduce farm production diversity and reduce dietary quality. Different scholars reckon that governments' development policy interventions sometimes ignore the variability in smallholder farming (Pervarah, 2024). Therefore, it requires a deep understanding of how innovations can benefit smallholders in enhancing farm production, livelihood strategies, and food security at the micro-level. This dissertation aims to contribute to this crucial policy dialogue. It encapsulates three essays, each in Chapters Two, Three and Four, respectively.

The first essay investigates the impact of one of the innovations, rice-aquaculture adoption, on smallholders' dietary quality in Chapter Two. Rice-aquaculture is considered an innovative adaptation for rural households (Yifan et al., 2023). It is a potential intervention that aims to increase farm productivity and diverse food availability. In existing literature, the impact of rice-aquaculture adoption is ambiguous. Some claim that rice-aquaculture increases food production (Ahmed et al., 2014; Ngamsnae, 2025), ensures efficient water use (WorldFish, 2020) and increases farm income (Berg et al., 2023; Berg & Tam, 2018). Others find a negative impact of adoption, i.e. rice-aquaculture does not increase farm productivity and may even reduce rice yields, subject to stock density and other farm-level management factors (Hu et al., 2016; Sun et al., 2019; Wang et al., 2024). It is labour-intensive and high capital-demanding (Dey et al., 2024), indicating adoption may have broader effects on household livelihood strategies and outcomes. The existing literature has mainly focused on the economic and environmental effects of rice-aquaculture adoption, rather than dietary outcomes. Positive economic outcomes like productivity and income effects do not necessarily translate into improved diets and nutrition (Knößlsdorfer et al., 2021). Hence, Chapter Two investigates the impact of rice-aquaculture adoption on household dietary outcomes. The key objectives of this Chapter are to examine: **(i) the mean association between rice-aquaculture adoption and dietary quality of household and individuals, (ii) possible heterogenity in this association by differentiating between agricultural seasons and various farm and household characteristics, and (iii) possible channels through which adoption may influence diets, particularly focusing on time allocation, income, and farm production diversity.**

Smallholders can learn different innovative farming methods that increase production and farm income via their access to information and communication technology, consequently improving food security (Gouvea et al., 2022; Nakasone & Torero, 2016). Chapter Three focuses on the impact of technology adoption, i.e. internet use, on smallholders. The internet can disseminate real-time weather forecasts and reduce farmers' losses (Tuheirwe-Mukasa et al., 2019). Besides, access to farming information (Wei & Li, 2024), and the reduction of information asymmetry about input and output markets (Ullah et al., 2020), online training, and climate-smart farming techniques (Gemtou et al., 2025) help farmers adopt the right farming strategies subject to climate vulnerabilities (salinity-resistant seeds, water-resistant seed, etc). It increases production (Ngulube, 2025), reduces waste (Babu & Anjan Babu, 2018) and crop losses (Mowla et al., 2023). Different empirical papers investigate the impact of internet use on farm production, efficiency and other outcomes (Kaila & Tarp, 2019; Nguyen et al., 2023; Zheng et al., 2022). However, to the best of our knowledge, no study has jointly analysed the effects of internet use on smallholders' production and food consumption within the same farm households. As smallholders consume a large proportion of what they produce on the farm, such joint analysis of production and consumption aspects, which we pursue in Chapter Three, may add value in existing literature to better understand the effects of internet use for improving livelihood and dietary quality for rural smallholders. Therefore, the objectives of Chapter Three are to explore **the effects of using the internet on (iii) smallholder food production activities and (iv) food consumption choices.**

Even though the farmers have access to knowledge about new farming methods, the adoption of agricultural innovations is often constrained by land fragmentation (Zheng et al., 2022; Das et al., 2025). Hence, the third essay examines the impact of land fragmentation on smallholders in Chapter Four. Fragmented landholdings with tiny plots are detrimental to economic gain, discouraging smallholders from adopting agricultural innovations (Niroula & Thapa, 2005). Some empirical evidence finds that land fragmentation improves food security (Cholo et al., 2019; Knippenberg et al., 2020). However, some find that fragmented landholdings are barriers to the adoption of modern technology (Aslam & Fazal, 2025; Ya-hui et al., 2019), increase production costs (Wang et al., 2023; Wang et al., 2020), and reduce farm performance (Latruffe & Piet, 2013); consequently, rural livelihoods become precarious, especially for smallholders. Land fragmentation also increases farming time, so it is very likely that it shrinks time available for other nonfarm activities, especially for women who perform the dual responsibility of domestic work, caregiving, and farm activities. Till now, no empirical paper has investigated the impact of land fragmentation on female non-farm activities, which is the key premise of Chapter Four. This Chapter aims to analyse the impacts of land fragmentation on **(v) women's time allocation for non-farm employment and different domestic and unpaid work activities, and (vi) investigate the impacts on women's dietary diversity**.

This dissertation contributes to literature from different angles. First, to the best of our knowledge, no empirical paper has investigated the effects of rice-aquaculture adoption on household dietary quality during the agricultural normal and lean seasons. Detailed contribution is discussed in Chapter Two. Second, regarding the effects of internet use to date, there are no studies that jointly analyse the effects of the internet on smallholders' production outcomes and food consumption choices. A detailed contribution to better understanding the effects and their underlying mechanisms is discussed in Chapter Three. Last, different studies have examined the impacts of land fragmentation on household-level non-farm employment, but no studies have examined the impacts on women's non-farm employment and dietary quality. Further details on the fact that we are the first to examine the effect of land fragmentation on women's time allocation to different non-farm activities and women's dietary diversity are provided in Chapter Four. The empirical investigation of these three Chapters uses primary data from a field survey that the author planned and conducted in the south-west region of Bangladesh in 2023. A detailed justification for choosing this specific region is explained in section 1.2 of the research context.

1.2 Research context

Bangladesh is selected as a suitable study site as 18.7% of the people at the national level are poor. The poverty head count is 20.5% for rural areas (HIES, 2022). Approximately 60 million people are suffering from food insecurity, of which 12 million are chronically food insecure (IPC, 2022). The contribution of the agricultural sector in the GDP of Bangladesh is decreasing, and in 2024, it was only 11.4% (World Bank, 2024). Despite the small contribution to GDP, 44.42% of total employment is still dependent on the agricultural sector (BBS, 2023c). The agricultural sector is dominated by rice production, but the production pattern of smallholders is slowly transforming towards farm diversification, with a focus on high-value food groups, including fruits and vegetables, livestock, and fisheries (ADB, 2023). However, Bangladesh is severely affected by various types of natural hazards and climate change (Ecker, 2018; Rahman et al., 2022), which decrease agricultural output (Financial Express, 2017). For instance, droughts and insufficient rainfall are affecting rice farming, and experts predict that rice and wheat yields will decrease by 8% and 32%, respectively, by 2050 (Sheikh & Pervez, 2025), which is alarming for future food security in Bangladesh.

To improve the agricultural sector, the Bangladesh government is implementing different interventions to cope with increased food demand and climatic impacts. The Bangladesh Delta

Plan 2100 and Five-Year Plan (2021–2025) is designed to promote diversified food production and agricultural commercialization (CEGIS, 2025; GOB, 2021). These strategic plans focus on productivity gain and sustainable intensification of climate-resilient, diverse agricultural production, aiming to ensure food and nutritional security, including for women and vulnerable poor communities (ADB, 2023).

The coastal areas, particularly the south-west region of Bangladesh, are more vulnerable to climate change than the eastern and central coastal zones (Ahsan et al., 2024). From this south-west region, we chose Khulna, Bagerhat, and Satkhira as our study districts, as the livelihood strategies of these regions are very similar, mostly agriculture-dependent, accounting for 12% of the national rice production (IPAD, 2025). Farmers in these areas are experiencing crop loss, and reduced farm income, which is elevating food insecurity (Ahmed, 2024). The food crisis turns out even worse during the agricultural lean season. Due to the geographical challenges, smallholders in this region are adopting various innovative farming strategies to mitigate income loss and reach the food security frontier, making these three districts important sites for study.

1.3 Research methodology

1.3.1. Sampling

We employed a *multi-stage sampling* approach to select the study regions. First, we selected Khulna, Bagerhat, and Satkhira as our study districts. The poverty scenario of these three regions is very similar, and it is evident that more than 35% people of these regions are poor (World Bank, 2016). In Figure 1.1, we can also see that the three districts are positioned very close to the Bay of Bengal and the world's largest mangrove forest. The three districts share the same characteristics, considering socio-economic conditions, geographic positioning, and climate vulnerability.

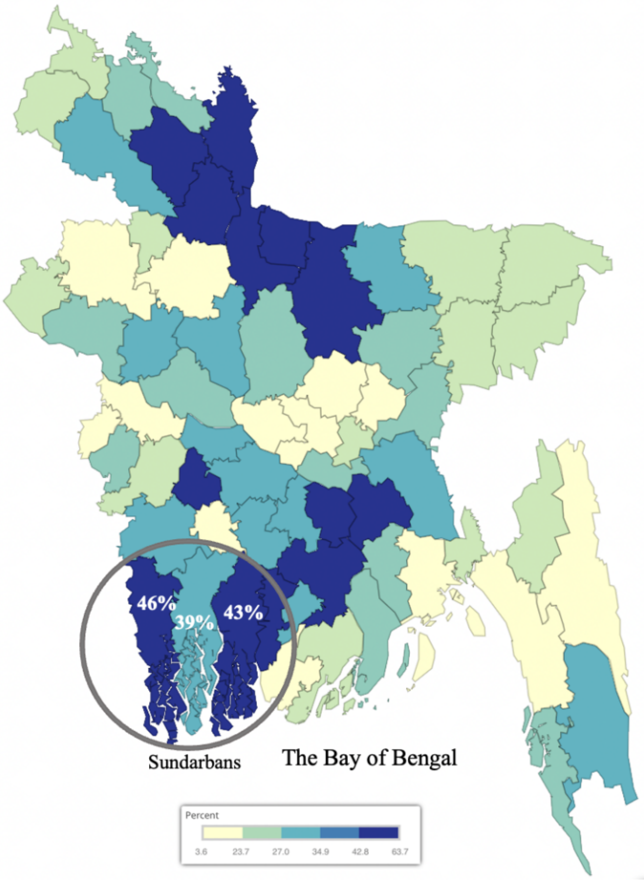

Figure 1.1: Study area (three study districts – Khulna, Bagerhat, and Satkhira –circled)

In the second stage, we randomly selected eight *Upazilas* (sub-districts) from the three chosen districts. Here, the number of chosen *Upazilas* from each of the districts was proportional to the districts' population size. Here, *Dacope, Koyra, and Paikgachha Upazilas* are from Khulna district, *Mongla* and *Sarankhola* are from Bagerhat district, *Assasuni, Kaliganj, and Shyamnagar* are from Satkhira district. Table 1.1 provides a detailed outline of the household distribution in these eight *Upazilas.*

In the next stage, we randomly selected 36 villages from the eight *Upazilas.* According to the 2022 population and housing census, these eight *Upazilas* are home to 484,761 households, which we consider as our population (BBS, 2023b). Using Cochran's formula for sample size calculation for a finite population at a 95% confidence level and a 5% margin of error, we obtain a sample size of 384. Given our available resources, manpower, and time, we surveyed 20 households in each of the 36 villages, resulting in a total sample of 720 households, which is almost double the sample size we calculated using Cochran's formula.

Table 1.1: Household distribution in different districts and *Upazilas*

District with no. of households in parentheses	*Upazila*	No.of households
Bagerhat district (408840)	Mongla	41605
	Sharankhola	30788
Khulna district (482282)	Dacope	42186
	Koyra	55518
	Paikgachha	74000
Satkhira district (566752)	Ashashuni	71857
	Kaliganj	78690
	Shyamnagar	90117
	Total	484761

Source: BBS (2023)

1.3.2. Data collection

The three essays in this dissertation are focused on quantitative data analysis. We use primary data collected from a household survey. For this, we developed a structured questionnaire and translated it into the local language. We then hired local enumerators following three main criteria. First, all enumerators have completed at least an undergraduate level of education. Second, they have prior experience in data collection and third, they have proper orientation on using SurveyCTO for data collection. Once we finalised the enumerator selection, we gave them intensive three-day training on the questionnaire programmed in SurveyCTO. After training, these enumerators were sent to the field for a two-day pilot survey. After the pilot survey, we received feedback and observations from them, revised the questionnaire programmed in SurveyCTO and finally started the household survey. The quantitative data collection took place in 2023.

To gather households' farm production-related data, we administered this part of the survey either with the household head or a household head-nominated male adult who is directly involved in farm activities and present in the farm household throughout the year. To collect dietary data from households in the agricultural normal and lean seasons, we surveyed the household head-nominated woman responsible for meal preparation and present in the household throughout the year. For individual dietary data, we selected one adult man, one adult woman, and one child from each household. A detailed explanation of the criteria for choosing individual dietary data is given in Chapter Two. We have also collected time-use data for one adult male and one adult female from each household. The detailed data-collection process and the types of data gathered for time use are clearly described in relevant Chapters.

1.3.3. Data analysis

In the first essay, we employ the endogenous treatment effect model (Vella & Verbeek, 1999) to investigate the impact of rice-aquaculture adoption on the dietary quality of rural households during the agricultural normal and lean seasons. We utilise an instrumental variable approach to estimate endogenous treatment-effect models, [Objective (i) & (ii)], thereby addressing endogeneity. We also explore the impact pathways, considering different outcomes [Objective (iii)]. We have integrated a set of econometric analyses as a robustness check of our findings. Further methodological details are in Chapter Two.

In the second essay, we apply Propensity Score Matching (PSM) (Kane et al., 2020) as the main model to assess the effect of internet use on smallholders' farm production [Objective (iv)] and dietary outcome for agricultural normal and lean season [Objective (v)]. We also employ a set of regression analyses as a robustness check. In addition to quantitative data collection, we conducted qualitative interviews to cross-check the findings obtained from the econometric analysis. Further details on methodological specification are provided in Chapter Three.

In the third essay, we apply the control function approach (Avogadro & Ramos, 2025; Murtazashvili & Wooldridge, 2016; Wooldridge, 2015) with an instrumental variable to explore the effects of land fragmentation on female non-farm employment, time allocation for non-farm activities and women's dietary quality [Objective (vi) & (vii)]. Besides, in this essay, we also explore the effect pathways following time allocation for farm activities, farm productivity and farm production diversity as outcome variables using the Ordinary Least Squares method (Wang et al., 1994). A complete methodological explanation is given in Chapter Four.

1.4.4. Ethical approval

For ethical approval, we drafted a comprehensive data collection protocol that includes the interview questionnaire, information about the study subjects, and consent forms for potential study participants. This was submitted to the Research Ethics Board of the Center for Development Research (ZEF) at the University of Bonn, Germany. The Research Ethics Board of ZEF reviewed it and provided feedback. After addressing their observation, we finally received ethical approval from the Research Ethics Board. A copy of the approval is provided in Appendix A1.

1.4 Organisation of the thesis

The entire thesis is structured as follows. Chapter One provides a comprehensive overview of the research motivation, the conceptual framework, the research objectives, the study area context, and the methods of data collection. Chapter Two addresses objectives (i)-(iii), quantitative data from the field survey is used in this regard. Applying the endogenous treatment effect as the main model, in this Chapter, we conceptualise how the adoption of rice-aquaculture affects rural households' dietary quality in the agricultural normal and lean seasons. The third and fourth research objectives are addressed in Chapter Three. Again, we use quantitative data in Chapter Three to examine the effect of internet use on household farm production and consumption outcomes. To explain the results, we conducted qualitative interviews that were consistent with the quantitative findings we obtained in Chapter Three. In Chapter Four, the control function approach is used to trace out the impact of land fragmentation on women's time allocation for non-farm activities and dietary quality, addressing objectives (vi) and (vii). Finally, the dissertation concludes by outlining the study's findings and the relevant policy implications in Chapter Five.

CHAPTER 2

2 Rice-aquaculture systems and dietary quality in Bangladesh[1]

Abstract

Rice-aquaculture is promoted in many countries as a system that could simultaneously improve land and water productivity and household diets and nutrition. However, studies evaluating the effects of rice-aquaculture adoption on household diets do not yet exist. Here, we address this research gap, using data from a survey of 720 households in rural Bangladesh and different statistical techniques to control for possible selection bias. Contrary to expectations, our data suggest that adopting rice-aquaculture is associated with a decrease in household dietary quality, especially during the agricultural lean season. Households with young household heads, low education levels, and small landholdings are over-proportionally affected. We also analyze possible mechanisms of these unexpected negative associations between rice-aquaculture adoption and dietary quality. Adopting households spend much more time on farming, leaving less time for cooking, other domestic tasks, and certain off-farm activities. Adopters have lower crop and livestock production diversity, lower income from forest extraction activities, and higher debts than non-adopters. Our findings suggest that policies to promote the adoption of rice-aquaculture should consider the broader implications for household livelihoods and provide sufficient support in order to avoid undesirable social outcomes.

Keywords: rice-aquaculture, dietary diversity, time allocation, farm production diversity

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Fariha Farjana developed the research idea, collected and analysed the data, and wrote the manuscript under the guidance and supervision of the co-authors.

2.1 Introduction

Malnutrition is a major global threat, affecting nearly one-third of the world's population (FAO, 2025). Safe and nutritious food is essential to maintaining an active and healthy life (Uwingabire & Gallai, 2024). Smallholder farmers in low- and middle-income countries are particularly vulnerable to malnutrition due to their limited access to healthy and diverse diets (Nguyen & Qaim, 2025). Since smallholder farmers tend to consume a large proportion of the food they produce, higher levels of farm production diversity are often promoted to improve household dietary quality and nutrition (Ruel et al., 2018; Sibhatu et al., 2015). Rice-aquaculture systems, where rice and aquatic species are grown in the same plots, stand out as a potential farm diversification strategy (CGIAR, 2023; FAO, 2024). Rice-aquaculture could potentially help improve land and water productivity, contribute to high-value protein and micronutrient supply (Freed et al., 2021; Ignowski et al., 2023; WorldFish, 2018a), and provide stable income and employment opportunities across seasons. The practice of rice-aquaculture is also considered a sustainable alternative to rice monoculture (Berg, 2002). Therefore, it is hypothesized that adopting rice-aquaculture could positively affect household diets and nutrition. However, this hypothesis has not yet been tested empirically. Previous studies on rice-aquaculture have mainly focused on economic and environmental effects, not on diet or nutrition outcomes. It is well known from other contexts that positive productivity and income effects do not always lead to improved diets and nutrition (Knößlsdorfer et al., 2021). Furthermore, harvested aquatic species might possibly be sold to markets in wealthier areas rather than being used for their own consumption and local markets (CGIAR, 2023). In this study, we analyze whether the adoption of rice-aquaculture is indeed associated with dietary improvements, as hypothesized.

Several studies examine the economic effects of adopting rice-aquaculture with ambiguous results. A few studies show that rice-aquaculture positively affects farm productivity and income (Dubois et al., 2019; Hu et al., 2016; Onoh et al., 2020; Saiful et al., 2015; Yu et al., 2023). Farming rice and aquatic species together in the same plot can benefit both species. Aquatic species (e.g., fish) can benefit rice by improving soil fertility and controlling pests, diseases, and weeds. Rice, in turn, may regulate the water environment for the aquatic species by reducing ammonia, providing shade, maintaining a suitable temperature, and offering supplemental feed sources such as planthoppers (Xie et al., 2011). Besides, farming diversification improves farm economic performance and input use efficiency (Nilsson et al., 2022). However, the assumption of mutually beneficial relationships may not always hold in reality. Studies suggest that in some situations rice-aquaculture does not increase farm productivity and may even reduce rice yields, depending on stocking density and other management factors (Sun et al., 2019; Vromant et al., 2002; Wang et al., 2024). Furthermore, rice-aquaculture systems are labor-intensive and require high initial capital investments (Dey et al., 2013). This means that adoption may have broader effects on household livelihoods and change the resource allocation to various farm and off-farm activities.

The main research objectives pursued in this study are (i) to examine the mean association between rice-aquaculture adoption and dietary quality, (ii) to investigate possible variations in this association by differentiating between agricultural seasons and various farm and household characteristics, and (iii) to examine possible channels through which adoption may influence diets, particularly focusing on time allocation, income, and farm production diversity. To our knowledge, all three objectives have not been analyzed before.

We use primary survey data from Bangladesh, where nutritional deficiencies are widespread. Recent statistics suggest that around one-third of the population in Bangladesh suffers from severe food insecurity during the lean season (GRFC, 2024). In Bangladesh, 80% of the total crop area is used for rice production. Rice-aquaculture systems have been promoted in the country by WorldFish, other international agricultural research centers, and national institutions to promote production diversity and nutrition-sensitive agriculture (Dey et al., 2013, WorldFish, 2018b).

The subsequent sections are structured as follows: Section 2.2 presents a conceptual framework, explaining the potential interrelationship between rice-aquaculture adoption and household dietary quality, as well as the possible impact mechanisms. Section 2.3 provides information on the study area, data collection, and the methods of data analysis. The empirical results are presented and discussed in section 2.4. Finally, section 2.5 summarizes the main findings and discusses policy implications.

2.2 Conceptual framework

Figure 2.1 presents the conceptual framework, illustrating the different mechanisms through which rice-aquaculture adoption could influence household dietary quality. In particular, we assume that adopting rice-aquaculture could influence household dietary quality through changes in household time, land, and capital allocation, all of which may affect income and food availability from different sources.

In terms of time allocation, rice-aquaculture is a labor-intensive system. As individuals are subject to time constraints, there is always a trade-off regarding time allocation to farming and other activities. If much of the household time is allocated to rice-aquaculture, less time may be available for other income-earning and household activities. For example, due to increased involvement in farming, household members may have less time for non-farm wage employment or seasonal migration, thus potentially also affecting income. Further, there may be less time for food preparation and other domestic tasks, which are often managed by women. Studies show that less time for domestic activities may be associated with negative diet and nutrition outcomes (Debela et al., 2021). Foods prepared in the household may be less diverse. Also, the increased time spent on farming might decrease the time spent on collecting wild foods, which are an important source of household dietary diversity in many rural contexts (Cheek et al., 2023; Iannotti et al., 2024; Sunderland, 2023).

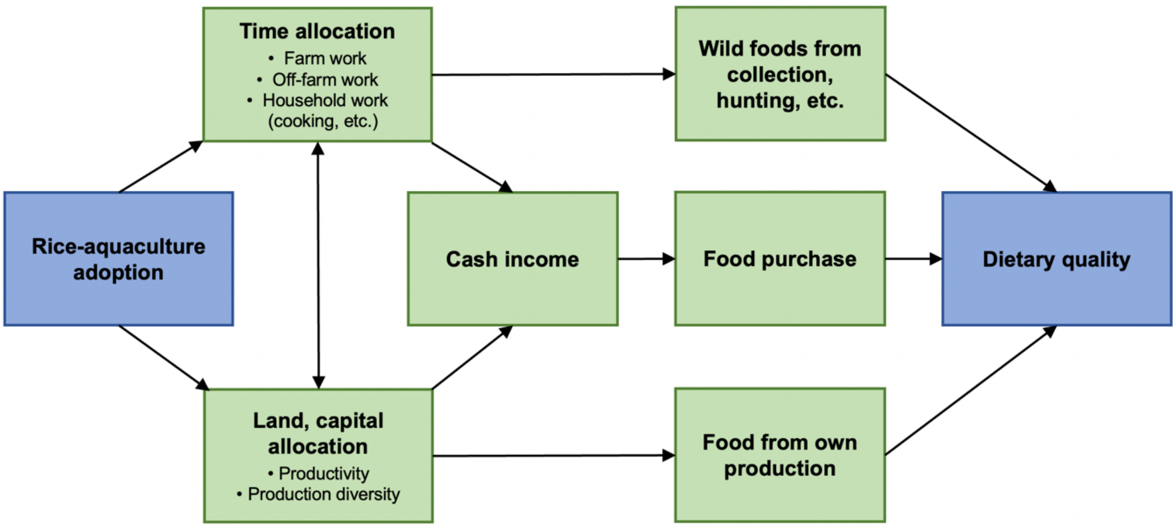


Figure 2.1: Conceptual framework

In terms of land and capital allocation, rice-aquaculture adoption may affect investments into various farming activities, thus influencing production patterns, productivity, and income. For instance, it is possible that adopting rice-aquaculture positively affects rice yields while generating additional income from fish production and sales. However, it is also possible that adoption leaves fewer resources for other farm enterprises. Assuming that the total income effects are positive, a higher income may increase food purchases and make diverse and healthy diets more affordable, even though the concrete outcomes also depend on how the additional cash income is spent.

Apart from the cash income pathway, adoption may influence household diets through the subsistence pathway by influencing the types of foods available for home consumption. Rice-aquaculture systems are typically adopted by rice farmers, so adding aquatic species may increase farm production diversity. Previous studies show that farm production diversity is positively correlated with household dietary quality in many situations, often through subsistence consumption (Headey et al., 2018, Nguyen & Qaim, 2025; Pandey et al., 2016; Powell et al., 2015; Sibhatu et al., 2015; Yan et al., 2024). However, smallholder rice farmers rarely grow rice as the only crop, and some may also keep livestock such as cattle or chicken. Adopting rice-aquaculture may possibly influence these other farming activities through competition for labor, land, and capital, meaning that the net effects on farm production diversity are uncertain. We will analyze these mechanisms empirically, using our data from farm households in Bangladesh.

2.3 Materials and methods

2.3.1. Study area and data collection

Data for this study were collected in three districts, namely, Khulna, Satkhira, and Bagerhat, located in the south-west region of Bangladesh. This region is densely populated, heavily dependent on agriculture, and has high levels of poverty and food insecurity. Around 40% of the local population in the study districts are engaged in the agricultural sector (Asiful Alam, 2017). Rice cultivation is the most common livelihood observed. Both men and women are involved in the agricultural labor force, with average daily working hours of 7.6 and 7.0, respectively (BBS, 2018). Around 30% of the local population suffers from severe food insecurity (Shuvo et al., 2024). The study area is adjacent to the Sundarbans, the world's largest mangrove forest. Apart from rice farming, forest extraction and aquaculture are also common local livelihood strategies.

Rice-aquaculture systems have been extensively researched in Bangladesh since the mid-1980s by various government and non-governmental organizations, including the Bangladesh Fisheries Research Institute (BFRI), the Bangladesh Rice Research Institute (BRRI), the Bangladesh Agricultural University (BAU), the Department of Fisheries (DOF), and the WorldFish Center (Dey et al., 2013). WorldFish, the International Rice Research Institute (IRRI), and the CGIAR more broadly expanding rice-aquaculture for additional income generation and to make local smallholder farming more nutrition-sensitive (IRRI, 2019a; IRRI, 2019b; WorldFish, 2018b). We collected data from both rice-aquaculture adopting and non-adopting households.

Our sample of farm households in the three districts of south-west Bangladesh was selected using a three-stage random sampling procedure. First, eight *Upazilas* (sub-district communities) were randomly selected, whereby the number of *Upazilas* chosen in each district was proportional to the district population size. Next, we randomly selected 36 villages from the eight *Upazilas* (Figure 2.2). Finally, we randomly selected 20 farm households from each village, resulting in a total sample of 720 households. All sample households grow rice. Out of the 720 households, 157 (22%) have adopted rice-aquaculture while 653 have not. As we use a random sample, this adoption rate can be considered representative for the study area.

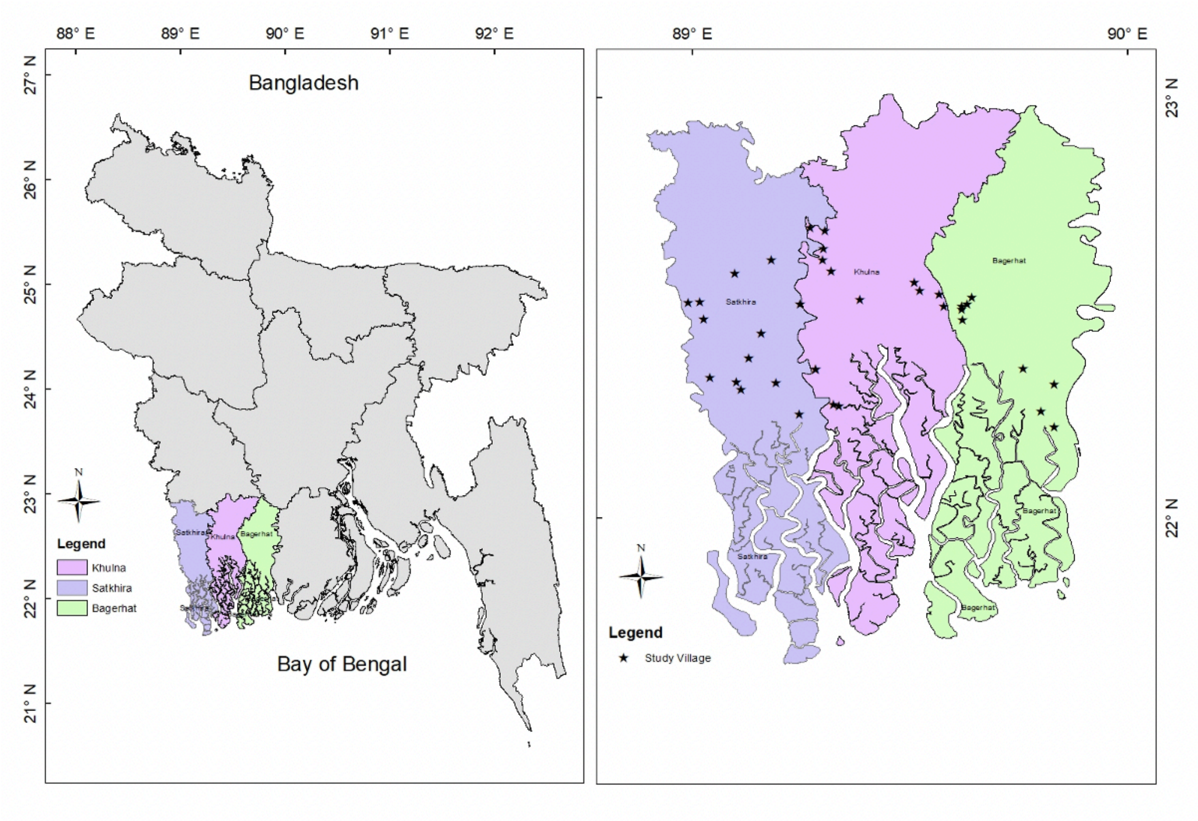


Figure 2.2: Map of the study area

The survey was implemented in October and November 2023, using a structured questionnaire for personal interviews with household heads and other household members. The questionnaire included sections on general household demographics, education levels, agriculture and aquaculture production, forest extraction activities, non-farm wage employment, vulnerability and resilience, household assets, savings, and credit access. Details on food consumption and diets were collected through food frequency questions. At the household level, the household head or the person responsible for cooking was asked about the number of times the household had consumed specific food items during the last seven days. The survey took place during the "normal season", where local food availability is better than during the lean season. However, since aquaculture is less affected by seasonality than rice and other crops, we separately also asked for the household consumption of food items during an "average week" in the lean season.

In addition to the household-level food consumption, we collected data on individual-level diets by asking household members whether they had eaten various food groups during the last 24 hours. This individual dietary information was collected only for the "normal season" from one male adult, one female adult, and one child in each household, whenever available. For children under the age of 10, the dietary questions were answered by the primary caregiver.

From male and female adults, we also collected details on individual time use per day, employing a list of 16 common work- and non-work-related activities in the study area during different seasons of the year (Lader et al., 2006; Stinson, 1999). For the "normal season", we asked individuals for their time use during the last 24 hours prior to the survey. For the "lean season", we asked for their time use during an average lean season day. Following Mehraban et al. (2022), we asked respondents about which concrete activity they performed during 30-minute intervals between 5:00 am and midnight (assuming that the remaining time would be occupied with sleeping and/or resting).

The agricultural section of the questionnaire covered information on planted areas, crop species grown, production costs, output quantities, and sales. The livestock and aquaculture sections included details on species kept, production costs, main products and by-products, revenues, and potential losses. For non-farm income sources, including wage employment, self-employment, and remittances and transfers, we recorded information for all household members on a monthly basis. We explicitly tried to capture individual income for an average month during the last one year, considering that economic activities may vary seasonally. In addition, we collected data on household consumption over the last one month, including food and non-food goods and services (e.g., transportation, communication, health care, education, personal care and clothing, etc.).

2.3.2. Outcome variables

Indicators of dietary quality

Dietary quality refers to how well the food intake of people matches with recommendations for balanced and healthy nutrition. A variety of diet quality metrics exist, with different data requirements (Miller et al., 2020). Most metrics – such as the mean nutrient adequacy ratio, the healthy eating index, or the global diet quality score – require details of the types and quantities of all food items consumed. Alternative metrics are dietary diversity scores, for which less detailed data are needed, as these scores only count the number of different food groups consumed by households or individuals during a pre-defined recall period (FAO, 2011). While dietary diversity scores are less precise in capturing all aspects of healthy nutrition, they are typically reasonable proxies of nutrient adequacy and therefore widely used in empirical research (Muthini et al., 2020; Ruel et al., 2018; Verger et al., 2021)

As we do not have data on the exact food quantities consumed, we measure dietary quality in terms of dietary diversity scores at the household and individual levels. Household dietary diversity is assessed using the household dietary diversity score (HDDS), counting the number of different food groups the household consumed over a 7-day recall period. We consider the following 12 groups, as recommended by FAO (2011): (1) cereals, (2) white roots and tubers, (3) vegetables, (4) fruits, (5) meat, (6) eggs, (7) fish, (8) legumes, nuts, and seeds, (9) milk and dairy products, (10) oils and fats, (11) sugar and sweets, and (12) spices, condiments, and beverages. We refer to this indicator as HDDS12. However, the last three of the 12 food groups are generally considered less healthy (low in micronutrients), which is why HDDS with the first nine food groups is sometimes calculated as an alternative proxy of household dietary quality (Parlasca et al., 2020; Sibhatu et al., 2015). We do so as well and refer to this alternative indicator as HDDS9. Both, HDDS12 and HDDS9 are calculated separately for the "normal season" and the "lean season" because we collected household-level food consumption data for both seasons, as explained above.

For the normal season, we also have individual-level 24h dietary data from several household members, which we use to calculate women's dietary diversity score (WDDS), men's dietary diversity score (MDDS), and children's dietary diversity score (CDDS). Each of these individual-level scores has its own food group classification to account for different nutritional needs (FAO, 2011). In particular, for MDDS and WDDS we use the following nine food groups: (1) starchy staples, (2) dark green leafy vegetables, (3) other vitamin A-rich fruits and vegetables, (4) other fruits and vegetables, (5) organ meat, (6) meat and fish, (7) eggs, (8) legumes, nuts, and seeds, and (9) milk and dairy products (Muthini et al., 2020). For CDDS, we use the following seven food groups: (1) grains and tubers, (2) legumes and nuts, (3) milk and dairy products, (4) flesh foods (meat, organ meat, and fish), (5) eggs, (6) vitamin A-rich fruits and vegetables, and (7) other fruits and vegetables (Agbadi et al., 2017; Muthini et al., 2020).

Other outcomes for analysis of mechanisms

As explained in the conceptual framework, rice-aquaculture adoption may influence dietary diversity through various mechanisms, including time allocation, income, and farm production diversity. To construct useful indicators of time use, we aggregate the various activities of male and female adults into six categories, namely (1) farm activities, (2) non-farm activities, including wage employment and self-employment, (3) commuting, also including the travel time between the homestead and the farm's fields, (4) cooking and other domestic activities, (5) forest extraction such as wild food collection, logging, and hunting, and (6) other activities (e.g., sleeping, eating, personal care, taking care of children and older members). Forest extraction is separately included because this is an important source of food and income for many households, especially during the lean season. We calculate the average daily number of minutes spent on each activity for the normal season and the lean season.

We calculate monthly income in per capita terms from various sources, namely farm income, off-farm income, forest extraction income, remittances and transfers, and total income. In addition, we are interested in how the income is spent and calculate monthly per capita consumption expenditures for total consumption and various expenditure categories of interest, namely food, transportation and communication, electricity and water, health care, education, and other non-food items (e.g., personal care and clothing, social gatherings, fees, fines, etc.). Income and expenditures are measured in Bangladeshi taka (BDT).

Farm production diversity is measured by counting the number of food groups a household produces. We use the same food group classification as for HDDS12 and HDDS9 and separately calculate farm production diversity scores with twelve food groups (PDS12) and nine food groups (PDS9). In addition, we create a production diversity indicator by simply counting the number of crop, livestock, and aquaculture species produced by each household.

2.3.3. Regression models

To examine the effects of adopting rice-aquaculture on dietary diversity we estimate regression models of the following type:

$$DDS_i = \theta + \beta A_i + \gamma X_i + \alpha D_i + \varepsilon_i \quad (1)$$

where DDS_i is the dietary diversity score of household i or an individual belonging to household i. We estimate separate models for HDDS12 and HDDS9 during the normal and lean seasons. In addition, we estimate individual-level dietary diversity for adults and children (MDDS, WDDS, CDDS). A_i is a binary variable indicating whether or not the household has adopted rice-aquaculture. X_i is a vector of household and contextual control variables, and D_i is a vector of district fixed effects. Control variables include age and education of the household head, household size, the number of dependent members, farm size, agroecological conditions, market access, and ownership of various assets. A detailed list of all variables and how they are measured is provided in Table B1 in the Appendix. We are particularly interested in the coefficient β, which indicates the effect of rice-aquaculture adoption on dietary diversity. The same type of models as shown in equation (1) are also estimated with time allocation, various income sources, and farm production diversity indicators as dependent variables to analyze potential mechanisms, as explained in the conceptual framework.

Furthermore, we are interested in understanding whether the effects of aquaculture adoption vary for different types of households. To examine heterogeneous effects, we re-estimate the models in equation (1) for various subsamples. To understand the role of education, we divide the total sample into low-education and high-education households by using mean years of schooling as the threshold. Regarding age, we classify households as younger and older households if the age of the household head is below or above the sample mean age. In the same way, we also differentiate between farms with smaller and larger land sizes.

2.3.4. Dealing with endogeneity

A potential problem in estimating the effects of rice-aquaculture with the models in equation (1) is endogeneity. Households' decisions to adopt rice-aquaculture are likely not only determined by observed factors (e.g., farm size, education levels) but may also be influenced by unobserved factors (e.g., personal preferences and abilities). If unobserved factors are jointly correlated with rice-aquaculture adoption and the outcome variables, the estimates of the coefficient β would be biased. Another potential source of endogeneity is reverse causality, which could occur if households would decide to adopt rice-aquaculture (or would be targeted especially by promoting organizations) because they have particularly high or low levels of dietary quality.

Fully controlling for possible endogeneity bias with cross-section observational data is difficult. Instrumental variable (IV) approaches are commonly used (Di Falco et al., 2011; Mishra et al., 2022), but finding convincing instruments that meet all criteria of validity is hard, especially when dealing with multiple outcome variables. We use a classical IV treatment effect approach as our preferred method, as described below. However, as our instrument seems to be valid only for some of the outcome variables, we additionally use several other approaches as robustness checks. What gives us some confidence is that the different approaches all yield similar results and support the same conclusions, which suggests that the findings are not driven by any particular method. Nevertheless, as we are unlikely to eliminate all potential sources of endogeneity, we do not claim to identify causal effects and interpret our estimates only as associations.

For our preferred IV approach (endogenous treatment effect models), we use the share of farmers adopting rice-aquaculture in the *Upazila* neighborhood as the instrument for individual adoption. This leave-one-out instrument is defined as the number of farmers surveyed in the respective *Upazila* who have adopted rice-aquaculture (excluding the individual household) divided by the total number of farmers surveyed in the *Upazila.* Using such local or regional leave-one-out instruments for individual behavior is a common approach in the literature (Hossain et al., 2024; Mishra et al., 2022; Melaku et al., 2024), as individual behavior and decisions are likely influenced by the behavior and decisions of others in the local context through social network effects. The share of farmers adopting rice-aquaculture in the eight *Upazilas* in our sample ranges from 0% to 40%, as shown in Table B2 in the Appendix.

The first-stage regression results are shown in Table B3 in the Appendix. In this model, with individual rice-aquaculture adoption as the dependent variable, our instrument (share of adopters in the *Upazila* neighborhood) has a positive estimation coefficient, as expected, and this coefficient is statistically significant at the 1% level. We conclude that the instrument is relevant and not weak.

A second condition for the instrument to be valid is the exclusion restriction, which requires that it is not correlated with the outcome variables through mechanisms other than individual rice-aquaculture adoption. While own dietary quality is unlikely to be affected by rice-aquaculture adoption of others directly, there may be indirect mechanisms that could violate the exclusion restriction. First, higher adoption rates at the *Upazila* level could possibly mean that fish and other aquaculture products are more available and affordable in local markets, which might influence dietary quality also among the local non-adopters. However, when we compare mean values of fish consumption between *Upazilas* with higher and lower rice-aquaculture adoption rates, we do not find significant differences (Table B4 in the Appendix). Fish consumption is high in all villages. This is because rice-aquaculture systems are not the only source of fish in the local context; river fishing is common, and many households also maintain small fish ponds near their homestead. Second, adoption rates at the *Upazila* level may be correlated with other regional characteristics, such as agroecological and/or infrastructure conditions, which could influence dietary quality through various mechanisms. However, in our models, we control for various agroecological and market access conditions and also include district fixed effects to account for unobserved regional factors.

To further analyze empirically whether the exclusion restriction holds we carry out falsification tests, as suggested by Di Falco et al. (2011), regressing the outcome variables on the instrument for the subsample of non-adopters while controlling for other covariates. The results of these falsification tests are shown in Table B5 in the Appendix. They suggest that our instrument is not significantly correlated with our household-level dietary quality indicators, HDDS12 and HDDS9 in the normal and lean seasons. For these and several other outcome variables, the exclusion restriction seems to hold, meaning that the instrument is valid. However, several other outcomes, including individual-level dietary diversity scores and household time allocation, are significantly correlated with the instrument, meaning that the exclusion restriction is unlikely to hold. Unfortunately, we were unable to identify alternative instruments that would pass the validity tests in these other models. This is also the main reason why we refrain from any causal interpretation.

As mentioned above, in addition to the classical IV approach, we use a suite of alternative methods and estimators as robustness checks. Specifically, we show simple ordinary least squares (OLS) estimates, and also use propensity score matching (PSM), a control function approach (CFA), and an alternative IV approach with heteroscedasticity-based instruments

(Lewbel, 2018). All of these approaches have their limitations, so the individual estimates have to be interpreted with caution. However, the estimates across the different approaches are quite similar, which means that interpretation in terms of associations should be in order.

2.4 Results and discussion

2.4.1. Descriptive statistics

Table 2.1 compares household characteristics between adopters and non-adopters of rice-aquaculture. Note that all households grow rice as their main staple crop, but not all combine rice cultivation with aquaculture. As mentioned above, of the 720 total households in our sample, 157 (22%) have adopted rice-aquaculture while 563 have not. On average, adopters have lower education levels and are less likely to be affected by drought than non-adopters. Adopters also have higher debts than non-adopting households. In terms of wealth and living standards, adopting households have somewhat larger farm sizes, other asset values, and incomes than non-adopting households, even though some of these differences are not statistically significant. In contrast, food consumption expenditures (including the value of home consumption) are somewhat lower among adopters than non-adopters.

Table 2.1: Household characteristics by adoption of rice-aquaculture

Variables	Measurement unit	(1) Full sample	(2) Non-adopters	(3) Rice-aquaculture adopters	(3)- (2)
Household size	Number	4.52	4.48	4.66	0.18
		(1.64)	(1.68)	(1.50)	
Age head	Years	50.09	50.09	50.13	0.04
		(12.16)	(12.43)	(11.19)	
Male head	Dummy	0.96	0.96	0.97	0.01
		(0.20)	(0.20)	(0.18)	
Education head	Years of schooling	5.04	5.25	4.32	-0.93**
		(4.31)	(4.34)	(4.17)	
Dependents	Number	1.43	1.41	1.49	0.08
		(1.19)	(1.20)	(1.15)	
Having TV	Dummy	0.34	0.33	0.39	0.06
		(0.48)	(0.47)	(0.49)	
Having motorbike	Dummy	0.14	0.13	0.18	0.06*
		(0.35)	(0.33)	(0.39)	
Having smartphone	Dummy	0.59	0.60	0.59	0.01
		(0.49)	(0.49)	(0.49)	
Farm size	Hectare	0.38	0.37	0.41	0.04
		(0.46)	(0.42)	(0.57)	
Asset value per capita	Thousand BDT	10.77	10.51	11.73	1.24
		(10.90)	(10.61)	(11.84)	
Distance to market	Kilometer	1.94	1.96	1.91	-0.04
		(1.30)	(1.29)	(1.37)	
Flood	Dummy	0.03	0.03	0.01	-0.02
		(0.17)	(0.18)	(0.11)	
Drought	Dummy	0.08	0.09	0.04	-0.05**
		(0.01)	(0.01)	(0.01)	
Total income per capita	Thousand BDT	4.31	4.22	4.62	0.40*
		(0.10)	(0.11)	(0.21)	
Farm income per capita	Thousand BDT	2.28	2.16	2.74	0.58***
		(0.07)	(0.08)	(0.17)	
Off-farm income per capita	Thousand BDT	1.59	1.57	1.68	0.12
		(0.07)	(0.08)	(0.17)	
Total consumption per capita	Thousand BDT	4.13	4.17	3.96	0.21
		(0.08)	(0.09)	(0.14)	
Food consumption per capita	Thousand BDT	1.70	1.73	1.60	-0.13*
		(0.03)	(0.04)	(0.05)	
Non-food consumption per capita	Thousand BDT	2.42	2.44	2.36	0.08
		(0.06)	(0.08)	(0.11)	
Debt value	Thousand BDT	33.56	27.73	54.46	26.73***
		(2.13)	(1.98)	(6.35)	
No. of observations		720	563	157	

*Notes: *** p < 0.01, **p < 0.05, * p < 0.1; Standard deviations in parentheses.*

Table 2.2 compares the various dietary diversity indicators between rice-aquaculture adopters and non-adopters. During the normal season, adopters of rice-aquaculture appear to have slightly lower dietary diversity scores than non-adopters, both at household and individual levels, but most of these differences are not statistically significant. Yet, during the lean season, rice-aquaculture adopters have significantly lower dietary diversity than non-adopters. Additional descriptives in Tables B6 and B7 in the Appendix show differences in the consumption of specific food groups during both seasons. In the lean season, adopters are less likely to consume roots and tubers, seeds and nuts, eggs, dairy products, vegetables, and fruits, but more likely to consume fish and oils and fats than non-adopters.

Table 2.2: Dietary diversity indicators by adoption of rice-aquaculture

	Normal season			Lean season		
	(1) Non-adopters	(2) Rice-aquaculture adopters	(2)-(1)	(4) Non-adopters	(5) Rice-aquaculture adopters	(5)-(4)
Household dietary diversity, 12 food groups (HDDS12)	9.66	9.43	-0.22	9.45	9.01	-0.44**
	(1.77)	(1.92)		(1.96)	(2.16)	
Household dietary diversity, 9 food groups (HDDS9)	7.00	6.75	-0.25*	6.97	6.50	-0.47***
	(1.49)	(1.67)		(1.59)	(1.81)	
Men's dietary diversity score (MDDS)	3.91	3.75	-0.16	-	-	-
	(1.30)	(1.31)				
Women's dietary diversity score (WDDS)	3.96	3.78	-0.18	-	-	-
	(1.33)	(1.28)				
Child dietary diversity score (CDDS)	3.92	3.86	-0.06	-	-	-
	(1.23)	(1.16)				

*Notes: *** p<0.01, ** p<0.05, * p<0.1; Standard deviations in parentheses.*

2.4.2. Associations between rice-aquaculture adoption and household diets

We now present the results of the regression models explained in equation (1). We use the IV treatment effect model estimates as our main results (robustness checks with various other approaches are discussed further below). Table 2.3 shows the estimated associations between rice-aquaculture adoption and household dietary diversity.

Table 2.3: Association between rice-aquaculture adoption and household dietary diversity

	Normal season			Lean season
	(1)	(2)	(3)	(4)
	HDDS12	HDDS9	HDDS12	HDDS9
Rice-aquaculture	-0.461	-0.565	-1.418**	-1.074***
	(0.440)	(0.357)	(0.571)	(0.364)
Household size	0.064	0.071	0.104*	0.103**
	(0.058)	(0.046)	(0.062)	(0.050)
Age head	-0.004	-0.005	-0.008	-0.009
	(0.006)	(0.005)	(0.007)	(0.005)
Male head	0.153	0.251	0.059	0.119
	(0.299)	(0.252)	(0.378)	(0.308)
Education head	0.027	0.025	-0.008	0.002
	(0.019)	(0.015)	(0.021)	(0.017)
No. of dependent	0.119	0.067	-0.001	-0.005
	(0.078)	(0.065)	(0.089)	(0.071)
Having TV	0.166	0.144	0.432***	0.303**
	(0.144)	(0.123)	(0.166)	(0.136)
Having motorbike	-0.002	-0.006	0.089	-0.033
	(0.209)	(0.174)	(0.244)	(0.194)
Having smartphone	0.208	0.238*	0.355**	0.270*
	(0.153)	(0.127)	(0.173)	(0.139)
Distance to market	0.078	0.078*	0.097*	0.086*
	(0.052)	(0.042)	(0.056)	(0.044)
Farm size	0.289**	0.284***	0.356**	0.298**
	(0.130)	(0.107)	(0.168)	(0.128)
Asset value per capita (ln)	0.248***	0.181**	0.191*	0.163**
	(0.090)	(0.075)	(0.101)	(0.081)
Flood	-0.134	0.057	-0.124	0.160
	(0.337)	(0.253)	(0.398)	(0.320)
Drought	-0.095	-0.178	0.119	0.049
	(0.200)	(0.169)	(0.238)	(0.185)
Khulna district	-0.270	-0.173	-0.410**	-0.248
	(0.176)	(0.148)	(0.207)	(0.154)
Satkhira district	0.288	0.329**	-0.108	-0.078
	(0.182)	(0.153)	(0.215)	(0.168)
Constant	6.525***	4.457***	7.402***	5.081***
	(0.860)	(0.719)	(0.964)	(0.783)
Wald chi^2	79.19	95.69	74.59	80.18
p-value	0.00	0.00	0.00	0.00
Obs.	720	720	720	720

*Notes: *** $p < 0.01$, **$p < 0.05$, * $p < 0.1$; Robust standard errors in parentheses; HDDS12: Household dietary diversity score with 12 food groups considered. HDDS9: Household dietary diversity score with 9 food groups considered. Regression results obtained from IV endogenous treatment effect models.*

The estimates in columns (1) and (2) of Table 2.3 refer to the normal season. The results suggest that rice-aquaculture adoption is negatively associated with household dietary diversity, even though these estimates are not statistically significant. Columns (3) and (4) of Table 2.3 refer to the lean season, where the negative associations between rice-aquaculture adoption and household dietary diversity are more pronounced and statistically significant. Rice-aquaculture adoption is associated with a 1.4 and 1.1 reduction in HDDS12 and HDDS9, respectively. These are sizeable negative associations.

During the lean season, food supplies are generally low, as the food stocks from the last harvest are almost exhausted and the next harvest is not yet in. This is the time when many rural households in Bangladesh try to pursue other income-earning activities, including non-farm jobs and seasonal migration (Lain & Brunelin, 2024; Rana & Qaim, 2024; Tojo-Mandaharisoa et al., 2023). Rice-aquaculture systems are actually expected to mitigate seasonal food and income shortfalls, as aquaculture production continues also during the lean season. However, as mentioned, rice-aquaculture systems are labor-intensive. They require frequent and careful observation of the fields also during the lean season. This may hinder household members to pursue other activities, which may explain the negative associations between rice-aquaculture adoption and dietary diversity. These mechanisms are analyzed in more detail below.

The control variables in Table 2.3 suggest that farm size (land owned by the household) and the value of other assets owned are positively associated with dietary diversity, as one would expect. We also observe regional differences, as indicated by the district dummies. Several other control variables, such as education, age, and sex of the household head, as well as ownership of motorbikes, are not statistically significant. This is likely due to some correlation of these variables with farm size and asset values. We tested for possible multicollinearity by estimating variance inflation factors (VIFs). The mean VIF is 1.43, and each of the explanatory variables has a VIF score of less than 4 (Table B8 in the Appendix), meaning that multicollinearity is not an issue. The Wald chi^2 and *p*-values in Table 2.3 also suggest that the models are all significant.

Figure 2.3 shows the estimated associations between rice-aquaculture adoption and individual-level dietary diversity during the normal season (as mentioned, individual-level diet data were not collected for the lean season). We show results for the separate regression models for men (MDDS), women (WDDS), and children (CDDS), only presenting the point estimates for the main explanatory variable of interest, namely rice-aquaculture adoption, with their 95%

confidence intervals. Full model results with all control variables are shown in Table B9 in the Appendix. As can be seen in Figure 2.3, the association between rice-aquaculture adoption and child dietary diversity (CDDS) is not statistically significant, as the confidence interval crosses the vertical zero line. However, the coefficients for men and women are both negative and significant. That is, rice-aquaculture adoption is associated with a reduction in MDDS and WDDS. The magnitude of the association indicates that men and women in adopting households consume almost one food group less than their counterparts in non-adopting households, after controlling for other relevant factors.

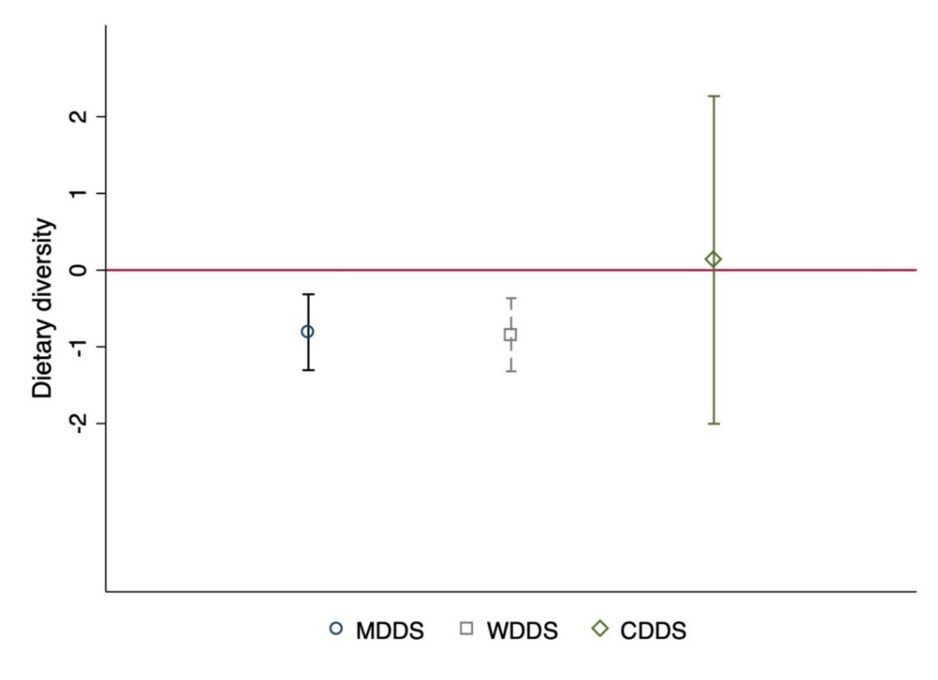


Figure 2.3: Associations between rice-aquaculture adoption and individual dietary diversity

Notes: Coefficient estimates from endogenous treatment effect models are shown with 95% confidence intervals. MDDS: Men's dietary diversity score; WDDS: Women's dietary diversity score; CDDS: Child dietary diversity score. Full model results are shown in Table B9 in the Appendix.

Figure 2.4 shows heterogeneous results for various subsamples of farm households differentiating by education, age, and farm size. Here, low and high education, young and old household heads, and small and large farms refer to observations below and above the sample means for the respective variables. During the normal season, we do not see statistically significant associations between rice-aquaculture adoption and household dietary diversity for any of the subsamples, whereas during the lean season, we do see significant patterns.

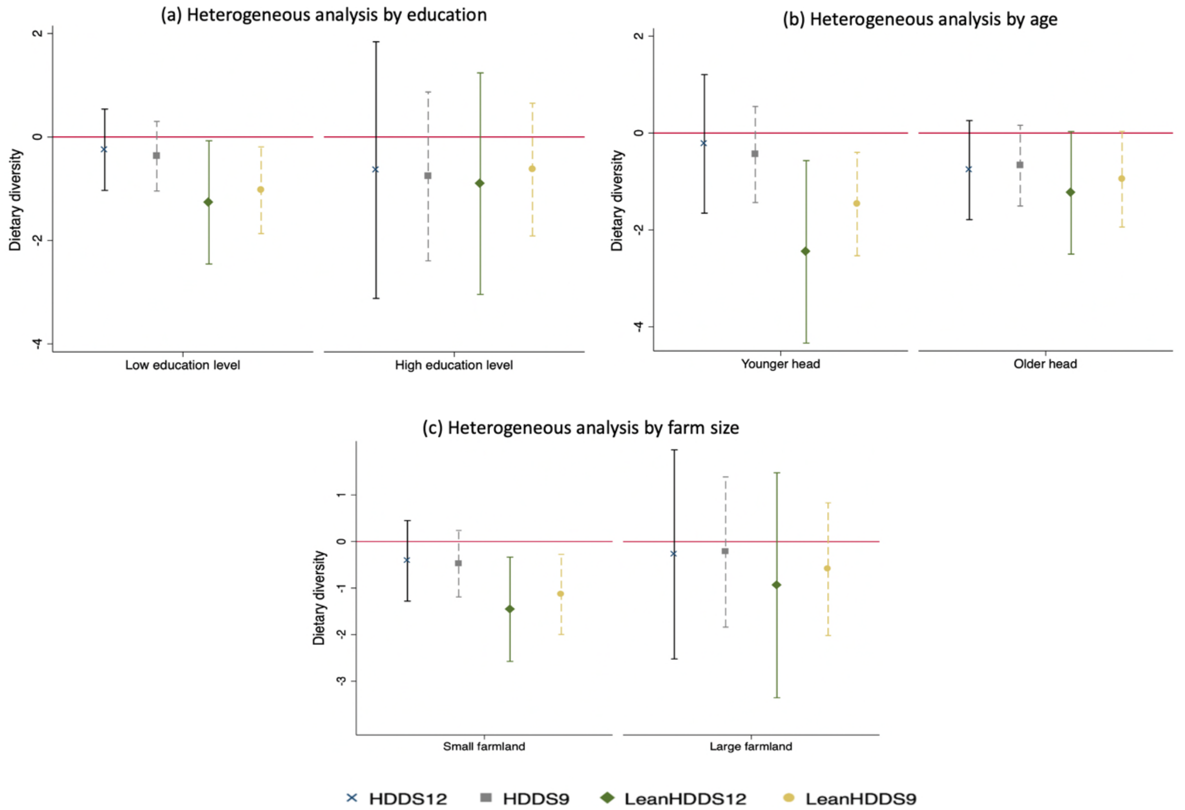


Figure 2.4: Heterogeneous associations between rice-aquaculture adoption and household dietary diversity

Notes: Coefficient estimates from endogenous treatment effect models are shown with 95% confidence intervals. HDDS12 and HDDS9 refer to household dietary diversity during the normal season; LeanHDDS12 and Lean HDDS9 refer to household dietary diversity during the lean season. Full model results are shown in Tables B10-B15 in the Appendix.

Panel (a) in Figure 2.4 reveals that rice-aquaculture adoption has significantly negative associations with lean-season HDDS12 and HDDS9 for households with lower education levels, but not for households with above-average education. This is plausible, as rice-aquaculture systems are knowledge-intensive, and farmers with low education levels may lack the technical knowledge needed for proper management (Islam et al., 2015). Without sufficient technical knowledge and skills in terms of water quality management, fingerling care, and disease and pest control, the economic success of the enterprise may suffer (Islam et al., 2015; Nabi, 2008), contributing to lower instead of better dietary quality for the farming household.

Panel (b) of Figure 2.4 shows heterogeneous associations for households with younger and older household heads. During the lean season, we observe negative associations between rice-aquaculture adoption and HDDS12 and HDDS9 for both types of households, but these associations are more pronounced for the younger group. This may be related to the fact that younger household heads tend to have smaller households and thus fewer family members who could support the labor-intensive rice-aquaculture business. Also, young household heads tend to have less experience and fewer financial resources for investments into proper technology, which may result in lower productivity and income.

Panel (c) of Figure 2.4 differentiates by farm size. Rice-aquaculture adoption has significantly negative associations with lean season dietary diversity for small farm households, but not for larger farm households. This may be related to the lower ability of small farm households to invest into proper technology. In addition, the management of rice-aquaculture systems is more challenging on small plots, due to the limited space for both rice and aquaculture production (Dey et al., 2013; Nabi, 2008). In particular, when the fish density is too high, disease pressure increases and rice yields may suffer (Hu et al., 2016).

Note that the differences between the subsample estimates in Figure 2.4 are only suggestive, due to relatively large confidence intervals. Instead of using separate models for each subsample, we also estimate full sample models with interaction terms between rice-aquaculture adoption and the different socioeconomic characteristics (Tables B16-B18 in the Appendix). These interaction terms are not statistically significant, suggesting that the results in terms of heterogenous associations should not be overinterpreted. However, the interaction terms assume continuous differences and cannot necessarily identify threshold effects that may possibly exist.

2.4.3. Mechanisms of the associations

We now analyze the mechanisms through which rice-aquaculture adoption may be associated with dietary diversity. We start by looking at time allocation. For this analysis, we sum up the time spent on various activities by male and female adults during the normal and lean seasons, respectively. Table B19 in the Appendix compares mean values for adopting and non-adopting households. Figure 2.5 illustrates the associations between adoption and time allocation, estimated with our endogenous treatment effect regression models. As discussed above, the exclusion restriction for our instrument may not hold for some of the time allocation variables and other outcomes in this analysis of potential mechanisms. We cautiously interpret these IV results nevertheless because the estimates are very similar to those obtained with other econometric approaches, as we show below in the robustness checks.

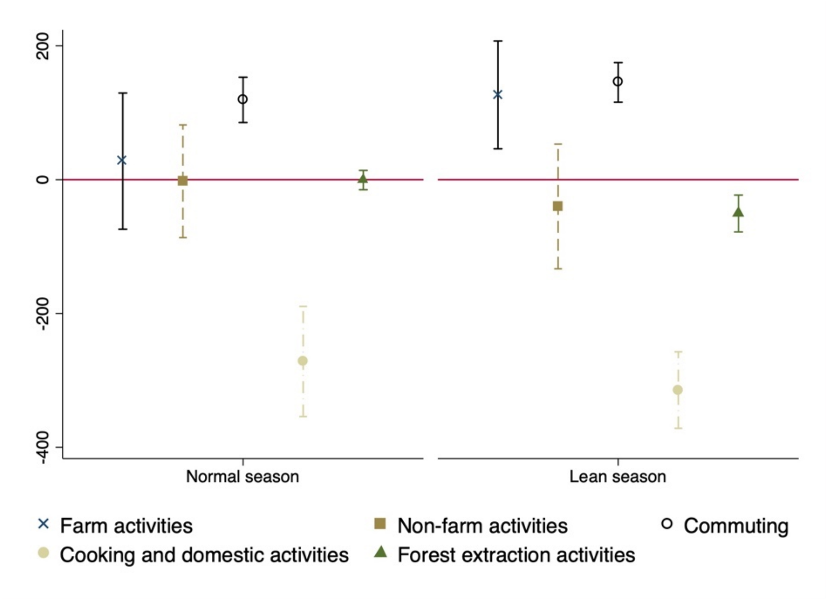


Figure 2.5: Associations between rice-aquaculture adoption and household time allocation

Notes: Coefficient estimates from endogenous treatment effect models are shown with 95% confidence intervals. Full model results are shown in Tables B20 and B21 in the Appendix.

The regression results shown in Figure 2.5 largely confirm the patterns observed in the descriptive statistics. In both seasons, rice-aquaculture adoption is positively associated with the household time spent on commuting, as the fields have to be visited more frequently for irrigation, disease control, monitoring water levels, and feeding fish. During the lean season, adoption is also positively associated with farm activities. Conversely, during both seasons, rice-aquaculture adoption is significantly associated with reductions in the time spent on cooking and other domestic activities. With limited time for cooking and domestic activities, households might prefer less diverse calorie-rich meals, which are often quicker to prepare than more diverse and healthy diets. Furthermore, during the lean season, rice-aquaculture adoption is negatively associated with the time spent on forest extraction activities, including the collection of wild foods and hunting, which may also help explain the negative implications for dietary diversity. Forest extraction activities are much less common during the normal season, when all households are more busy with their own farming activities.

Next, we look at income as a potential mechanism, for which results are summarized in Figure 2.6, panel (a). Rice-aquaculture adoption is not significantly associated with total income and farm income. For farm income, we would actually have expected a positive association through the additional aquaculture production in the rice fields, but such a positive incident is not observed. Obviously, the additional time spent on farming is not rewarded by a higher farm income among adopting households. However, rice-aquaculture adoption is negatively associated with the income from forest extraction activities, which is plausible, given the lower time spent on this activity during the lean season. In addition, adoption has a slight negative association with income from remittances and transfers (including seasonal migration income).

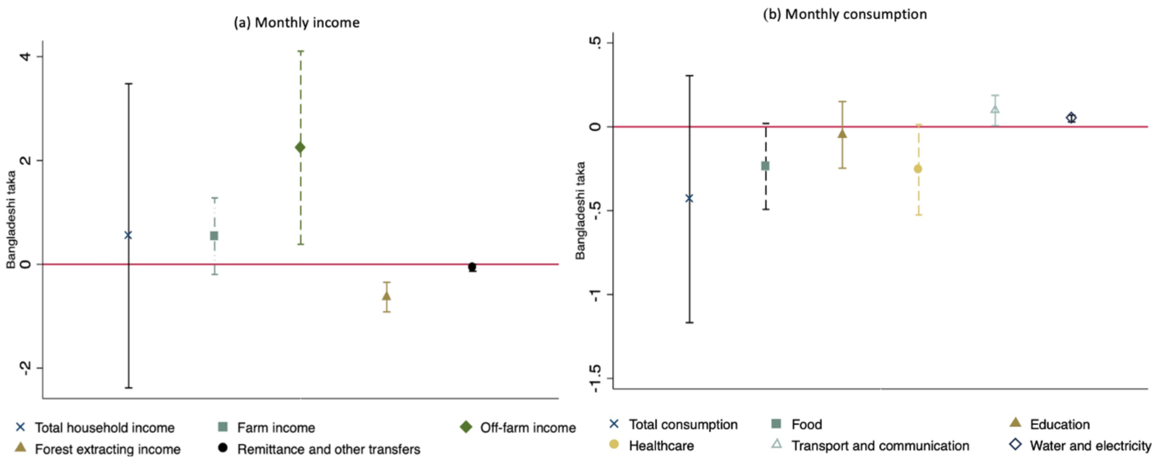


Figure 2.6: Associations between rice-aquaculture adoption and per capita household income and consumption

Notes: Coefficient estimates from endogenous treatment effect models are shown with 95% confidence intervals. Full model results are shown in Table B22 and B23 in the Appendix.

Panel (b) of Figure 2.6 shows associations between rice-aquaculture adoption and household consumption. The coefficients for total consumption, food consumption, and healthcare expenditures are negative but not statistically significant. However, rice-aquaculture adoption is significantly associated with increases in the expenditures on transportation and communication, and water and electricity. These results need to be interpreted with some caution, as some of these items (e.g., water, electricity, transportation) are actually used for aquaculture production rather than for consumption purposes, so they may not indicate an actual increase in household wellbeing.

Finally, we analyze associations between rice-aquaculture adoption and farm production diversity. Descriptive comparisons between adopters and non-adopters are shown in Table B24 in the Appendix. Regression results are summarized in Figure 2.7. They suggest that rice-aquaculture adoption is negatively associated with farm production diversity (PDS12 and PDS9), which may be surprising at first sight, as adoption means additionally introducing aquatic species. Further disaggregation shows that adoption is indeed positively associated with the number of aquatic species produced, but is negatively associated with the number of crop and livestock species and therefore also the number of food groups produced by households. This mechanism suggests that some of the negative association between rice-aquaculture adoption and dietary diversity may also be channelled through lower food diversity from subsistence production.

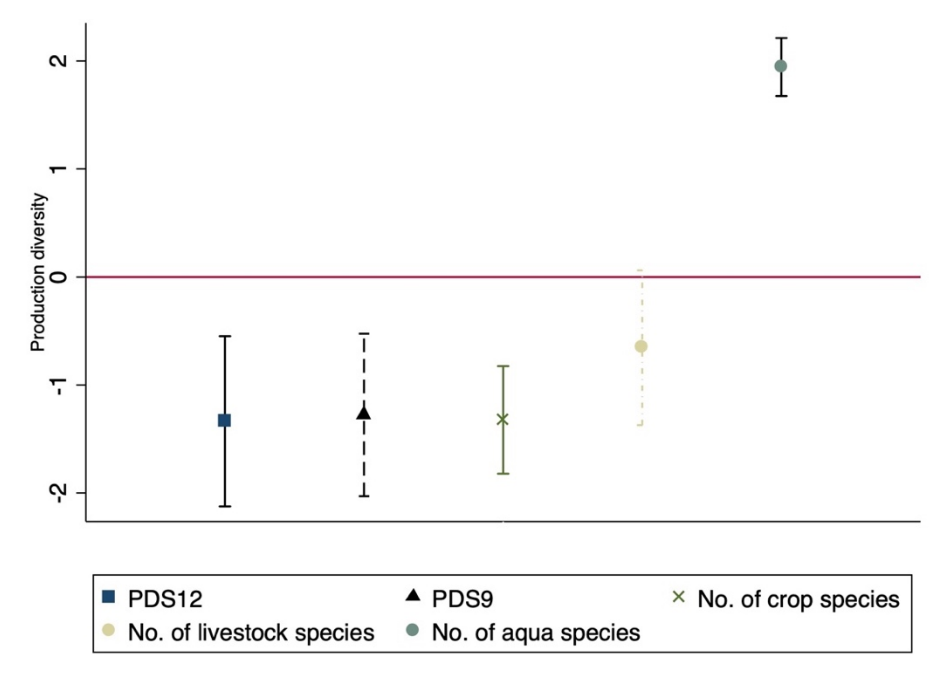


Figure 2.7: Association between rice-aquaculture adoption and farm production diversity

Notes: Coefficient estimates from endogenous treatment effect models are shown with 95% confidence intervals. PDS12 and PDS9 delineate farm production diversity scores with 12 and 9 food groups, respectively. Full model results are shown in Table B25 in the Appendix.

2.4.4. Robustness checks

As explained above, we also use a suite of alternative econometric approaches to test the robustness of our results. In particular, we use OLS, PSM, CFA, and IV models with heteroscedasticity-based instruments to examine the associations between rice-aquaculture adoption, dietary diversity, time allocation, income and consumption, and farm production diversity. Results obtained from these alternative models are presented in Tables B26-B31 in the Appendix. Generally, these results are consistent with those from the endogenous treatment effect models presented above.

Rice-aquaculture adoption is negatively associated with dietary diversity, and these negative associations are especially pronounced during the lean season (Table B26). Adoption is positively associated with the time spent on farming and commuting, and negatively associated with the time spent on cooking and other domestic activities, and forest extraction (Table B28). In some of the models, adoption is significantly positively associated with farm income, but is consistently negatively associated with income from forest extraction (Table B29). Adopters spend more on water, electricity, transportation, and communication, whereas the associations with total consumption and food consumption are mostly insignificant, and significantly negative in some of the models (Table B30). Rice-aquaculture adoption is positively associated with farm production diversity in models that do not control for unobserved heterogeneity (OLS and PSM), but negatively associated in models with IVs (CFA, heteroscedasticity-based instruments, Table B31). Overall, the main findings seem to be quite robust.

2.5 Conclusion and policy implications

Rice-aquaculture systems are widely promoted in many countries. It is typically assumed that adoption would increase yields and incomes from the production of rice and aquatic species while also enhancing farm household diets and nutrition. However, previous studies analyzing the actual implications for diets and nutrition do not exist. We have addressed this research gap and have investigated associations between rice-aquaculture adoption and dietary quality, measured in terms of household-level and individual-level dietary diversity scores. We have also examined heterogeneous results for different types of households. Furthermore, we have investigated possible mechanisms of how rice-aquaculture adoption may influence dietary quality, namely through changes in household time allocation, income, and farm production diversity.

Our findings reveal that rice-aquaculture adoption is negatively associated with household dietary diversity, women's dietary diversity, and men's dietary diversity, thus contradicting the hypothesis of positive implications for dietary quality. The negative associations are especially pronounced during the lean season, when many rice farmers in Bangladesh experience dietary shortfalls. The hope that these seasonal shortfalls would be mitigated through additionally integrating aquaculture species into the production system is not confirmed in our study. On the contrary, rice-aquaculture adopters are more affected by lean season dietary shortfalls than non-adopters.

It could be argued that the negative dietary associations observed may be due to a potential selection bias in the sense that poorer households with lower dietary quality are possibly the ones mostly targeted by organizations promoting rice-aquaculture systems in Bangladesh and are therefore more likely to be among the adopters. This could even lead to a reverse causality problem. However, in our data we do not observe that poorer and more marginalized households are the main group of adopters. On the contrary, farmers with larger landholdings are significantly more likely to adopt rice-aquaculture systems (see Table B3 in the Appendix). Adopting farmers are also somewhat richer and wealthier than non-adopters (Table 2.1). Hence, if anything, a potential selection bias would point in the opposite direction and would rather lead to an underestimation of the negative dietary effects. This would imply that our results may actually be interpreted as conservative estimates.

The observed negative dietary associations are likely due to the large initial financial investments required for adopting rice-aquaculture, limited yield and income gains, and considerable amounts of time needed for managing the system. We show that adoption of rice-aquaculture is associated with a significant increase in the household time spent on farming activities and a decrease in the time spent on cooking and other domestic tasks. Especially during the lean season, rice-aquaculture adoption is also associated with a decrease in the household time spent on forest extraction activities, such as wild food collection, logging, and hunting. These forest extraction activities are not only a source of off-farm income, but also a source of food diversity, during periods when other income and food sources are scarce. Further, we show that rice-aquaculture adoption is negatively associated with transfers and remittances, including income from seasonal migration. While adoption is positively associated with the diversity of aquatic species produced on the farm, it is negatively associated with farm diversity in terms of other crop and livestock species. Finally, our findings show that rice-aquaculture adopters bear a significantly higher debt burden than non-adopters.

Our results do not imply that rice-aquaculture could not benefit smallholder farmers in general. But in the particular context analyzed here, the economic benefits seem to be small. This is likely due to the complexity of the system, which may be difficult to manage for typical smallholders. This interpretation is supported by our analysis of heterogenous associations: negative diet and nutrition associations of rice-aquaculture adoption are particularly observed among farmers with low education levels, limited experience, and small landholdings.

Our study has a few limitations. First, we have used cross-section observational data, which has drawbacks for the identification of causal effects. We have employed different approaches to control for possible endogeneity bias. All approaches support the same conclusions, which is reassuring. Nevertheless, we may not control for all potential sources of endogeneity, which is why we interpret our estimates as associations, and not as rigorously identified causal effects. Moreover, cross-sectional data do not allow us to analyze possible dynamics of adoption, such as increasing benefits over time due to farmers gaining additional experience. Longitudinal data could provide a more comprehensive understanding. Second, we have tried to differentiate between normal season and lean season effects, which seems to be important, but our lean season data were collected through recall questions and may therefore be associated with inaccuracies. Repeated surveys during different seasons could lead to more reliable estimates. Third, we have used dietary diversity scores as proxies of dietary quality. Additional data on food quantities consumed could help to construct additional indicators of dietary quality, such as nutrient adequacy ratios for various micro- and macronutrients. Follow-up research with more comprehensive data will be useful to gain additional insights into the nutrition effects of rice-aquaculture adoption and the underlying mechanisms.

In spite of these limitations, our findings have important policy implications. Rice-aquaculture systems are complex and time-intensive to manage. Adoption cannot be assumed to improve household incomes and diets in all situations. If not properly managed, rice-aquaculture adoption may even lower dietary quality, as it draws away household time from other economic activities and domestic tasks. The additional on-farm time requirements for managing rice-aquaculture are not a problem per se, if the rice-aquaculture enterprise is more lucrative than the alternative time uses, such as forest extraction activities during agricultural lean seasons. Reducing farmers' forest extraction activities may even be desirable from an environmental perspective because the mangrove forests in south-west Bangladesh are overexploited anyway. However, for smallholder farmers in the region, rice-aquaculture adoption is not yet sufficiently lucrative to offset the opportunity cost of household labor time.

The best option to address this issue and increase farmers' productivity and income gains from rice-aquaculture adoption is to provide better training and technical support. Successfully growing rice and raising fish simultaneously in the same fields needs special knowledge and technical skills (Ahmed & Garnett, 2011; Dey et al., 2013; Samaddar et al., 2025). Training should be provided by the agricultural extension system, possibly in cooperation with local NGOs. Cost-effective extension models to reach a larger number of farmers will need to be developed. These should be designed in gender-sensitive and gender-transformative ways to strengthen the role of women in income-generation. Training of farmer groups could help reduce extension costs. Farmer collective action in terms of investments, input procurement, labor supply, and marketing could also contribute to efficiency gains and mutual learning, thus making rice-aquaculture farming more profitable for smallholders. Combining agricultural training and extension with nutrition education may also be useful to improve dietary quality.

CHAPTER 3

3 The effects of internet use on smallholder farmers' income and dietary quality in Bangladesh[2]

Abstract

Internet access in rural areas of low- and middle-income countries is expanding at a rapid rate and affects how people produce and consume food and other goods and services. This may have implications for the incomes and diets of smallholder farm households, where poverty and undernutrition are still commonplace. In this study, we use primary data collected from 720 farm households in Bangladesh to analyze how internet use affects agricultural production and food consumption. Employing propensity score matching and instrumental variable methods, we show that internet use is positively associated with farm production diversity, commercialization, and income. We also find positive effects on dietary diversity, even though the results depend on the specific dietary indicators used. Internet use increases household and women's dietary diversity, whereas the effects on child dietary diversity are statistically insignificant. Internet use encourages the production of certain nutritious foods but does not always lead to an increase in their consumption. Our results highlight the important role of the internet in enhancing farm productivity, income, and potentially diets.

Keywords: internet, farm production, consumption behavior, seasonality, Bangladesh

[2] This is a joint paper by Fariha Farjana with Thanh-Tung Nguyen and Matin Qaim. A previous version was presented at the European Association of Agricultural Economists Congress. This international conference was organised by the University of Bonn on August 26 – 29, 2025, in Bonn, Germany.
This paper is also published as ZEF Discussion Papers on Development Policy No. 364, Center for Development Research, Bonn, June 2025, pp. 39. doi: https://doi.org/10.48565/bonndoc-578
Fariha Farjana developed the research idea, collected and analysed the data, and wrote the manuscript under the guidance and supervision of the co-authors.

3.1 Introduction

The internet is expanding at a rapid rate, affecting different aspects of people's daily lives, which is true even in rural areas of low- and middle-income countries. The internet can be associated with numerous benefits by facilitating access to knowledge, information, and various types of innovations and services, thereby potentially improving productivity and income (Chang & Just, 2009; Liu et al., 2024; Nguyen et al., 2023). In addition, the internet may positively influence people's nutrition and health by providing relevant information on healthy diets and lifestyles (Chen & Liu, 2022; Luo et al., 2024; Pollard et al., 2015). It is assumed that the internet could play an important role in improving peoples' lives, particularly those with limited or null access to information, markets, and services, such as smallholder farmers. However, the internet can potentially also have negative effects on people. For instance, it may encourage people to excessively engage in online gaming and entertainment activities, which could harm productivity, income, and health (Ayran et al., 2021; Duke & Montag, 2017; Vandelanotte et al., 2009). Exposure to online advertising for unhealthy foods might influence people to consume them, leading to lower dietary quality (Coleman et al., 2022; Pettigrew et al., 2013). In this study, we analyze the effects of internet use on economic and dietary outcomes among smallholder farm households in Bangladesh.

A few previous studies have examined the effects of internet use on food consumption choices, mostly in China. For instance, Deng et al. (2024) and Yang et al. (2023) show that internet use contributes to an increase in the consumption of healthy foods and dietary diversity. In contrast, Ning et al. (2024) suggest that the internet promotes unhealthy dietary habits. Other studies analyze the effects of internet use on farm production in different countries of Asia and generally find improvements in farm economic performance (Kaila & Tarp, 2019; Nguyen et al., 2023; Zheng et al., 2022). To the best of our knowledge, there are no studies jointly analyzing the effects of internet use on agricultural production and food consumption in farming households. Since smallholder farmers tend to consume a large proportion of what they produce, our joint analysis contributes to a better understanding of the underlying dynamics.

Our study has two main research objectives, namely to examine the effects of internet use on (i) smallholder food production activities and (ii) food consumption choices. In analyzing food consumption, we also consider seasonal differences, as diets in smallholder households often deteriorate during agricultural lean seasons.

We use survey data collected in Bangladesh from randomly selected farm households, including users and non-users of the internet, and employ quasi-experimental econometric approaches for data analysis. Bangladesh is an appropriate study country because internet use has increased rapidly over the last 10 years, from 7% of the total population in 2013 to 42% in 2023 (World Bank, 2025). Undernutrition and micronutrient deficiencies remain major public health problems in Bangladesh, especially in rural areas (Dey et al., 2024; Nguyen et al., 2025; Song et al., 2023).

The subsequent sections are structured as follows: Section 3.2 presents the conceptual framework, illustrating possible links between internet use and food production and consumption. Details about the study area, data collection procedures, and econometric methods are provided in section 3.3. The empirical results are presented in section 3.4, while section 3.5 concludes with a brief summary and some policy implications.

3.2 Conceptual framework

Figure 3.1 presents the conceptual framework, illustrating the links between internet use and household food production and consumption.

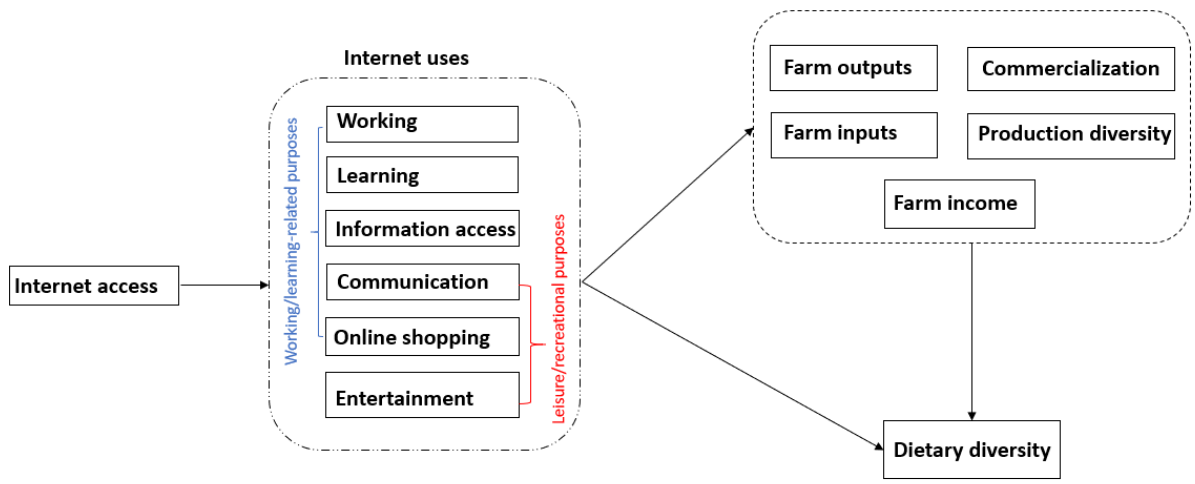


Figure 3.1: Conceptual framework

People use the internet for various purposes, which can be broadly categorized into working and learning-related purposes on the one hand, and leisure and recreational purposes on the other. For working and learning-related purposes, people might use the internet to search for information on new farming techniques, market prices, and weather forecasts (Wei et al., 2023; Zheng et al., 2022). Farmers may also use the internet to communicate, build business networks, sell their products, and purchase agricultural inputs (Khan et al., 2022; Li et al., 2018). For leisure and recreational purposes, people may use the internet for social networking, chatting with friends, entertainment (e.g., watching movies, listening to music, playing online games), or online shopping (Chang, 2013; Ioannidis et al., 2018). Depending on the various uses of the internet, the effects on farm production and dietary choices can be different.

Regarding production, if farmers primarily use the internet for working and learning-related purposes, it can lead to higher agricultural output and income (Chandio et al., 2023). Access to better farming techniques enhances efficiency, while knowledge of market prices helps in making more informed production and sales decisions. The internet also enables farmers to reach out to more input suppliers, find lower priced inputs, and adopt cost-effective farming methods (Rejeb et al., 2022; Zheng et al., 2021). Internet use can promote farm commercialization by making it easier to connect with buyers and sell products beyond local markets (Birner et al., 2021; Strzębicki, 2015). It may also affect production diversity—some farmers might specialize on the most profitable crops, while others may diversify based on market trends to maximize their returns. However, excessive internet use for entertainment may have negative effects if farmers become less engaged in their work, leading to inefficiencies or reduced output.

Regarding consumption, presumed that internet use has positive effects on farm income, higher earnings can improve household diets by enabling families to afford more nutritious foods. Positive effects on farm commercialization might lead to improved dietary diversity if the income from selling farm products is used to purchase a variety of nutritious foods. However, the impact is not automatically positive. If households sell their food products but spend the earnings on less-healthy foods or non-food items, dietary diversity may decline (Ali et al., 2022). Regarding links between production and consumption diversity, if farmers diversify the foods produced, positive diet and nutrition effects may also occur through the pathway of home consumption.

The internet may also influence dietary choices more directly. For instance, in rural China, it was shown that e-commerce helps improve dietary quality by increasing households' access to diverse, nutritious foods (Shen et al., 2023). Diet and nutrition knowledge obtained through the internet may contribute to healthier food choices and eating habits (Deng et al., 2024; Ma & Jin, 2022; Pollard et al., 2015). Additionally, the internet could help households locate and purchase nutritious foods at better prices (Cui et al., 2024b). However, exposure to online advertisements promoting unhealthy foods may negatively affect dietary choices, possibly leading to increased consumption of ultra-processed foods and snacks (Byun et al., 2021; Tsochantaridou et al., 2023). Such effects and mechanisms are analyzed empirically below.

3.3 Materials and methods

3.3.1. Study area and data collection

We collected data in the south-west region of Bangladesh, particularly in the districts of Khulna, Satkhira, and Bagerhat (Figure 3.2). In the study area, most households are agriculture-dependent (ADB, 2023). Rice is the major crop grown, as is true also in other parts of Bangladesh. The south-west region accounts for 12% of Bangladesh's total rice production (IPAD, 2025). Other crops commonly grown in Bangladesh – such as vegetables, potato, sweet potato, and maize – are also cultivated in the study region (Hajong et al., 2021). Across the country, food insecurity remains a major problem, affecting more than 20% of the population (BBS, 2024, Bhattacharjee & Sassi, 2021). In the study region, as in other parts of the country, rice and fish are the most commonly consumed foods. Bangladesh is rich in natural water resources (rivers, coasts), so fish is widely available in most areas and is considered the key source of protein (Bogard et al., 2015; Belton et al., 2011).

The first internet connection in Bangladesh was established in 1996, in few urban areas (Azam, 2007). Since 2005, mobile internet through GPRS (general packet radio service) started to spread all over the country (Islam, 2018). People in our study area in rural regions of south-west Bangladesh mainly access the internet through smartphones. Most internet users buy prepaid cellular data packages offered by different mobile network operators (e.g., Grameenphone, Robi, Banglalink, Teletalk). The supply of 4G networks by these different mobile operators ensures mobile data availability also in remote villages. Broadband internet services are hardly available in the study area. In our sample, 43% of the households have at least one internet user (Table C1 in the Appendix), which is very close to the national average of internet use of 45% in 2025 (GOB, 2025).

Households for our survey were selected through a three-stage sampling procedure. First, eight *Upazilas* were purposively selected, proportional to the population size of each district. *Upazila* is an administrative unit of Bangladesh, below the district and above the village level. Second, in these eight *Upazilas*, 36 villages were randomly selected. Last, in each village, 20 farming households were randomly selected, resulting in a total sample of 720 households. As complete household lists at the village level were rarely available, we used random walks to select the households, after meetings with the village head to obtain information on the village population, size, and geographic extension.

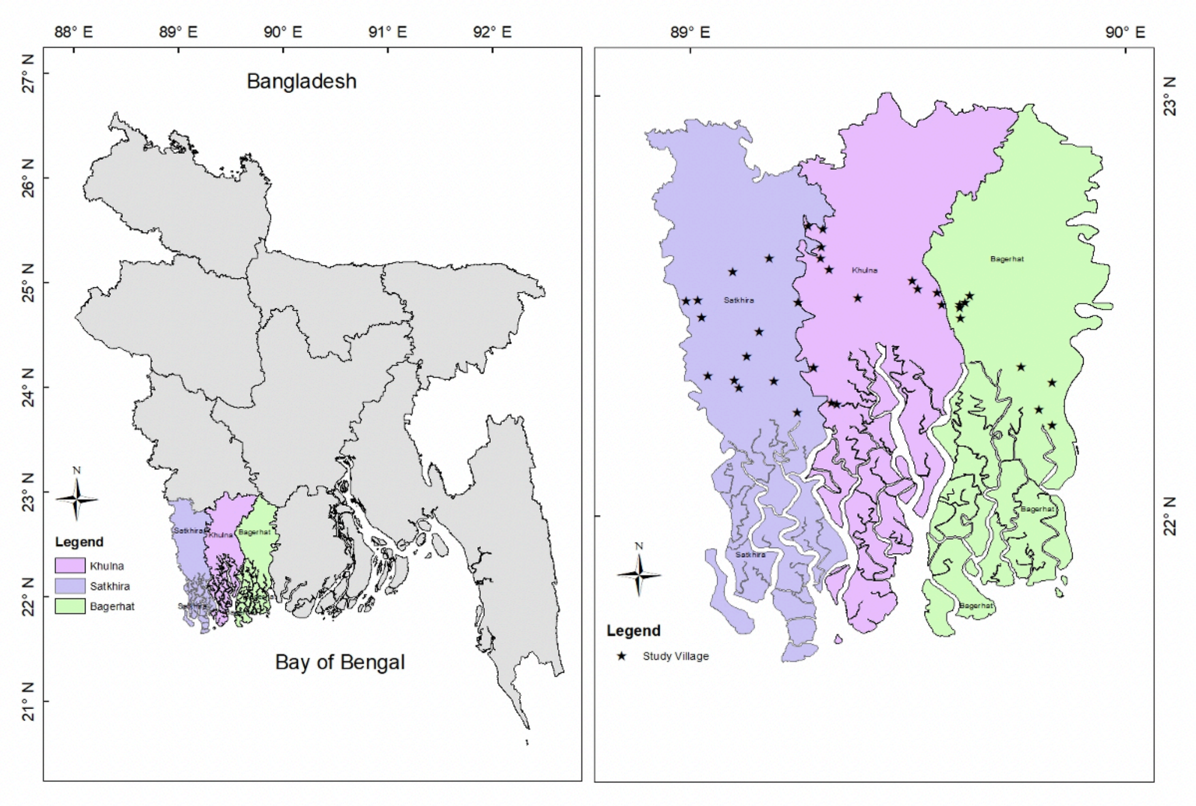


Figure 3.2: Map of the study area

The data were collected through personal interviews with the household heads conducted in October and November 2023. The interviews were conducted in local languages by a team of 20 local enumerators who were recruited, trained, and supervised by the researchers. A structured questionnaire was used, which was pre-tested and revised prior to the actual survey. The questionnaire included questions on general household demographics, such as the age, sex, education levels, religion, and occupation of all household members. Agricultural production details were captured in terms of the crop, livestock, and aquaculture species produced, inputs used, production costs, harvested quantities, household consumption and sales, and market prices obtained, among others. The production-related questions covered the last 12 months prior to the survey. Regarding internet use, we collected information on the household's last monthly internet bill (money spent), and whether or not they had used the internet during the last 30 days.

We also collected detailed data on household food consumption, using food frequency questions. These questions were asked to the person in the household responsible for cooking. Respondents were asked about the number of times the household had consumed specific food items during the last seven days. The survey occurred during the "normal season", when local food availability is better than during the agricultural lean season. To explore the impact of internet use on household dietary diversity during the lean season, we also collected recall data on household consumption of food items during an "average week" in the lean season.

In addition to the household-level food consumption data, we collected individual-level dietary data from one male adult, one female adult, and one child in each household through separate 24-hour recalls. The male adult was typically the household head (96% of the household heads in our sample are male), the female adult was typically the spouse. The child was randomly selected from the children available in the household (up to adolescent age), whereby we excluded children that were exclusively breastfed. For small children, the 24-hour dietary data were provided by the caregiver.

3.3.2. Definition of key variables

We analyze the effects of internet use on various farm production and household food consumption outcomes. In this subsection, we define the key variables of interest and explain how they are measured.

Internet use

The treatment variable in our analysis is internet use, which we define as a dummy that takes a value of one if any household member had used the internet in the last 30 days prior to the survey, and zero otherwise. This is the way the question was asked in the survey. In principle, it is possible that a household uses the internet only very sporadically and had not accessed it during the last 30 days. In this case, we would falsely classify the household as a non-user. However, field observations and informal discussions with the survey respondents suggest that most internet users access the internet on a frequent basis (i.e., daily, or at least weekly). Hence, we argue that our assumption of not accessing the internet during the last 30 days being equivalent to never using the internet does not lead to significant measurement error. In addition to our dummy treatment variable, we use the monthly internet bill as a continuous treatment variable in a robustness check.

Production outcomes

Farm output value. This is the sum of the value of all agricultural outputs the household produced in the last 12 months, including crop, livestock, and aquaculture production. Total output quantities are multiplied with the respective market prices, regardless of whether the products were sold or kept for home consumption. Farm output value is measured in thousand Bangladeshi Taka (BDT).

Farm production cost. This includes all costs associated with agricultural production activities. For crop production, we account for all costs incurred for land preparation, seeds, irrigation, pesticides, fertilizer, and hired labor during the past 12 months. For livestock, we include the cost of livestock purchases during the last 12 months, feed, vaccination and healthcare, hired labor, and others. For aquaculture, we consider small fish and shrimp purchases, feed, pond preparation, labor, and other costs over the past 12 months. These production costs are summed up and expressed in thousand BDT.

Farm income. This is the total farm output value minus farm production costs during the past 12 months, expressed in thousand BDT.

Commercialization ratio. This is the value of any sales of farm output during the last 12 months divided by the total farm output value. This is the most common way of defining the level of commercialization among smallholder farmers (Ogutu & Qaim, 2019). The commercialization ratio can take values between zero and one, where zero indicates complete subsistence and one full commercialization.

Production diversity. This is defined as the number of food groups produced by the farm during the last 12 months (Nguyen & Qaim, 2025). We consider 12 different food groups, which we define in the same way as on the consumption side (see below). We calculate production diversity scores (PDS) by counting the number of different food groups produced. In addition, we also define dummy variables for each of the 12 food groups produced.

Consumption outcomes

On the consumption side, we are particularly interested in dietary quality, which we measure in terms of five different types of dietary diversity scores, as shown in Table 3.1. The first two of these scores are defined at the household level (FAO, 2011), namely the standard household dietary diversity score with 12 food groups (HDDS12), and an alternative household dietary diversity score with 9 food groups (HDDS9), as shown in columns (1) and (2) of Table 3.1. The last three food groups of the HDDS12 contain low amounts of micronutrients and therefore contribute less to healthy diets than the other 9 groups, which is why HDDS9 without these less nutritious three food groups included is often considered a better indicator of dietary quality (Parlasca et al., 2020; Sibhatu et al., 2015). These two household-level dietary diversity scores are calculated separately for the normal season and the lean season. To get deeper insights into which food groups are being consumed in each season, we also construct separate dummies for each of the food groups considered.

In addition to the household-level metrics, we calculate individual-level dietary diversity scores to better reflect possible differences in intra-household food distribution (Verger et al., 2019). Specifically, following Agbadi et al. (2017) and Muthini et al. (2020), we calculate men's dietary diversity scores (MDDS), women's dietary diversity scores (WDDS), and children's dietary diversity scores (CDDS), using our individual-level 24-hour dietary recall data and the food group classifications shown in Table 3.1 (columns 3-5). These individual-level data are only available for the normal season.

Table 3.1: Food group classifications for dietary diversity scores

	(1)	(2)	(3)	(4)	(5)
Number	Household dietary diversity score (HDDS12)	Household dietary diversity score (HDDS9)	Men's dietary diversity score (MDDS)	Women's dietary diversity score (WDDS)	Child dietary diversity score (CDDS)
1	Cereals	Cereals	Starchy staples	Starchy staples	Grains, roots, and tubers
2	White roots and tubers	White roots and tubers	Dark green leafy vegetables	Dark green leafy vegetables	Legumes and nuts
3	Vegetables	Vegetables	Other vitamin A rich fruits and vegetables	Other vitamin A rich fruits and vegetables	Dairy products (milk, yoghurt, cheese)
4	Fruits	Fruits	Other fruits and vegetables	Other fruits and vegetables	Flesh foods (meat, fish, poultry, and liver/organ meats)
5	Meat	Meat	Organ meat	Organ meat	Eggs
6	Eggs	Eggs	Meat and fish	Meat and fish	Vitamin A rich fruits and vegetables
7	Fish	Fish	Eggs	Eggs	Other fruits and vegetables
8	Legumes, nuts, and seeds	Legumes, nuts, and seeds	Legumes, nuts, and seeds	Legumes, nuts, and seeds	
9	Milk	Milk	Milk and milk products	Milk and milk products	
10	Oils and fat				
11	Sugar and sweets				
12	Spices, condiments, beverages				

Source: Based on FAO (2011) and Muthini et al. (2020).

3.3.3. Regression models

We use propensity score matching (PSM) as our main approach to examine the effects of internet use on food production and consumption. In addition, we use various robustness checks, as explained further below. The PSM approach includes two main steps (Kane et al., 2020). First, we estimate a probit model to obtain the propensity scores for internet use based on a large number of farm, household, contextual variables. Second, we use the propensity scores to match the treatment and control groups and estimate the average treatment effects of internet use.

The probit model is specified as follows:

$$P(x) = Pr(D_{ij} = 1|X_{ij}) \quad (1)$$

where D_{ij} indicates the likelihood that household i in village j is using the internet, and X_{ij} is a vector of observable explanatory variables, such as age, gender, religion, ethnicity, and education of the household head, household size, land ownership, value of other assets owned, agroecological and market access conditions, among others. A full list of variables used and the probit estimation results are shown in Tables C2 and C3 in the Appendix.

For the matching in the second step, we use the five nearest-neighbor matching (NNM) algorithm for the main analysis. Figure C1 in the Appendix presents the estimated propensity scores for the treatment and control groups and confirms that the common support condition is fulfilled. Table C4 shows that almost all households (718 out of 720) are in the common support region. Different quality checks also indicate good matching performance. For instance, Table C5 shows that before matching, some of the control variables, i.e. education, religion, ethnicity, assets, and distance to market, differ significantly between the treatment and control groups, whereas after matching, we do not find any significant differences. Additional quality checks of the matching results are shown in Table C6. A likelihood ratio test leads to rejection of the hypothesis of joint significance of the covariates after matching. Therefore, our PSM is considered successful regarding the balancing of the distribution for the covariates between the treatment and control groups (Do et al., 2019).

For measuring the effects of internet use on the different outcomes, we calculate the average treatment effects on the treated (ATTs) as follows:

$$ATT = E(Y^T|D = 1, P(X)) - E(Y^C|D = 1, P(X)) \quad (2)$$

where superscripts C and T refer to control and treatment groups, respectively, and Y denotes the outcome of interest. The results are presented in the next section.

One limitation of PSM is that it addresses potential selection bias due to observable factors but cannot account for unobservable factors that may jointly influence treatment assignment and outcomes. Therefore, we also use a control function approach (CFA), which accounts for unobserved heterogeneity if a valid instrumental variable (IV) is available (Ogutu & Qaim, 2019; Wooldridge, 2015). The CFA regressions are specified as follows:

$$Y_i = \beta_0 + \beta_1 D_i + \beta_2 X_i + \beta_3 R_i + \gamma \partial_i + \varepsilon_i \tag{3}$$

where Y_i is the outcome variable of household i, D_i is the internet use dummy variable, X_i is a vector of controls, R_i is a vector of district fixed effects, ∂_i denotes the residuals estimated from a first-stage regression with the IV, and ε_i is a random error term.

To estimate the first-stage regression to obtain the residuals (∂_i), we use the share of households using the internet at the village level as our IV, leaving out the specific household of interest. More specifically, it is the total number of internet-using households we have found in the village from our field survey minus the internet-using household dummy divided by the total number of samples we have at our hand for the respective village. Similar leave-one-out instruments at village or neighborhood levels were used in previous studies on the impacts of internet use (Nguyen et al., 2022; Zheng et al., 2021). We calculate our IV for each household based on the data from the 20 households collected in each village. Results of the first-stage regression are shown in Table C7 in the Appendix. The share of village households using the internet is positively and significantly associated with own internet use, implying that our IV satisfies the relevance assumption. An additional condition for a valid IV is the exclusion restriction, which we test through falsification tests, as shown in Table C8 in the Appendix. While the exclusion restriction seems to hold for some of our outcome variables, this is not true for others. Unfortunately, we were not able to find IVs that are valid in all our models. This is why we use the PSM estimates as our main findings and only apply the CFA as a robustness check. The results from both approaches are similar for all outcome variables and support the same conclusions, which we interpret such that unobserved heterogeneity is unlikely to bias our results significantly.

3.3.4. Additional robustness and plausibility checks

We conduct a number of additional robustness and plausibility checks to further increase the confidence in our findings. First, for the PSM approach, besides the NNM algorithm, we also estimate effects using kernel and radius matching. We report these estimates obtained with the various matching algorithms in Tables C9-C13 in the Appendix with very similar and consistent results.

Second, we re-estimate the PSM models by using village-level instead of district-level fixed effects, which may better account for certain unobserved factors at the local level. All results, including the probit model, the balancing tests, and the ATTs obtained with different matching algorithms, are very similar, as shown in Tables C14-22 and Figure C2 in the Appendix.

Third, we re-estimate the models by using the monthly internet bill as a continuous treatment variable, instead of the internet use dummy, to check the robustness of the findings. These models are estimated with CFA, which is more flexible than PSM for continuous treatment variables. Results are shown in Tables C23-C25 in the Appendix. The signs and significance levels of these alternative estimates support the same conclusions.

Fourth, as most internet users in our context access the internet through their smartphones, it is possible that internet and mobile phone effects overlap, which could lead to overestimation of the true effects of internet use. We test for such possible overestimation by computing the effects of owning a mobile phone without internet access on the same outcome variables of interest, excluding the smartphone users with internet access. These alternative PSM results are shown in Tables C26 and C27 in the Appendix. Mobile phones without internet access seem to have no significant effects on any of the outcomes, which increases our confidence that our estimated effects of internet use are not confounded by simple mobile phone effects.

Finally, to test the plausibility of our estimated effects, we conducted several follow-up phone interviews with randomly selected sample farmers and village heads in the study area to ask more specifically for the main purposes of using the internet and discuss the main findings. A brief overview of these follow-up phone interviews is provided in Tables C28 and C29 in the Appendix. Even though these were qualitative interviews and discussions with a small subsample, the feedback supports our findings and the relevance of the hypothesized underlying mechanisms. A few literal quotes from these interviews are shown in the text below in connection with the estimation results.

3.4 Results

3.4.1. Descriptive statistics

Table 3.2 presents descriptive statistics on the production and consumption of different food groups among sample households. Almost all produce cereals (mostly rice), and many also produce eggs, meat, and fish. On the consumption side, we see some differences between the normal and lean seasons (columns 2 and 3), as expected.

Table 3.2: Production and consumption of different food groups

Food groups	(1) Share of farms producing (%)	(2) Share of households consuming, normal season (%)	(3) Share of households consuming, lean season (%)
Cereals	99	93	100
	(0.07)	(0.25)	(0.00)
Roots and tubers	1	83	80
	(0.09)	(0.37)	(0.40)
Eggs	57	87	77
	(0.50)	(0.34)	(0.42)
Fish	53	95	94
	(0.50)	(0.22)	(0.24)
Vegetables	6	99	98
	(0.23)	(0.09)	(0.13)
Fruits	10	60	71
	(0.31)	(0.49)	(0.45)
Meat	56	56	53
	(0.50)	(0.50)	(0.50)
Legumes, nuts, and seeds	4	81	72
	(0.20)	(0.40)	(0.45)
Milk and dairy products	28	41	42
	(0.45)	(0.49)	(0.49)
Oils and fats	2	92	92
	(0.13)	(0.27)	(0.27)
Spices, condiments, and beverages	0.27	98	93
	(0.05)	(0.15)	(0.26)
Sugar and sweets	0.27	76	64
	(0.05)	(0 .43)	(0.48)
Observations	720	720	720

Note: Standard deviations in parentheses.

Table 3.3 compares household characteristics between internet users and non-users. Around 43% of the sample households use the internet, while 57% do not. On average, households with internet use tend to have more household members. They are also wealthier, better educated, and more likely to belong to the ethnic majority.

Table 3.3: Household characteristics by internet use

Variable	Measurement units	(1) Full sample	(2) Internet non-user	(3) Internet user	(3)-(2) Difference
Household size	people	4.52	4.42	4.64	0.22*
		(1.64)	(1.62)	(1.66)	
Age head	years	50.10	50.20	49.97	-0.23
		(12.16)	(11.72)	(12.74)	
Male head	1=male; 0=otherwise	0.96	0.96	0.96	0.00
		(0.20)	(0.20)	(0.19)	
Married head	1=married; 0=otherwise	0.98	0.99	0.98	-0.01
		(0.13)	(0.12)	(0.15)	
Ethnic majority head	1=Bangladeshi; 0=otherwise	0.94	0.92	0.98	0.06***
		(0.23)	(0.28)	(0.15)	
Muslim head	1=Muslim; 0=otherwise	0.68	0.72	0.64	-0.07**
		(0.47)	(0.45)	(0.48)	
Education head	years of schooling	5.04	4.54	5.72	1.18***
		(4.31)	(4.01)	(4.61)	
No. of dependents	people	1.43	1.47	1.37	-0.11
		(1.19)	(1.19)	(1.20)	
Assets per capita	thousand BDT	10.77	9.08	13.02	3.94***
		(0.98)	(0.98)	(0.93)	
Food expenditure	thousand BDT	86.48	80.38	94.60	14.23***
		(40.33)	(33.81)	(46.47)	
Non-food expenditure	thousand BDT	96.96	81.67	117.29	35.62***
		(82.88)	(61.24)	(101.56)	
Weather shock	1=yes; 0=otherwise	0.16	0.15	0.18	0.04
		(0.37)	(0.35)	(0.39)	
Distance to market	kilometers	1.95	1.86	2.06	0.21**
		(1.30)	(1.23)	(1.39)	
Observations		720	411	309	

*Notes: *** p < 0.01, **p < 0.05, * p < 0.1; Standard deviations in parentheses.*

Table 3.4 shows farm production outcomes by internet use. Internet users have higher farm incomes, commercialization ratios, and production diversity scores than non-users. Table 3.5 shows various dietary diversity indicators by internet use. All household- and individual-level dietary diversity scores are higher among the internet-users than among the non-users, and these differences are statistically significant, except for children. Whether these differences also hold after controlling for confounding factors is analyzed in the following.

Table 3.4: Farm production outcomes by internet use

	(1)	(2)	(3)	(3)-(2)
Variable	All	Internet non-users	Internet users	Difference
Farm income (thsd. BDT)	77.63	50.99	113.06	62.07***
	(172.67)	169.36	170.92	
Production cost (thsd. BDT)	117.54	125.27	107.26	-18.01*
	(129.47)	(130.74)	(127.23)	
Farm output value (thsd. BDT)	195.17	176.26	220.31	44.05**
	(239.56)	(232.04)	(247.36)	
Commercialization ratio	0.57	0.55	0.60	0.04**
	(0.283)	(0.288)	(0.276)	
PDS9	4.36	4.19	4.59	0.40***
	(1.73)	(1.67)	(1.78)	
PDS12	3.91	3.68	4.20	0.52***
	(1.85)	(1.72)	(1.98)	
Observations	720	411	309	

*Notes: *** p < 0.01, **p < 0.05, * p < 0.1; Standard deviations in parentheses; PDS9: Production diversity score with 9 food groups; PDS12: Production diversity score with 12 food groups.*

Table 3.5: Dietary diversity outcomes by internet use

	(1)	(2)	(3)	(3)-(2)
Variable	All	Internet non-users	Internet users	Difference
Normal season				
HDDS9	6.95	6.75	7.21	0.46***
	(1.53)	(1.57)	(1.45)	
HDDS12	9.61	9.39	9.89	0.50***
	(1.81)	(1.83)	(1.75)	
MDDS	3.88	3.73	4.08	0.35***
	(1.30)	(1.31)	(1.27)	
WDDS	3.92	3.72	4.18	0.46***
	(1.32)	(1.25)	(1.37)	
CDDS	3.91	3.82	4.03	0.21
	(1.21)	(1.11)	(1.33)	
Lean season				
HDDS9	6.87	6.69	7.11	0.42***
	(1.65)	(1.61)	(1.68)	
HDDS12	9.36	9.10	9.69	0.59***
	(2.01)	(1.94)	(2.06)	
No. of observations	720	411	309	

*Notes: *** p < 0.01, **p < 0.05, * p < 0.1; Standard deviations in parentheses. HDDS9: Household dietary diversity score with 9 food groups; HDDS12: Household dietary diversity score with 12 food groups; MDDS: Men's dietary diversity score; WDDS: Women's dietary diversity score; CDDS: Child dietary diversity score.*

3.4.2. The effects of internet use on food production and consumption

Table 3.6 shows the estimated effects of internet use on farm production outcomes, after controlling for confounding factors. Panel A in the upper part of Table 3.6 illustrates the estimates from PSM, which we consider as our main results. Panel B in the lower part shows results obtained with CFA, which we use as a robustness check, as explained above. Results obtained with both approaches suggest that internet use has significantly positive effects on farm income, commercialization, and production diversity.

Table 3.6: Effects of internet use on farm production outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
	Farm income	Production cost	Farm output value	Commercialization ratio	PDS9	PDS12
Panel A: Estimates from PSM						
Internet use	65.943***	-9.93	56.013***	0.057**	0.761***	0.736***
	(13.731)	(11.864)	(20.011)	(0.027)	(0.166)	(0.168)
Panel B: Estimates from CFA						
Internet use	63.941***	-26.654***	31.575*	0.049**	0.625***	0.610***
	(16.142)	(9.839)	(18.952)	(0.023)	(0.139)	(0.141)

*Notes: *** p<0.01, ** p<0.05, * p<0.1; Robust standard errors in parentheses. PSM: Propensity score matching (average treatment effects on the treated are shown); CFA: Control function approach; PDS9: Production diversity score with 9 food groups; PDS12:Production diversity score with 12 food groups.*

The estimates suggest that internet use more than doubles net farm incomes (column 1 of Table 3.6). This is a big effect, which remains in a similar magnitude also in all alternative model specifications (see results with alternative matching algorithms in Table C9 and with village-level fixed effects in Table C18 in the Appendix). Farm incomes increase because farmers use the internet to get up-to-date information on new farming techniques, market prices, and weather forecasts, which helps increase outputs and decrease production costs (see columns 2 and 3 of Table 3.6). Similar effects were also shown in previous studies (Lio & Liu, 2006; Ma et al., 2020). In our qualitative follow-up interviews, one farmer stated for instance:

'Yes, the internet helps us increase production in several ways. We get knowledge on high-yield seeds, improved irrigation, and disease control through online resources like Krishi Math (farmer's field school). This year our crop production is more, and we make profit. My son gave us information about the weather in advance, which helped a lot! We harvested the crop a bit earlier, knowing about the storm, and thus reduced our crop losses.'

The results in Table 3.6 also suggest that internet use increases the farm commercialization ratio by 5-6 percentage points (column 4). This is reasonable given that farmers have better real-time information about market prices, which may help them negotiate better deals. The internet also facilitates networking with agricultural extension officers, other farmers, and traders, possibly encouraging more market-oriented behavior. A follow-up interview with a farmer and village head revealed the following:

'... We mainly use the internet to know about the current market price of the product in the capital city; then we contact the wholesaler so that he (the wholesaler) cannot ask for a low price. We also use the internet to sell livestock on social networking platforms for Eid-ul-Adha (a religious festival of the Muslim community for which slaughtering cows or goats is a ritual). As homegrown animals are more organic and healthy, people are interested in these livestock for consumption. Besides, young people in our villages also use the internet to sell fish and shrimps to retail markets to a diverse array of customers through online platforms besides selling to local markets.'

Columns (5) and (6) of Table 3.6 show the effects of internet use on farm production diversity scores. These are also positive and statistically significant, which is plausible with better access to information about profitable crop, livestock, and aquaculture species. In a previous study in China, Zheng et al. (2022) showed that internet use leads to the adoption of additional crop species and varieties. In our context, a follow-up phone interview with a farmer revealed:

'...internet use enables me to cultivate diverse fish and livestock due to quick access to new farming concepts through online platforms. Internet use helps me learn about diverse paddy, fish, and poultry breeds. This knowledge makes me confident to attempt new farming methods. From YouTube, I also learned a lot about better cultivation of diverse crops, such as mustard, lentils, and vegetables. I have observed that the diversity of farm production increases financial success in my village. People have started to cultivate multiple fruits and vegetables for home consumption and sales.'

Table 3.7 illustrates the effects of internet use on household- and individual-level dietary diversity scores. Again, PSM and CFA lead to consistent results. The internet has significantly positive effects on household dietary diversity during the normal season and the lean season, and for both indicators, HDDS9 and HDDS12. This finding is consistent with Cui et al. (2024), who found positive effects of internet use on household-level dietary quality in rural China.

Table 3.7: Effects of internet use on dietary diversity scores

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	HDDS9	HDDS12	HDDS9 (lean)	HDDS12 (lean)	MDDS	WDDS	CDDS
Panel A: Estimates from PSM models							
Internet use	0.279**	0.353**	0.259*	0.454**	0.187	0.285**	0.228
	(0.14)	(0.165)	(0.149)	(0.182)	(0.125)	0.122	0.178
Panel B: Estimates from CFA models							
Internet use	0.318***	0.350**	0.329**	0.491***	0.098	0.237**	0.116
	(0.118)	(0.142)	(0.130)	(0.159)	(0.097)	(0.102)	(0.139)

*Notes: *** p<0.01, ** p<0.05, * p<0.1; Robust standard errors in parentheses. PSM:Propensity score matching (average treatment effects on the treated). CFA: Control function approach; All dietary diversity scores refer to the normal season, except for those where the lean season is specified.HDDS9: Household dietary diversity score with 9 food groups; HDDS12: Household dietary diversity score with 12 food groups; MDDS: Men's dietary diversity score; WDDS: Women's dietary diversity score; CDDS: Child dietary diversity score.*

Interestingly, however, the effects on HDDS shown in Table 3.7 are smaller than the effects on PDS shown in Table 3.6, meaning that not all additional food groups produced are also consumed by household members. For the individual-level dietary diversity scores in Table 3.7, we find positive effects of internet use, but these are relatively small and statistically significant only for women.

Table 3.8 presents the effects of internet use on the production and consumption of specific food groups. The results suggest that internet use increases the likelihood of producing fish, meat, and legumes, nuts, and seeds. As mentioned, access to better information increases farmers' openness to adopt additional species and aquatic breeds (Ragkos et al., 2019). Apart from general information, many farmers also share personal success stories and videos of producing new species and breeds through local social media platforms, which encourages other households with internet access to also try those species. In one of the follow-up phone interviews, a farmer stated:

'Definitely, the internet helps me to increase the production of different things. This works in different ways: by getting expert knowledge, learning about high-yield seeds, good livestock and aquatic breeds, improved fertilizers, cost-effective irrigation methods, and pest control……. I do mainly fish farming, and a bit of crops and livestock. Online platforms motivate me to produce more fish, as these have good market prices…… Through YouTube videos, I acquired knowledge about efficient methods of fish farming, including feeding practices and disease prevention; this knowledge minimizes my farming expenses. …….

Improved fish cultivation methods …. lead to higher production and income……If I can manage everything, in the near future, I will expand my business more.'

In Table 3.8, we also see more fish consumption among internet users, but the effects are smaller than on the production side. This further underlines that some of the species are primarily produced for market sales and not for home consumption. On the consumption side, we also hardly see any positive effects for meat, legumes, nuts, and seeds, especially not in the normal season. On the other hand, we see that internet use increases the likelihood of consuming fruits, vegetables, and oils and fats.

Table 3.8: Effects of internet use on food production and household food consumption choices

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Cereals	Roots and tubers	Eggs	Fish	Vegetables	Fruits	Meat	Legumes nuts, and seeds	Milk and dairy	Oils and fats	Spices and condiments	Sugar and sweets
Panel A. Estimates from PSM models												
Food production choices												
	0.056	-0.001	0.090**	0.251***	0.023	0.025	0.165***	0.094**	0.057	-0.010	-0.008**	-0.007
	(0.086)	(0.008)	(0.046)	(0.062)	(0.022)	(0.037)	(0.046)	(0.037)	(0.041)	(0.012)	(0.004)	(0.006)
Food consumption in normal season												
	0.018	0.036	0.00	0.066***	0.005	0.101**	0.051	0.003	-0.003	0.064**	0.016	-0.007
	(0.022)	(0.035)	(0.032)	(0.022)	(0.009)	(0.045)	(0.046)	(0.037)	(0.046)	(0.026)	(0.014)	(0.04)
Food consumption in lean season												
	-	0.055	-0.011	0.081***	0.004	0.066	0.053	-0.014	0.024	0.082***	0.080***	0.033
	-	(0.037)	(0.039)	(0.023)	(0.012)	(0.042)	(0.046)	(0.042)	(0.046)	(0.026)	(0.025)	(0.045)
Panel B. Estimates from CFA models												
Food production												
	0.074	-0.001	0.056	0.174***	0.035	0.014	0.133***	0.118***	0.022	-0.003	-0.006	-0.005
	(0.071)	(0.007)	(0.039)	(0.055)	(0.021)	(0.025)	(0.038)	(0.035)	(0.035)	(0.011)	(0.005)	(0.004)
Food consumption in normal season												
	0.012	0.042	-0.007	0.051***	0.010*	0.119***	0.049	0.023	0.019	0.040*	0.007	-0.015
	(0.018)	(0.031)	(0.028)	(0.017)	(0.006)	(0.038)	(0.040)	(0.031)	(0.040)	(0.022)	(0.012)	(0.033)
Food consumption in lean season												
	-	0.042	0.031	0.059***	0.002	0.074**	0.090**	-0.010	0.040	0.060***	0.063***	0.039
	-	(0.032)	(0.033)	(0.020)	(0.010)	(0.034)	(0.039)	(0.036)	(0.040)	(0.020)	(0.021)	(0.036)

*Notes: *** p<0.01, ** p<0.05, * p<0.1; Robust standard errors in parentheses. PSM: Propensity score matching; CFA: Control function approach; Consumption of food groups based on 7-day recall data at the household level. The models on cereal consumption during the lean season could not be estimated because all households consumed cereals.*

3.5 Discussion and conclusion

Using recent primary data from 720 farm households in rural Bangladesh and quasi-experimental econometric techniques, we have analyzed the effects of internet use on farm production and food consumption patterns. We make novel contributions to the literature in that we are the first to examine the effects of internet use on smallholder farmers by jointly capturing production and consumption decisions and by considering seasonal differences in household dietary quality.

Regarding the production side, our results suggest that internet use has positive effects on farm output values, income, and commercialization. We also show that internet use increases the number of different food groups produced on the farm, especially in terms of increasing the likelihood of producing fish, meat, and legumes, nuts, and seeds. These food groups are particularly nutritious and therefore potentially improve dietary quality in the local context.

Regarding the consumption side, our findings suggest that internet use increases household dietary diversity in both the normal and lean seasons. However, the effects on dietary diversity are relatively small and smaller than the effects on farm production diversity. Using individual-level food consumption data, we find positive effects of internet use on women's dietary diversity scores, whereas the effects on men's and children's dietary diversity scores are not statistically significant. Our estimates reveal that internet use increases the likelihood of fish consumption, but not the likelihood of consuming meat, legumes, nuts, and seeds, even though these food groups were found to be increased on the production side. It seems that some of the additional food groups are primarily produced for market sales instead of home consumption.

Based on our findings, we provide a few policy recommendations. First, since internet use clearly increases farm outputs, market orientation, and incomes, internet access and adoption should be facilitated through appropriate action. So far, fewer than half of the farm households in the study area use the internet, so there is much potential for further enhancement. Public and private sector interventions to increase adoption should include improvements in the internet infrastructure, such as supplying 4G or 5G networks also in remote rural areas, as this enables people to use various apps efficiently. Our results suggest that farmers do not only benefit from standard websites but also from using social media and video platforms for learning about new farming techniques. In addition, offering affordable internet use and data packages will likely boost internet adoption, as will the development of user-friendly apps in local languages tailored to the needs of smallholder farmers (e.g., infos on relevant farming innovations, market data, and weather forecasts). Training programs to increase the digital literacy of farmers, including those with lower levels of formal education, may also help to increase internet use and its benefits.

Second, the positive effects of the internet on smallholder household diets are welcome but could be further increased. Suitable interventions may include the provision of locally-relevant online and social media content on healthy food and nutrition habits, including cooking shows and workshops with the promotion of healthy recipes. While we did not collect detailed data on who in the household uses the internet, field observations and follow-up discussions suggest that there is a certain bias towards male household members, whereas women are often those making decisions on what foods to use and prepare. Hence, improving women's access to the internet may help to further enhance the diet and nutrition outcomes. Needless to say that other interventions unrelated to the internet are also important to improve nutrition, such as increasing the efficiency of local markets for nutritious foods.

In closing, we acknowledge a few limitations of our study. First, while we collected some information on how people use the internet in qualitative follow-up interviews, our quantitative survey data lack details on who in the households exactly used the internet, how often, and for what concrete purposes. Second, we use cross-section observational data, which means that we are not perfectly able to deal with all possible sources of endogeneity. Third, by comparing users and non-users of the internet in the same settings, we implicitly assume that only those who actively use the internet themselves could benefit. In reality, there might be spillover effects in the sense that households not using the internet themselves might still benefit from better access to information obtained from friends or neighbors using the internet. Such information spillovers would lead to underestimation of the true benefits of internet use. Fourth, our study refers to one specific area in Bangladesh. While some of the findings may also be applicable to other contexts, broad generalizations are likely not appropriate. Follow-up research with more comprehensive data from different contexts may help to further increase the internal and external validity of our findings.

CHAPTER 4

4 Impacts of land fragmentation on women's time allocation and dietary quality in the small farm sector[3]

Abstract

Land fragmentation in the small farm sector of many countries in Africa and Asia is widely criticized as a source of farming inefficiency, yet little is known about its effects beyond agricultural performance. Defragmentation may be useful, but concerns have also been raised that this could reduce production diversity and thus possibly also dietary diversity. Here, we examine the impacts of land fragmentation on women's time allocation and dietary diversity in Bangladesh. Our findings show that land fragmentation significantly increases the time women spend on farming activities, consequently leading to a significant decrease in the time available for cooking and food preparation. Among women with low educational levels and young children, land fragmentation is also associated with less time spent on non-farm employment activities. Regarding dietary diversity, we do not find statistically significant effects. These findings imply that land defragmentation should be promoted, as it does not harm household diets, while improving farm productivity, reducing women's farming workloads, and freeing up time for non-farm employment. In addition, policies that enhance women's education could further improve access to profitable non-farm jobs and support better household dietary quality.

Keywords: Land fragmentation, women's non-farm activities, time-allocation, dietary diversity

[3] This is a joint paper with Thanh-Tung Nguyen, who contributed to conceptualising the research and to revising and editing the draft manuscript. I developed the research idea, collected and analyzed the data, and drafted the manuscript

4.1 Introduction

Land fragmentation is widely considered a major cause of farming inefficiency (Aslam & Fazal, 2025; Bizimana et al., 2004; Looga et al., 2018; Rahman & Rahman, 2009; Tan et al., 2010). With the increase of population, by 2050 food production will require to increase by 60% to feed the 9.7 billion world population (Hu et al., 2025). The ownership of dispersed and small plots increases the time and effort required to travel to and monitor land parcels, hinders the use of machinery on farms, raises production costs, and decreases farm productivity (Alemu et al., 2017; Deininger et al., 2017; Wang et al., 2020; Zhang & Chen, 2021). Consequently, governments in many developing countries are implementing policies to promote land consolidation (Pun et al., 2024; Zang et al., 2021). However, because farming households are often involved in different livelihood activities and face time and resource constraints, land fragmentation may affect not only farming activities but also a range of non-farm outcomes. These effects should be taken into account by policymakers. In particular, the effects on women's non-farm activities remain not answered yet in the literature. Women often bear heavy workloads in farm and household tasks, and providing them with greater opportunities for non-farm employment is considered an important instrument for improving gender equality (CGIAR, 2025; Grassi et al., 2015; Taye & Tesfaye, 2024; UNDP, 2021). We hypothesise that land fragmentation may increase their farming workload, thereby reducing the time available for non-farm employment and other activities. In addition, as women are mainly responsible for food preparation, the reduction in time allocation for cooking and food preparation might have negative effects on household diets and nutrition (Bonis-Profumo et al., 2021). In this study, we analyse the impacts of land fragmentation on women non-farm activities and their dietary diversity.

Many empirical studies have examined the impacts of land fragmentation on farm productivity and production costs. On the one hand, it is shown that land fragmentation leads to a reduction in farm productivity and an increase in production costs (Huang et al., 2025; Lu et al., 2018; Tanrıvermiş et al., 2024, Tran & Vu, 2019; Yucer et al., 2016). However, others argue that land fragmentation can improve farm diversification, thereby reducing production and market risks (Bentley, 1987; Yu et al., 2022). While many studies have focused on the impacts on farm performance, little is known about the impacts of land fragmentation on non-farm labour. Lu et al. (2019) show that land fragmentation decreases farm productivity and promotes the non-agricultural labour supply. Jia & Petrick (2014) found positive but insignificant impacts on non-agricultural labour supply. Meanwhile, Vien et al. (2025) show that land fragmentation might increase labour intensity in farming activities and negatively affect labour supply for non-farm wage employment. Regarding the impacts on household diets, it remains unclear whether land fragmentation affects dietary diversity. The increase in production diversity from land fragmentation could lead to an increase in the diversity of household diets (Cholo et al. 2019; Knippenberg et al., 2020; Vien et al., 2025). However, the negative association with income and farm productivity might lead to negative impacts on household diets.

Against this background, our study aims to (1) examine the impacts of land fragmentation on women's time allocation for non-farm employment and different domestic and unpaid work activities, and (2) investigate the impacts on women's dietary diversity. Our study makes several novel contributions to the literature as follows. While few studies have examined the impacts of land fragmentation on household-level non-farm employment, no studies have examined the impacts on women's non-farm employment. In addition, we are the first study to examine women's time allocation to different activities, including non-farm employment, domestic, and unpaid work activities. We are also the first study to examine the impacts on women's dietary diversity, whereas previous studies have focused solely on household-level dietary diversity. Our study selects Bangladesh as the study area for the following reasons. In Bangladesh, more than 26% (23.6 million people) are food insecure, and 18.7% of the population lives below the national poverty line (WFP, 2025). The per capita agricultural land holding has been decreasing over time (Rai et al., 2017) and it is approximately 0.5 hectare at present (World Bank, 2021). Hence, rising land fragmentation is shrinking the size of farmland (Ali et al., 2024; Siddik & Rahman, 2022). Bangladesh is not only experiencing a rapid decline in farm sizes but also a sharp increase in the number of operational holdings. The number of small farms is sharply increasing at the expense of large and medium-sized farms. The overall increased land fragmentation and operational landholdings reduce average farm size in Bangladesh (Rahman & Rahman, 2009). In Bangladesh, women contribute approximately 65% of the farm labor force in rural areas. In addition to farming responsibilities, they are also responsible for cooking, caregiving for children and the elderly, and other domestic tasks (Rahman et al., 2023), which account for about 25% of their daily time (BBS, 2023a). Women face multifaceted inequality in rural Bangladesh due to discriminatory social norms, excessive workload, limited land ownership rights, and restricted control over resources (Ashad et al., 2024; Rahman et al., 2023). All these issues make Bangladesh an important area to study.

The remainder of the paper is structured as follows: Section 4.2 presents the conceptual framework, illustrating the interlinkages between land fragmentation, women's time allocation, and dietary diversity. Section 4.3 provides an overview of the study area, data collection procedures, and econometric methods. Results are presented and discussed in section 4.4. Finally, section 4.5 offers concluding remarks and policy recommendations based on the research findings.

4.2 Conceptual framework

Figure 4.1 illustrates the conceptual framework, providing an overview of the interlinkages between land fragmentation, labour allocation, and dietary diversity.

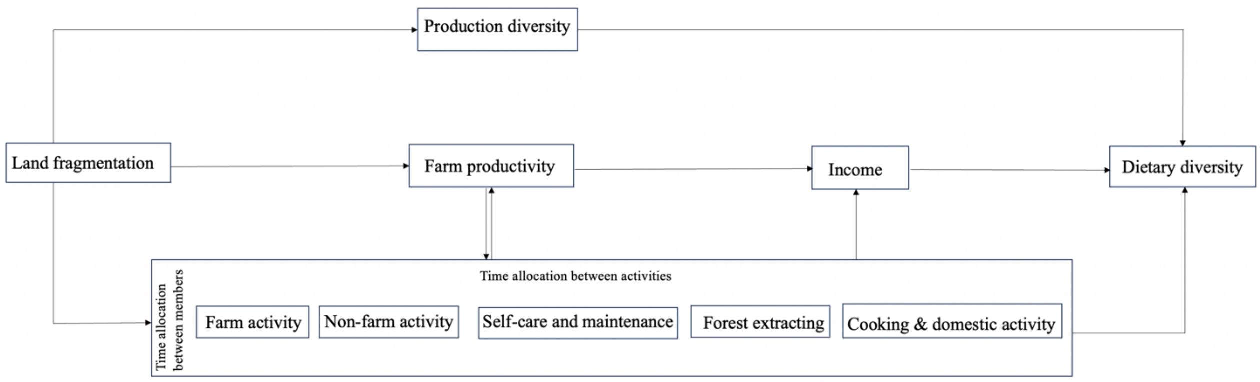


Figure 4.1: Conceptual framework

Regarding the impacts of land fragmentation on household time allocation, we assume that fragmentation may increase the time households spend on farming because farmers need more time to travel, monitor practices across different plots, and limit the application of machines (Van Hung et al., 2007). As households face time and resource constraints, this increased farming time reduces time available for other activities. On the other hand, since fragmentation negatively affects productivity, farming becomes less attractive (Alemu et al., 2017; Niroula & Thapa, 2007; Tran & Vu, 2019). Farmers may be encouraged to reduce their farming time or abandon farm work to search for non-farm jobs (Salam & Bauer, 2022). The direction for impacts on time allocated to non-farm work may depend on how the effect of fragmentation on farm productivity and on opportunities in the non-farm labour market. For the time allocation on domestic and unpaid work, we assume the impacts of land fragmentation are negative. Regarding intra-household time allocation between household members, we assume that the reduced attractiveness of farming may push men to seek non-farm jobs, leaving women with more farming responsibilities. This is because women, due to constraints from education, cultural norms, and domestic duties, often have fewer opportunities than men to access non-farm employment (Das & Mahanta, 2023).

Regarding the impacts of land fragmentation on household diets, on one hand, fragmentation can promote production diversity, which may increase dietary diversity as households consume much of what they produce (Ntihinyurwa et al., 2019). On the other hand, reduced farm income and productivity due to land fragmentation may limit the ability to purchase food from markets. The literature shows that food purchased from markets often plays an important role in household diets, even more important than subsistence food (Muthini et al., 2020; Ntakyo & van den Berg, 2019; Usman & Haile, 2022). Additionally, we assume that the increasing time burden in farming for women may reduce the time available for cooking and food preparation, thereby negatively affecting household diets (Jia & Petrick, 2014; Mishra et al., 2017). Komatsu et al. (2018) and Machio (2021) show that the increase in time on farm or non-farm employment of women would reduce their time for taking domestic tasks, and consequently negatively affect household diet and nutrition.

4.3 Methodology

4.3.1 Study setting and data collection

We conducted a household survey in three districts, i.e. Khulna, Satkhira and Bagerhat districts of the south-west region of Bangladesh (Figure 4.2). The study districts are heavily dependent on agricultural activities, and approximately 40% of the local labor force is engaged in the agricultural sector (Asiful Alam, 2017). In these agriculture-dependent areas of Bangladesh, women are engaged in farming activities in various capacities (IWMI, 2024), but they are gradually becoming involved in off-farm activities (Islam et al., 2022).

Our sample are selected using a multistage sampling procedure. First, we purposively selected eight *Upazilas* proportionate to the population size of each district. Second, within these eight *Upazilas,* we randomly select 36 villages. In the final stage, we randomly select 20 farming households from each of the villages. Therefore, for this study, 20 randomly picked samples from each of the 36 villages yield a total sample of 720 farm households. In addition to interviewing the household head or a male member nominated by the household head, we also surveyed one female from each household. Women who are primarily responsible for food preparation and other household activities were nominated by the household head. The enumerator collected time allocation and dietary data from these women for this study. In some households, no female members were available, so we do not have time allocation or dietary quality data for those households. The final dataset includes 699 women from the 720 surveyed households for further analysis.

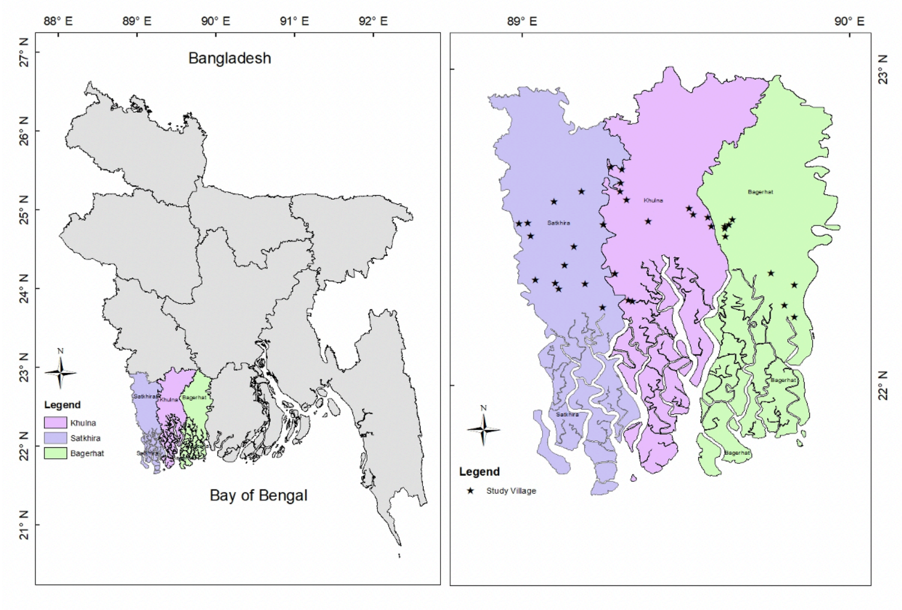


Figure 4.2: Map of the study area

The structured questionnaire developed for this purpose included questions at the household and individual levels. The socio-demographic data include age, sex, education levels, religion, nationality, occupation and income of all household members. Besides, data on agricultural production details, ownership of land parcels, the number of species under farming, farm income, and farm productivity are collected at the household level. Regarding time use, we followed Lader et al. (2006) and Stinson (1999) and developed a list of 16 common activities. We collected the time use data for different activities on a recall basis, considering the day before the survey, Kumar et al. (2018) also did the same. Following Mehraban et al. (2022), we asked respondents about which concrete activity they performed during 30-minute intervals, which start early morning, i.e., 5:00 am, and end at midnight (12.00 am). Therefore, we basically collected time use data for 19 hours, assuming that the remaining time would be occupied with sleeping.

A separate section of the questionnaire was used to collect information on individual diets during the last 24 hours of the agricultural normal season. This dietary data were collected from the female household member nominated by the household head who is responsible for meal preparation. Data from one woman per household were used to calculate the women's dietary diversity score (WDDS) following the food groups proposed by FAO (2011). Specifically, WDDS comprises nine food groups: (1) starchy staples, (2) dark green leafy vegetables, (3) other vitamin A-rich fruits and vegetables, (4) other fruits and vegetables, (5) organ meats, (6) meat and fish, (7) eggs, (8) legumes, nuts, and seeds, and (9) milk and dairy products (Muthini et al., 2020).

4.3.2. Regression models

Impacts of land fragmentation on women's non-farm activities

To examine the impacts of land fragmentation on women's non-farm activities, we apply the control function approach because our key variable of interest, land fragmentation, is likely to be endogenous. The models consist of two main steps. In the first step, land fragmentation is estimated using the following equation:

$$F_i = \beta_0 + \beta_1 X_i + \beta_3 Z_i + \varepsilon_i \quad (1)$$

where F is the number of agricultural land plots, an indicator for land fragmentation which is commonly used in previous studies (Latruffe & Piet, 2013; Postek et al., 2019; Wang et al., 2020). X_i, the vector of control variables, including age, education and marital status of the household head, household size, number of dependent members, farm land area, asset value per capita, agroecological and market access conditions, and village-level infrastructure, and district dummies. More detailed definitions of the control variables are provided in Table D1 in the Appendix. ε_i is a random error term. Z is the share of neighbouring farmers in the village who have rented in or out land, and we use this variable as the excluded instrument (IV). It is defined as the total number of surveyed farmers in the village who have rented in or out land (excluding the individual household, i.e., leave one out) divided by the total number of surveyed villagers. A higher share of farmers renting in or out land may indicate a more developed land rental market, which facilitates land transfer and enables farms to access additional productive land without substantial capital investment (Nguyen et al., 2021; Jia & Petrick, 2014). Sometimes it is perceived that land rental markets can facilitate land consolidation by facilitating smallholders to rent additional land parcels. But it may even form more contiguous landholdings and exacerbate land fragmentation when rented-in or rented-out parcels are scattered and irregular in size (Duangbootsee, 2024). The coefficient at the first stage regression model is positive and significant (see Appendix Table D2), implying the IV satisfies the relevance assumption. We also argue that this IV satisfies the exclusion restriction assumption. The development of the land rental market affects women's time allocation to non-farm activities only through its impact on farming activities. Falsification tests show that our IV satisfy this assumption (Appendix Table D3).

In the second step, the impacts of land fragmentation on women's non-farm activities are estimated as follows:

$$N_i = \alpha_0 + \alpha_1 X_i + \alpha_2 F_i + \alpha_3 \hat{R}_i + \epsilon_i \quad (2)$$

In equation (2), N_i is the outcome variable, indicating time allocation for different non-farm activities of the woman. From the list of 16 activities we have collected, we group them into six major sub-groups, namely, non-farm activities, farm activities, forest extracting activities, cooking, domestic work and caregiving activities, leisure and personal care time, commuting and other activities. We also examine the impacts of land fragmentation on the other two non-farm outcomes, including non-farm income and the dummy of having non-farm jobs or not. Table D4 in the Appendix shows a detailed explanation of these outcome variables concerning time allocation. $\widehat{\mathrm{R}}_{\mathrm{i}}$ is the residuals estimated from Equation 1. F, X are defined as the same in Equation 1.

Impacts of land fragmentation on women's dietary diversity

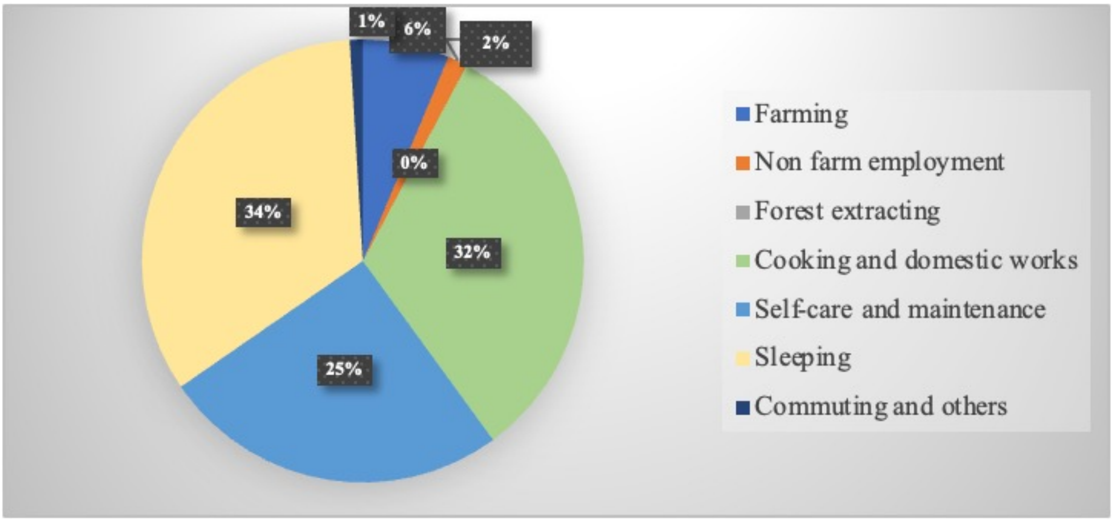
To examine the impacts of land fragmentation on women's dietary diversity, we also apply the control function approach. The estimation involves two main steps. The first step is to estimate land fragmentation as presented in Equation (1). In the second step, the estimation is specified as follows:

$$D_i = \alpha_0 + \alpha_1 X_i + \alpha_2 F_i + \alpha_3 \hat{R}_i + \epsilon_i \quad (3)$$

where D is the dietary diversity score (WDDS). Following Muthini et al. (2020) we construct WDDS with these nine food groups: (1) starchy staples, (2) dark green leafy vegetables, (3) other vitamin A-rich fruits and vegetables, (4) other fruits and vegetables, (5) organ meat, (6) meat and fish, (7) eggs, (8) legumes, nuts, and seeds, and (9) milk and dairy products. X, F, and $\hat{R}$ are defined the same as in Equation (2).

4.4 Results and discussion

4.4.1 Descriptive statistics



Notes: We collected data from 5am to 12 pm, assuming the rest of the time is spent sleeping. Here we have converted those five hours into minutes and added them to the sleeping time (minutes/day).

Figure 4.3: Women's time allocation

Figure 4.3 presents women's time allocation across different activities. It shows that, aside from sleeping, women spend approximately 32% of their daily time on cooking and domestic tasks, which account for the largest share of their time. About 25% of daily time is spent on self-care and personal maintenance. For work-related activities, women devote roughly 6% of their daily time to farming and 3% to non-farm employment and natural resource extraction.

Table 4.1 illustrates the consumption of different food groups among women and their dietary diversity score. On average, surveyed women consumed 4 food groups per day, which is lower than the minimum dietary diversity score recommended by the FAO. Starchy staples and fish were the most commonly consumed food groups. In contrast, organ meats and vitamin A–rich fruits and vegetables were consumed by less than 10% of surveyed women. Only 13% of female farmers reported consuming milk in the past day. Eggs were also not commonly consumed, with only 30% reporting intake.

Table 4.1: Consumption of different food groups

Food groups	Mean	Std. Dev.
Starchy staples	0.88	0.32
Dark green vegetables	0.58	0.49
Vitamine A rich fruits and vegetables	0.07	0.26
Other fruits and vegetables	0.57	0.50
Organ meat	0.01	0.11
Meat and fish	0.85	0.36
Eggs	0.30	0.46
Seeds and nuts	0.40	0.49
Milk and milk products	0.13	0.34
WDDS	3.80	1.41
No. of observations	699	

4.4.2. Effects of land fragmentation on non-farm activities

Table 4.2 presents the effect of land fragmentation on women's non-farm employment. Column 1 shows the impact on the likelihood of having a non-farm job, while Column 2 reports the impact on non-farm income, measured in Bangladeshi taka (BDT) per thousand. Our results indicate that land fragmentation is not significantly correlated with either non-farm income or the likelihood of non-farm employment. Regarding individual and household characteristics, the education levels of female farmers are positively associated with both non-farm income and the likelihood of having non-farm employment. This is reasonable as higher education may provide women with better opportunities to obtain non-farm jobs (DeBrauw et al., 2002; Huffman, 1980; Janvry & Sadoulet, 2001). In contrast, household size is negatively associated with the likelihood of non-farm employment, likely due to increased domestic responsibilities (care work, cooking, etc.) that limit women's participation in income-generating activities (Samtleben & Müller, 2022). Additionally, agricultural land area is negatively associated with the likelihood of non-farm employment, which makes sense as larger landholdings may require more labour on the farm, reducing time available for non-farm work (Taye & Tesfaye, 2024; USDA, 2018).

Table 4.3 presents regression coefficients from the CFA model on the impacts of land fragmentation on women's time allocation for different non-farm activities, including non-farm employment (column 1), forest extraction (column 2), cooking and domestic tasks (column 3), self-care and maintenance (column 4), and commuting and others (column 5).

Our findings show that land fragmentation significantly affects women's cooking and domestic work. Having a higher number of fragmented land plots reduces women's time availability for household chores. This is reasonable, as more fragmented land increases the burden of farm activities (Zhou et al., 2024). As part of the farm household, females are expected to share the farm responsibilities. Hence, increased farm responsibilities reduce time for cooking and domestic work. Johnston et al., (2015) similarly find that time spent on agricultural activities and domestic work involves trade-offs—particularly for women—since farming competes with leisure, caregiving, and food preparation, often creating unintended negative impacts on nutritional outcomes. In addition, our findings show that greater land fragmentation increases women's commuting time. This is reasonable, as traveling between multiple scattered plots requires additional time for movement and management. Perujo Villanueva & Colombo, (2017) also argue that greater fragmentation increases the number of trips per parcel. The larger distances between plots lead to time loss and farm management inefficiencies (Tan et al., 2010; Wang et al., 2020).

Table 4.2: Impacts of land fragmentation on women's non-farm employment

Variables	(1) Non-farm employment	(2) Non-farm income
Land fragmentation	0.007	-48.602
	(0.010)	(69.738)
Woman age	0.002*	28.326*
	(0.001)	(15.027)
Woman education	0.029***	332.464***
	(0.007)	(88.046)
Woman married	0.047	-39.247
	(0.086)	(916.128)
Woman Bangladeshi	-0.117*	-690.847
	(0.070)	(610.499)
Woman muslim	-0.022	-290.622
	(0.026)	(190.068)
Household size	-0.016*	-85.067
	(0.008)	(103.379)
Age head	-0.000	11.587
	(0.001)	(13.088)
Male head	-0.174**	-493.561
	(0.083)	(480.897)
Married head	0.075**	-47.992
	(0.032)	(384.396)
Education head	-0.001	-49.531*
	(0.003)	(25.338)
Number of dependents	0.017	119.220
	(0.014)	(105.377)
Land amount	-0.051*	-33.775
	(0.028)	(242.887)
Per capita asset (Ln)	0.002	155.997
	(0.012)	(105.946)
Flood dummy	-0.036	-456.134
	(0.042)	(316.675)
Drought dummy	0.008	-127.225
	(0.040)	(356.307)
Distance to market (Kilometre)	-0.000	-32.033
	(0.010)	(86.510)
Local level infrustructure index	0.010	77.624
	(0.056)	(441.029)
Khulna	-0.005	-249.677
	(0.037)	(256.165)
Satkhira	-0.017	-88.337
	(0.032)	(277.368)
Predicted residuals	-0.010	-92.278
	(0.041)	(316.390)
Constant	0.045	-2,442.185
	(0.203)	(2,412.968)
Observations	699	698
R-squared	0.125	0.148

*Notes: *** p < 0.01, **p < 0.05, * p < 0.1; Robust standard errors in parentheses; Coefficient estimates from CFA models.*

Table 4.3: Impacts of land fragmentation on women's time allocation

	(1)	(2)	(3)	(4)	(5)
	Non farm employment	Forest extracting	Cooking and domestic works	Self-care and maintenance	Commuting and others
Land fragmentation	0.524	-0.020	-14.626***	-5.382	6.391***
	(2.683)	(0.021)	(5.012)	(4.055)	(1.660)
Woman age	0.847*	0.006	-0.785	-0.384	-0.218
	(0.438)	(0.005)	(0.752)	(0.610)	(0.235)
Woman education	7.187***	0.014	-0.723	-3.169*	2.209***
	(2.052)	(0.016)	(2.585)	(1.673)	(0.715)
Woman married	29.839***	0.013	94.395*	16.070	-168.611**
	(10.282)	(0.096)	(56.158)	(24.588)	(73.313)
Woman Bangladeshi	-23.372	0.113	107.405***	-100.220***	-0.604
	(17.752)	(0.116)	(24.822)	(20.735)	(9.343)
Woman muslim	-5.952	-0.053	3.155	14.589	-0.386
	(7.059)	(0.090)	(12.777)	(10.077)	(4.163)
Household size	0.929	0.001	-5.930	9.054**	0.015
	(2.357)	(0.023)	(4.796)	(4.227)	(1.450)
Age head	0.366	-0.003	-2.217***	0.705	0.368**
	(0.341)	(0.002)	(0.579)	(0.460)	(0.185)
Male head	-27.993	0.080	114.524***	55.110***	-27.840***
	(21.716)	(0.071)	(30.571)	(18.891)	(8.144)
Married head	11.095	0.096	31.430	-54.099**	-3.163
	(9.379)	(0.074)	(40.401)	(27.422)	(6.473)
Education head	-0.543	-0.001	0.906	1.772	-1.066**
	(0.850)	(0.014)	(1.558)	(1.170)	(0.444)
Number of dependents	2.626	0.037	24.794***	-21.449***	-3.611
	(4.058)	(0.065)	(7.050)	(5.569)	(2.212)
Land amount	-3.231	0.059	1.860	17.232	-3.028
	(6.981)	(0.118)	(15.047)	(11.580)	(5.491)
Per capita asset (Ln)	3.712	-0.042	1.495	1.389	1.346
	(3.662)	(0.032)	(6.455)	(4.839)	(2.034)
Flood dummy	-21.257	-0.098	-50.858*	37.164**	-2.834
	(13.426)	(0.102)	(30.567)	(18.201)	(5.390)
Drought dummy	2.999	-0.043	-8.624	9.432	-2.465
	(11.392)	(0.046)	(19.283)	(14.290)	(6.626)
Distance to market (Kilometre)	-1.230	0.019	1.834	-3.788	0.795
	(2.651)	(0.034)	(4.423)	(3.200)	(1.183)
Local level infrustructure index	15.623	0.049	-50.447**	51.091**	-4.437
	(13.909)	(0.088)	(25.397)	(23.429)	(6.018)
Khulna	-7.930	0.068	14.442	-26.459*	7.294
	(10.925)	(0.134)	(20.979)	(15.137)	(6.933)
Satkhira	-11.931	0.093	41.573**	-57.950***	5.781
	(9.918)	(0.068)	(17.749)	(13.471)	(5.421)
Predicted residuals	-14.586	0.018	-7.385	-7.180	3.947
	(10.603)	(0.193)	(21.011)	(16.765)	(7.085)
Constant	-68.250	-0.163	281.687***	445.372***	159.346**
	(54.047)	(0.460)	(103.629)	(72.187)	(78.778)
Observations	699	699	699	699	699
R-squared	0.088	0.013	0.165	0.138	0.253

*Notes: *** p < 0.01, **p < 0.05, * p < 0.1; Robust standard errors in parentheses; Coefficient estimates from CFA models.*

Table 4.4: Impacts of land fragmentation on women's non-farm employment and time allocation (minutes/day) by education and women having child care responsibility

Panel A	Non-farm employment	non-farm income	Non farm employment time	Forest extracting time	Cooking and domestic works time	Self-care and maintenance time	Commuting and others time
Low education	-0.008	-85.771	-4.661**	0.000	-8.551	-2.518	4.721***
	(0.008)	(66.983)	(2.323)	(0.000)	(6.282)	(5.366)	(1.786)
High education	0.033	13.109	8.549	-0.044	-23.784***	-11.021*	8.856***
	(0.023)	(160.203)	(6.038)	(0.041)	(8.648)	(5.777)	(2.827)
Panel B	**Non-farm employment**	**non-farm income**	**Non farm employment time**	**Forest extracting time**	**Cooking and domestic works time**	**Self-care and maintenance time**	**Commuting and others time**
Woman with child	0.001	-16.563	-7.637*	-0.085	-3.555	-7.369	3.719*
	(0.020)	(88.935)	(3.887)	(0.076)	(9.490)	(5.883)	(2.140)
Woman without child	0.010	-68.433	4.478	0.000	-18.557***	-5.228	7.996***
	(0.012)	(90.333)	(3.324)	(0.000)	(5.900)	(5.323)	(2.092)

*Notes: *** p < 0.01, **p < 0.05, * p < 0.1; Robust standard errors in parentheses; Coefficient estimates from CFA models; Low and high education refer to observations below and above sample means for the respective variables; Woman with child indicates a woman has at least one child to look after. Full regression models are added in Appendix Table D5-D8.*

We assume that the impacts of land fragmentation may not be homogeneous across the population. Therefore, we examine the heterogeneity by education levels and by the presence of small children. Results in Panel A, Table 4.4 shows that land fragmentation is negatively associated with time allocated to non-farm employment for women with lower education levels. For women with higher education, the effect is positive but not statistically significant. In contrast, the effect on time allocated to cooking is negative and significant for women with lower education levels. This is reasonable, as women with higher education levels may face fewer difficulties in accessing higher-skilled and more profitable non-farm jobs (Islam et al., 2022; Yousefy & Baratali, 2011) They may also be more willing to sacrifice time for cooking in order to balance farming and non-farm activities. Results in Panel B, Table 4.4 shows the heterogeneity by whether women have children or not. Land fragmentation is negatively associated with non-farm employment time for women with children, while it is negatively associated with cooking time for women without children. Women with small children may reduce their time in non-farm jobs when land fragmentation increases, but they cannot reduce cooking time due to their caregiving responsibilities. In contrast, women without childcare burdens may be more willing to reduce time spent on cooking, while maintaining their time in non-farm employment.

4.4.3. Impacts of land fragmentation on women's dietary diversity

Table 4.5 presents the effect of land fragmentation on women's dietary diversity. Our findings show that land fragmentation is negatively, but not significantly, correlated with women's dietary diversity. The insignificant impact of land fragmentation on WDDS also holds when we examine subsamples by education level and the presence of young children in Table 4.6. In all estimations, the effects on WDDS remain statistically insignificant. In section 4.4, we present results on the impacts of land fragmentation on productive delivery, farm activities, and crop productivity, which may help explain the null effect on women's dietary diversity.

Regarding other household and individual characteristics, women's education levels are positively and significantly correlated with their dietary diversity scores. This result is consistent with Makate & Nyamuranga (2023) and Rashid et al. (2011). Educated women may possess better nutritional knowledge Pavicic et al. (2024). Meanwhile, the education level of household heads, usually male, is not correlated with dietary diversity, which is expected as male members are less involved in cooking. Asset value, an indicator of household well-being, is positively correlated with women's dietary diversity (Anyanwu et al., 2022; Gaillard et al., 2022), suggesting that poorer farmers generally consume less diverse foods. Household size is negatively correlated with WDDS (Saaka et al., 2021), which is reasonable since larger households may prioritize calorie-dense, easy-to-prepare foods rather than a wide variety of food groups. Our findings also show that Muslim women appear to have lower WDDS. This is plausible, as Muslim households may face greater dietary restrictions due to religious or cultural practices. Furthermore, drought reduces WDDS, as droughts cause economic losses that consequently affect household income and dietary diversity. This finding is also consistent with (Oduor et al., 2023).

Table 4.5: Impact of land fragmentation on women's dietary diversity

	WDDS
Land fragmentation	-0.011
	(0.052)
Woman age	0.009
	(0.007)
Woman education	0.039*
	(0.022)
Woman married	0.462
	(0.481)
Woman Bangladeshi	1.247***
	(0.197)
Woman muslim	-0.206
	(0.135)
Household size	-0.083*
	(0.046)
Age head	0.001
	(0.006)
Male head	0.070
	(0.250)
Married head	0.595
	(0.462)
Education head	0.025*
	(0.014)
Number of dependents	0.078
	(0.060)
Land amount	0.085
	(0.147)
Per capita asset (Ln)	0.118**
	(0.059)
Flood dummy	-0.151
	(0.290)
Drought dummy	-0.335*
	(0.200)
Distance to market (Kilometre)	0.006
	(0.039)
Local level infrustructure index	-1.065***
	(0.232)
Khulna	0.297
	(0.207)
Satkhira	1.161***
	(0.184)
Predicted residuals	0.450**
	(0.203)
Constant	-1.037
	(0.936)
Observations	699
R-squared	0.210

*Notes: *** $p < 0.01$, **$p < 0.05$, * $p < 0.1$; Robust standard errors in parentheses; Coefficient estimates from CFA models; WDDS: Women's diet diversity score.*

Table 4.6: Heterogeneous impacts of land fragmentation on women's dietary diversity

Panel A	WDDS
Low education of woman	-0.069
	(0.088)
High education of woman	0.049
	(0.067)
Panel B	**WDDS**
Woman with at least one child	-0.022
	(0.077)
Woman without child	0.008
	(0.068)

*Notes: *** p < 0.01, **p < 0.05, * p < 0.1; Robust standard errors in parentheses; Coefficient estimates from CFA models; WDDS: Women's diet diversity score. Low and high education refer to observations below and above the sample means for the respective variables. Woman with child indicates a woman has at least one child to look after. Full regression models are added in the Appendix Table D9-D10.*

4.4.4 Association between land fragmentation and farming outcomes

To better understand how land fragmentation affects time allocation to non-farm activities and women's dietary diversity, it is important to examine its impacts on farming activities. This section presents the association between land fragmentation and various farm outcomes, including production diversity, crop productivity, farm income, and time allocation to farming activities by male and female household members. Since the falsification test indicates that our IV does not satisfy the exclusion restriction assumption for farming outcomes, we apply OLS models in this section to show associations rather than causal effects of land fragmentation on farming activities.

Table 4.7 shows the association between land fragmentation and time allocation for farming activities among male and female farmers. Regardless of gender, land fragmentation is positively associated with the time spent on farming activities, indicating that owning more fragmented land increases the labor burden for farmers. Nguyen (2014) also shows that land fragmentation requires more labor on the farm. The magnitude of this association appears stronger for female household members, suggesting that they bear a larger share of the additional workload. This may explain why women need to reduce time spent on cooking and non-farm employment.

Table 4.8 shows the association between land fragmentation and crop productivity and production diversity. Land fragmentation is negatively but insignificantly correlated with crop productivity. Regarding the association between land fragmentation and production diversity, more fragmented land is associated with higher production diversity. The result is consistent with Ndip et al. (2023), they also find a positive association between land fragmentation and farm diversification. This is reasonable, as households may grow different crops on different parcels depending on the suitability of each plot.

The increase in production diversity could potentially improve dietary diversity. However, these gains appear to be offset by the negative impacts on dietary diversity due to reduced time spent on cooking, as well as slight decreases in crop productivity and non-farm income. This helps explain why the effects of land fragmentation on women's dietary diversity are negative but statistically insignificant.

Table 4.7: Association between land fragmentation and time allocation on farming activities

	(1) Women's time allocated to farming (Minutes)	(2) Men's time allocated to farming (Minutes)
Land fragmentation	17.775***	13.520**
	(3.074)	(6.004)
Household controls	Yes	Yes
District fixed effect	Yes	Yes
R-squared	0.177	0.199

*Notes: *** p < 0.01, **p < 0.05, * p < 0.1; Robust standard errors in parentheses; Coefficient estimates from OLS models. Full regression models are added in the Appendix Table D11.*

Table 4.8: Association between land fragmentation and crop productivity, and production diversity

	(1) Crop productivity	(2) Number of species
Land fragmentation	-6.487	1.281***
	(4.963)	(0.053)
Household controls	Yes	Yes
District fixed effect	Yes	Yes
R-squared	0.178	0.587

*Notes: *** p < 0.01, **p < 0.05, * p < 0.1; Robust standard errors in parentheses; Coefficient estimates from OLS models. Full regression models are added in the Appendix Table D12.*

4.5 Conclusion and policy recommendation

Land fragmentation is common in rural agrarian systems in many developing countries. It is often criticized as a major source of farming inefficiency, as it can increase travel costs and limit the use of machinery. Consequently, many countries are considering policies to promote agricultural land consolidation. However, there are concerns that reducing land fragmentation might lower household dietary diversity by decreasing production diversity. Moreover, while many studies have examined the impacts of land fragmentation on farm outcomes, little is known about its effects on other household livelihood activities. In particular, to the best of our knowledge, no studies have investigated the impacts of land fragmentation on women’s non-farm activities. Accordingly, our study uses the CFA approach to examine the effects of land fragmentation on women’s non-farm activities and dietary diversity, based on data from 699 female farmers in rural Bangladesh.

Our findings show that land fragmentation is significantly and negatively correlated with women’s time allocation for cooking and domestic work. Among women with low education levels and young children, land fragmentation is also associated with less time for non-farm employment. The negative effects on time allocated to cooking, domestic work, and non-farm employment can be attributed to the increased time demands for farming activities.

Regarding the impact on women’s dietary diversity, contrary to previous studies reporting positive effects of land fragmentation on household dietary diversity, our results indicate negative but insignificant effects. Although land fragmentation can increase production diversity, this benefit is offset by reduced time for cooking, slight decreases in crop productivity, and lower non-farm income. As a result, the gains in dietary diversity from increased production are completely neutralized, making the overall impact statistically insignificant.

For other household and individual characteristics, higher education levels are associated with higher non-farm income and an increased likelihood of non-farm employment. Living in larger households is negatively associated with the likelihood of engaging in non-farm employment. Regarding dietary diversity, women’s education levels are positively and significantly correlated with their dietary diversity scores. Women in better-off households tend to have higher dietary diversity, while household size is negatively correlated with WDDS. Muslim women appear to have lower WDDS. Droughts will reduce the diversity in women’s diets.

Our study provides policy implications suggesting that policies promoting land consolidation should be promoted. Concerns about reduced farm production diversity can be offset by increased farm income, greater non-farm employment opportunities for women, and more time available for household care. Moreover, policies that promote women’s education should be promoted, as they can increase participation in profitable non-farm employment and improve household dietary quality.

CHAPTER 5

5 Conclusion and policy recommendation

5.1 Summary

Access to a healthy and diverse diet is essential to maintain an individual's nutritional requirements. In developing countries, rural smallholders are most vulnerable to poor dietary quality. Agricultural seasonality, increased time allocation for farm activities, climate change, and the limited scope of non-farm employment reduce the potential for farm income, resulting in poor dietary quality. Technical innovation and access to information about different farming methods can help overcome the challenges. However, sometimes land characteristics, especially land fragmentation, are considered a barrier to agricultural mechanization. This mechanization may increase farm income or save time on farm activities, thereby increasing non-farm income. This dissertation explores how smallholders may benefit from innovation and access to knowledge about new farming technologies, and how land fragmentation, as a barrier to technology adoption, impacts farm and non-farm income and time allocation.

Chapter Two explores the effect of rice-aquaculture adoption by smallholders on household dietary quality in the agricultural normal and lean seasons. We find that the adoption of rice-aquaculture is negatively associated with household dietary diversity in the agricultural normal season and the lean season. During the agricultural lean season, rice-aquaculture adopters are even more affected, as food availability is low because food stocks from the last harvest are about to be exhausted and the new harvest has yet to come. Rice-aquaculture is very labour-demanding, and it limits the adopters' additional income potential from other non-farm activities and seasonal migration. In our investigation for heterogeneous association between rice aquaculture adoption and household dietary diversity, we have found that households with younger heads, low education and small land holdings are overproportionally affected. We can understand that young rice-aquaculture adopters are less experienced, and this may reduce their farm production and income. Adopters with low levels of education may have a limited understanding of water quality and farm management. It may increase the risk of different fungal diseases of fish and rice, which is also likely to cut profit margin, consequently reducing dietary diversity. For rice-aquaculture adopters with large landholdings, operationalising rice-aquaculture is more convenient on large farmland, as it helps farmers enjoy the benefits of economies of scale. For a small landowner adopting rice-aquaculture, the chances of achieving economies of scale are very slim; on the other hand, farm management is somewhat expensive, shrinking profit margins, which also affects households' dietary quality. We also explore the potential mechanisms of these unexpected negative diet effects. We have found that households adopting rice-aquaculture spend a substantial portion of their daily time on farm activities, leaving less time available for cooking, caregiving, and other domestic activities, and certain off-farm activities. Besides, the rice-aquaculture adopters have lower crop and livestock production diversity, lower income from forest extraction activities, and higher debts than non-adopters, which reasonably explains the negative association between rice-aquaculture adoption and household dietary quality.

Chapter Three investigates the effect of internet use on smallholders' farm production and consumption outcomes. We find that internet use improves farm production outcomes. Households with internet use have higher farm output value, farm income and agricultural output commercialization. Households that use the internet are more likely to produce nutrient-rich food groups (fish, meat, legumes, nuts, and seeds). We also conducted qualitative interviews to find an explanation for our findings. The qualitative data reveal that access to the internet increases the availability of information about new farming techniques, eases communication with agricultural extension officers and experienced farmers within the shortest possible time. Success stories from different farmers make internet-using smallholders confident to try new seed varieties, new high-breed aquatic and livestock species, which increase farm output and reduce production costs. Access to market price information, reducing information asymmetry, helps farmer sell their product online and offline at better prices that leverage farm commercialization and farm profit. Strikingly, using the internet seems to improve farm production outcomes and production of certain nutritious and profitable food groups, but it does not always lead to improved household consumption outcomes. The magnitude of the effects of internet use on household dietary diversity scores is relatively smaller than the farm production diversity. Zooming in on individual-level food consumption data, we find that internet use has a positive effect on women's dietary diversity, but not on men's or children's dietary diversity scores. Regression estimates on different food group consumption demonstrate that using the internet increases the likelihood of only fish consumption, but not other food groups.

In Chapter Four, we examine the effect of land fragmentation as a structural barrier on rural smallholders', especially women's—, non-farm employment and income, time allocation for non-farm activities, and women's dietary diversity. Data analysis applying quantitative methods reveals that land fragmentation is positive and statistically significantly associated with the time women spend on farming activities. Exclusive engagement in farming activities reduces the time available for other non-farm activities, especially time allocation for cooking and food preparation. Heterogeneous impact analysis demonstrated that women with low educational levels and who bear the responsibility of at least one young child, land fragmentation is also associated with less time available for non-farm employment opportunities. Our results also reveal that the effects of land fragmentation are negative, but it is not statistically significant. Our impact mechanism analysis shows that land fragmentation is positive and statistically significantly associated with farm production diversity, so it may increase the WDDS. However, these gains may be offset by the reduced time spent on cooking, as well as slight decreases in crop productivity and non-farm income.

5.2 Policy recommendations

Based on the findings obtained from the three essays of this dissertation, three specific policies are recommended:

1. ***Provision of better training and technical support is inevitable to enhance farmers' productivity and income gains from rice-aquaculture adoption and dietary outcomes***

Rice-aquaculture farming is complex and demands more time and technical skill. Without proper knowledge, adoption may fail to improve household income or nutritional outcomes. Excessive involvement in farm activities limits the income potential of rice-aquaculture adopters from other income-generating activities. Hence, better training and technical support should be provided to adopters to secure farm productivity with fewer labour hours. Different training options tailored by agricultural extension services and local NGOs should focus on farmers' technical skills development and labour-saving techniques for managing rice and fish production on the same plot. Furthermore, training on the benefits of collective farming may reduce the production cost and workload of the smallholders, may increase profit margin, and save daily labour hours for other income-generating activities and domestic work. Integrating nutrition education with technical training for rice-aquaculture adopters can further improve household dietary outcomes alongside the monetary gain from rice and fish.

2. ***Expansion of internet use based digital literacy and promotion of nutrition-focused recipes with locally grown food items can improve farm production and consumption outcomes, respectively***

Since access to knowledge and information via the internet use clearly improves farm outputs, and incomes, production diversity and commercialization, it is essential to promote internet use. It can include improved internet infrastructure in remote areas of the country with 4G or 5G network coverage. It should be easily accessible and affordable for smallholders at a reasonable price to boost internet adoption rates. Besides, it is imperative to promote digital literacy among farmers through various training programs, including user-friendly apps in local languages. These apps should be tailored to fulfil the needs of smallholder farmers, encapsulating information on relevant farming innovations, market data, weather forecasts, etc.

The positive effects of the internet on household dietary diversity are small in magnitude. The positive effects as such are welcome but they could be further improved through appropriate action. To translate the benefits of smallholders' farm production outcomes into household consumption outcomes, disseminating recipes featuring locally grown food groups on online platforms may improve dietary quality. Online content on healthy food habits, knowledge of the nutritional value of different food groups, and cooking shows and workshops promoting healthy recipes can be helpful in this regard.

3. ***Promotion of land consolidation and women's education to promote non-farm employment and dietary quality***

Based on the findings from the third essay, we can say that the government should promote land consolidation. Concerns may arise about farm production diversity, as fragmented land promotes it, so land consolidation may reduce it. But land consolidation and agricultural mechanisation can increase farm productivity and farm income, and save labour hours in the field. Hence, reduced farm production diversity can be offset by increased farm income, greater non-farm employment opportunities for women, and more time available for household care. Besides, policies to promote women's education should be prioritised. It can improve women's working efficacy and increase their participation in different profitable non-farm employment, consequently improving household dietary quality.

From the overall findings from these three essays of this dissertation, we can understand how diets and livelihood activities are shaped by rice-aquaculture adoption, internet access, and land fragmentation. Even though we have seen that rice–aquaculture increases income, the benefit rarely trickles down to household diets. The young, less educated, and small landholder household heads are more affected. In contrast, households with internet use enrich farmers' farming knowledge with different information and improve farm production outcomes, diversification, and commercialization. Land fragmentation adds additional farm workload, especially for women, and limits non-farm employment and domestic work time. Women with low educational levels experiencing land fragmentation are also associated with having less time available for non-farm employment opportunities. Taken together, these findings suggest government intervention for the expansion of education irrespective of gender. An educated farmer can better adopt modern and innovative farming, and educated men or women may also engage in other non-farm employment and improve household dietary quality even if they have low farm income or fragmented land holdings. In addition, specialised technical and nutritional training integrating digital literacy should be promoted for smallholders. Skilled farmers may adopt innovative farming techniques with confidence, and expanded digital literacy may improve farm production diversity, commercialization, and farm income. Therefore, through farm production diversity, and increased farm and off-farm income, household and individual dietary quality may improve.

5.3 Overall conclusion, limitations, and further research needs

This dissertation discusses the complex interactions between agricultural innovation, access to information, and structural constraints in shaping smallholders' livelihood activities, time allocation and dietary quality. While adoption of new farming techniques such as rice-aquaculture comes with some challenges, it increases farm income. Using the Internet as a source of information and knowledge improves smallholders' farm production and consumption outcomes. Even though the benefits from internet use on farm production outcomes and consumption outcomes are uneven. But the positive impact is welcome, and further scale up of the internet use may be more beneficial. Land fragmentation reduces women's income potentials and dietary quality, which calls for land consolidation and agricultural mechanisation. The findings underscore that promoting innovation alone is insufficient; enabling policies to address structural barriers, reducing gendered time burdens, and providing access to knowledge can help improve smallholders' farm production and income, enhance nutritional knowledge, diversify income generation, and improve food security in rural Bangladesh.

The data collected for this dissertation is only from the south-west region of Bangladesh. Data collected from other regions on the same research objective could have provided more nuanced findings. However, due to budget and time constraints, we were unable to extend our survey to other districts in Bangladesh. For the same reason, the data collected for our research are limited to cross-sectional data.

The three essays in this dissertation use cross-sectional data and instrumental variables to address endogeneity. Hence, drawing causal inferences is not always robust. Additionally, during the agricultural lean season, the dietary data used in Chapters Two and Three are based on respondents' recall. Cross-country panel data collection during the agricultural normal and lean seasons could be an avenue for further research. Additionally, how rice-aquaculture adoption, internet use, and land fragmentation affect more precise micro- and macro-nutrient outcomes for smallholders (at the household and individual levels) requires further research.

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Appendix A: Appendix to Chapter 1

Appendix A1 : Ethics approval

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Ethical Clearance

The following research has been pre-reviewed for ethical standards by the ZEF Research Ethics Committee. The researcher named below applied for ethical reviews before commencing the research. The application was independently reviewed by two reviewers of the Committee and found to be ethically sound. The ZEF Research Ethics Committee includes senior researchers from ZEF and the Institute for Food and Resource Economics (ILR), both University of Bonn. The Ethical Clearance is based on the ZEF Ethics Policy[1].

Registration code:	16b_23 Fariha Farjana
Title of the research study:	Role of Mixed Farming to Improve Food Security and Forest Conservation: An Empirical Study on the Coastal Area of Bangladesh
Location(s) of field research	Khulna Division, Bangladesh
If applicable, name of a larger project:	
Name of the researcher:	Fariha Farjana
Working group / affiliated institute:	ZEFb
Source of funding:	BMZ via DAAD/EPOS
Date of approval of the ethical clearance:	02.11.23

[1] https://www.zef.de/fileadmin/webfiles/downloads/doc-program/Website_2014_various/ZEF_ethic_policy-web.pdf

Appendix B: Appendix to Chapter 2

Rice-aquaculture systems and dietary quality in Bangladesh

Table B1. Name and definition of control variables

Name	Measurement unit	Definition
Rice- aquaculture	Dummy (1=yes, 0=otherwise)	Household has adopted the farming system which rice and aquatic species are grown in the same parcel
Household size	Number	Total number of household member
Age head	Years	Age of the household head
Male head	Dummy (1=male, 0=female)	Gender of the household head
Education head	Years	Years of schooling of the household head
No. of dependent	Number	Number of dependent people in the household
Having TV	Dummy (1=yes, 0=no)	Household have a television is =1 and 0 =otherwise
Having motorbike	Dummy (1=yes, 0=no)	Household have a motorbike is =1 and 0 =otherwise
Having smart phone	Dummy (1=yes, 0=no)	Household have a smartphone is =1 and 0 =otherwise
Distance	Kilometer	Distance between house and the local market
Land size	Hectare	Total amount of land owned by the household
District	District dummy1 District dummy2	District dummy 1 (1=Khulna, 0=otherwise) District dummy 2 (1= Satkhira, 0=otherwise)
Flood	Dummy (1=yes, 0=no)	If household experienced flood in last 12 months=1, 0=otherwise
Drought	Dummy (1=yes, 0=no)	If household experienced drought in last 12 months=1, 0=otherwise

Table B2. Share of rice-aquaculture adopters by *Upazila*

Upazila Name	Share of rice-aquaculture adopters (%)
Assasuni	40.0
Dacope	17.5
Kaliganj	12.5
Koyra	18.8
Mongla	20.0
Paikgachha	40.0
Sarankhola	0
Shyamnagar	18.0

Table B3. First-stage regression (probit model)

Variables	Rice-aquaculture adoption
Household size	0.034
	(0.048)
Age head	-0.006
	(0.005)
Male head	0.128
	(0.311)
Years of school of head	-0.051***
	(0.015)
No. of dependent	-0.008
	(0.065)
Having TV	0.187
	(0.126)
Having motorbike	0.295
	(0.184)
Having smartphone	0.041
	(0.130)
Distance to market	0.008
	(0.044)
Farm size	0.256**
	(0.125)
Asset value per capita	0.049
	(0.074)
Flood	-0.373
	(0.425)
Drought	-0.233
	(0.236)
Khulna district	0.186
	(0.181)
Satkhira district	0.085
	(0.186)
Share of rice-aquaculture adoption in the *Upazila* neighborhood (instrument)	0.033***
	(0.005)
Constant	-2.034***
	(0.747)
Wald chi2(16)	88.09
Prob > chi2	0.0000
Observations	720

*Notes: *** p<0.01, ** p<0.05, * p<0.1; Robust standard errors in parentheses.*

Table B4. Proportion of households consuming fish during 7-day recall period in *Upazila*s with low and high levels of rice-aquaculture adoption

	*Upazila*s with low adoption	*Upazilas* with high adoption	Difference	P-value
Fish consumption (1/0)	0.95	0.96	0.01	0.70
	(0.22)	(0.21)		

Notes: Upazilas were classified based on overall mean adoption rates. Standard errors in parentheses.

Table B5. Falsification test considering rice-aquaculture non-adopter households

List of dependent/outcome variables	No. of observations	Share of rice-aquaculture adoption in the *Upazila*	Robust standard error
HDDS12	563	-0.002	(0.007)
HDDS9	563	-0.006	(0.006)
HDDS12 lean	563	-0.007	(0.008)
HDDS9 lean	563	-0.007	(0.007)
MDDS	546	-0.009*	(0.005)
WDDS	544	-0.012**	(0.005)
CDDS	201	-0.001	(0.007)
Farm activities in normal season	563	-1.938**	(0.808)
Non-farm activities in normal season	563	0.862	(0.758)
Commuting in normal season	563	1.733***	(0.337)
Cooking and domestic activities in normal season	563	-0.335	(0.714)
Forest extraction activities in normal season	563	0.127	(0.176)
Other activities in normal season	563	3.937**	(1.565)
Farm activities in lean season	563	-0.778	(0.727)
Non-farm activities in lean season	563	0.387	(0.859)
Commuting in lean season	563	2.502***	(0.313)
Cooking and domestic activities in lean season	563	-0.998	(0.708)
Forest extraction activities in lean season	563	-1.242***	(0.359)
Other activities in lean season	563	3.140*	(1.708)
PDS12	563	-0.026***	(0.008)
PDS9	563	-0.025***	(0.008)
Number of crop species cultivated in normal season	563	-0.020***	(0.006)
Number of livestock species in normal season	563	-0.012**	(0.005)
Number of aquatic species in normal season	563	0.017***	(0.003)
Total income	563	0.029**	(0.012)
Farm income	563	0.009	(0.007)
Off-farm income	563	0.024***	(0.009)
Forest extracting income	563	-0.004	(0.006)
Remittance, stipend and public transfer	563	-0.001	(0.001)
Total consumption	563	-0.007	(0.007)
Food	563	-0.004	(0.003)
Education	563	-0.004*	(0.002)
Health	563	-0.006*	(0.004)
Transport and communication	563	0.000	(0.001)
Water and electricity	563	0.002***	(0.000)
Other non-food consumption	563	0.005*	(0.002)

*Notes: *** p<0.01, ** p<0.05, * p<0.1; Each table row represents a separate OLS regression model, regressing the shown outcome on the instrument (Share of rice-aquaculture adoption in the Upazila neighborhood) and all control variables (household size, age, sex, education of household head, dependents, TV, motorbike, smartphone, distance to market, land size, asset value per capita, flood, drought, Khulna district, Satkhira district). We only show the instrument coefficient for brevity.*

Table B6. Different food groups consumption by rice-aquaculture adoption in the normal season

Food groups	(1) Full sample	(2) Non-adopters	(3) Rice-aquaculture adopters	(3)-(2) Difference
Cereals	0 .934	0.948	0.885	-0.063***
	(0.247)	(0.221)	(0.320)	
Roots and tubers	0.837	0.847	0.803	-0.045
	(0.369)	(0.360)	(0.399)	
Eggs	0.868	0.865	0.879	0.014
	(0.339)	(0.342)	(0.327)	
Fish	0.95	0.950	0.949	-0.001
	(0.291)	(0.218)	(0.221)	
Seeds and nuts	0 .805	0.829	0.720	-0.110***
	(0.396)	(0.376)	(0.451)	
Milk and dairy product	0 .405	0.425	0.338	-0.087**
	(0.491)	(0.495)	(0.474)	
Oils and fat	0.9222	0.904	0.987	0.083***
	(0.268)	(0.295)	(0.113)	
Spices and condiments	0.9777	0.975	0.987	0.012
	(0.148)	(0.156)	(0.113)	
Sweets	0.759	0.774	0.707	-0.067*
	(0.427)	(0.418)	(0.457)	
Vegetables	0.990	0.989	0.994	0.004
	(0.981)	(0.103)	(0.080)	
Fruits	0.59	0.597	0.599	0.002
	(0.490)	(0.491)	(0.492)	
Meat	0.559	0.552	0.586	0.034
	(0.497	(0.498)	(0.494)	
Observations	720	563	157	

*Notes: *** p < 0.01, **p < 0.05, * p < 0.1; Standard deviation in parentheses.*

Table B7. Different food groups consumption by rice-aquaculture adoption in the lean season

Food groups	(1) Full sample	(2) Non-adopters	(3) Rice-aquaculture adopters	(3)-(2) Difference
Cereals	1.00	1.000	1.000	0.000
	(0.000)	(0.000)	(0.000)	
Roots and tubers	0 .801	0.815	0.752	-0.064*
	(0.399)	(0.388)	(0.434)	
Eggs	0 .768	0.801	0.650	-0.151***
	(0.422)	(0.400)	(0.479)	
Fish	0.936	0.927	0.968	0.041*
	(0.244)	(0.260)	(0.176)	
Seeds and nuts	0.722	0.760	0.586	-0.174***
	(0.448)	(0.427)	(0.494)	
Milk and dairy product	0.418	0.439	0.344	-0.095**
	(0.494)	(0.497)	(0.477	
Oils and fat	0.923	0.902	1.000	0.098***
	(0.266)	(0.297)	(0.000)	
Spices and condiments	0.927	0.927	0.930	0.003
	(0.259)	(0.260)	(0.256)	
Sweets	0.637	0.654	0.580	-0.074*
	(0.481)	(0.476)	(0.495)	
Vegetables	0.983	0.988	0.968	-0.019*
	(0.128)	(0.111)	(0.176)	
Fruits	0 .714	0.732	0.650	-0.082**
	(0.452)	(0.443)	(0.479)	
Meat	0.525	0.510	0.580	0.070
	(0.500)	(0.500)	(0.495)	
Observations	720	563	157	

*Notes: *** p < 0.01, **p < 0.05, * p < 0.1; Standard deviation in parentheses.*

Table B8. Variance inflation factors (VIF) for regression models in Table 2.3

Variable	VIF	1/VIF
Rice-aquaculture	1.06	0.95
Household size	2.42	0.41
Age head	1.18	0.85
Male head	1.03	0.97
Education head	1.35	0.74
Dependents	2.23	0.45
Having TV	1.18	0.85
Having motorbike	1.34	0.75
Having smartphone	1.36	0.73
Distance to market	1.05	0.95
Land size	1.24	0.80
Asset value per capita (ln)	1.80	0.56
Flood	1.06	0.95
Drought	1.06	0.95
Khulna district	1.72	0.58
Satkhira district	1.83	0.55
Mean VIF	1.43	

Table B9. Associations between rice-aquaculture adoption and individual dietary diversity

	(1)	(2)	(3)
	MDDS	WDDS	CDDS
Rice-aquaculture	-0.867***	-0.901***	0.149
	(0.262)	(0.251)	(1.470)
Household size	-0.065	-0.122**	-0.159*
	(0.041)	(0.048)	(0.086)
Age head	0.006	0.004	0.006
	(0.004)	(0.004)	(0.009)
Male head	0.011	0.244	-0.501
	(0.267)	(0.260)	(0.308)
Education head	0.098*	0.065	0.070
	(0.054)	(0.054)	(0.092)
No. of dependent	-0.004	0.100*	0.138*
	(0.054)	(0.057)	(0.083)
Having TV	-0.026	0.138	0.451***
	(0.112)	(0.114)	(0.151)
Having motorbike	0.172	0.174	0.153
	(0.150)	(0.167)	(0.325)
Having smartphone	0.190*	0.219*	0.006
	(0.111)	(0.117)	(0.195)
Distance to market	0.099***	0.084**	0.004
	(0.036)	(0.035)	(0.052)
Land size	0.299***	0.264**	0.213
	(0.099)	(0.113)	(0.207)
Asset value per capita (ln)	0.041	0.058	0.033
	(0.063)	(0.067)	(0.099)
Flood	-0.372	-0.205	-0.299
	(0.281)	(0.281)	(0.355)
Drought	-0.002	-0.248	0.235
	(0.193)	(0.188)	(0.299)
Khulna district	0.143	-0.010	-1.075**
	(0.131)	(0.140)	(0.455)
Satkhira district	1.095***	0.898***	0.167
	(0.134)	(0.144)	(0.343)
Constant	2.701***	2.702***	4.196***
	(0.644)	(0.651)	(0.852)
Wald chi^2	187.93	192.58	126.98
p-value	0.00	0.00	0.00
Observations	701	693	267

*Notes: *** p<0.01, ** p<0.05, * p<0.1; Robust standard errors in parentheses*

Table B10. Association between rice-aquaculture adoption and diet diversity among farmers with low education levels

	Normal season			Lean season
	(1)	(2)	(3)	(4)
	HDDS12	HDDS9	HDDS12	HDDS9
Rice-aquaculture	-0.243	-0.375	-1.353**	-1.071**
	(0.421)	(0.366)	(0.681)	(0.459)
Household size	0.083	0.086	0.069	0.080
	(0.075)	(0.061)	(0.080)	(0.064)
Age head	-0.008	-0.010	-0.011	-0.010
	(0.008)	(0.007)	(0.009)	(0.007)
Male head	0.417	0.540*	0.640	0.623
	(0.356)	(0.297)	(0.554)	(0.437)
No. of dependent	0.193*	0.127	0.068	0.064
	(0.100)	(0.085)	(0.117)	(0.095)
Having TV	0.093	0.132	0.322	0.188
	(0.180)	(0.157)	(0.225)	(0.182)
Having motorbike	-0.195	-0.227	0.020	-0.121
	(0.328)	(0.273)	(0.396)	(0.318)
Having smartphone	0.077	0.170	0.160	0.165
	(0.177)	(0.151)	(0.215)	(0.173)
Distance to market	0.048	0.062	0.055	0.053
	(0.068)	(0.055)	(0.076)	(0.060)
Land size	0.198	0.297*	-0.090	-0.028
	(0.220)	(0.172)	(0.293)	(0.217)
Asset value per capita (ln)	0.309***	0.230**	0.184	0.164
	(0.104)	(0.090)	(0.126)	(0.101)
Flood	-0.270	-0.139	-0.213	0.157
	(0.514)	(0.416)	(0.646)	(0.530)
Drought	-0.209	-0.271	0.194	0.091
	(0.286)	(0.256)	(0.327)	(0.264)
Khulna district	-0.478**	-0.298	-0.465	-0.247
	(0.227)	(0.192)	(0.284)	(0.212)
Satkhira district	0.124	0.236	-0.000	0.041
	(0.213)	(0.185)	(0.264)	(0.205)
Constant	6.142***	4.042***	7.419***	4.900***
	(1.072)	(0.906)	(1.303)	(1.035)
Wald chi^2	44.63	55.58	33.83	34.14
p-value	0.00	0.00	0.00	0.00
Observations	437	437	437	437

*Notes: *** $p < 0.01$, **$p < 0.05$, * $p < 0.1$; Robust standard errors in parentheses.*

Table B11. Associations between rice-aquaculture adoption and diet diversity among farmers with high education levels

	Normal season		Lean season	
	(1)	(2)	(3)	(4)
	HDDS12	HDDS9	HDDS12	HDDS9
Rice-aquaculture	-0.692	-0.803	-0.953	-0.642
	(1.691)	(1.004)	(1.226)	(0.683)
Household size	0.021	0.037	0.187*	0.159**
	(0.093)	(0.075)	(0.097)	(0.078)
Age head	0.003	0.001	-0.002	-0.007
	(0.009)	(0.007)	(0.009)	(0.007)
Male head	-0.220	-0.137	-0.753	-0.514
	(0.599)	(0.468)	(0.484)	(0.390)
No. of dependent	0.038	0.002	-0.118	-0.116
	(0.131)	(0.105)	(0.131)	(0.104)
Having TV	0.184	0.122	0.416*	0.344*
	(0.237)	(0.200)	(0.242)	(0.201)
Having motorbike	0.157	0.187	0.067	-0.024
	(0.315)	(0.245)	(0.312)	(0.246)
Having smartphone	0.516*	0.430*	0.768***	0.502**
	(0.288)	(0.233)	(0.281)	(0.231)
Distance to market	0.122	0.107	0.146*	0.117*
	(0.091)	(0.072)	(0.085)	(0.068)
Land size	0.404*	0.349**	0.458**	0.387**
	(0.222)	(0.163)	(0.217)	(0.160)
Asset value per capita (ln)	0.218	0.152	0.288*	0.246*
	(0.165)	(0.135)	(0.157)	(0.130)
Flood	0.105	0.316	0.187	0.322
	(0.558)	(0.332)	(0.527)	(0.369)
Drought	0.070	-0.039	0.023	-0.017
	(0.273)	(0.220)	(0.348)	(0.265)
Khulna district	0.087	0.072	-0.387	-0.318
	(0.332)	(0.255)	(0.319)	(0.232)
Satkhira district	0.536	0.469*	-0.439	-0.413
	(0.354)	(0.275)	(0.355)	(0.280)
Constant	6.758***	4.862***	6.293***	4.514***
	(1.495)	(1.223)	(1.481)	(1.209)
Wald chi^2	41.60	42.62	70.46	68.05
p-value	0.00	0.00	0.00	0.00
Observations	283	283	283	283

*Notes: *** p < 0.01, **p < 0.05, * p < 0.1; Robust standard errors in parentheses.*

Table B12. Association between rice-aquaculture adoption and diet diversity among households with older heads

	Normal season			Lean season
	(1)	(2)	(3)	(4)
	HDDS12	HDDS9	HDDS12	HDDS9
Rice-aquaculture	0.239	-0.231	-1.864	-1.115**
	(0.654)	(0.517)	(1.630)	(0.534)
Household size	-0.013	0.001	-0.008	-0.002
	(0.095)	(0.079)	(0.114)	(0.086)
Male head	0.260	0.265	0.159	0.204
	(0.386)	(0.317)	(0.478)	(0.388)
Education head	0.183*	0.148*	0.005	0.060
	(0.099)	(0.079)	(0.141)	(0.090)
No. of dependent	0.154	0.123	0.076	0.051
	(0.111)	(0.094)	(0.131)	(0.098)
Having TV	0.217	0.239	0.486**	0.400**
	(0.200)	(0.165)	(0.248)	(0.186)
Having motorbike	0.258	0.205	0.159	0.005
	(0.264)	(0.219)	(0.330)	(0.257)
Having smart Phone	0.260	0.237	0.492**	0.311*
	(0.206)	(0.169)	(0.233)	(0.179)
Distance to market	-0.035	0.003	-0.068	-0.024
	(0.072)	(0.056)	(0.082)	(0.060)
Land size	0.347**	0.299**	0.489***	0.453***
	(0.140)	(0.120)	(0.180)	(0.135)
Asset value per capita (ln)	0.115	0.093	0.014	0.020
	(0.116)	(0.099)	(0.140)	(0.111)
Flood	-0.733	-0.554	-0.088	0.418
	(0.573)	(0.441)	(0.800)	(0.460)
Drought	-0.367	-0.407	-0.354	-0.301
	(0.320)	(0.252)	(0.418)	(0.305)
Khulna district	-0.354	-0.215	-0.149	-0.169
	(0.247)	(0.199)	(0.433)	(0.225)
Satkhira district	0.583**	0.563***	0.177	0.075
	(0.245)	(0.207)	(0.341)	(0.227)
Constant	7.594***	5.160***	8.964***	6.273***
	(1.144)	(0.956)	(1.325)	(1.073)
Wald chi^2	76.10	82.48	34.26	45.10
p-value	0.00	0.00	0.00	0.00
Observations	360	360	360	360

*Notes: *** p < 0.01, **p < 0.05, * p < 0.1; Robust standard errors in parentheses.*

Table B13. Associations between rice-aquaculture adoption and diet diversity among households with younger heads

	Normal season		Lean season	
	(1)	(2)	(3)	(4)
	HDDS12	HDDS9	HDDS12	HDDS9
Rice-aquaculture	-0.724	-0.690	-1.253*	-0.936*
	(0.614)	(0.499)	(0.726)	(0.561)
Household size	0.116	0.119**	0.156*	0.152**
	(0.074)	(0.060)	(0.080)	(0.065)
Male head	-0.069	0.319	-0.220	-0.114
	(0.412)	(0.387)	(0.638)	(0.422)
Education head	0.052	0.086	-0.114	-0.064
	(0.113)	(0.094)	(0.120)	(0.099)
No. of dependent	0.038	-0.022	-0.050	-0.046
	(0.115)	(0.098)	(0.135)	(0.109)
Having TV	0.135	0.065	0.434*	0.245
	(0.207)	(0.181)	(0.235)	(0.197)
Having motorbike	-0.178	-0.161	0.135	0.000
	(0.341)	(0.288)	(0.378)	(0.302)
Having smart Phone	0.123	0.238	0.174	0.194
	(0.233)	(0.194)	(0.265)	(0.220)
Distance to market	0.190***	0.153**	0.238***	0.178***
	(0.072)	(0.062)	(0.076)	(0.062)
Land size	0.281	0.291*	0.130	0.069
	(0.207)	(0.168)	(0.260)	(0.206)
Asset value per capita (ln)	0.345**	0.228**	0.342**	0.285**
	(0.136)	(0.113)	(0.144)	(0.120)
Flood	0.270	0.437	-0.274	-0.047
	(0.418)	(0.294)	(0.474)	(0.415)
Drought	0.087	-0.016	0.335	0.216
	(0.254)	(0.224)	(0.303)	(0.234)
Khulna district	-0.259	-0.146	-0.618**	-0.354*
	(0.254)	(0.215)	(0.270)	(0.215)
Satkhira district	-0.027	0.100	-0.436	-0.291
	(0.265)	(0.220)	(0.286)	(0.238)
Constant	5.583***	3.541***	5.834***	3.684***
	(1.157)	(0.986)	(1.305)	(1.035)
Wald chi^2	43.70	59.20	64.35	63.43
p-value	0.00	0.00	0.00	0.00
Observations	360	360	360	360

*Notes: *** $p < 0.01$, **$p < 0.05$, * $p < 0.1$; Robust standard errors in parentheses.*

Table B14. Associations between rice-aquaculture adoption and diet diversity among households with small farm areas

	Normal season			Lean season
	(1)	(2)	(3)	(4)
	HDDS12	HDDS9	HDDS12	HDDS9
Rice-aquaculture	-0.441	-0.504	-1.544**	-1.188**
	(0.482)	(0.396)	(0.628)	(0.477)
Household size	0.148*	0.124*	0.129	0.108
	(0.079)	(0.067)	(0.087)	(0.073)
Age head	-0.009	-0.008	-0.014	-0.012
	(0.008)	(0.007)	(0.009)	(0.007)
Male head	0.000	0.157	0.409	0.383
	(0.392)	(0.329)	(0.480)	(0.378)
Education head	0.027	0.059	-0.189	-0.127
	(0.106)	(0.088)	(0.123)	(0.099)
No. of dependent	0.105	0.072	-0.017	-0.006
	(0.100)	(0.087)	(0.113)	(0.094)
Having TV	0.259	0.232	0.442**	0.325*
	(0.173)	(0.150)	(0.205)	(0.170)
Having motorbike	0.012	0.028	-0.057	-0.121
	(0.284)	(0.237)	(0.324)	(0.261)
Having smart Phone	-0.000	0.120	0.219	0.216
	(0.174)	(0.148)	(0.203)	(0.166)
Distance to market	0.148**	0.131**	0.132*	0.122**
	(0.066)	(0.054)	(0.072)	(0.057)
Asset value per capita (ln)	0.259**	0.188**	0.218*	0.192*
	(0.109)	(0.093)	(0.122)	(0.104)
Flood	-0.465	-0.286	0.141	0.286
	(0.460)	(0.336)	(0.567)	(0.452)
Drought	0.072	-0.031	0.302	0.254
	(0.268)	(0.238)	(0.324)	(0.260)
Khulna district	-0.414*	-0.268	-0.598**	-0.292
	(0.221)	(0.183)	(0.263)	(0.206)
Satkhira district	0.149	0.248	-0.154	-0.033
	(0.220)	(0.185)	(0.259)	(0.209)
Constant	6.612***	4.426***	7.351***	4.825***
	(1.096)	(0.936)	(1.238)	(1.030)
Wald chi^2	47.44	53.90	49.33	45.47
p-value	0.00	0.00	0.00	0.00
Observations	475	475	475	475

*Notes: *** p < 0.01, **p < 0.05, * p < 0.1; Robust standard errors in parentheses.*

Table B15. Associations between rice-aquaculture adoption and diet diversity among households with large farm areas

	Normal season			Lean season
	(1)	(2)	(3)	(4)
	HDDS12	HDDS9	HDDS12	HDDS9
Rice-aquaculture	-0.530	-0.476	-0.989	-0.735
	(0.796)	(0.559)	(0.862)	(0.483)
Household size	-0.030	0.017	0.076	0.096
	(0.078)	(0.060)	(0.086)	(0.069)
Age head	0.007	0.002	-0.003	-0.008
	(0.009)	(0.007)	(0.010)	(0.008)
Male head	0.458	0.430	-0.819	-0.579
	(0.442)	(0.304)	(0.713)	(0.604)
Education head	0.232**	0.182**	0.168	0.142
	(0.105)	(0.084)	(0.123)	(0.096)
No. of dependent	0.127	0.053	0.038	0.021
	(0.118)	(0.096)	(0.136)	(0.105)
Having TV	-0.122	-0.101	0.128	0.067
	(0.259)	(0.220)	(0.278)	(0.222)
Having motorbike	0.243	0.105	0.590	0.325
	(0.338)	(0.275)	(0.397)	(0.303)
Having smart Phone	0.742**	0.535**	0.803***	0.474**
	(0.288)	(0.234)	(0.311)	(0.241)
Distance to market	-0.027	0.010	0.033	0.030
	(0.079)	(0.067)	(0.086)	(0.070)
Asset value per capita (ln)	0.237	0.188	0.161	0.145
	(0.148)	(0.121)	(0.171)	(0.127)
Flood	0.395	0.569**	-0.297	0.110
	(0.422)	(0.256)	(0.534)	(0.413)
Drought	-0.385	-0.416*	-0.086	-0.200
	(0.290)	(0.225)	(0.347)	(0.256)
Khulna district	-0.064	-0.056	-0.223	-0.223
	(0.279)	(0.232)	(0.304)	(0.225)
Satkhira district	0.336	0.336	-0.365	-0.349
	(0.312)	(0.259)	(0.367)	(0.291)
Constant	6.127***	4.231***	8.064***	6.018***
	(1.354)	(1.097)	(1.630)	(1.272)
Wald chi^2	58.15	73.71	36.89	33.28
p-value	0.00	0.00	0.00	0.00
Observations	245	245	245	245

*Notes: *** p < 0.01, **p < 0.05, * p < 0.1; Robust standard errors in parentheses.*

Table B16. Heterogeneity analysis with adoption-education interaction term

	Normal season		Lean season	
	HDDS12	HDDS9	HDDS12	HDDS9
Endogenous treatment effect model				
Rice-aquaculture x head education	-0.216	-0.146	-0.206	-0.147
	(0.159)	(0.135)	(0.171)	(0.145)
Rice-aquaculture	-0.297	-0.445	-1.263**	-0.941**
	(0.457)	(0.369)	(0.579)	(0.377)
OLS model				
Rice-aquaculture x head education	-0.206	-0.122	-0.181	-0.141
	(0.155)	(0.133)	(0.167)	(0.142)
Rice-aquaculture	-0.008	-0.129	-0.223	-0.309
	(0.245)	(0.212)	(0.270)	(0.228)
Observations	720	720	720	720

*Notes: *** p<0.01, ** p<0.05, * p<0.1; Robust standard errors in parentheses.*

Table B17. Heterogeneity analysis with adoption-age interaction term

	Normal season		Lean season	
	HDDS12	HDDS9	HDDS12	HDDS9
Endogenous treatment effect model				
Rice-aquaculture x head age	-0.007	-0.006	0.001	0.002
	(0.014)	(0.011)	(0.015)	(0.013)
Rice-aquaculture	-0.054	-0.226	-1.466	-1.148
	(0.795)	(0.667)	(0.948)	(0.761)
OLS model				
Rice-aquaculture x head age	-0.008	-0.007	0.001	0.001
	(0.014)	(0.012)	(0.016)	(0.014)
Rice-aquaculture	0.158	0.078	-0.462	-0.523
	(0.679)	(0.569)	(0.793)	(0.692)
Observations	720	720	720	720

*Notes: *** p<0.01, ** p<0.05, * p<0.1; Robust standard errors in parentheses.*

Table B18. Heterogeneity analysis with adoption-land size interaction term

		Normal season		Lean season
	HDDS12	HDDS9	leanHDDS12	leanHDDS9
Endogenous treatment effect model				
Rice-aquaculture x land size	0.013	-0.046	0.121	0.029
	(0.218)	(0.180)	(0.291)	(0.235)
Rice-aquaculture	-0.437	-0.526	-1.430**	-1.058***
	(0.438)	(0.359)	(0.579)	(0.373)
OLS model				
Rice-aquaculture x land size	0.020	-0.039	0.148	0.040
	(0.220)	(0.181)	(0.296)	(0.237)
Rice-aquaculture	-0.240	-0.247	-0.477**	-0.477**
	(0.203)	(0.174)	(0.232)	(0.195)
Observations	720	720	720	720

*Notes: *** p<0.01, ** p<0.05, * p<0.1; Robust standard errors in parenthese.*

Table B19. Time allocation indicators by rice-aquaculture adoption

	(1) Full sample	(2) Non-adopters	(3) Rice-aquaculture adopters	(3)-(2) Difference
Panel A: Normal season				
Farm activities	368.645	350.409	434.045	83.636***
	(212.150)	(194.918)	255.072	
Non-farm activities	90.00	87.469	99.076	11.608
	(189.157)	(186.303)	199.408	
Commuting	111.167	105.346	132.038	26.692***
	(79.357)	(79.066)	77.095	
Cooking and domestic activities	409.812	422.185	365.446	-56.739***
	(192.016)	(198.871)	157.863	
Forest extraction activities	4.583	4.689	4.204	-0.485
	(49.861)	(49.786)	50.292	
Other activities	1161.75	1164.805	1150.796	-14.008
	(399.460)	(410.306)	358.884	
Panel B: Lean season				
Farm activities	234.291	211.838	314.809	102.971***
	(206.078)	(185.342)	(252.265)	
Non-farm activities	111.708	112.380	109.299	-3.081
	(210.844)	(214.044)	(199.591)	
Commuting	101.104	91.412	135.860	44.448***
	(79.164)	(74.888)	(84.414)	
Cooking and domestic activities	405.604	422.078	346.529	-75.549***
	(192.214)	(199.182)	(151.218)	
Forest extraction activities	16.770	19.769	6.019	-13.750*
	(92.101)	(100.061)	(53.651)	
Other activities	1286.5	1289.414	1276.051	-13.363
	(436.01)	(450.119)	(382.265)	

*Notes: *** $p < 0.01$, **$p < 0.05$, * $p < 0.1$; Standard deviations in parentheses.*

Table B20. Associations between rice-aquaculture adoption and time use during the normal season

	(1)	(2)	(3)	(4)	(5)	(6)
	Farm activities	Non-farm activities	Commuting	Cooking & domestic activities	Forest extraction activities	Other activities
Rice-aquaculture	27.710	-2.354	119.220***	-271.660***	-0.580	203.478***
	(51.914)	(42.958)	(17.275)	(41.981)	(7.359)	(72.157)
Household size	6.334	7.077	8.271***	7.720	0.805	36.157**
	(7.428)	(6.568)	(2.890)	(7.751)	(1.207)	(17.951)
Age head	-3.090***	0.779	-0.201	-3.295***	-0.085	-4.256***
	(0.681)	(0.737)	(0.279)	(0.718)	(0.133)	(1.586)
Male head	46.386	-6.191	3.298	193.731***	6.349*	232.737**
	(48.698)	(28.084)	(17.328)	(38.181)	(3.331)	(113.641)
Education head	-8.531***	5.162**	1.160	-7.512***	-0.837	2.235
	(2.135)	(2.045)	(0.878)	(2.195)	(0.611)	(4.248)
No. of dependent	-28.858***	7.977	-8.382**	-18.296*	-1.496	-33.201*
	(9.107)	(8.826)	(4.063)	(9.617)	(1.991)	(20.029)
Having TV	28.252*	10.613	-14.857**	21.448	-3.560	-63.700*
	(17.032)	(16.052)	(7.374)	(17.215)	(4.129)	(34.039)
Having motorbike	3.313	32.321	-11.606	-5.652	-8.452**	56.769
	(24.796)	(25.595)	(10.809)	(25.519)	(3.482)	(44.732)
Having smartphone	1.068	4.429	7.332	15.335	1.557	18.719
	(17.604)	(16.087)	(7.318)	(18.249)	(4.390)	(35.139)
Distance to market	3.000	-2.185	-5.162**	-0.191	1.973	-8.789
	(5.768)	(5.116)	(2.390)	(5.859)	(1.959)	(12.044)
Land size	30.430*	-16.846	-8.193	12.916	-4.492	-44.875
	(17.594)	(13.957)	(7.943)	(18.272)	(3.279)	(35.040)
Asset value per capita (ln)	-13.460	13.040	8.898**	-7.947	5.209**	-15.708
	(10.929)	(8.857)	(4.238)	(10.253)	(2.306)	(19.288)
Flood	20.671	56.371	-5.117	-75.124	-2.776	-5.690
	(50.226)	(48.267)	(17.495)	(45.976)	(2.176)	(87.911)
Drought	2.247	3.786	2.126	-0.708	-6.446**	37.031
	(26.271)	(27.418)	(11.803)	(27.681)	(3.018)	(52.981)
Khulna district	-18.636	-63.874***	7.086	64.284***	-7.137	56.824
	(21.461)	(20.945)	(8.402)	(21.945)	(7.569)	(43.627)
Satkhira district	90.235***	-48.517**	-2.348	53.734**	-14.405*	-66.171
	(22.419)	(21.020)	(8.868)	(21.733)	(7.435)	(44.887)
Constant	593.189***	-86.988	-4.244	485.217***	-32.547**	1,154.779***
	(106.239)	(87.490)	(42.440)	(95.979)	(15.282)	(215.954)
Wald chi^2	94.79	44.29	98.95	91.28	7.64	46.15
p-value	0.00	0.00	0.00	0.00	0.95	0.00
Observations	720	720	720	720	720	720

*Notes: *** p < 0.01, **p < 0.05, * p < 0.1, Robust standard errors in parentheses.*

Table B21. Associations between rice-aquaculture adoption and time use during the lean season

	(1) Farm activities	(2) Non-farm activities	(3) Commuting	(4) Cooking & domestic activities	(5) Forest extraction activities	(6) Other activities
Rice-aquaculture	126.650***	-40.001	145.374***	-314.415***	-50.558***	182.424**
	(41.074)	(47.529)	(15.100)	(29.161)	(14.023)	(83.362)
Household size	-2.661	14.959**	9.588***	12.438	0.129	31.703*
	(6.664)	(7.343)	(2.956)	(7.971)	(2.580)	(19.241)
Age head	-0.410	0.274	-0.147	-2.443***	-0.926**	-7.393***
	(0.619)	(0.760)	(0.285)	(0.710)	(0.367)	(1.682)
Male head	-10.183	-25.887	10.891	194.835***	26.704***	296.358***
	(43.242)	(41.351)	(15.888)	(37.639)	(8.366)	(108.270)
Education head	-1.492	2.666	1.077	-6.904***	-2.071**	-2.606
	(1.976)	(2.304)	(0.886)	(2.097)	(0.998)	(4.495)
No. of dependent	-13.878	1.068	-9.485**	-26.838***	1.145	-32.855
	(8.772)	(9.634)	(4.093)	(9.876)	(4.265)	(21.860)
Having TV	-10.904	22.546	-20.577***	17.698	-8.673	-27.814
	(17.046)	(18.035)	(7.322)	(17.926)	(6.445)	(37.254)
Having motorbike	1.916	27.980	-2.148	-4.180	21.295	45.231
	(24.374)	(27.780)	(11.187)	(27.010)	(13.771)	(48.412)
Having smartphone	-5.636	-4.814	8.649	15.162	1.443	30.141
	(17.928)	(18.151)	(7.413)	(18.353)	(8.014)	(37.719)
Distance to market	6.756	-2.764	-5.572**	-1.635	1.775	-11.772
	(5.469)	(5.695)	(2.362)	(5.931)	(2.622)	(13.024)
Land size	28.302	-17.839	-8.393	19.272	-10.769*	-48.274
	(20.338)	(15.373)	(7.581)	(18.676)	(5.589)	(35.911)
Asset value per capita (ln)	-12.191	10.341	3.097	-2.938	6.755*	-11.873
	(10.591)	(10.088)	(4.302)	(10.193)	(4.001)	(20.496)
Flood	-45.371	157.951***	-9.813	-60.496	-13.952**	-72.174
	(43.497)	(55.724)	(17.262)	(51.619)	(6.832)	(94.735)
Drought	1.186	29.163	12.909	-11.581	-15.541	16.880
	(23.783)	(32.346)	(11.656)	(27.048)	(9.758)	(58.594)
Khulna district	-11.627	-50.324**	-0.884	82.840***	-17.234*	22.586
	(19.524)	(22.439)	(8.105)	(21.499)	(10.252)	(47.983)
Satkhira district	86.305***	-41.860*	-5.181	62.329***	-34.566***	-79.963
	(21.295)	(23.358)	(8.518)	(22.329)	(10.951)	(49.391)
Constant	341.665***	-11.384	21.441	381.830***	17.741	1,401.786***
	(105.374)	(99.176)	(41.339)	(97.410)	(44.969)	(222.119)
Wald chi^2	55.17	42.80	170.24	161.72	24.11	50.59
p-value	0.00	0.00	0.00	0.00	0.08	0.00
Observations	720	720	720	720	720	720

*Notes: *** p < 0.01, **p < 0.05, * p < 0.1, Robust standard errors in parentheses.*

Table B22. Associations between rice-aquaculture adoption and households' per capita monthly income

	(1) Total income	(2) Farm income	(3) Off-farm income	(4) Forest extracting income	(5) Remittance, stipends and transfers
Rice-aquaculture	0.549	0.541	2.245**	-0.632***	-0.067*
	(1.495)	(0.376)	(0.949)	(0.146)	(0.035)
Household size	-0.235**	-0.361***	0.164	-0.052	-0.008
	(0.114)	(0.064)	(0.100)	(0.042)	(0.007)
Age head	0.014	-0.002	0.019**	-0.001	0.000
	(0.010)	(0.005)	(0.008)	(0.007)	(0.001)
Male head	0.353	0.200	-0.236	0.341**	-0.177*
	(0.523)	(0.379)	(0.476)	(0.145)	(0.098)
Education head	-0.038	0.003	0.029	-0.048***	-0.000
	(0.038)	(0.019)	(0.027)	(0.018)	(0.003)
No. of dependent	-0.449***	-0.075	-0.356***	-0.015	-0.004
	(0.109)	(0.071)	(0.102)	(0.052)	(0.009)
Having TV	0.313	0.267*	0.238	-0.244**	-0.017
	(0.202)	(0.140)	(0.186)	(0.105)	(0.017)
Having motorbike	0.306	-0.208	0.473	-0.072	0.016
	(0.331)	(0.221)	(0.292)	(0.148)	(0.029)
Having smartphone	-0.091	-0.135	0.339*	-0.305**	0.023
	(0.205)	(0.144)	(0.174)	(0.135)	(0.016)
Distance to market	0.036	-0.052	0.071	0.017	0.002
	(0.070)	(0.046)	(0.066)	(0.038)	(0.006)
Land size	0.794***	1.048***	-0.378*	0.008	-0.015
	(0.307)	(0.201)	(0.203)	(0.124)	(0.020)
Asset value per capita (ln)	0.516***	0.133	0.077	0.304***	0.013
	(0.134)	(0.102)	(0.098)	(0.076)	(0.011)
Flood	0.854	0.337	0.997**	-0.289**	-0.042*
	(0.656)	(0.401)	(0.453)	(0.116)	(0.022)
Drought	-0.811**	-0.401**	-0.142	-0.166	-0.038*
	(0.319)	(0.205)	(0.277)	(0.142)	(0.021)
Khulna district	-0.833**	-0.184	-0.412	-0.514***	-0.020
	(0.408)	(0.181)	(0.269)	(0.192)	(0.027)
Satkhira district	-0.554*	0.114	-0.090	-0.756***	-0.051*
	(0.336)	(0.193)	(0.237)	(0.203)	(0.029)
Constant	0.568	2.383***	-0.870	-1.146**	0.208**
	(1.264)	(0.923)	(1.128)	(0.574)	(0.094)
Wald chi^2	117.32	104.25	62.13	48.02	22.00
p-value	0.00	0.00	0.00	0.00	0.14
Observations	720	720	720	720	720

*Notes: *** $p < 0.01$, **$p < 0.05$, * $p < 0.1$, Robust standard errors in parentheses.*

Table B23. Associations between rice-aquaculture adoption and household's per capita monthly consumption

	(1) Total consumption	(2) Food	(3) Education	(4) Health	(5) Transport and communicatio n	(6) Water and electricity	(7) Other non-food consumption
Rice-aquaculture	-0.431	-0.236*	-0.048	-0.256*	0.097**	0.049***	0.728***
	(0.376)	(0.131)	(0.101)	(0.138)	(0.046)	(0.010)	(0.103)
Household size	-0.277***	-0.169***	0.024	-0.063	-0.014	-0.007***	-0.054***
	(0.071)	(0.041)	(0.017)	(0.040)	(0.009)	(0.003)	(0.018)
Age head	0.012**	0.006**	-0.002	0.006*	-0.001	0.000	0.002
	(0.006)	(0.003)	(0.001)	(0.003)	(0.001)	(0.000)	(0.003)
Male head	-0.131	0.139	-0.124	-0.207	-0.007	-0.014	0.060
	(0.408)	(0.154)	(0.157)	(0.268)	(0.047)	(0.017)	(0.066)
Education head	-0.002	0.004	0.033	-0.020	0.006	-0.002	0.022
	(0.072)	(0.034)	(0.027)	(0.033)	(0.012)	(0.005)	(0.022)
No. of dependent	-0.210***	-0.058*	-0.085***	-0.011	-0.041***	-0.005	-0.007
	(0.076)	(0.032)	(0.024)	(0.043)	(0.013)	(0.004)	(0.025)
Having TV	-0.108	0.064	-0.007	-0.172**	0.030	0.003	-0.053
	(0.146)	(0.081)	(0.044)	(0.085)	(0.021)	(0.009)	(0.047)
Having motorbike	0.477*	0.118	-0.110	0.242	0.275***	0.010	-0.109
	(0.248)	(0.093)	(0.069)	(0.181)	(0.042)	(0.020)	(0.074)
Having smart Phone	0.110	-0.091	0.022	0.064	0.118***	-0.007	0.000
	(0.153)	(0.074)	(0.044)	(0.087)	(0.020)	(0.007)	(0.047)
Distance to market	-0.107**	-0.061**	-0.008	-0.026	-0.008	-0.000	-0.004
	(0.046)	(0.024)	(0.017)	(0.022)	(0.007)	(0.002)	(0.016)
Land size	0.257*	0.185**	0.062	-0.082	0.044	0.018*	-0.023
	(0.146)	(0.074)	(0.039)	(0.075)	(0.029)	(0.009)	(0.063)
Asset value per capita (ln)	0.516***	0.132***	0.131***	0.121**	0.009	0.025***	0.098***
	(0.095)	(0.045)	(0.026)	(0.057)	(0.012)	(0.004)	(0.035)
Flood	0.342	-0.003	0.161	0.240	-0.028	0.024	0.042
	(0.422)	(0.143)	(0.219)	(0.162)	(0.045)	(0.026)	(0.076)
Drought	-0.186	-0.055	-0.057	-0.057	-0.027	-0.019**	0.078
	(0.201)	(0.095)	(0.050)	(0.118)	(0.031)	(0.010)	(0.072)
Khulna district	-0.716***	-0.240***	-0.048	-0.136	-0.108***	-0.034***	-0.281***
	(0.187)	(0.078)	(0.045)	(0.126)	(0.029)	(0.010)	(0.077)
Satkhira district	-0.479**	-0.144*	0.020	-0.098	-0.105***	-0.010	-0.227***
Constant	(0.202)	(0.083)	(0.052)	(0.141)	(0.026)	(0.012)	(0.085)
	0.699	1.201***	-0.488**	-0.106	0.330***	-0.062	-0.281
	(0.846)	(0.361)	(0.223)	(0.519)	(0.119)	(0.043)	(0.347)
Wald chi^2	182.93	129.86	70.15	42.14	194.28	108.85	123.00
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Observations	720	720	720	720	720	720	720

*Notes: *** $p < 0.01$, **$p < 0.05$, * $p < 0.1$, Robust standard errors in parentheses.*

Table B24. Farm level production diversity by rice-aquaculture adoption

	(1) Full sample	(2) Non-adopters	(3) Rice-aquaculture adopters	(3)-(2) Difference
PDS12	3.897	3.831	4.134	0.302*
	(1.849)	(1.857)	(1.808)	
PDS9	3.873	3.805	4.121	0.316**
	(1.825)	(1.836)	(1.766)	
Number of crops species	2.313	2.378	2.083	-0.296**
	(1.476)	(1.496)	(1.382)	
Number of livestock species	1.991	2.020	1.892	-0.128
	(1.282)	(1.226)	(1.466)	
Number of aquatic species	0.712	0.512	1.433	0.922***
	(0. 756)	(0.671)	(0.591)	

*Notes: *** p < 0.01, **p < 0.05, * p < 0.1; Standard deviations in parentheses.*

Table B25. Associations between rice-aquaculture adoption and farm production diversity

	(1) PDS12	(2) PDS9	(3) No. of crop species	(4) No. of livestock species	(5) No. of aquatic species
Rice-aquaculture	-1.337***	-1.278***	-1.324***	-0.655*	1.944***
	(0.402)	(0.384)	(0.254)	(0.366)	(0.137)
Household size	-0.004	-0.001	0.016	0.095**	-0.019
	(0.065)	(0.064)	(0.049)	(0.042)	(0.027)
Age head	0.000	0.000	0.003	-0.001	0.001
	(0.006)	(0.006)	(0.005)	(0.004)	(0.002)
Male head	0.036	0.044	0.134	-0.392	0.250**
	(0.350)	(0.348)	(0.251)	(0.239)	(0.110)
Education head	-0.028	-0.027	-0.008	-0.021	0.017**
	(0.020)	(0.020)	(0.016)	(0.013)	(0.008)
No. of dependent	0.073	0.065	0.084	-0.031	0.005
	(0.087)	(0.086)	(0.070)	(0.058)	(0.035)
Having TV	0.134	0.149	0.160	-0.044	-0.123**
	(0.168)	(0.164)	(0.134)	(0.105)	(0.061)
Having motorbike	0.097	0.083	0.084	-0.077	-0.059
	(0.260)	(0.256)	(0.202)	(0.166)	(0.089)
Having smartphone	0.233	0.245	-0.106	0.214**	0.072
	(0.160)	(0.157)	(0.136)	(0.105)	(0.066)
Distance to market	0.088*	0.088*	0.081*	0.070**	-0.033*
	(0.051)	(0.051)	(0.047)	(0.033)	(0.020)
Land size	0.480**	0.472**	0.149	0.051	0.117*
	(0.201)	(0.198)	(0.157)	(0.110)	(0.070)
Asset value per capita (ln)	0.233**	0.231**	0.229***	0.195***	-0.036
	(0.095)	(0.094)	(0.074)	(0.063)	(0.038)
Flood	-0.811**	-0.765**	-0.217	-0.136	0.067
	(0.364)	(0.363)	(0.280)	(0.234)	(0.144)
Drought	0.203	0.156	0.293	-0.056	0.018
	(0.328)	(0.312)	(0.252)	(0.171)	(0.082)
Khulna district	-0.600***	-0.592***	0.139	-0.306**	-0.407***
	(0.206)	(0.204)	(0.145)	(0.135)	(0.075)
Satkhira district	-0.043	-0.078	0.137	0.370***	-0.260***
	(0.218)	(0.214)	(0.168)	(0.138)	(0.076)
Constant	1.833**	1.809**	-0.209	0.305	0.569
	(0.908)	(0.898)	(0.714)	(0.586)	(0.353)
Wald chi^2	93.24	93.29	79.47	118.51	220.01
p-value	0.00	0.00	0.00	0.00	0.00
Observations	720	720	720	720	720

*Notes: *** $p < 0.01$, **$p < 0.05$, * $p < 0.1$, Robust standard errors in parentheses, PDS12: Production diversity scores with 12 food groups; PDS9: Production diversity scores with 9 food groups.*

Table B26. Robustness checks for the associations between rice-aquaculture adoption and HDDS

	Normal season		Lean season	
	HDDS12	HDDS9	HDDS12	HDDS9
OLS	-0.231	-0.261*	-0.420**	-0.459***
	(0.166)	(0.142)	(0.188)	(0.158)
PSM	-0.315*	-0.327**	-0.501**	-0.476***
	(0.192)	(0.164)	(0.216)	(0.179)
CFA	-0.590	-0.769	-1.870***	-1.626***
	(0.599)	(0.505)	(0.706)	(0.587)
Heteroskedasticity-based instruments	-0.408	-0.607	-1.664***	-1.400***
	(0.437)	(0.371)	(0.543)	(0.434)

*Notes: *** p < 0.01, **p < 0.05, * p < 0.1, Robust standard errors in parentheses. HDDS12: Household dietary diversity score with 12 food groups considered. HDDS9: Household dietary diversity score with 9 food groups considered.*

Table B27. Robustness checks for the associations between rice-aquaculture adoption and individual dietary diversity

	MDDS	WDDS	CDDS
OLS			
	-0.163	-0.210*	0.019
	(0.115)	(0.117)	(0.148)
PSM			
	-0.283	-0.321	0.042
	(0.139)	(0.138)	(0.19)
CFA	-1.241***	-1.184***	0.090
	(0.415)	(0.390)	(0.540)
Heteroskedasticity-based instruments			
	-0.773***	-1.071***	-0.212
	(0.257)	(0.294)	(0.318)

*Notes: *** p < 0.01, **p < 0.05, * p < 0.1, Robust standard errors in parentheses, MDDS: Men's dietary diversity score; WDDS: Women's dietary diversity score; CDDS: Child dietary diversity score.*

Table B28. Robustness check for the associations between rice-aquaculture adoption and household labor allocation

	(1) Farm activities	(2) Non-farm activities	(3) Commuting	(4) Cooking & domestic activities	(5) Forest extraction activities	(6) Other activities
Panel A: Lean season						
OLS	100.912***	8.797	40.385***	-87.332***	-12.674	-33.595
	(18.374)	(19.168)	(7.012)	(17.122)	(8.391)	(39.246)
	83.827***	8.673	22.923**	-67.712***	0.423	-25.192
PSM	(23.733)	(19.994)	(8.051)	(18.11)	(5.121)	(38.415)
CFA	154.546**	-31.756	226.950***	-283.539***	-68.488***	215.614
	(76.335)	(67.057)	(26.887)	(55.144)	(24.298)	(132.402)
Heteroskedasticity-based instruments	111.663**	-38.882	105.640***	-177.176***	-26.411**	120.407
	(49.976)	(49.983)	(17.759)	(39.738)	(11.806)	(88.808)
Panel B: Normal season						
OLS	78.051***	23.885	21.526***	-66.579***	0.134	-31.673
	(18.497)	(17.197)	(7.156)	(17.149)	(4.614)	(36.140)
PSM	105.5	2.423	42.519	-88.635	-18.077	-34.00
	(23.41)	(21.062)	(8.405)	(17.692)	(8.235)	(41.52)
CFA	0.919	6.189	153.021***	-171.245***	-6.020	285.496**
	(75.777)	(61.709)	(26.170)	(56.860)	(11.855)	(119.354)
Heteroskedasticity-based instruments	88.417*	-9.731	65.236***	-107.022***	-4.303	81.586
	(50.534)	(46.394)	(16.659)	(39.171)	(10.882)	(80.719)

*Notes: * p < 0.01, **p < 0.05, * p < 0.1, Robust standard errors in parentheses.*

Table B29. Robustness check for the association between rice-aquaculture adoption and household income (thousands BDT)

	(1) Total income	(2) Farm income	(3) Off-farm income	(4) Forest extracting income	(5) Remittance, stipend and public transfer
OLS	0.424**	0.602***	0.067	-0.246***	-0.021
	(0.212)	(0.170)	(0.183)	(0.087)	(0.018)
PSM	0.458*	0.549***	0.125	-0.216**	-0.236
	(0.272)	(0.206)	(0.21)	(0.104)	722
CFA	0.521	0.507	0.976	-0.962***	-0.063
	(0.890)	(0.599)	(0.726)	(0.357)	(0.070)
Heteroskedasticity-based instruments	0.030	0.359	0.119	-0.448***	-0.025
	(0.362)	(0.249)	(0.329)	(0.135)	(0.027)

*Notes: * p < 0.01, **p < 0.05, * p < 0.1, Robust standard errors in parentheses.*

Table B30. Robustness check for the association between rice-aquaculture and household consumption (thousands BDT)

	(1) Total consump-tion	(2) Food	(3) Education	(4) Health care	(5) Transport and communication	(6) Water and electricit y	(7) Other non-food consumption
OLS	-0.020	-0.094	0.082	-0.057	0.105***	0.051***	-0.066*
	(0.143)	(0.062)	(0.052)	(0.070)	(0.028)	(0.012)	(0.029)
PSM	-0.06	-0.129	0.055	-0.01	0.076**	0.041***	-0.092**
	(0.173)	(0.082)	(0.058)	(0.068)	(0.035)	(0.012)	(0.044)
CFA	-0.273	-0.207	-0.145	-0.339	0.082	0.041	0.295*
	(0.557)	(0.228)	(0.187)	(0.315)	(0.101)	(0.041)	(0.167)
Heteroskeda sticity-based instruments	-0.591*	-0.437***	-0.084	-0.127	-0.008	0.031*	0.039
	(0.315)	(0.148)	(0.124)	(0.153)	(0.073)	(0.018)	(0.076)

*Notes: * p < 0.01, **p < 0.05, * p < 0.1, Robust standard errors in parentheses.*

Table B31. Robustness check for the association between rice-aquaculture and farm production diversity

	(1)	(2)	(3)	(4)	(5)
	PDS12	PDS9	No. of crop species	No. of livestock species	No. of aquatic species
OLS	0.383***	0.395***	-0.308**	-0.115	0.952***
	(0.148)	(0.144)	(0.123)	(0.115)	(0.056)
PSM	0.327*	0.342*	-0.031	-0.104	0.968***
	(0.18)	(0.177)	(0.024)	(0.14)	(0.063)
CFA	-1.071**	-1.036**	-1.848***	-0.756*	1.871***
	(0.536)	(0.525)	(0.495)	(0.407)	(0.200)
Heteroskedasticity-based instruments	-0.167	-0.138	-0.928***	-0.523*	1.273***
	(0.350)	(0.347)	(0.323)	(0.269)	(0.133)

*Notes: * p < 0.01, **p < 0.05, * p < 0.1, Robust standard errors in parentheses. PDS12: Production diversity scores with 12 food groups; PDS9: Production diversity scores with 9 food groups.*

Appendix C: Appendix to Chapter 3

The effects of internet use on smallholder farmers' income and dietary quality in Bangladesh

Table C1. Share of internet users in the study sample

	Frequency (number)	Percentage	Cumulative frequency
Internet non-user households	411	57.08	57.08
Internet user households	309	42.92	100
Total	720	100.00	

Table C2. Definition of treatment and control variables

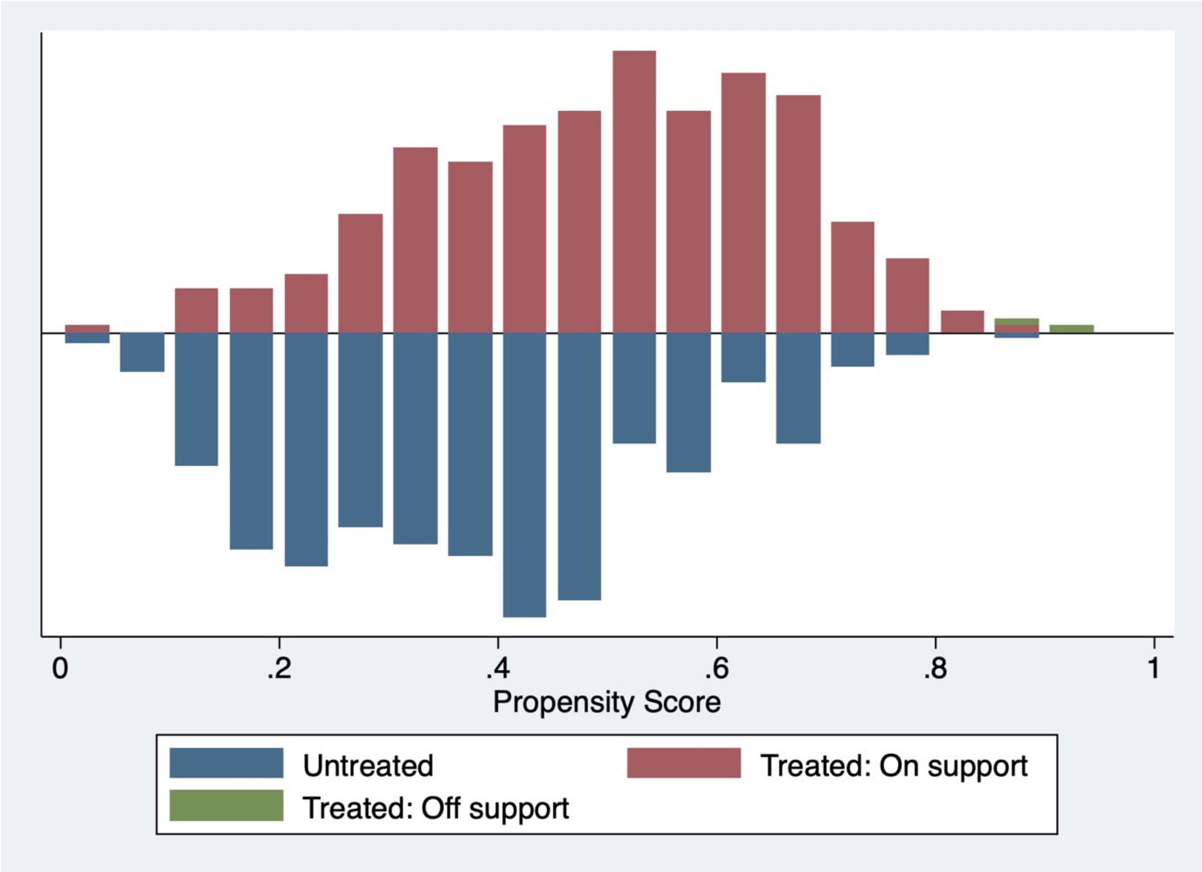
Name	Measurement unit	Definition
Internet use	Dummy (1=yes, 0=otherwise)	At least one household member has used the internet in the past 30 days
Household size	People	Total number of household member
Age head	Years	Age of the household head
Male head	Dummy (1=male, 0=female)	Sex of the household head is male
Married head	Dummy (1=married, 0=otherwise)	Marital status of the household head
Muslim head	Dummy (1=Muslim, 0=otherwise)	Religion of the household head
Education head	Years	Years of schooling of the household head
No. of dependent	People	Number of dependent people in the household
Tenant farmer	Dummy (1=yes, 0=no)	It the household head is tenant farmer=1, 0=otherwise
Asset per capita	BDT	Value of key assets owned by the household in per capita terms (log-transformed)
Weather shock	Dummy (1=yes, 0=no)	If the households experienced flood or drought or both during the last 12 months
Distance	Kilometer	Distance between house to the local market
District	District dummy1 District dummy2	District dummy 1 (1=Bagerhat, 0=otherwise) District dummy 2 (1= Khulna, 0=otherwise)

Table C3. Propensity score estimation (probit regression of internet use)

Variables	Coefficient	Standard error
Household size	0.167***	0.046
Age head	0.001	0.004
Male head	-0.098	0.256
Married head	-0.262	0.379
Ethnic majority head	1.361***	0.260
Education head	0.027**	0.013
Muslim head	-0.362***	0.119
No. of dependents	-0.137**	0.061
Tenant dummy	-0.063	0.105
Asset per capita	0.329***	0.056
Weather shock	-0.029	0.136
Distance to market	0.049	0.039
Bagerhat	0.075	0.134
Khulna	0.138	0.128
Constant	-4.660***	0.773
Observations		720
Log likelihood		-433.58
LR chi2		96.47
Prob. > chi^2		0.000
Pseudo R^2		0.098

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

Figure C1. Propensity score distribution and common support for propensity score estimation by groups



Note: "Treated: on support'' presents the households using the internet that have a suitable match (n=307), while ''Treated: off support'' presents the households using the internet that do not have a suitable match (n=2); "Untreated" presents the households without internet use (n=411).

Table C4. Common support condition for PSM (treated and untreated units)

	Support		
Treatment assignment	Off support	On support	Total
Untreated	0	411	411
Treated	2	307	309
Total	2	718	720

Table C5. Balancing tests

Variable		Mean Treated	Control	Difference	p-value
Household size	Unmatched	4.64	4.42	0.22*	0.07
	Matched	4.61	4.65	-0.04	0.76
Age head	Unmatched	49.97	50.20	-0.23	0.80
	Matched	49.95	50.16	-0.21	0.83
Male head	Unmatched	0.96	0.96	0.00	0.87
	Matched	0.96	0.96	0.00	0.87
Married head	Unmatched	0.98	0.99	-0.01	0.42
	Matched	0.98	0.99	-0.01	0.26
Ethnic majority	Unmatched	0.98	0.92	0.06***	0.00
	Matched	0.98	0.98	0.00	0.87
Education head	Unmatched	5.72	4.54	1.18***	0.00
	Matched	5.70	5.70	0.00	0.99
Muslim head	Unmatched	0.64	0.72	-0.07**	0.03
	Matched	0.64	0.65	-0.01	0.81
No. of dependents	Unmatched	1.37	1.47	-0.11	0.24
	Matched	1.36	1.34	0.01	0.91
Tenant farmer	Unmatched	0.50	0.56	-0.06*	0.09
	Matched	0.50	0.49	0.01	0.75
Asset per capita	Unmatched	9.10	8.64	0.45***	0.00
	Matched	9.09	9.08	0.01	0.85
Weather shock	Unmatched	0.18	0.15	0.04	0.20
	Matched	0.18	0.20	-0.02	0.44
Distance to market	Unmatched	2.06	1.86	0.21**	0.04
	Matched	2.05	2.03	0.02	0.83
Bagerhat	Unmatched	0.25	0.25	0.00	0.90
	Matched	0.25	0.27	-0.01	0.70
Khulna	Unmatched	0.39	0.39	0.00	0.98
	Matched	0.39	0.36	0.03	0.50

*Notes: *** p<0.01, ** p<0.05, * p<0.1.*

Table C6. Quality test for propensity score matching (NNM)

Type of statistic		Value
Pseudo R^2	Before matching	0.098
Pseudo R^2	After matching	0.004
LR test (p-value)	Before matching	0.000
LR test (p-value)	After matching	0.999
Mean standardized bias	Before matching	13.5
Mean standardized bias	After matching	2.8
Percent of bias reduction	$\frac{(\text{MeanBias}_{\text{unmatched}} - \text{MeanBias}_{\text{matched}})}{\text{MeanBias}_{\text{unmatched}}} \boldsymbol{x100}$	79.26%

Table C7. First-stage regression results for CFA

Variables	Coefficient
Share of households using the internet in the village	0.014***
	(0.003)
Household size	0.174***
	(0.044)
Age head	0.000
	(0.005)
Male head	-0.130
	(0.246)
Married head	-0.168
	(0.392)
Ethnic majority head	1.306***
	(0.297)
Muslim head	-0.324***
	(0.122)
Education head	0.027**
	(0.013)
No. of dependents	-0.141**
	(0.061)
Tenant dummy	-0.040
	(0.105)
Asset per capita (ln)	0.332***
	(0.057)
Weather shock dummy	-0.021
	(0.135)
Distance to market	0.036
	(0.038)
Bagerhat	0.085
	(0.133)
Khulna	0.138
	(0.130)
Constant	-5.318***
	(0.817)
Observations	720
Wald chi2	100.99
P-value	0.00

*Notes: *** p<0.01, ** p<0.05, * p<0.1; Robust standard errors in parentheses. The dependent variable is the internet use dummy.*

Table C8. Falsification tests

Dependent variables	No. of observations	Coefficient	Std. error
Farm production activities			
Total farm income	720	0.015	(0.404)
Total cost	720	-0.090	(0.266)
Farm output value	720	0.220	(0.515)
Total commercialization	720	-0.002***	(0.001)
PDDS12	720	-0.006*	(0.004)
PDDS9	720	-0.007*	(0.004)
Household consumption outcome			
HDDS9	720	-0.009**	(0.004)
HDDS12	720	-0.010**	(0.005)
HDDS9 lean	720	-0.015***	(0.004)
HDDS12 lean	720	-0.015***	(0.005)
MDDS	701	0.010***	(0.003)
WDDS	693	0.010***	(0.003)
CDDS	267	-0.003	(0.005)
Household food consumption choices in normal season			
Cereals	720	0.001*	(0.001)
Roots and tubers	720	-0.002**	(0.001)
Eggs	720	-0.001	(0.001)
Fish	720	0.001**	(0.000)
Vegetables	720	0.000*	(0.000)
Fruits	720	-0.002*	(0.001)
Meat and organ meat	720	-0.003**	(0.001)
Legumes, seeds and nuts	720	-0.002**	(0.001)
Milk and dairy	720	-0.001	(0.001)
Oils and fats	720	0.000	(0.000)
Spices and condiments	720	0.000	(0.000)
Sweets	720	-0.001	(0.001)
Household food consumption choices in lean season			
Cereals	720	0.000	(0.000)
Roots and tubes	720	-0.003**	(0.001)
Eggs	720	-0.002**	(0.001)
Fish	720	0.000	(0.000)
Vegetables	720	-0.001	(0.000)
Fruits	720	0.001	(0.001)
Meat and organ meat	720	-0.004***	(0.001)
Legumes, seeds and nuts	720	-0.003*	(0.001)
Milk and dairy	720	-0.003***	(0.001)
Oils and fats	720	0.001	(0.000)
Spices and condiments	720	0.002***	(0.001)
Sweets	720	-0.002	(0.001)
Household food production choices			
Cereals	720	-0.007***	(0.002)

Dependent variables	No. of observations	Coefficient	Std. error
Roots and tubes	720	-0.000	(0.000)
Egg	720	0.002**	(0.001)
Fish	720	0.004***	(0.002)
Vegetables	720	-0.001*	(0.000)
Fruits	720	-0.003***	(0.001)
Meat and organ meat	720	0.004***	(0.001)
Legumes, seeds and nuts	720	-0.003***	(0.001)
Milk and dairy	720	-0.003***	(0.001)
Oils and fats	720	-0.000	(0.000)
Spices and condiments	720	-0.000	(0.000)
Sweets	720	-0.000	(0.000)

*Notes: *** p<0.01, ** p<0.05, * p<0.1; Robust standard errors in parentheses. Each table row represents a separate OLS regression model, regressing the shown outcome on the instrument (share of households using the internet in the village-leave one out) and all control variables. We only show the instrument coefficients for brevity.*

Table C9. Effects of internet use on farm production outcomes using PSM and different matching algorithms

	(1)	(2)	(3)	(4)	(5)	(6)
	Farm income	Production cost	Farm output value	Commercialization ratio	PDS9	PDS12
Panel A: ATT from NNM						
Internet use	65.943***	-9.93	56.013***	0.057**	0.761***	0.736***
	(13.731)	(11.864)	(20.011)	(0.027)	(0.166)	(0.168)
Panel B: ATT from kernel matching						
Internet use	52.697***	-25.478**	27.219	0.035	0.628***	0.61***
	(14.585)	(11.097)	(20.482)	(0.024)	(0.156)	(0.158)
Panel C: ATT from radius matching						
Internet use	52.894***	-25.549**	27.345	0.036	0.623***	0.605***
	(14.555)	(11.073)	(20.442)	(0.024)	(0.155)	(0.158)

*Notes: *** p<0.01, ** p<0.05, * p<0.1; Robust standard errors in parentheses. ATT: Average treatment effects; PSM: Propensity score matching; NNM: Nearest neighbor matching; PDS9: Production diversity score with 9 food groups; PDS12: Production diversity score with 12 food groups.*

Table C10. Effects of internet use on dietary diversity scores using PSM and different matching algorithms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	HDDS9	HDDS12	HDDS9 (lean)	HDDS12 (lean)	MDDS	WDDS	CDDS
Panel A: ATT from NNM							
Internet use	0.279**	0.353**	0.259*	0.454**	0.187	0.285**	0.228
	(0.14)	(0.165)	(0.149)	(0.182)	(0.125)	0.122	0.178
Panel B: ATT from kernel matching							
Internet use	0.223*	0.270*	0.189	0.375**	0.143	0.300***	0.228
	(0.13)	(0.154)	(0.141)	(0.172)	(0.113)	(0.113)	(0.172)
Panel C: ATT from radius matching							
Internet use	0.224*	0.270*	0.189	0.377**	0.14	0.296***	0.217
	(0.13)	(0.154)	(0.141)	(0.171)	(0.113)	(0.113)	(0.172)

*Notes: *** p<0.01, ** p<0.05, * p<0.1; Robust standard errors in parentheses. ATT: Average treatment effects; PSM: Propensity score matching; NNM: Nearest neighbor matching; All dietary diversity scores refer to the normal season, except for those where lean season is specified. HDDS9: Household dietary diversity score with 9 food groups; HDDS12: Household dietary diversity score with 12 food groups; MDDS: Men's dietary diversity score; WDDS: Women's dietary diversity score; CDDS: Child dietary diversity score.*

Table C11. Effects of internet use on food production choices using PSM and different matching algorithms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Cereals	Roots and tubers	Eggs	Fish	Vegetables	Fruits	Meat	Legumes nuts, and seeds	Milk and dairy	Oils and fats	Spices and condiments	Sugar and sweets
Panel A. ATT from NNM												
Internet use	0.056	-0.001	0.09**	0.251***	0.023	0.025	0.165***	0.094**	0.057	-0.01	-0.008**	-0.007
	(0.086)	(0.008)	(0.046)	(0.062)	(0.022)	(0.037)	(0.046)	(0.037)	(0.041)	(0.012)	(0.004)	(0.006)
Panel B. ATT from kernel matching												
Internet use	0.033	0.00	0.071*	0.213***	0.026	0.017	0.162***	0.098***	0.008	-0.004	-0.008*	-0.006
	(0.079)	(0.008)	(0.042)	(0.057)	(0.022)	(0.036)	(0.042)	(0.035)	(0.039)	(0.012)	(0.004)	(0.004)
Panel C. ATT from radius matching												
Internet use	0.029	0	0.071*	0.212***	0.026	0.019	0.16***	0.098***	0.007	-0.004	-0.008*	-0.006
	(0.079)	(0.008)	(0.042)	(0.057)	(0.022)	(0.036)	(0.042)	(0.035)	(0.039)	(0.012)	(0.004)	(0.004)

*Notes: *** p<0.01, ** p<0.05, * p<0.1; Robust standard errors in parentheses. ATT: Average treatment effects; PSM: Propensity score matching; NNM: Nearest neighbor matching.*

Table C12. Effects of internet use on household food consumption choices in the normal season using PSM and different matching algorithms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Cereals	Roots and tubers	Eggs	Fish	Vegetables	Fruits	Meat	Legumes nuts, and seeds	Milk and dairy	Oils and fats	Spices and condiments	Sugar and sweets
Panel A. ATT from NNM												
Internet use	0.018	0.036	0.00	0.066***	0.005	0.101**	0.051	0.003	-0.003	0.064**	0.016	-0.007
	(0.022)	(0.035)	(0.032)	(0.022)	(0.009)	(0.045)	(0.046)	(0.037)	(0.046)	(0.026)	(0.014)	(0.04)
Panel B. ATT from kernel matching												
Internet use	0.012	0.032	-0.011	0.058***	0.008	0.097**	0.027	0.002	-0.003	0.064***	0.013	-0.03
	(0.021)	(0.032)	(0.029)	(0.019)	(0.008)	(0.042)	(0.043)	(0.034)	(0.042)	(0.023)	(0.013)	(0.037)
Panel C. ATT from radius matching												
Internet use	0.013	0.031	-0.01	0.057***	0.008	0.097*	0.028	0.002	-0.002	0.063***	0.013	-0.03
	(0.021)	(0.032)	(0.029)	(0.018)	(0.008)	(0.042)	(0.043)	(0.034)	(0.042)	(0.023)	(0.013)	(0.037)

*Notes: *** p<0.01, ** p<0.05, * p<0.1; Robust standard errors in parentheses. PSM: Propensity score matching; NNM: Nearest neighbor matching.*

Table C13. Effects of internet use on household food consumption choices in the agricultural lean season using PSM and different matching algorithms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Cereals	Roots and tubers	Eggs	Fish	Vegetables	Fruits	Meat	Legumes nuts, and seeds	Milk and dairy	Oils and fats	Spices and condiments	Sugar and sweets
Panel A. ATT from NNM												
Internet use	-	0.055	-0.011	0.081***	0.004	0.066	0.053	-0.014	0.024	0.082***	0.08***	0.033
	-	(0.037)	(0.039)	(0.023)	(0.012)	(0.042)	(0.046)	(0.042)	(0.046)	(0.026)	(0.025)	(0.045)
Panel B. ATT from kernel matching												
Internet use	-	0.031	-0.01	0.068***	-0.001	0.064	0.051	-0.019	0.006	0.077***	0.092***	0.017
	-	(0.034)	(0.036)	(0.021)	(0.011)	(0.039)	(0.043)	(0.039)	(0.042)	(0.023)	(0.022)	(0.041)
Panel C. ATT from radius matching												
Internet use	-	0.031	-0.01	0.066***	-0.002	0.063	0.052	-0.019	0.007	0.077***	0.093***	0.018
	-	(0.034)	(0.036)	(0.021)	(0.011)	(0.038)	(0.043)	(0.038)	(0.042)	(0.023)	(0.022)	(0.041)

*Notes: *** p<0.01, ** p<0.05, * p<0.1; Robust standard errors in parentheses. ATT: Average treatment effects; PSM: Propensity score matching, NNM: Nearest neighbor matching.*

Table C14. Probit model of internet use with village-level fixed effects

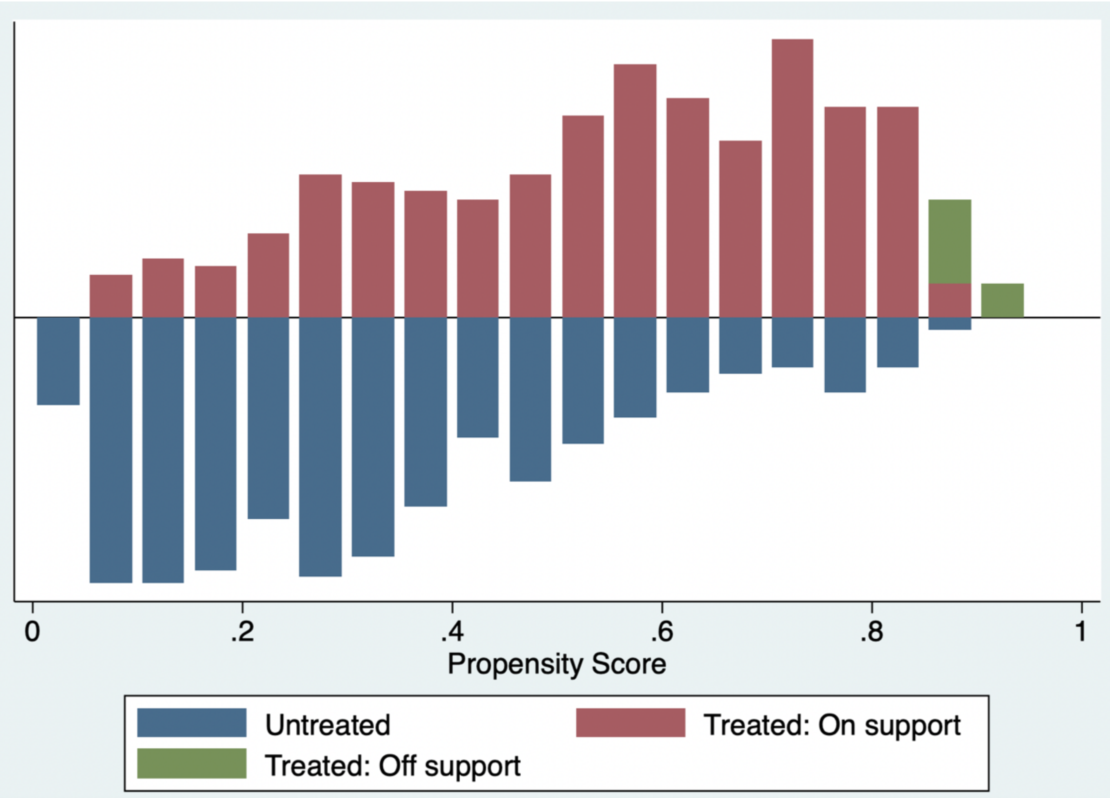
Variables	Coefficient
Household size	0.202***
	(0.047)
Age head	0.001
	(0.005)
Male head	-0.160
	(0.267)
Married head	-0.161
	(0.398)
Ethnic majority head	1.581***
	(0.317)
Education head	0.029**
	(0.014)
Muslim head	-0.537***
	(0.185)
No. of dependents	-0.144**
	(0.065)
Tenant dummy	-0.008
	(0.115)
Asset per capita	0.428***
	(0.062)
Weather shock	0.112
	(0.151)
Distance to market	0.100*
	(0.053)
Bogi/Village2	0.856*
	(0.460)
Rajapur/Village3	0.513
	(0.476)
Sonatala/Village4	0.440
	(0.438)
Malgazi/Village5	0.404
	(0.485)
Ulubunia/Village6	1.154**
	(0.451)
Joykhan/Village7	0.521
	(0.470)
Purbo Matbari/Village8	1.555***
	(0.470)
Ghatakhali/Village9	0.915**
	(0.444)
Malikhali/Village10	0.825*
	(0.479)
Paschim Bajua/Village11	0.326
	(0.498)
Bajua/Village12	0.858*
	(0.514)

Variables	Coefficient
Odabunia/Village13	0.514
	(0.493)
Laudubi/Village14	0.509
	(0.468)
Uludanga/Village15	-0.362
	(0.473)
Maukhali/Village16	0.393
	(0.474)
Batikhali /Village17	1.608***
	(0.480)
Puraikati/Village18	1.218**
	(0.483)
Silemanpur/Village19	0.575
	(0.464)
Khatuamari/Village20	-0.031
	(0.532)
Braja Patali/Village21	-0.761
	(0.514)
Sadpur/Village22	-0.001
	(0.444)
Manpur/Village23	0.458
	(0.453)
Gazipur/Village24	0.318
	(0.456)
Chakla Telikhali/Village25	1.152**
	(0.455)
Kearganti/Village26	1.460***
	(0.484)
Hajipur/Village27	0.980**
	(0.458)
Nurnagar/Village28	0.535
	(0.460)
Showalia/Village29	1.018**
	(0.458)
Mahmudpur/Village30	0.702*
	(0.422)
Ishwaripur/Village31	0.939**
	(0.432)
Kashimpur/Village32	0.173
	(0.453)
Narkeltola/Village33	0.799*
	(0.454)
Pankhali/Village34	0.870**
	(0.439)
Gatirgiri/Village35	0.676
	(0.484)
Purbo Nalta/Village36	-0.194
	(0.496)

Variables	Coefficient
Constant	-6.539***
	(0.953)
Log pseudolikelihood	-399.0196
Wald chi^2	162.92
Prob. > chi^2	0.0000
Pseudo R^2	0.1887
Observations	720

*Notes: *** p<0.01, ** p<0.05, * p<0.1; Robust standard errors in parentheses, Village 1 is considered as reference dummy.*

Figure C2. Propensity score distribution and common support for propensity score estimation by groups with village-level fixed effects



Note: "Treated: on support'' presents the households using the internet that have a suitable match(n=295), while ''Treated: off support'' presents the households using the internet that do not have a suitable match (n=14); "Untreated" presents the households without internet use (n=411).

Table C15. Common support condition with village-level fixed effect (treated and untreated units)

	Support		
Treatment assignment	Off support	On support	Total
Untreated	0	411	411
Treated	14	295	309
Total	14	706	720

Table C16. Balancing test with village-level fixed effects

Variable		Treated	Mean Control	Difference	p>t
Household size	Unmatched	4.644	4.4209	0.2231	0.071
	Matched	4.5966	4.6563	-0.0597	0.658
Age head	Unmatched	49.968	50.197	-0.229	0.802
	Matched	49.786	49.168	0.618	0.538
Male head	Unmatched	0.96117	0.95864	0.00253	0.865
	Matched	0.95932	0.95661	0.00271	0.87
Married head	Unmatched	0.97735	0.9854	-0.00805	0.422
	Matched	0.97966	0.98102	-0.00136	0.906
Bangladeshi head	Unmatched	0.97735	0.91727	0.06008	0.001
	Matched	0.97627	0.98169	-0.00542	0.647
Years of schooling	Unmatched	5.7217	4.5426	1.1791	0
	Matched	5.5898	5.6149	-0.0251	0.944
Muslim head	Unmatched	0.64078	0.71533	-0.07455	0.033
	Matched	0.64746	0.67119	-0.02373	0.544
No of dependents	Unmatched	1.3657	1.472	-0.1063	0.237
	Matched	1.3559	1.4156	-0.0597	0.539
Tenant farmer	Unmatched	0.49838	0.56204	-0.06366	0.09
	Matched	0.50847	0.50508	0.00339	0.935
Asset	Unmatched	9.0984	8.6439	0.4545	0
	Matched	9.0564	9.0122	0.0442	0.554
Weather shock	Unmatched	0.18123	0.14599	0.03524	0.203
	Matched	0.17288	0.14847	0.02441	0.42
Distance to market	Unmatched	2.0647	1.8589	0.2058	0.036
	Matched	2.0237	2.0359	-0.0122	0.911
Bogi/village 2	Unmatched	0.03236	0.02433	0.00803	0.517
	Matched	0.0339	0.03051	0.00339	0.816
Rajapur/village 3	Unmatched	0.02265	0.03163	-0.00898	0.469
	Matched	0.02373	0.0339	-0.01017	0.461
Sonatala /village 4	Unmatched	0.02589	0.0292	-0.00331	-0.79
	Matched	0.02712	0.03186	-0.00474	0.734
Malgazi /village5	Unmatched	0.03236	0.02433	0.00803	0.517
	Matched	0.03051	0.03864	-0.00813	0.589
Ulubunia /village 6	Unmatched	0.0356	0.0219	0.0137	0.269
	Matched	0.03729	0.04814	-0.01085	0.516
Joykhan /village7	Unmatched	0.02589	0.0292	-0.00331	0.79
	Matched	0.02712	0.02169	0.00543	0.67
Purbo Matbari/village 8	Unmatched	0.04854	0.01217	0.03637	0.003
	Matched	0.04068	0.04068	0	1
Ghatakhali /village 9	Unmatched	0.02913	0.02676	0.00237	0.849
	Matched	0.03051	0.02576	0.00475	0.728
Malikhali /village 10	Unmatched	0.04207	0.01703	0.02504	0.043
	Matched	0.04407	0.0339	0.01017	0.524
Paschim Bajua /village 11	Unmatched	0.02589	0.0292	-0.00331	0.79
	Matched	0.02034	0.01966	0.00068	0.953
Bajua /village 12	Unmatched	0.02589	0.0292	-0.00331	0.79

Variable		Treated	Mean Control	Difference	p>t
	Matched	0.02712	0.02508	0.00204	0.877
Odabunia /village 13	Unmatched	0.01618	0.0365	-0.02032	0.101
	Matched	0.01695	0.0122	0.00475	0.631
Laudubi /village 14	Unmatched	0.02913	0.02676	0.00237	0.849
	Matched	0.03051	0.01627	0.01424	0.253
Uludanga /village 15	Unmatched	0.01618	0.0365	-0.02032	0.101
	Matched	0.01695	0.01898	-0.00203	0.853
Maukhali /village 16	Unmatched	0.01942	0.03406	-0.01464	0.237
	Matched	0.02034	0.03186	-0.01152	0.381
Batikhali /village 17	Unmatched	0.0356	0.0219	0.0137	0.269
	Matched	0.03729	0.03864	-0.00135	0.931
Puraikati/village 18	Unmatched	0.02913	0.02676	0.00237	0.849
	Matched	0.03051	0.04949	-0.01898	0.24
Silemanpur/village 19	Unmatched	0.01942	0.03406	-0.01464	0.237
	Matched	0.02034	0.01831	0.00203	0.858
Khatuamari/village 20	Unmatched	0.00647	0.0438	-0.03733	0.003
	Matched	0.00678	0.00746	-0.00068	0.922
Braja Patali /village 21	Unmatched	0.01294	0.03893	-0.02599	0.036
	Matched	0.01356	0.01153	0.00203	0.825
Sadpur /village 22	Unmatched	0.01942	0.03406	-0.01464	0.237
	Matched	0.02034	0.02169	-0.00135	0.909
Manpur /village 23	Unmatched	0.02589	0.0292	-0.00331	0.79
	Matched	0.02712	0.03119	-0.00407	0.769
Gazipur /village 24	Unmatched	0.02265	0.03163	-0.00898	0.469
	Matched	0.02373	0.0278	-0.00407	0.756
Chakla Telikhali /village 25	Unmatched	0.04207	0.01703	0.02504	0.043
	Matched	0.04068	0.04136	-0.00068	0.967
Kearganti /village 26	Unmatched	0.0356	0.0219	0.0137	0.269
	Matched	0.0339	0.0522	-0.0183	0.274
Hajipur /village 27	Unmatched	0.04207	0.01703	0.02504	0.043
	Matched	0.03729	0.03051	0.00678	0.65
Nurnagar /village 28	Unmatched	0.01618	0.0365	-0.02032	0.101
	Matched	0.01695	0.01424	0.00271	0.791
Showalia/village 29	Unmatched	0.04531	0.0146	0.03071	0.013
	Matched	0.04068	0.04203	-0.00135	0.934
Mahmudpur/village 30	Unmatched	0.03236	0.02433	0.00803	0.517
	Matched	0.03051	0.01288	0.01763	0.142
Ishwaripur /village 31	Unmatched	0.0356	0.0219	0.0137	0.269
	Matched	0.03729	0.04203	-0.00474	0.768
Kashimpur/village 32	Unmatched	0.01618	0.0365	-0.02032	0.101
	Matched	0.01695	0.01492	0.00203	0.844
Gatirgiri/village 33	Unmatched	0.04531	0.0146	0.03071	0.013
	Matched	0.04746	0.03593	0.01153	0.485
Narkeltola/village 34	Unmatched	0.03236	0.02433	0.00803	0.517
	Matched	0.03051	0.02441	0.0061	0.651
Pankhali /village 35	Unmatched	0.02913	0.02676	0.00237	0.849
	Matched	0.03051	0.02644	0.00407	0.767

Variable		Treated	Mean Control	Difference	p>t
Purbo Nalta /village 36	Unmatched	0.01294	0.03893	-0.02599	0.036
	Matched	0.01356	0.01492	-0.00136	0.89

*Notes: *** p<0.01, ** p<0.05, * p<0.1.*

Table C17. Quality tests for propensity score matching (NNM)

Type of statistic		Value
Pseudo R^2	Before matching	0.189
Pseudo R^2	After matching	0.016
LR test (p-value)	Before matching	0.000
LR test (p-value)	After matching	1.000
Mean standardized bias	Before matching	10.0
Mean standardized bias	After matching	3.5
Percent of bias reduction	$\frac{(\text{MeanBias}_{\text{unmatched}} - \text{MeanBias}_{\text{matched}})}{\text{MeanBias}_{\text{unmatched}}} \boldsymbol{x100}$	65%

Table C18. Effects of internet use on farm production outcomes using PSM with village-level fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)
	Farm income	Production cost	Farm output value	Commercialization ratio	PDS9	PDS12
Panel A: ATT from PSM: NNM						
Internet use	56.695***	-19.081	37.615	0.061**	0.728***	0.715***
	(17.439)	(12.138)	(24.046)	(0.028)	(0.175)	(0.178)
Panel B: ATT from PSM: Kernel matching						
Internet use	53.825***	-26.733**	27.092	0.057**	0.726***	0.717***
	(16.049)	(11.695)	(21.975)	(0.027)	(0.171)	(0.173)
Panel C: ATT from PSM: Radius matching						
Internet use	53.866***	-27.44**	26.426	0.057**	0.72***	0.711***
	(16.043)	(11.685)	(21.964)	(0.027)	(0.171)	(0.173)

*Notes: *** p<0.01, ** p<0.05, * p<0.1; Robust standard errors in parentheses. ATT: Average treatment effects; PSM: propensity score matching; NNM: Nearest neighbor matching; PDS9: Production diversity score with 9 food groups; PDS12: Production diversity score with 12 food groups.*

Table C19. Effects of internet use on dietary diversity scores using PSM with village-level fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	HDDS9	HDDS12	HDDS9 (lean)	HDDS12 (lean)	MDDS	WDDS	CDDS
Panel A: ATT from NNM							
Internet use	0.401***	0.43**	0.414**	0.609***	0.158	0.26**	0.22
	(0.152)	(0.177)	(0.163)	(0.197)	(0.132)	(0.127)	(0.208)
Panel B: ATT from kernel matching							
Internet use	0.451***	0.493***	0.475***	0.662***	0.124	0.253**	0.193
	(0.144)	(0.17)	(0.155)	(0.188)	(0.126)	(0.123)	(0.209)
Panel C. ATT from radius matching							
Internet use	0.454***	0.498***	0.476***	0.665***	0.129	0.245**	0.193
	(0.144)	(0.169)	(0.154)	(0.187)	(0.126)	(0.123)	(0.21)

*Notes: *** p<0.01, ** p<0.05, * p<0.1; Robust standard errors in parentheses. ATT: Average treatment effects; PSM:Propensity score matching; NNM: Nearest neighbor matching; All dietary diversity scores refer to the normal season, except for those where lean season is specified. HDDS9: Household dietary diversity score with 9 food groups; HDDS12: Household dietary diversity score with 12 food groups; MDDS: Men's dietary diversity score; WDDS: Women's dietary diversity score; CDDS: Child dietary diversity score.*

Table C20. Effects of internet use on food production choices using PSM with village-level fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Cereals	Roots and tubers	Eggs	Fish	Vegetables	Fruits	Meat	Legumes nuts, and seeds	Milk and dairy	Oils and fats	Spices and condiments	Sugar and sweets
Panel A. ATT from NNM												
Internet use	0.175**	-0.001	0.074	0.157**	0.023	0.042	0.117**	0.119***	0.022	-0.002	-0.008	-0.003
	(0.092)	(0.008)	(0.049)	(0.065)	(0.025)	(0.039)	(0.049)	(0.036)	(0.044)	(0.014)	(0.006)	(0.006)
Panel B. ATT from kernel matching												
Internet use	0.192**	-0.001	0.077*	0.141**	0.027	0.031	0.116**	0.118***	0.025	-0.002	-0.005	-0.003
	(0.087)	(0.008)	(0.047)	(0.062)	(0.024)	(0.04)	(0.047)	(0.037)	(0.042)	(0.014)	(0.005)	(0.005)
Panel C. ATT from radius matching												
Internet use	0.188**	-0.001	0.076*	0.142***	0.027	0.03	0.114**	0.119***	0.024	-0.002	-0.005	-0.002
	(0.087)	(0.008)	(0.047)	(0.062)	(0.024)	(0.04)	(0.047)	(0.037)	(0.042)	(0.014)	(0.005)	(0.005)

*Notes: *** p<0.01, ** p<0.05, * p<0.1; Robust standard errors in parentheses. ATT: Average treatment effects; PSM: Propensity score matching; NNM: Nearest neighbor matching.*

Table C21. Effects of internet use on household food consumption choices in the normal season using PSM with village-level fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Cereals	Roots and tubers	Eggs	Fish	Vegetables	Fruits	Meat	Legumes nuts, and seeds	Milk and dairy	Oils and fats	Spices and condiments	Sugar and sweets
Panel A. ATT from NNM												
Internet use	0.034	0.087**	0.012	0.051**	0.001	0.141***	0.029	0.063	-0.018	0.043	-0.001	-0.014
	(0.024)	(0.037)	(0.034)	(0.023)	(0.007)	(0.049)	(0.049)	(0.04)	(0.049)	(0.028)	(0.014)	(0.042)
Panel B. ATT from kernel matching												
Internet use	0.039*	0.101***	0.009	0.046**	0.003	0.143***	0.039	0.066*	0.004	0.044	0.006	-0.008
	(0.024)	(0.035)	(0.032)	(0.021)	(0.01)	(0.046)	(0.047)	(0.038)	(0.046)	(0.026)	(0.014)	(0.04)
Panel C. ATT from radius matching												
Internet use	0.039*	0.102**	0.008	0.046**	0.003	0.145***	0.038	0.065*	0.008	0.044*	0.006	-0.006
	(0.024)	(0.035)	(0.032)	(0.021)	(0.01)	(0.046)	(0.047)	(0.037)	(0.046)	(0.026)	(0.014)	(0.04)

*Notes: *** p<0.01, ** p<0.05, * p<0.1; Robust standard errors in parentheses. PSM:Propensity score matching, ATT: Average treatment effects; NNM: Nearest neighbor matching.*

Table C22. Effects of internet use on household food consumption choices in the agricultural lean season using PSM with village-level fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Cereals	Roots and tubers	Eggs	Fish	Vegetables	Fruits	Meat	Legumes nuts, and seeds	Milk and dairy	Oils and fats	Spices and condiments	Sugar and sweets
Panel A. ATT from NNM												
Internet use	-	0.077**	0.003	0.078***	-0.007	0.127***	0.094**	0.021	0.021	0.061**	0.063**	0.071
	-	0.04	0.042	0.026	0.012	0.045	0.049	0.045	0.049	0.028	0.027	0.048
Panel B. ATT from kernel matching												
Internet use	-	0.093**	0.014	0.068***	-0.001	0.127***	0.098**	0.034	0.042	0.059**	0.061**	0.067
	-	0.038	0.04	0.024	0.012	0.043	0.047	0.043	0.047	0.026	0.025	0.046
Panel C. ATT from radius matching												
Internet use	-	0.093**	0.014	0.067***	-0.001	0.126***	0.099**	0.034	0.044	0.059**	0.061**	0.069
	-	0.038	0.04	0.024	0.012	0.043	0.047	0.042	0.046	0.026	0.025	0.045

*Notes: *** p<0.01, ** p<0.05, * p<0.1; Robust standard errors in parentheses. ATT: Average treatment effects; PSM: Propensity score matching, NNM: Nearest neighbor matching.*

Table C23. Effects of internet use measured in terms of monthly internet expenditures (in thousand BDT) on farm production outcomes using CFA

	(1)	(2)	(3)	(4)	(5)	(6)
	Farm income	Production cost	Farm output value	Commercialization ratio	PDS9	PDS12
Internet use (expn.)	98.287***	0.203	104.622	0.085*	1.900***	1.876***
	(31.605)	(51.305)	(66.783)	(0.047)	(0.331)	(0.333)

*Notes: *** p<0.01, ** p<0.05, * p<0.1; Robust standard errors in parentheses. CFA: Control function approach; PDS9:Production diversity score with 9 food groups; PDS12: Production diversity score with 12 food groups.*

Table C24. Effects of internet use measured in terms of monthly internet expenditures (in thousand BDT) on dietary diversity scores using CFA

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	HDDS9	HDDS12	HDDS9 (lean)	HDDS12 (lean)	MDDS	WDDS	CDDS
Internet use (expn.)	0.878***	1.062***	0.865***	1.267***	0.396*	0.672***	0.513**
	(0.223)	(0.263)	(0.270)	(0.326)	(0.203)	(0.228)	(0.255)

*Notes: *** p<0.01, ** p<0.05, * p<0.1; Robust standard errors in parentheses. CFA: Control function approach; All dietary diversity scores refer to the normal season, except for those where lean season is specified. HDDS9: Household dietary diversity score with 9 food groups; HDDS12: Household dietary diversity score with 12 food groups; MDDS: Men's dietary diversity score; WDDS: Women's dietary diversity score; CDDS: Child dietary diversity score.*

Table C25. Effects of internet use measured in terms of monthly internet expenditures (in thousand BDT) on food production and household food consumption choices using CFA

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Cereals	Roots and tubers	Eggs	Fish	Vegetables	Fruits	Meat	Legumes nuts, and seeds	Milk and dairy	Oils and fats	Spices and condiments	Sugar and sweets
Food production choices												
Internet use (expn.)	0.290*	0.008	0.309***	0.549***	0.031	0.017	0.369***	0.302***	0.025	-0.004	-0.011	-0.009
	(0.161)	(0.017)	(0.070)	(0.128)	(0.039)	(0.049)	(0.074)	(0.112)	(0.075)	(0.019)	(0.008)	(0.007)
Food consumption in normal season												
Internet use (expn.)	0.044	0.139**	0.005	0.098***	0.020*	0.251***	0.157**	0.065	0.101	0.114**	0.021	0.049
	(0.030)	(0.058)	(0.052)	(0.032)	(0.010)	(0.077)	(0.078)	(0.059)	(0.084)	(0.052)	(0.023)	(0.066)
Food consumption in lean season												
Internet use (expn.)	0.000	0.132**	0.001	0.151***	0.014	0.194***	0.183**	0.047	0.142*	0.150***	0.151***	0.101
	(0.000)	(0.062)	(0.073)	(0.034)	(0.016)	(0.067)	(0.079)	(0.069)	(0.085)	(0.042)	(0.039)	(0.076)

*Notes: *** p<0.01, ** p<0.05, * p<0.1; Robust standard errors in parentheses. CFA: Control function approach; Consumption of food groups based on 7-day recall data at the household level. The models on cereal consumption during the lean season could not be estimated because all households consumed cereals.*

Table C26. Effects of using a mobile phone without internet on farm production outcomes using PSM (excluding those with internet use)

	(1)	(2)	(3)	(4)	(5)	(6)
	Farm income	Production cost	Farm output value	Commercialization ratio	PDS9	PDS12
Panel A: ATT from NNM						
Phone without internet	-57.289	-43.777	-94.85	-0.064	-0.628	-0.601
	(43.67)	(39.505)	(66.261)	(0.072)	(0.54)	(0.542)
Panel B: ATT from kernel matching						
Phone without internet	-60.284	-46.571	-98.786	-0.07	-0.674	-0.649
	(42.613)	(38.536)	(64.633)	(0.07)	(0.527)	(0.528)
Panel C: ATT from radius matching						
Phone without internet	-58.923	-45.624	-96.832	-0.074	-0.687	-0.662
	(42.581)	(38.507)	(64.583)	(0.07)	(0.527)	(0.528)

*Notes: *** p<0.01, ** p<0.05, * p<0.1; Robust standard errors in parentheses. ATT: Average treatment effects; PSM: Propensity score matching; NNM: Nearest neighbor matching; PDS9: Production diversity score with 9 food groups; PDS12: Production diversity score with 12 food groups.*

Table C27. Effects of using a mobile phone without internet on dietary diversity using PSM (excluding those with internet use)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	HDDS9	HDDS12	HDDS9 (lean)	HDDS12 (lean)	MDDS	WDDS	CDDS
Panel A: ATT from NNM							
Phone without internet	-0.4	0.042	-0.463	-0.165	0.334	-0.013	0.268
	(0.346)	(0.473)	(0.508)	(0.635)	(0.355)	(0.399)	(0.396)
Panel B: ATT from kernel matching							
Phone without internet	-0.39	0.024	-0.405	-0.103	0.378	-0.037	0.036
	(0.339)	(0.462)	(0.496)	(0.62)	(0.344)	(0.388)	(0.541)
Panel C: ATT from radius matching							
Phone without internet	-0.412	-0.01	-0.419	-0.121	0.389	-0.05	0.096
	(0.338)	(0.462)	(0.496)	(0.62)	(0.344)	(0.389)	(0.539)

*Notes: *** p<0.01, ** p<0.05, * p<0.1; Robust standard errors in parentheses. ATT: Average treatment effects; PSM: Propensity score matching; NNM: Nearest neighbor matching; All dietary diversity scores refer to the normal season, except for those where lean season is specified. HDDS9: Household dietary diversity score with 9 food groups; HDDS12: Household dietary diversity score with 12 food groups; MDDS: Men's dietary diversity score; WDDS: Women's dietary diversity score; CDDS: Child dietary diversity score.*

Table C28. Implications of internet use for farm production activities (qualitative follow-up interviews)

Themes discussed	Summary findings from the interviews	Example response from interviewees
Access to information	Smallholder farmers use YouTube and Facebook to learn about different farming techniques, proper timing of land preparation for farming, cost-effective organic ways to pest control, making organic fertilizer, etc. WhatsApp, Emo, Messenger make information access easier from the agricultural extension office, expert farmers and farmers'school.	*"We get knowledge on high-yield seeds, improved irrigation, and disease control through online resources like Krishi Math (farmer's field school)."*
Cheaper and faster means of communication and access to advice	Knowing about input details, current market prices at different regional markets, and seeking expert suggestions in case of emergency, is easier, faster and cheaper with the help of the internet.	*"….I can send my question using a voice message and get a reply from other expert farmers or agricultural extension officers. Now I don't need to expend my money for transportation to reach an expert farmer or an agricultural extension officer. The internet saves both my time and money"*
Decision making and risk preparedness	Weather forecast news, climate-oriented shock mitigation techniques, help smallholders to reduce damage of crops, livestock and aquatic species	*"My son gave us information about the weather in advance, which helped a lot! We harvested the crop a bit earlier, knowing about the storm, and thus reduced our crop losses."*
Production cost reduction	Internet use reduces smallholders' production costs by sharing various methods for making organic fertilizers and pest control techniques. But the internet does not help much to reduce input costs. Farmers do not have warranty on seeds purchased from the online market, but in local markets, they have. From the internet, they only acquire information about different seeds, fish, and livestock breeds, for purchasing them, farmers have so far preferred in-person dealings.	*"I purchase everything from the local market, which is expensive. As I do not trust online….. But I check the internet to see reviews of new seed varieties, detail information about seed quality, yield quality, new aquatic and livestock breeds. It helps me to make the correct decision."*
Increased yield and income	New seed varieties, the use of organic fertilizer, and knowing about different weed control techniques reduce the cost of production and increase output. Access to information about good breeds of fish and livestock also gives farmers the knowledge to produce them commercially and earn money. An increase in production volume typically leads to higher household income.	*"..I watch YouTube and follow paddy farming guidelines word-for-word; my paddy yield increased this year, my paddy yield increased to 30 maund, which was 25 maund last year."*
Farm production diversification	Information about soil quality, the cultivation of multiple species on the same land, and the use of land for vegetable or fruit farming between two paddy farming seasons increases farm production diversity. Information on new breeding varieties, including their pros and cons, helps determine which species are suitable for each other in a multi-species farming system. For example, rice-aquaculture, fish farming and vegetable farming by creating hanging vegetable beds using bamboo frames.	*".. Internet use helps me learn about diverse paddy, fish, and poultry breeds. This knowledge makes me confident to attempt new farming methods………………. cultivate multiple fruits and vegetables for home consumption and sales".* *"Online access enables me to cultivate diverse fishing and livestock species."*
Farm commercialization	Through the internet, farmers can easily get price information on different products in different nearby markets in the village as well as in the city area. It makes their decision-making easier regarding their product sale and increases bargaining power. It also reduces the likelihood that the middleman will pay them less for their products.	*"I check market prices so local bapari (middleman) cannot ask for a low price."*

Note: Telephone interviews were conducted with ten individuals.

Table C29. Implications of internet use for food consumption (qualitative follow-up interviews)

Themes discussed	Summary findings from the interview	Example response from interviewees
Divers food access	The internet improves access to knowledge about different farming techniques, crop rotation and proper timing, doing aquaculture and rice farming, and livestock rearing also promote farm production diversity. Farmers can now utilize the same land parcel to cultivate a variety of crops, including vegetables, fruits, and traditional crops. Hence, increased production diversity ultimately translates into households' increased consumption diversity. Advisory support from different online platforms also makes farmers confident to start working with diverse range of species. It ultimately increases access to diverse food groups.	"*Internet use help me use my land in the lean period. Two to three years ago, my land was unused for 4 months, but now I use it for vegetable and fruit farming, especially watermelon in summer. It has high demand and last year I got a good price.*"
Income improves dietary pattern	Diversified production and increased commercialization via the internet use also increase income. Households can purchase a diverse range of foods, including fruits and animal-based products. Even in the lean season, farmers do not experience food scarcity as they have higher food production diversity.The internet also educates people about the importance of diverse food consumption. A combination of income, production diversity, and knowledge-driven behaviour leads to higher dietary diversity in both agricultural normal and lean seasons for the internet-using households.	"*Through internet use I learn food preservation and in lean season it is used for eating"*

Note: Telephone interviews were conducted with ten individuals.

Appendix D: Appendix to Chapter 4

Impacts of land fragmentation on women's time allocation and dietary quality in the small farm sector

Table D1. Name and definition of control variables

Name	Measurement unit	Definition
Land fragmentation	Number	Number of plots used for farming activities
Woman age	Years	Age of the woman
Woman education	Years	Years of schooling of the woman
Woman married	Dummy	Marital status of the woman
Woman Bangladeshi	Dummy (1=Bangladeshi, 0=otherwise)	Ethnicity of the woman
Woman Muslim	Dummy (1=muslim, 0=otherwise)	Religion of the woman
Household size	People	Total number of household member
Age head	Years	Age of the household head
Male head	Dummy (1=male, 0=female)	Gender of the household head
Married head	Dummy (1=married, 0=otherwise)	Marital status of the household head
Education head	Years	Years of schooling of the household head
No. of dependent	People	Number of dependent people in the household
Asset per capita	BDT	Logarithmic transformation of the parcapita asset under household's ownership
Land amount	Hectare	Total area of land in hectare
Flood	Dummy (1=yes, 0=no)	If the households experience flood in last 12 monthes during the survey period=1, 0=Otherwise
Drought	Dummy (1=yes, 0=no)	If the households experience flood in last 12 monthes during the survey period=1, 0=Otherwise
Distance	Kilometer	Distance between house to the local market
Local level Infrastructure index	Ranges from 0-1	Availability of different infrastructural facilities in the village
District	District dummy1 District dummy2	District dummy 1 (1=Bagerhat, 0=otherwise) District dummy 2 (1= Khulna, 0=otherwise)

Table D2. First stage regression model (IV: Share of villagers renting in or renting out land-leave one out)

Variables	Land fragmentation
Share of villagers renting in or renting out land	0.016***
	(0.003)
Woman age	0.001
	(0.005)
Woman education	0.004
	(0.014)
Woman married	-0.125
	(0.278)
Woman Bangladeshi	-0.288*
	(0.160)
Woman muslim	-0.033
	(0.101)
Household size	0.015
	(0.037)
Age head	-0.001
	(0.004)
Male head	0.241*
	(0.141)
Married head	0.007
	(0.357)
Education head	0.005
	(0.012)
Number of dependents	0.013
	(0.053)
Land amount	0.470***
	(0.108)
Per capita asset (Ln)	0.053
	(0.042)
Flood dummy	-0.170
	(0.210)
Drought dummy	0.186
	(0.163)
Distance to market (Kilometre)	0.039
	(0.035)
Local level infrustructure index	0.117
	(0.154)
Satkhira	-0.469***
	(0.124)
Khulna	-0.302**
	(0.123)
Constant	0.656
	(0.719)
Observations	699
R-squared	0.154

*Notes: *** $p < 0.01$, **$p < 0.05$, * $p < 0.1$; Robust standard errors in parentheses.*

Table D3. Falsification test (IV: Share of villagers renting in or renting out land)

Outcome variables for woman time allocation and dietary quality	Number of observations	Coefficients	Robust standard error
Non-farm activities	699	-0.225	(0.173)
Forest extracting activities	699	-0.000	(0.003)
Cooking and domestic work	699	-0.352	(0.334)
Self-care and maintenance	699	-0.201	(0.260)
Commuting and other activities	699	0.165	(0.119)
Woman non-farm employment	699	-0.000	(0.001)
Woman non-farm income	699	-2.257	(4.642)
WDDS	699	0.003	(0.002)

*Notes: *** p < 0.01, **p < 0.05, * p < 0.1; Robust standard errors in parentheses; Regression coefficient obtained from OLS and Robust standard errors in parentheses.*

Table D4. Grouping of different activities

Activities	Measurement unit	Explanation
Non-farm activities	Minutes/day	Time allocation for employment, running own business, and giving tutorship in exchange of remunaration
Farm activities	Minutes/day	Time allocation for crop farming, livestock rearing and aquaculture
Forest extracting activities	Minutes/day	Time allocation for different forest extraction activities (catching fish, nipa palm collection, fruits and honey collection, hunting of birds and deer etc.)
Cooking and domestic work	Minutes/day	Time allocation for meal preparation, domestic work (cleaning, dusting, watching cloths, water collection) and looking after the children and elderly people in the household
Self-care and maintenance	Minutes/day	Time allocation for eating and drinking, leisure (expending time with friends and family) and personal care (taking shawer, using rest room and doing prayers,)
Commuting and other activities	Minutes/day	Time allocation for commuting, shopping and attending educational institution

Table D5. Heterogeneous impacts of land fragmentation on women's non-farm employment and time allocation (minutes/day) for less educated women

Variables	(1) Non-farm employment	(2) Non-farm income	(3) Non farm employment time	(4) Forest extracting time	(5) Cooking and domestic works time	(6) Self-care and maintenance time	(7) Commuting and others time
Land fragmentation	-0.008	-85.771	-4.661**	0.000	-8.551	-2.518	4.721***
	(0.008)	(66.983)	(2.323)	(0.000)	(6.282)	(5.366)	(1.786)
Woman age	-0.002	-5.142	-0.239	0.000	-0.774	0.296	-0.128
	(0.001)	(5.262)	(0.463)	(0.000)	(1.110)	(1.101)	(0.217)
Woman married	0.057*	111.039	9.861	0.000	-20.146	11.543	12.245
	(0.034)	(432.664)	(17.435)	(0.000)	(17.950)	(18.259)	(11.640)
Woman Bangladeshi	-0.159	-573.739	-20.028	0.000	64.949*	- 105.414***	17.750***
	(0.101)	(574.743)	(15.871)	(0.000)	(35.317)	(33.221)	(6.290)
Woman muslim	-0.017	-159.642	-8.956	0.000	0.995	15.607	-2.872
	(0.028)	(170.242)	(8.680)	(0.000)	(17.807)	(14.764)	(4.505)
Household size	-0.010	-54.252	0.741	0.000	-3.052	2.225	1.228
	(0.009)	(91.970)	(2.052)	(0.000)	(6.271)	(5.183)	(1.223)
Age head	-0.000	-1.112	0.787*	0.000	-1.753*	1.187	0.086
	(0.002)	(5.795)	(0.466)	(0.000)	(0.963)	(0.956)	(0.201)
Male head	-0.149	-821.234	-74.134**	0.000	103.885**	65.513**	-22.932**
	(0.105)	(679.308)	(33.269)	(0.000)	(44.886)	(27.289)	(10.951)
Married head	0.045	110.537	-5.820	0.000	-12.797	-49.960	5.154
	(0.050)	(150.234)	(14.518)	(0.000)	(50.559)	(40.309)	(6.291)
Education head	0.001	-23.782	-0.468	0.000	-2.523	2.342	-0.028
	(0.004)	(19.201)	(0.739)	(0.000)	(2.292)	(1.878)	(0.493)
Number of dependents	0.015	113.292	5.823	0.000	11.287	-11.586	-1.843
	(0.016)	(90.687)	(4.521)	(0.000)	(9.982)	(7.768)	(1.982)
Land amount	-0.058*	-326.781	-5.210	0.000	21.452	-10.973	1.296

Variables	(1) Non-farm employment	(2) Non-farm income	(3) Non farm employment time	(4) Forest extracting time	(5) Cooking and domestic works time	(6) Self-care and maintenance time	(7) Commuting and others time
	(0.032)	(237.888)	(7.804)	(0.000)	(20.507)	(16.938)	(4.610)
Per capita asset (Ln)	-0.003	5.839	0.233	0.000	7.137	8.313	-2.516
	(0.012)	(45.208)	(4.309)	(0.000)	(9.342)	(6.894)	(2.081)
Flood dummy	-0.012	-202.260	1.347	0.000	-95.249**	5.932	4.452
	(0.024)	(159.084)	(22.346)	(0.000)	(46.668)	(23.148)	(8.186)
Drought dummy	0.005	-57.205	4.641	0.000	-36.265	21.211	-3.361
	(0.040)	(136.875)	(15.526)	(0.000)	(28.125)	(22.463)	(5.382)
Distance to market (Kilometre)	0.003	5.220	-2.303	0.000	-2.158	-6.216	2.925**
	(0.011)	(67.721)	(3.106)	(0.000)	(6.703)	(4.720)	(1.418)
Local level infrustructure index	-0.037	-433.023	-12.859	0.000	-23.270	35.884	-7.969
	(0.065)	(531.747)	(17.862)	(0.000)	(36.007)	(33.078)	(6.403)
Khulna	0.075**	40.277	-7.269	0.000	-5.532	-42.036*	19.231***
	(0.036)	(185.483)	(12.655)	(0.000)	(28.891)	(21.687)	(6.601)
Satkhira	0.036	159.605	-6.053	0.000	35.053	-90.680***	15.269***
	(0.034)	(302.047)	(13.116)	(0.000)	(24.994)	(19.031)	(5.444)
Fitted values	0.041	162.700	-13.479	0.000	-14.691	-24.816	7.640
	(0.046)	(326.265)	(12.825)	(0.000)	(28.680)	(23.522)	(6.096)
Constant	0.294*	1,847.297*	115.739*	0.000	434.514***	389.168***	-19.947
	(0.162)	(1,107.160)	(59.406)	(0.000)	(125.839)	(107.923)	(25.571)
Observations	386	385	386	386	386	386	386
R-squared	0.089	0.043	0.100		0.106	0.163	0.104

*Notes: *** p < 0.01, **p < 0.05, * p < 0.1; Robust standard errors in parentheses; Coefficient estimates from CFA models; Low education refers to observations below the sample means of women's years of schooling.*

Table D6. Heterogeneous impacts of land fragmentation on women's non-farm employment and time allocation (minutes/day) for more educated women

Variables	(1) Non-farm employment	(2) Non-farm income	(3) Non farm employment time	(4) Forest extracting time	(5) Cooking and domestic works time	(6) Self-care and maintenance time	(7) Commuting and others time
Land fragmentation	0.033	13.109	8.549	-0.044	-23.784***	-11.021*	8.856***
	(0.023)	(160.203)	(6.038)	(0.041)	(8.648)	(5.777)	(2.827)
Woman age	0.003	16.201	0.510	0.014	-0.599	-0.664	-0.565
	(0.002)	(21.276)	(0.620)	(0.013)	(1.033)	(0.767)	(0.397)
Woman married	-0.031	-913.793	28.624*	-0.126	105.626*	26.267	-208.064**
	(0.107)	(1,168.706)	(14.946)	(0.272)	(59.683)	(30.931)	(82.772)
Woman Bangladeshi	-0.110	-874.781	-31.736	0.161	136.358***	-88.051***	-11.928
	(0.107)	(1,174.062)	(33.013)	(0.198)	(36.226)	(28.026)	(14.181)
Woman muslim	-0.065	-887.015**	-12.933	-0.126	9.669	9.790	-1.279
	(0.048)	(386.205)	(11.842)	(0.177)	(18.608)	(13.306)	(7.013)
Household size	-0.025	-231.477	1.015	-0.021	-11.749	14.468**	-0.165
	(0.020)	(261.933)	(5.277)	(0.060)	(8.242)	(5.987)	(3.894)
Age head	0.001	30.896	0.692	-0.004	-2.293***	0.178	0.485*
	(0.002)	(22.386)	(0.558)	(0.004)	(0.743)	(0.545)	(0.279)
Male head	-0.204	28.455	20.966	0.128	117.373***	41.537	-30.381**
	(0.145)	(676.817)	(15.580)	(0.117)	(41.191)	(26.853)	(12.278)
Married head	0.106	736.034	34.075	0.190	70.206	6.963	0.905
	(0.108)	(991.384)	(27.439)	(0.283)	(87.404)	(15.576)	(11.904)
Education head	0.006	57.301	2.276	-0.002	2.088	-0.252	-0.748
	(0.005)	(44.272)	(1.446)	(0.026)	(2.110)	(1.572)	(0.694)
Number of dependents	0.030	325.376	-0.884	0.112	41.998***	-31.061***	-5.167
	(0.028)	(263.036)	(8.067)	(0.166)	(11.218)	(8.103)	(4.695)
Land amount	0.002	658.613	0.961	0.145	-12.802	29.842*	-2.730
	(0.047)	(467.758)	(11.235)	(0.277)	(20.464)	(16.232)	(10.074)
Per capita asset (Ln)	0.009	338.303	6.900	-0.093	-4.945	-1.985	6.171

Variables	(1) Non-farm employment	(2) Non-farm income	(3) Non farm employment time	(4) Forest extracting time	(5) Cooking and domestic works time	(6) Self-care and maintenance time	(7) Commuting and others time
	(0.023)	(233.591)	(6.345)	(0.069)	(8.771)	(6.964)	(3.807)
Flood dummy	-0.033	-204.902	-28.107**	-0.207	-19.738	47.081*	-4.111
	(0.078)	(620.698)	(13.736)	(0.260)	(40.031)	(25.090)	(8.751)
Drought dummy	0.013	-178.189	3.822	-0.099	16.775	-10.816	-2.525
	(0.073)	(719.030)	(17.396)	(0.098)	(24.444)	(17.876)	(12.444)
Distance to market (Kilometre)	0.005	41.936	1.102	0.042	5.760	-2.146	-1.161
	(0.016)	(162.463)	(4.263)	(0.079)	(6.056)	(4.346)	(2.030)
Local level infrustructure index	0.140	1,461.543*	60.389**	0.161	-86.147**	60.772*	2.132
	(0.101)	(754.070)	(24.055)	(0.223)	(37.583)	(32.234)	(10.165)
Khulna	-0.109	-717.376	-12.446	0.136	46.054	-13.807	-7.580
	(0.072)	(571.571)	(18.335)	(0.277)	(30.931)	(20.921)	(12.281)
Satkhira	-0.069	-311.474	-19.516	0.259	55.618**	-19.436	-7.398
	(0.065)	(565.402)	(15.541)	(0.189)	(26.250)	(19.498)	(10.580)
Fitted values	-0.115	-763.141	-20.250	-0.020	10.019	14.378	-3.062
	(0.072)	(578.175)	(18.171)	(0.430)	(31.157)	(24.041)	(12.137)
Constant	0.365	-1,398.951	-130.495	0.132	210.384	360.607***	212.221**
	(0.365)	(3,863.899)	(84.894)	(1.252)	(151.220)	(88.706)	(95.229)
Observations	313	313	313	313	313	313	313
R-squared	0.084	0.089	0.085	0.029	0.276	0.168	0.364

*Notes: *** p < 0.01, **p < 0.05, * p < 0.1; Robust standard errors in parentheses; Coefficient estimates from CFA models; More educated refers to observations above the sample means of women's years of schooling.*

Table D7. Heterogeneous impacts of land fragmentation on women's non-farm employment and time allocation (minutes/day) for women having at least one child

Variables	(1) Non-farm employment	(2) Non-farm income	(3) Non farm employment time	(4) Forest extracting time	(5) Cooking and domestic works time	(6) Self-care and maintenance time	(7) Commuting and others time
Land fragmentation	0.001	-16.563	-7.637*	-0.085	-3.555	-7.369	3.719*
	(0.020)	(88.935)	(3.887)	(0.076)	(9.490)	(5.883)	(2.140)
Woman age	0.005**	34.388*	1.886***	0.019	-3.117**	-0.614	0.403**
	(0.002)	(17.658)	(0.688)	(0.015)	(1.208)	(0.910)	(0.191)
Woman education	0.025**	246.520**	6.258**	0.048	3.068	-3.672	0.515
	(0.010)	(112.920)	(3.142)	(0.042)	(4.563)	(3.052)	(0.858)
Woman married	-0.043	-745.957	-24.406	0.091	11.183	-32.870	13.714**
	(0.060)	(492.188)	(18.905)	(0.556)	(35.814)	(45.964)	(6.562)
Woman Bangladeshi	-0.037	-702.250	-8.618	0.432	73.290*	-74.497**	8.367
	(0.121)	(955.290)	(27.249)	(0.379)	(39.554)	(34.188)	(6.562)
Woman muslim	-0.062	-445.016	-12.096	-0.128	34.875	-10.744	-3.113
	(0.049)	(359.856)	(14.890)	(0.321)	(25.131)	(18.701)	(4.356)
Household size	-0.017	99.628	-1.557	-0.080	-1.795	10.578	-0.776
	(0.013)	(129.478)	(3.941)	(0.062)	(7.968)	(6.451)	(1.270)
Age head	-0.001	-10.439	-0.002	-0.004	-0.994	0.871	0.011
	(0.002)	(17.346)	(0.506)	(0.005)	(0.860)	(0.622)	(0.141)
Male head	-0.124	-1,008.366	-66.551	0.285	72.321	46.398	-0.882
	(0.121)	(910.498)	(45.701)	(0.228)	(53.551)	(36.691)	(9.780)
Married head	-0.033	242.230	-5.857	0.033	287.643***	-36.060	4.227
	(0.052)	(450.536)	(17.483)	(0.246)	(36.702)	(31.092)	(6.011)
Education head	-0.001	-25.192	-1.247	-0.004	1.920	1.841	-0.257
	(0.005)	(30.741)	(1.428)	(0.041)	(2.761)	(1.883)	(0.516)
Number of dependents	0.041*	101.514	8.421	0.117	-1.783	-16.992*	-0.438
	(0.021)	(225.999)	(7.885)	(0.172)	(11.830)	(8.639)	(1.885)

Variables	(1) Non-farm employment	(2) Non-farm income	(3) Non farm employment time	(4) Forest extracting time	(5) Cooking and domestic works time	(6) Self-care and maintenance time	(7) Commuting and others time
Land amount	-0.024	286.457	14.765	0.281	-24.191	45.784**	-1.146
	(0.046)	(443.928)	(14.454)	(0.395)	(26.841)	(19.413)	(4.605)
Per capita asset (Ln)	0.002	251.649*	8.008	-0.133	0.487	-1.320	-2.537
	(0.019)	(144.661)	(6.780)	(0.102)	(11.201)	(7.343)	(2.575)
Flood dummy	-0.078*	-1,031.150**	-23.062	-0.229	-11.509	37.953	-3.227
	(0.041)	(481.222)	(23.703)	(0.262)	(41.813)	(28.253)	(6.014)
Drought dummy	0.014	517.568	-0.322	-0.237	8.572	-0.517	-6.466
	(0.084)	(1,029.933)	(24.081)	(0.182)	(36.145)	(23.726)	(4.869)
Distance to market (Kilometre)	-0.010	8.021	-1.565	0.063	3.976	-5.448	0.867
	(0.016)	(137.275)	(5.546)	(0.103)	(8.797)	(5.120)	(1.414)
Local level infrustructure index	-0.180**	-84.209	-30.178	0.179	-74.185	124.578***	-6.052
	(0.075)	(348.982)	(18.711)	(0.431)	(45.171)	(41.557)	(7.874)
Khulna	-0.050	-1,248.074*	-50.524*	0.260	42.245	-5.086	8.778
	(0.071)	(754.356)	(28.460)	(0.450)	(43.506)	(23.584)	(8.722)
Satkhira	-0.008	-987.770*	-48.933*	0.310	57.294	-30.226	12.139*
	(0.067)	(578.983)	(25.433)	(0.232)	(37.626)	(21.283)	(7.050)
Fitted values	-0.024	-857.606	-44.581*	0.043	17.136	-8.190	5.955
	(0.065)	(565.332)	(23.752)	(0.612)	(38.559)	(26.998)	(7.840)
Constant	0.180	59.373	100.813	-0.381	127.009	443.407***	-30.491
	(0.277)	(2,468.154)	(101.860)	(1.674)	(151.010)	(109.321)	(25.274)
Observations	230	230	230	230	230	230	230
R-squared	0.151	0.168	0.141	0.041	0.186	0.244	0.090

*Notes: *** p < 0.01, **p < 0.05, * p < 0.1; Robust standard errors in parentheses; Coefficient estimates from CFA models for women having at least one child to look after.*

Table D8. Heterogeneous impacts of land fragmentation on women's non-farm employment and time allocation (minutes/day) for women with no child

Variables	(1) Non-farm employment	(2) Non-farm income	(3) Non farm employment time	(4) Forest extracting time	(5) Cooking and domestic works time	(6) Self-care and maintenance time	(7) Commuting and others time
Land fragmentation	0.010	-68.433	4.478	0.000	-18.557***	-5.228	7.996***
	(0.012)	(90.333)	(3.324)	(0.000)	(5.900)	(5.323)	(2.092)
Woman age	-0.000	14.109	0.146	0.000	0.931	-0.146	-0.837**
	(0.002)	(21.545)	(0.637)	(0.000)	(1.005)	(0.918)	(0.402)
Woman education	0.030***	377.204***	8.043***	0.000	-2.292	-3.539*	2.778***
	(0.008)	(115.394)	(2.575)	(0.000)	(3.093)	(2.083)	(0.928)
Woman married	0.096	222.718	46.867***	0.000	93.169	26.483	-202.117**
	(0.106)	(1,102.396)	(16.989)	(0.000)	(59.795)	(29.970)	(82.079)
Woman Bangladeshi	-0.135	-750.429	-30.014	0.000	118.787***	-109.881***	-0.673
	(0.085)	(753.651)	(22.104)	(0.000)	(30.945)	(25.842)	(11.666)
Woman muslim	-0.009	-271.373	-4.019	0.000	-8.476	24.091*	1.393
	(0.030)	(229.793)	(7.877)	(0.000)	(14.837)	(12.420)	(5.873)
Household size	-0.014	-134.329	1.018	0.000	-8.126	5.483	-0.023
	(0.013)	(150.619)	(3.612)	(0.000)	(6.955)	(6.058)	(2.319)
Age head	0.001	27.288	0.770	0.000	-3.042***	0.374	0.791**
	(0.002)	(20.837)	(0.529)	(0.000)	(0.840)	(0.715)	(0.354)
Male head	-0.193*	-367.006	-7.622	0.000	130.971***	63.976***	-42.715***
	(0.112)	(540.323)	(22.270)	(0.000)	(39.124)	(20.137)	(11.354)
Married head	0.036	-752.862	-8.525	0.000	42.387	-38.199	-21.528*
	(0.056)	(632.926)	(16.651)	(0.000)	(43.012)	(33.807)	(12.261)
Education head	-0.001	-64.082*	-0.188	0.000	0.305	2.106	-1.442***
	(0.004)	(34.954)	(1.058)	(0.000)	(1.862)	(1.502)	(0.533)
Number of dependents	0.011	99.004	-0.772	0.000	32.098***	-19.560**	-5.054
	(0.019)	(134.045)	(5.279)	(0.000)	(9.386)	(7.760)	(3.495)
Land amount	-0.055	-210.049	-5.713	0.000	7.176	2.089	-1.751

Variables	(1) Non-farm employment	(2) Non-farm income	(3) Non farm employment time	(4) Forest extracting time	(5) Cooking and domestic works time	(6) Self-care and maintenance time	(7) Commuting and others time
	(0.034)	(281.408)	(7.858)	(0.000)	(18.150)	(14.153)	(7.330)
Per capita asset (Ln)	0.001	129.755	2.708	0.000	2.407	3.130	2.062
	(0.015)	(142.376)	(4.415)	(0.000)	(7.983)	(6.295)	(2.633)
Flood dummy	0.030	253.005	-22.391*	0.000	-107.202***	25.837	1.017
	(0.081)	(526.374)	(12.120)	(0.000)	(29.612)	(22.754)	(11.013)
Drought dummy	0.011	-265.032	7.550	0.000	-19.624	7.125	1.060
	(0.047)	(238.143)	(12.989)	(0.000)	(22.074)	(18.155)	(9.688)
Distance to market (Kilometre)	0.004	-54.783	1.174	0.000	0.747	-4.484	-0.065
	(0.012)	(111.841)	(3.010)	(0.000)	(5.102)	(4.133)	(1.569)
Local level infrustructure index	0.080	89.162	39.040**	0.000	-40.114	20.926	-6.264
	(0.072)	(603.800)	(17.308)	(0.000)	(31.179)	(28.888)	(7.543)
Khulna	0.018	103.179	5.580	0.000	-4.478	-34.286*	14.098*
	(0.046)	(258.915)	(10.536)	(0.000)	(23.932)	(19.657)	(8.445)
Satkhira	-0.017	262.529	-0.845	0.000	33.864*	-67.172***	7.865
	(0.039)	(344.849)	(9.997)	(0.000)	(20.184)	(17.864)	(6.589)
Fitted values	0.005	202.545	-6.117	0.000	-20.800	-2.715	5.852
	(0.054)	(404.798)	(11.952)	(0.000)	(25.534)	(21.609)	(9.003)
Constant	0.056	-2,746.177	-113.565*	0.000	271.432**	433.214***	211.977**
	(0.267)	(3,090.607)	(63.813)	(0.000)	(116.657)	(87.006)	(91.528)
Observations	469	468	469	469	469	469	469
R-squared	0.145	0.169	0.136	---	0.182	0.118	0.347

*Notes: *** p < 0.01, **p < 0.05, * p < 0.1; Robust standard errors in parentheses; Coefficient estimates from CFA models for women do not have any child to look after.*

Table D9. Heterogeneous effect of land fragmentation on women's dietary diversity by education

Variables	(1) WDDS for less educated woman	(2) WDDS for more educated woman
Land fragmentation	-0.069	0.049
	(0.088)	(0.067)
Woman age	0.020**	0.002
	(0.010)	(0.010)
Woman married	0.323	0.519
	(0.532)	(0.973)
Woman Bangladeshi	1.406***	1.033***
	(0.273)	(0.291)
Woman muslim	-0.231	-0.177
	(0.199)	(0.185)
Household size	-0.111	-0.071
	(0.071)	(0.063)
Age head	0.000	0.005
	(0.007)	(0.010)
Male head	-0.174	0.213
	(0.446)	(0.271)
Married head	-1.097***	0.659
	(0.375)	(0.498)
Education head	0.024	0.014
	(0.018)	(0.022)
Number of dependents	0.108	0.086
	(0.096)	(0.082)
Land amount	0.136	0.100
	(0.193)	(0.269)
Per capita asset (Ln)	0.103	0.153*
	(0.080)	(0.086)
Flood dummy	-0.248	0.015
	(0.424)	(0.427)
Drought dummy	-0.529*	-0.175
	(0.290)	(0.293)
Distance to market (Kilometre)	0.023	-0.017
	(0.056)	(0.057)
Local level infrustructure index	-1.487***	-0.769**
	(0.384)	(0.302)
Khulna	0.257	0.346
	(0.325)	(0.268)
Satkhira	1.027***	1.278***
	(0.283)	(0.239)
Fitted values	0.396	0.527**
	(0.325)	(0.268)
Constant	1.579	-1.587
	(1.215)	(1.430)
Observations	313	386
R-squared	0.221	0.211

*Notes: *** p < 0.01, **p < 0.05, * p < 0.1; Robust standard errors in parentheses; WDDS: Women's diet diversity score. Less and more educated woman refers to observations below and above the sample means of women's years of schooling. Coefficient estimates from CFA models.*

Table D10. Heterogeneous effect of land fragmentation on women's dietary diversity by having a child

Variables	(1) WDDS for woman with child	(2) WDDS for woman with no child
Land fragmentation	-0.022	0.008
	(0.077)	(0.068)
Woman age	0.007	0.012
	(0.012)	(0.009)
Woman education	0.006	0.045*
	(0.039)	(0.027)
Woman married	1.636***	0.192
	(0.611)	(0.561)
Woman Bangladeshi	2.001***	0.986***
	(0.436)	(0.221)
Woman muslim	-0.277	-0.224
	(0.269)	(0.158)
Household size	-0.038	-0.097
	(0.088)	(0.065)
Age head	0.000	-0.001
	(0.010)	(0.007)
Male head	-0.203	0.252
	(0.436)	(0.323)
Married head	-1.647***	0.870*
	(0.406)	(0.476)
Education head	0.025	0.029
	(0.024)	(0.018)
Number of dependents	0.030	0.133*
	(0.104)	(0.080)
Land amount	-0.277	0.248
	(0.260)	(0.180)
Per capita asset (Ln)	0.158	0.115
	(0.099)	(0.075)
Flood dummy	-0.040	-0.014
	(0.421)	(0.395)
Drought dummy	-0.371	-0.263
	(0.440)	(0.229)
Distance to market (Kilometre)	-0.076	0.032
	(0.070)	(0.049)
Local level infrustructure index	-1.616***	-0.926***
	(0.474)	(0.260)
Khulna	0.631	0.181
	(0.418)	(0.250)
Satkhira	1.258***	1.148***
	(0.367)	(0.227)
Fitted values	-2.260	-0.272
	(1.598)	(1.054)
Constant	1.435***	0.034
	(0.376)	(0.241)
Observations	230	469
R-squared	0.241	0.218

*Notes: *** p < 0.01, **p < 0.05, * p < 0.1; Robust standard errors in parentheses; WDDS: Women's diet diversity score. Coefficient estimates from CFA models.*

Table D11. Association between land fragmentation and time allocation on farming activities

Variables	(1) Women's time allocated to farming	(2) Men's time allocated to farming
Land fragmentation	17.775***	13.520**
	(3.074)	(6.004)
Woman age	-0.007	5.481***
	(0.478)	(0.895)
Woman married	-4.183***	-0.247
	(1.379)	(1.971)
Woman Bangladeshi	27.343	-30.890
	(21.381)	(40.178)
Woman Muslim	-21.104***	-18.352
	(8.061)	(15.709)
Woman Bangladeshi	36.941**	-41.625
	(15.424)	(25.386)
Household size	-3.775	-5.918
	(3.349)	(6.508)
Age head	0.473	-4.451***
	(0.377)	(0.769)
Male head	-117.862***	92.696**
	(28.551)	(45.612)
Married head	14.660	138.258**
	(32.771)	(54.411)
Education head	-1.252	-4.909***
	(1.033)	(1.827)
Number of dependents	0.092	6.067
	(4.777)	(8.782)
Land amount	-4.490	26.692*
	(7.751)	(14.410)
Per capita asset (Ln)	-1.476	-7.461
	(4.018)	(7.186)
Flood dummy	29.283	35.035
	(24.374)	(45.138)
Drought dummy	2.543	-19.036
	(11.822)	(22.369)
Distance to market (Kilometre)	3.586	2.766
	(2.951)	(5.129)
Local level infrustructure index	-15.292	37.931
	(16.915)	(30.787)
Khulna	-8.604	3.506
	(9.099)	(17.645)
Satkhira	33.846***	68.021***
	(10.428)	(19.872)
Constant	136.827**	159.011
	(65.029)	(96.893)
Observations	699	690
R-squared	0.177	0.199

*Notes: *** p < 0.01, **p < 0.05, * p < 0.1; Robust standard errors in parentheses; Coefficient estimates from OLS models.*

Table D12. Association between land fragmentation and crop productivity, and production diversity

Variables	(1) Crop productivity	(2) Number of species
Land fragmentation	-6.487	1.281***
	(4.963)	(0.053)
Household size	-1.497	0.000
	(4.237)	(0.043)
Age head	0.056	0.003
	(0.447)	(0.004)
Male head	-19.119	-0.298
	(29.306)	(0.225)
Married head	21.864	0.454
	(30.305)	(0.347)
Education head	3.386**	-0.009
	(1.401)	(0.012)
Number of dependents	0.318	0.018
	(5.757)	(0.053)
Land amount	-30.305***	-0.171
	(11.067)	(0.116)
Per capita asset (Ln)	13.115**	0.190***
	(5.878)	(0.051)
Flood dummy	-0.647	-0.335
	(26.983)	(0.255)
Drought dummy	-29.923**	0.048
	(11.757)	(0.184)
Distance to market (Kilometre)	16.199***	0.051
	(4.523)	(0.035)
Local level infrustructure index	72.734***	-0.185
	(26.237)	(0.201)
Khulna	118.451***	-0.160
	(11.769)	(0.131)
Satkhira	92.252***	0.216*
	(11.744)	(0.126)
Constant	-40.438	-0.619
	(65.525)	(0.613)
Observations	720	720
R-squared	0.178	0.587

*Notes: *** p < 0.01, **p < 0.05, * p < 0.1; Robust standard errors in parentheses; Coefficient estimates from OLS models.*