A Geospatial Impact Evaluation of Stress-Tolerant Rice Varieties in Flood Prone Bangladesh

A Geospatial Impact Evaluation of Stress-Tolerant Rice Varieties in Flood Prone Bangladesh

by

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Dedicated

To My Parents,

Dewan Abdul Mazid and Rebeka Sultana,

Whose love and sacrifice have brought me here.

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Abstract

In Bangladesh, climate change poses a serious threat to agricultural production, with an increasing number of catastrophic floods in recent years that have led to extensive crop damage and food insecurity among households. In response, Bangladesh has introduced stress-tolerant rice varieties (STRVs) that can withstand flooding, allowing farmers to continue cultivating crops even in submerged fields. This study uses three years of panel data from rural Bangladesh to assess the impact of STRV adoption on household well-being. The findings reveal a significant upward trend in the adoption of STRVs, rising from approximately 8% in 2014 to a substantial 22% in 2022. This increase in adoption has resulted in a significant increase in average rice yields. Notably, STRV adopters have significantly higher yields compared to non-adopters. We demonstrates that all flood measures, including maximum flooding, mean flooding, the area under the curve (AUC) and neighborhood flooding, cause a reduction in rice yields. However, from TWFE analysis we find adopting STRV can mitigate this loss and positively influences rice yield. But from the TWFE-IV model we could not find any strong evidence to prove the insights of TWFE model. Also, we do not observe any yield benefit from STRVs in a flood-free conditions. These findings remain consistent regardless of the data set (household panel data or plot data). Acknowledging certain limitations, including sample size and study duration, is crucial. This research emphasizes the importance of adopting STRVs as a strategy to address the detrimental consequences of climate change on agricultural productivity in Bangladesh. By embracing STRVs, developing countries like Bangladesh can enhance resilience against recurrent floods, and ultimately improve the well-being of rural households.

Keywords: STRV Adoption, Impact Assessment, Remote Sensing, Household Welfare

Chapter 1
Introduction

Traditionally, South Asian households have rice in their daily diet as the primary source of carbohydrates. Most of the farmers in this region are smallholder and subsistence in nature, with very little access to off-farm income. They usually store a portion of their own produced rice for household consumption and sell the rest to earn a living. Sometimes farmers need to sell all of the rice to manage any unwanted shocks, which makes rice the most important crop for farmers in South Asia. Since rice farming is highly dependent on weather that causes a significant amount of yield variation; monsoon-driven flood is the greatest threat to it. As a result of early and sometimes lengthy flooding, farmers face a substantial amount of crop loss (Mishra et al., 2015), leading to the research and development of a rice variety that can bypass unfavorable rice-growing environments (Bairagi et al., 2021; Dar et al., 2013).

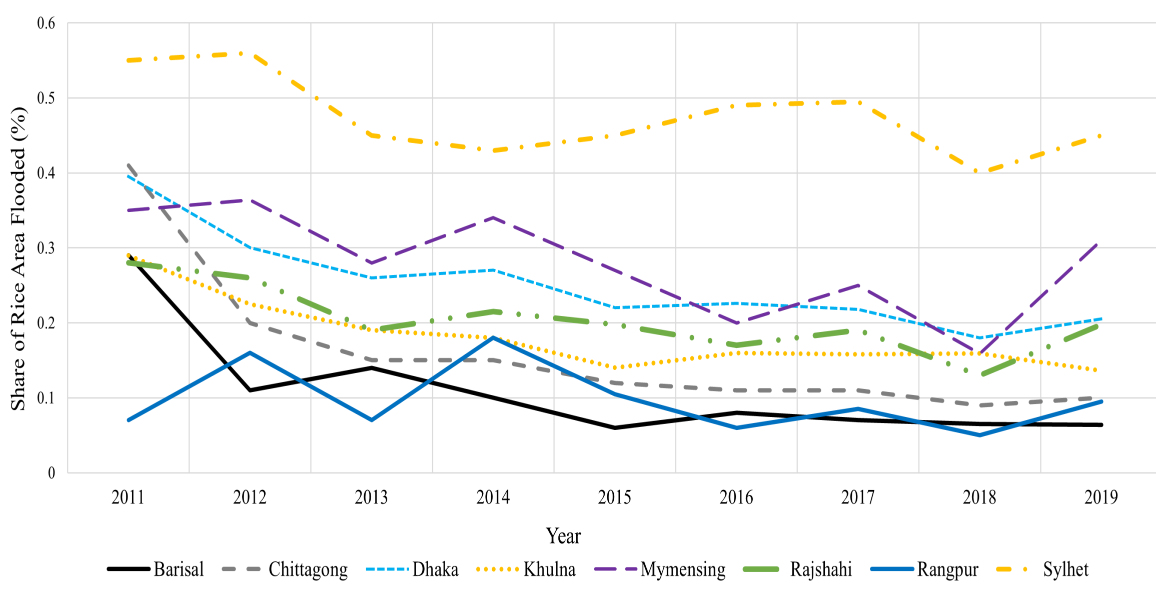
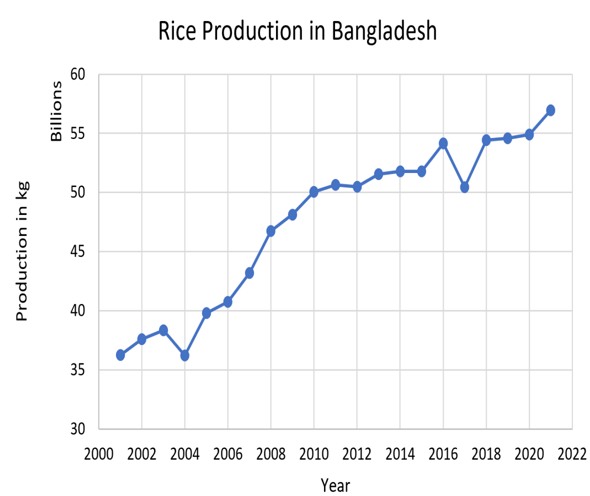


Figure 1.1. Share of Flooded Rice Area in Bangladesh (2011-2019)

Figure 1.1[1] shows that each year, all divisions (largest administrative unit) within Bangladesh encountered varying degrees of flooding, which causes substantial crop damage and poses a significant threat to food security in the country. To cope with the rising challenges of climate change and the challenges associated with feeding a growing population, the International Rice Research Institute (IRRI) developed and promoted Stress[2] Tolerant Rice Varieties (STRVs). STRVs are bred for using in regions that are exposed to specific abiotic stresses, such as submergence, drought, or extreme temperature. Thus, diffusion and adoption must be considered for the particular context where the technology is relevant, rather than for an entire region. In this study, we focus on adoption in flood-prone rice-growing regions of Bangladesh during the Aman season (planted in June-July and harvested in November-December). In the Aman season, farmers face more crop loss due to natural disasters like flood (Bairagi et al., 2021; Khan and Roy, 2020).



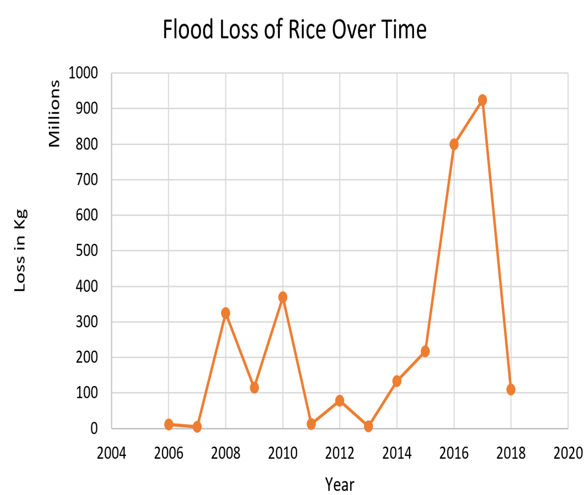


FIGURE 1.2. Rice Production and Loss Due to Flood in Bangladesh Over Time

The rice production in Bangladesh data in Figure 1.2 comes from FAO (2022), and the loss of rice due to flood data comes from several agricultural statistical yearbook from

[1]Rice area data come from MODIS composite products such as the 8-day 500m resolution while flood data comes from Dartmouth Observatory analysis of daily MODIS 250Share m images. Images are aggregated up to district level and converted to area (ha) values. District values are then aggregated to the Division-level.

[2]Stress refers to some unfavorable condition which affects the overall plant growth and development (Lichtenthaler, 1998)

BBS (2022, 2021, 2018, 2012). The rice production trend reveals that, every year there is an increase in production of rice with an exception in 2004 and 2017. The reason of this exception for 2017 is visible in the right hand side graph where there is a peak in loss of rice due to flood. Figure 1.2 summarize that though there is an overall upward trend in rice production, flood damages that production significantly.

Flood-tolerant rice varieties exhibit remarkable adaptability through the utilization of various mechanisms, including aerenchyma formation [3], submergence-tolerant roots, and resilient plants, enabling them to thrive even in submerged conditions. These varieties, developed through conventional breeding techniques and genetic engineering, offer substantial advantages, such as reducing the detrimental impacts of flood-induced crop loss, achieving better yields in flood-prone regions, and ultimately improving food security.

The aim of the first-generation STRV was to manage the lower yield only. As time passes, the demand for only high yielding rice variety has changed and the new generation of STRV is now available in the market to provide better rice production and to fight against biotic and abiotic stresses (Hossain et al., 2006). Different researches have argued that adoption of STRV can ensure a better yield compared to a traditional rice variety (Bairagi et al., 2021; Takahashi et al., 2020; Islam et al., 2019; Emerick et al., 2016). However, some studies criticize the argument that productivity and yield can differ depending on demographic regions and farmers' socioeconomic characteristics (Zeng et al., 2017; Awotide et al., 2016; Mottaleb et al., 2015), which makes the existing knowledge about the impact of STRV adoption patchy. Regardless of the productivity comparison Zeng et al. (2017); Awotide et al. (2016) found an increase in adoption rates. This increase in adoption results in a positive impact on yield resilience and synergies between STRVs and farmers' investments in mechanization and other technologies. Most of these studies have been either descriptive or able to establish causality but with limited external validity (Emerick et al., 2016; Dar et al., 2013).

With these limitations to infer the result at a large scale, previous works have been unable to portray a complete picture of the impact of STRV adoption on household welfare.

[3] Aerenchyma development is a structural alteration that occurs in plants when they are subjected to flooding or conditions with limited oxygen. This adaptation enhances the internal diffusion of atmospheric and photosynthetic oxygen from the aerial portions to the submerged roots, enabling the roots to maintain aerobic respiration. (Yamauchi et al., 2013).

Additionally, previous works fail to deliver clear evidence for returns on investment as there has been no systematic impact evaluation at scale. To address this knowledge gap, we propose to answer the following research question:

- Does increased adoption of STRVs result in an increase in household welfare measured in terms of rice yield?

This study generates evidence that currently does not exist on the impacts at large scale and the impact of STRVs on several household livelihood outcomes.

Prior to the release of the new round of Rice Monitoring Survey (RMS) data which we use for this study, we pre-specified our analysis and archived a pre-analysis plan (PAP) publicly on Open Science Foundation[4] *(OSF)*. In the PAP, we outline the data, variables, empirical specifications, and hypotheses used in this analysis. Also, we explain how we generate variables that we use to measure the impact of STRV adoption on rice yield. We outline our research question and the empirical strategies that we use to address it. Pre-specifying these components of the research before conducting any analysis mitigates the opportunity to cherry-pick, HARK, or p-hack results.

We find a significant increase in the adoption of STRVs, rising from approximately 8% in 2014 to 22% in 2022. This rise in adoption has resulted in a notable increase in average rice yields. Upon conducting a descriptive analysis, we find that farmers who adopted STRVs had significantly higher yields compared to non-adopters. Using household-level panel data and a Two-Way Fixed Effects (TWFE) model reveals that a variety of different ways to measure flooding all contribute to a loss in rice yield. Moreover, we find a strong evidence indicating that STRVs are effective in mitigating yield loss during flood events, as compared to non-STRVs. We also use plot-level data and find results which are mostly consistent with the original analysis with household-level panel data. However, in a TWFE-IV model using the household-level panel, we find no statistically significant evidence supporting the same conclusion as the TWFE model using household-level and plot-level data. Overall, these findings, highlight the positive impact of STRV adoption on rice yields over time. The study also underscores the adverse effects of various flood

[4] Rafi, Dewan A. A., Anna Josephson, Jeffrey D. Michler, and Valerien Pede. 2023. "Impact of Stress Tolerant Rice Varieties Adoption in Flood Prone Regions of South Asia." OSF. February 9. DOI:10.17605/OSF.IO/YE7PV.

measures on yield, while emphasizing the effectiveness of STRVs in mitigating such losses during flood events.

Chapter 2

Literature Review

The introduction of STRVs involves a multifaceted approach aimed at improving food security, minimizing the adverse impacts of crop loss, promoting sustainable agricultural livelihoods through increased yields (Byerlee, 1996), and building adaptive capacity to climate change-induced challenges, particularly the amplified frequency and intensity of stress events. Using a combination of traditional cross-breeding methods and advanced genetic engineering, the development of STRVs offers a promising and imperative avenue to mitigate risks of crop loss and strengthen agricultural resilience in stress-prone regions (Sevanthi et al., 2019).

Studies conducted in Bangladesh by Bairagi et al. (2021) focusing on flood-tolerant varieties and by Takahashi et al. (2020); Islam et al. (2019); Asfawa et al. (2016); Gauchan et al. (2012); Mendola (2007); Evenson and Gollin (2003) highlighting modern rice varieties have found a significant positive impact of their adoption on yield, profit, and rice consumption. These findings are consistent with studies by Zeng et al. (2017); Awotide et al. (2016); Hossain et al. (2006), which also reported similar positive outcomes and a high adoption rate of flood-tolerant rice varieties. The increase in crop production resulting from the adoption of STRVs have important implications for household-level food consumption and poverty reduction.

Improved rice varieties have been found to reduce production risks during adverse weather conditions, as highlighted by Emerick et al. (2016), who further emphasize that there is no yield penalty under normal weather conditions. STRVs mitigate the downside risks by enhancing strain-specific extreme weather tolerance capabilities. This highlights the significance of STRVSs in ensuring stable and resilient crop production and efficiency, irrespective of varying weather conditions. Furthermore, studies by Mishra et al. (2015); Mottaleb et al. (2015) reveal that increased abiotic stress reduces farmers' technical efficiency, leading to substantial yield losses. In a similar vein, Dar et al. (2013) quantify the vulnerability of rice to flood damage in India and the potential of STRVs to transform rice production. These studies emphasize the crucial role of STRVs in minimizing yield losses and improving overall agricultural productivity. Thus, STRVs have the potential to enhance farmers' resilience in the face of abiotic stress and contribute to regional and national sustainable agricultural development.

The current state of STRV adoption might vary in different regions, socioeconomic class of farmers, educational attainment of each individual along with farming type. Using instrumental variable regression with farm-level data, Sanglestsawai et al. (2014) provide strong evidence that poor smallholder farmers feel the need to adopt modern and improved crop varieties. This suggests that improved crop varieties can be considered a "Pro-Poor" technology. As the majority of rice farmers in South Asia are poor and less educated, there is a discrepancy between poor and wealthy farmers, with the latter gaining early access to modern farming techniques, hampering overall economic development (Campenhout, 2021). Bridging this gap and promoting the adoption of STRVs among poor farmers are crucial to achieving equitable agricultural development and poverty reduction.

With changing rice production scenarios due to climate change, farmers in Bangladesh and around the world are increasingly interested in adopting new and improved rice varieties. However, the first generation of modern rice varieties were not as productive compared to the second and third generations (Hossain et al., 2006), as their main goal were to manage lower yields. However Pandey (2012) criticizes these findings. The goal has now shifted to developing varieties that ensure biotic and abiotic stress tolerance while achieving higher production. This highlights the evolutionary nature of the development of rice varieties and the need for continuous innovation to address emerging challenges. By adopting STRVs, farmers can better adapt to changing environmental conditions and ensure their agricultural productivity.

Farm-level decision-making processes are heterogeneous in nature and influenced by a wide range of socioeconomic and plot-specific factors (Olagunju et al., 2020), and estimating and understanding these processes can be challenging. Factors such as public interventions (Devereux, 2007) and the dissemination and extension of region-specific policies (Olagunju et al., 2020; Zeng et al., 2017; Awotide et al., 2016) have been suggested to improve the adoption of STRVs, particularly among poor farmers. The influence of early adopter neighbors, as demonstrated by Yamano et al. (2018), sheds light on the importance of information flow in spreading the impact of adoption among farmers. These findings underscore the importance of targeted and customized strategies to promote the adoption of STRVs and facilitate knowledge transfer in agricultural communities.

In this study we aim to contribute significantly to the current knowledge base by extending our understanding of the impact of adoption of STRVss in Bangladesh. Using rich panel data, our empirical methodology seeks to establish a causal relationship between STRVs adoption and its impact on farmers' household welfare. Understanding the complex dynamics of adoption decisions, the factors influencing adoption rates and the subsequent impacts on farmers' well-being is essential for designing effective policies and interventions that promote sustainable agricultural development in stress-prone regions.

Chapter 3

Data

3.1 Brief Description of the Data

3.1.1 Data Source: Rice Monitoring Survey (RMS)

For this study, we used Rice Monitoring Survey[1] *(RMS)* data which had three rounds, 2014, 2017, and 2022. Throughout different rounds, the questions were the same except some minor changes in time. We kept the participants the same to create a balanced household panel.

Our balanced panel data covered the whole country - six divisions, namely Barisal, Dhaka, Khulna, Chittagong, Rajshahi, and Rangpur. There are three levels of data in the RMS. The levels are as follows:

- **Household data**: includes all household-related information such as demographics, assets, animal ownership, household membership with different organizations, access to electricity, farmers' opinions on different stress such as flood, drought, and salinity, and the availability of rice seed mini kits.
- **Plot data**: includes information about plots and varieties planted in a specific plot, such as, plot size, tenure of the plot along with current accessibility, land type. We also use remote sensing data to proximate rice yield and flood measures.
- **Crop data**: includes seasonal crop data. More specifically which rice variety was planted in which season, methods of planting, damage of crops by different abiotic shocks such as flood, drought, salinity, total production and spending of the yield in different sources, estimates of inundation and most recent flooding year.

Since we are using RMS data, it is worth mentioning the sampling process briefly. RMS uses a cluster sampling method for the survey. The sampling process has three clusters:

[1] Takashi, Y. (2017). Rice Monitoring Survey: South Asia (Version V1) [Dataset]. Harvard Dataverse. https://doi.org/10.7910/DVN/0VPRGD

division, district, and village. This survey used the list of census village in 2013 as the sampling frame. Because we select a fixed number of samples from a village, households living in small villages have a larger probability of being selected than households who live in large villages. Without accounting the village population size, the estimated statistics will not be representative of the target population. To correct the potential biases due to the sampling design, we use survey weights that take the clustered design into account. The weights are equal (or proportional) to the inverse of the probability of being sampled. Thus, a household living in a larger village will have a larger weight than a household living in smaller village. The weights could be considered as the number of households that the sample households represent. In our survey, households living with large rice area are more likely to be sampled than households living in smaller rice areas thus having smaller weights.

We construct a strongly balanced panel data set by using data collected during the 2014, 2017, and 2022 rounds. The data set only includes households that are interviewed in all three years using nearly identical questionnaires. The sampling distribution by division and year can be found in the appendix section (Table 7.1). The analysis specifically focuses on Aman season rice data since it is the most flood-prone rice season in Bangladesh. To ensure data relevance and accuracy, we exclude households that did not cultivate rice in the last 12 months and during Aman season. Furthermore, data points lacking key variables such as production or plot size are disregarded. By applying these rigorous criteria and practices, we construct a robust and reliable data set for analysis.

3.1.2 Data Source: Remote Sensing

In our study, we have collected data using satellite technology to understand the flooding situation in Bangladesh. This data includes four different measurements related to floods. In the first two rounds of the RMS, GPS coordinates were only collected for households only and not for rice plots. In the third round of the RMS, GPS coordinates were collected for both the household and the rice plots. This gives rise to a situation in which we know household locations in all three rounds but plot locations in only the last round. Since plot boundaries move from season-to-season and farmers buy, sell, and rent plots, we cannot use the GPS location of a given plot in 2022 to determine the location of a plot in the previous rounds. Because many plots in Bangladesh are close to the homes of farmers, we could use household GPS location as a proxy for plot location. However, some plots remain far away from the households and may be at a lower latitude than the house. In these cases, if we use the household GPS coordinates as a proxy of plot level GPS, it would not be accurate. To overcome this limitation, we compare 2022 flood data for the household with that from the plots to test if household flooding is an accurate proxy. We end up using household GPS coordinates to proxy for plot locations and construct historical flooding information for each household.

The process of collecting remote sensing flood data involves several steps. Initially we use the Google Earth Engine platform to extract data. In our case we have used Convolutional Neural Long Short-term Memory Network (CNN-LSTM) model where we have used the combination of Sentinel 2 and MODIS 500m satellite data. First, using Google Earth Engine we compile various data pertaining to water bodies in Bangladesh. Then using the CNN-LSTM model in the Global Flood Database[2] (GFD), we mask out permanent water bodies like rivers, ponds, and lakes, resulting in the identification of temporary water bodies. Leveraging this dataset of temporary water bodies, we proceed to acquire historical flood-related data spanning from 2001 to 2022. Then we combine the flood related data with the household panel data.

3.2 Variables

The RMS captures numerous variables, most focused on farming, but includes some socio-economic indicators. Our analysis relies on a subset of these variables. Specifically, we will use the following:

- **Yield:** calculated from the RMS for a specific plot in a given season. Yield is total rice production in kg divided by plot size in hectare.
- **Maximum Flooding:** from the remote sensing data we get the maximum portion of land affected by flooding during monsoon season of a year. We collect historical

[2]Tellman, B., Sullivan, J. P., Kuhn, C. C., Kettner, A. J., Doyle, C. S., Brakenridge, G. R., Erickson, T., & Slayback, D. (2021). Satellite imaging reveals increased proportion of population exposed to floods. Nature, 596(7870), 80–86. https://doi.org/10.1038/s41586-021-03695-w

flooding data for all our flood measures from 2001. We define the "max flood" variable as the highest amount of land that floods in a year and actively record it in our analysis. The unit of measurement for this variable is the maximum percentage of land inundation.

- **Neighborhood Flooding Duration:** the flood data set provides us with the flooding for all households from 2001 to 2022, which we use to calculate the neighborhood flooding. We organize the previous rounds of RMS data by village, where each village comprises around ten households. To determine the neighborhood flooding for a specific household in a village, we calculate the sum of the maximum proportion of land inundation for all households in that village and subtract the individual values from that sum. Then to get the normalized neighborhood flooding value, we divide the neighborhood flooding by the total number of households from that village.

- **Mean Flooding:** each household in our sample has more than one plot with some exceptions. Each plot has a different level and proportion of inundation over time. We calculated the average inundation of all plots of a household during the monsoon season. The unit of measurement for this variable is the average percentage of land inundation.

- **Area Under the Curve (AUC):** using the historical flooding experience of each household, we calculate the area under the curve (AUC) function. We integrate the fraction of land inundated during the monsoon period with respect to time t and multiply with the time span value for a satellite image, which is 8 days in our case.

- **STRV Adoption Dummy:** it is necessary to determine STRVs adoption in the households. The RMS data provides information regarding cultivating Aus, Aman, and Boro rice seasons. Using administrative information about rice variety releases from IRRI and Bangladesh Rice Research Institute (BRRI), we create a dummy variable for STRV adoption where 1 represents the adoption of STRVs and a 0 value represents non-adoption.

- **Lag of All Flood Measures:** we calculate 13 years of lag value for all flood measures described above for all households. The selection of this lag period entirely depends upon the data availability.

3.3 Data Limitation

In this study, we use RMS data from IRRI and the flood measures we collect from satellite image analysis. This data source has some limitations. First, in the 2022 round, we could not find all 1,500 samples from previous rounds since there is a long gap between our survey in 2017 and 2022. During this time, some respondents died, and some migrated to new places. Moreover, a household might produce rice in 2014, but in 2017, they might not produce the same. Then, we drop those households to build a strongly balanced panel data (see Table 7.1). Thus, we have fewer observations. Second, there are no plot GPS coordinates in 2014 or 2017. Even in 2022, when we collected plot-specific GPS, we could only collect the data for the most valuable and easily accessible plots. Sometimes, farmers were unwilling to take the enumerator to the distant plots. Because it is extremely time-consuming, especially when farmers have large numbers of plots, and those plots are located miles away from each other. So, we only have data about four plots for each farm household cultivating rice in the last 12 months.

Third, as mentioned previously, we can not track each plot over time. In Bangladesh, land ownership changes very frequently. For example, a landowner could buy one in 2014, rent out that land in 2017, and sell that in 2018. In this case, we have data until 2017. Hence, in the 2022 round, that land will not be included since the previous owner sold the land before the initiation of our 2022 round. Also, a farmer might have a plot that is flood-prone. The farmer then sells that land and possibly buys new land in a better position. In both examples, we can not track plots over time. This means we have a household-level panel data set but we are unable to construct a plot-level panel. As a robustness check, we conducted analysis on the pooled plot data and compare results to the household-panel. Fourth, we do not have any input-output price-related data. We only have the total amount of seed used to cultivate, total rice production, and spending on the produced rice in different sectors, such as saved for future use, consumed, sold, and used as a loan payment method. This lack of price data limits our ability to measure household welfare in income and expenditure form. Another way to calculate household welfare is the asset index. However, we need data about the age of the asset holding and the buying price of that asset. Thus, it is impossible to calculate the asset index as well. Last, the data integration process makes the dataset compact. This means we identify a household under STRV cultivation if that household has at least one STRV plot. Then, we take the average yield and flooding for all STRV plots and disregard other non-STRV plots. On the other hand, if there is no STRV plot in a household, then we identify that household as under non-adoption and take the average. So, our household data is more compact and thus has less variation than if we conducted the analysis at the plot-level.

Chapter 4

Methods

4.1 Conceptual Framework

Our Conceptual framework (Figure 4.1) begins with change rooted in the development and diffusion of STRVs. There is heterogeneity in adoption of any farm technology as each farmer optimizes their farm production decision subject to local conditions and constraints. Given that our study focuses on rural regions, farm production decisions will determine the amount of labor available to allocate outside the farm.

Having decided whether to produce rice, the farmer then assess the plot characteristics: Prone or not prone to flood. In our study we only focus on the appropriate context which refers to the land is prone to flood. At this point the farmer has two options. Either the farmer can adopt STRVs or dis-adopt. Having made the adoption decision, plots experience or do not experience a flood event represented by the black box in the Figure 4.1.

If inundation does not occur, the farmer will get typical yields. However, if flooding does occur, the path diverges for households who adopted or did not adopt STRVs. Although all plots in a given village experience different degrees of inundation, farm production outcomes vary depending on the adoption status of STRVs.

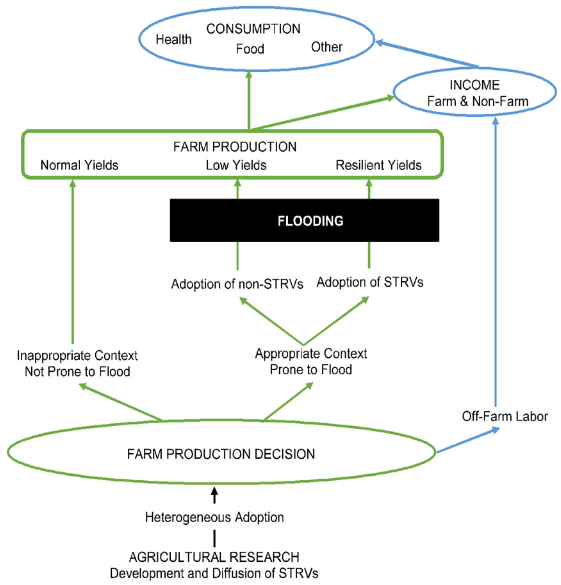


Figure 4.1. Impact Pathway - Theory of Change

Farm production allows the farmer to decide consumption. Farmers who adopt STRVs and experience flooding will have higher yields and, therefore, higher income and consumption than farmers who did not adopt STRVs and experienced a similar flood event. The increased farm production, income, and consumption directly tie to increased income and food security, as well as the cross-cutting theme of mitigating and adapting to climate change.

4.2 Empirical Model

The RMS data allows us to use standard panel data techniques to control for time-invariant household unobservables and compare changes in outcome within a household for those who adopt or dis-adopt STRVs. However, panel data methods are unlikely to allow us to identify the causal impacts of STRVs. Because the decision to adopt or dis-adopt will likely vary over households and time. To address this endogeneity arising from time variant characteristics of households, we use an instrumental variable (IV) strategy that relies on the historical flooding experience, which we have discussed in chapter 5.

To answer the research questions, we employed two-way fixed effect and Instrumental Variable (IV) model using a panel data that matches RMS household data to the pixel-level remote sensing data. The goal of theis analysis is to measure the causal effects of adoption of STRVs on rice yield as a proxy of household welfare. As part of our identification strategy, we will also use the remote sensing data as an inputs to the analysis. This micro-level analysis relies on two different models to estimate causal effects. One is the Two Way Fixed Effect Model (TWFE) and another one is the TWFE-Instrumental Variable (TWFE-IV).

4.2.1 Two Way Fixed Effect Model (TWFE):

In this study the TWFE model is estimated as:

$$Y_{it} = \sum_{i=1}^{n} \alpha_i + \sum_{t=1}^{r} \delta_t + \gamma STRV_{i,t} + \omega FLOOD_{i,t} + \beta(STRV_{i,t} * FLOOD_{i,t}) + \epsilon_{i,t} \quad (4.2.1)$$

The TWFE approach incorporates household-level fixed effects (α_i) and time-specific fixed effects (δ_t). The model uses a dummy variable, $STRV_{i,t}$, to denote the STRV adoption status of a household at a given time period, where a value of 1 signifies adoption and 0 represents non-adoption. The outcome variable, Y_{it}, captures household welfare measured as rice yield. The interaction term between STRV adoption status and flooding will capture the combined effect on the outcome variable. This approach enables us to assess the joint impact of these two factors on rice yield and to determine whether the effect of STRV adoption is contingent upon the presence of flooding. To explain the effect more clearly, we will use the linear combination of the parameters from Equation 4.2.1.

4.2.2 TWFE-Instrumental Variable (TWFE-IV):

Similar to the TWFE, this model controls for individual and time fixed effects, but also uses an instrumental variable to address endogeneity concerns arising from time variant attributes of households in the relationship between adoption of STRVs and rice yield. In the first stage, we estimate:

$$STRV_{i,t} = \sum_{i=1}^{n} \alpha_i + \sum_{t=1}^{r} \delta_t + \beta_1 Lag\ of\ Flooding\ _{i,t} + \mu_{i,t} \tag{4.2.2}$$

where i and t represent the individual household and time period. $Lag\ of\ Flooding_{i,t}$ is our instrument and use to predict STRV adoption. The idea is that the $Lag\ of\ Flooding_{i,t}$ affects the adoption decision directly but does not directly affect the rice yield, conditional of contemporaneous flooding, time and household fixed effects.

To introduce an instrument for each households i at time t, we use Inverse Mills Ratio (IMR) technique from Michler et al. (2019); Wooldridge (2003). The IMR is derived from the cumulative distribution function of a standard normal distribution, and represents the ratio of the density function to the cumulative distribution function. The reason of introducing the IMR into our TWFE-IV model is to tackle any sample selection bias which provides a way to correct for the potential biases and improve the accuracy of regression estimates in the presence of selection bias and endogeneity. This process includes several manual steps before proceeding to second stage IV method. After estimating equation 4.2.2, we calculate the linearly predicted value of $STRV_{it}$. We then calculate the IMR from the predicted STRV ($\widehat{STRV_{it}}$) value and interacted with different flood measures ($\widehat{STRV_{it}} \times FLOOD_{it}$).

The second stage of the TWFE-IV equation is:

$$Y_{it} = \sum_{i=1}^{n} \alpha_i + \sum_{t=1}^{r} \delta_t + \theta_1 \widehat{STRV_{i,t}} + \nu FLOOD_{i,t} + \theta_2 (\widehat{STRV_{i,t}} \times FLOOD_{i,t}) + \epsilon_{i,t} \tag{4.2.3}$$

Here, $\widehat{STRV_{i,t}}$ is the predicted value from the first stage *(equation 4.2.2)* regression. All other terms are as previously defined.

4.3 Reason for Including Household Level Fixed Effect

The inclusion of household-level fixed effects in the models holds significant methodological importance. By incorporating household level fixed effects, we actively address several crucial considerations in the analysis.

First, including household-level fixed effects allows us to control for unobservable time-invariant characteristics specific to individual households. These unobserved factors may be correlated with both adoption and the outcome variable (yield), potentially leading to biased estimates if we do not account for them properly. Including household fixed effects removes these unobservable household-specific factors so that we can accurately attribute the effect of STRV adoption on yield rather than unobserved heterogeneity that may confound it.

Second, household-level fixed effects actively capture time-invariant household-specific factors that may independently affect yield. These factors encompass various characteristics such as farming practices, infrastructure, or socio-economic attributes, which remain constant over time but may influence yield apart from the flood measures and STRV adoption. By accounting for these fixed effects, we actively control household heterogeneity. This allows us to focus on the within-household variation in flood measures and STRV adoption, leading to more precise and reliable estimates of their effects on yield. Moreover, including time fixed effects actively alleviates potential endogeneity concerns arising from unobservables that differ over time but are constant across households.

4.4 Assumptions of Instrumental Variables

We used the instrumental variable approach to take the omitted variable bias or unobserved heterogeneity into consideration, where simply the unobserved variable leaves into the error term but rather than using the general OLS model, the instrumental variable approach is utilized. Angrist et al. (1996) explained five assumptions for an instrumental variable, that we follow in our study. The assumptions are as follows:

1. **Stable Unit Treatment Value Assumption (SUTVA):** The instrument affects

only the subject and there are no different versions of the instrument that have different effects. Mathematically:

$$\forall d \in D, \forall i \in I : \text{if } D_i = d \text{ then } Y_i(d) = Y_i$$

where D represents the instrument, i shows the individual and Y_i is the outcome variable of each indidvuals. In other words, SUTVA states that the potential outcome for a unit is not influenced by the treatment status of other units. In the context of this study, SUTVA imply that the previous experience of flooding in one household does not affect by the lag values of flooding of other households. This is because the lag of flooding is a unit-level characteristic, and SUTVA states that unit-level characteristics are not influenced by the instrument value of other units.

- **Exogeneity of the Instrument**
  - *Unconfoundedness of the Instrument:* The unconfoundedness of the instrument can be expressed mathematically as follows:

    $$Corr(Z, U) = 0$$

    where Z is the instrumental variable, U is the unobservables that affect the outcome variable. The instrumental variable is not correlated with any unobservables that affect the outcome. That means, the distribution of the previous experience of flooding is correlated with STRV adoption through which we predicted our outcome variable yield.
  - *Exclusion Restriction:* The exclusion restriction can be expressed mathematically as follows:

    $$E(Z|X, Y) = 0$$

    where X is the STRV adoption, Y is the rice yield, and E refers to the expectation.There is no direct relationship between the previous flooding experience and rice yield. The only relationship is through the STRV adoption.
- **Monotonic Effect of Probability of Flooding on STRV Adoption:** This can be expressed mathematically as follows:

  $$\tfrac{d}{dP(FLOOD)}(X) > 0$$

where X is the STRV adoption, *P(FLOOD)* is the lag value or previous experience of flooding. In other words, the monotonic effect of previous flooding experience on STRV adoption assumption states that the STRV adoption is an increasing function of the lag value of flooding. So, an higher degree of experience of flooding motivates farmer to adopt STRVs. It is plausible that the adoption of STRVs provides a clear incentive and no disincentive to take the treatment.

- **Non-zero Effect of Instrument on Treatment:** To fullfill this assumption, the first stage estimation coefficient for previous flooding experience or simply lag of flood should be not equal zero. In other words, $\widehat{\beta_{1_{Z,X}}} \neq 0$ in equation 4.2.2

Chapter 5
Results

5.1 Summary Statistics

In this section, we present the summary statistics of the variables explained in chapter 3 section 3.2 at both household and plot levels. We conduct this analysis for three specific years, namely 2014, 2017, and 2022. Additionally, we examine the data based on the adoption status of STRV, distinguishing between STRV and non-STRV cases. This approach allows us to gain insights into the overall trends across the years and differences between the two adoption groups. Mann-Whitney tests and Pearson tests reveal the mean differences between groups and periods.

5.1.1 Summary Statistics: Household Level

Table 5.1 summarizes key variables by STRV adoption status, encompassing 2,874 observations. The data reveals that 87.4% of the cases are classified as non-STRV, while 12.6% are STRV adoption cases. Statistical tests show significant differences in the distribution across the years and various variables, such as the average Area Under the Curve (AUC), average of maximum values of inundation during the monsoon season, and average yield. Moreover, STRV adoption is translated into higher average yields. However, the two adoption groups have no statistically significant distinction in plot size. Curiously, these findings demonstrate that STRV adopters tend to cultivate rice in less flood-prone areas, which does not make much sense given the technology is to mitigate damage due to flooding. In addition to being less susceptible to flooding, the summary statistics show that, on average, adopters have higher yields than non-adopters. This may be evidence of sample selection bias, with skilled farmers being more likely to adopt the new technology.

TABLE 5.1. Summary Statistics of Key Variables by STRV Adoption at Household Level

	Adoption			
	Non-STRV	STRV	Total	Test
N**	2,513 (87.4%)	361 (12.6%)	2,874 (100.0%)	
Year**				
2014	884 (35.2%)	74 (20.5%)	958 (33.3%)	<0.001
2017	878 (34.9%)	80 (22.2%)	958 (33.3%)	<0.001
2022	751 (29.9%)	207 (57.3%)	958 (33.3%)	<0.001
AUC*	2.82 (1.84)	2.52 (1.78)	2.78 (1.83)	0.004
Max Flood*	0.33 (0.16)	0.30 (0.15)	0.32 (0.16)	0.002
Mean Flood Value*	0.12 (0.08)	0.11 (0.08)	0.12 (0.08)	0.004
Neighborhood flood*	0.31 (0.14)	0.29 (0.12)	0.31 (0.13)	0.003
Average Yield (kg/ha)*	3,904.04 (1,528.44)	4,574.77 (1,371.38)	3,988.29 (1,525.67)	<0.001
Plot Size (ha)*	0.67 (0.69)	0.64 (0.54)	0.66 (0.67)	0.474

**Mean (Standard deviation): p-value from a Mann-Whitney test.*
***Frequency (Percent %): p-value from Pearson test.*

TABLE 5.2. Summary Statistics of Key Variables by Year at Household level

	Year			
	2014	2017	2022	Total
N**	958 (33.3%)	958 (33.3%)	958 (33.3%)	2,874 (100.0%)
Adoption**				
Non-STRV	884 (92.3%)	878 (91.6%)	751 (78.4%)	2,513 (87.4%)
STRV	74 (7.7%)	80 (8.4%)	207 (21.6%)	361 (12.6%)
AUC*	2.93 (1.87)	2.76 (1.94)	2.66 (1.66)	2.78 (1.83)
Max Flood*	0.32 (0.16)	0.31 (0.17)	0.34 (0.15)	0.32 (0.16)
Mean Flood Value*	0.13 (0.08)	0.12 (0.08)	0.12 (0.07)	0.12 (0.08)
Neighborhood flood*	0.31 (0.14)	0.30 (0.14)	0.32 (0.12)	0.31 (0.13)
Average Yield (kg/ha)	3,993.85 (1,334.52)	3,735.03 (1,569.80)	4,236.00 (1,617.70)	3,988.29 (1,525.67)
Plot Size (ha)*	0.68 (0.73)	0.70 (0.60)	0.60 (0.67)	0.66 (0.67)

**Mean (Standard deviation), **Frequency (Percent%)*

Table 5.2 reveals the mean difference of some key variables based on different years. Specifically, the average AUC, an average of the maximum and mean flood value, and neighborhood flood differ slightly across the years, suggesting some variations in flood patterns in Bangladesh. Additionally, the average yield signifies the differences in agricultural productivity over the years, with 2017 having the lowest yields and 2022 the highest. Also it is clear from Table 5.2 that, STRV adoption has substantially increased over time. The adoption was around 8% in 2014 and increased to 22%.

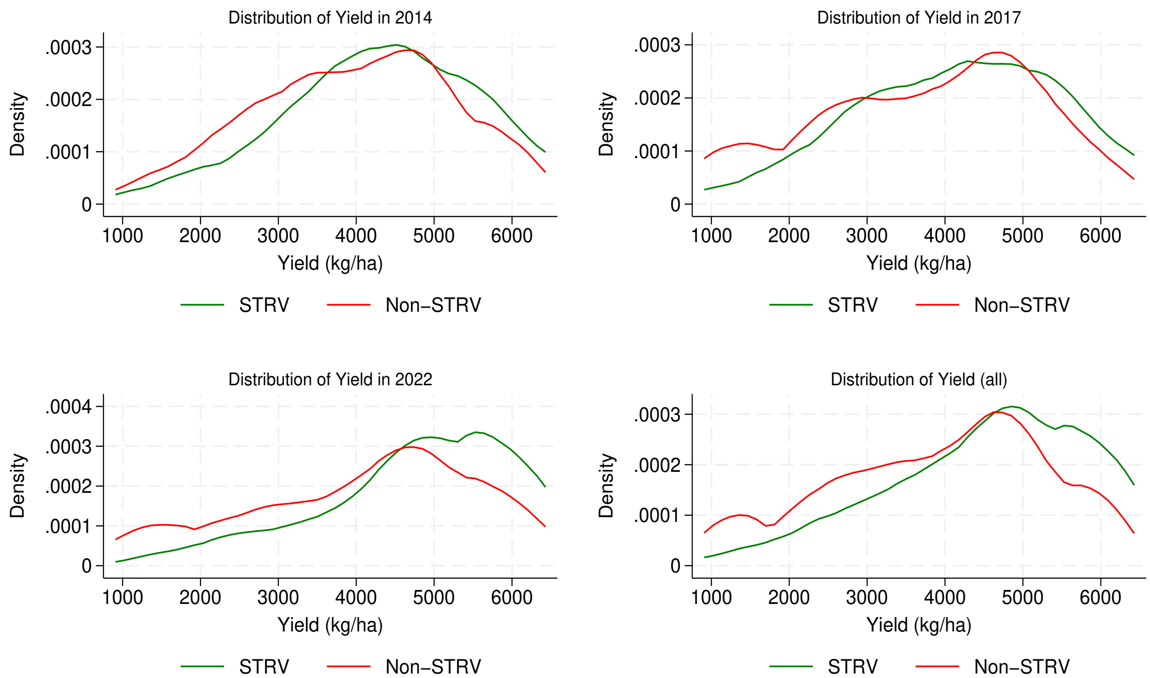


FIGURE 5.1. Distribution of Yield By Year and Rice Variety at Household Level

The kernel density plot in Figure 5.1 illustrates the yield distribution over rice variety type and year. We find that the yield of STRV rice is higher than the non-STRV counterparts over the year. This finding implies that STRV rice demonstrates higher crop efficiency and resilience against environmental factors that can potentially affect yield. The distributional findings align with the descriptive results in Table 5.1 and 5.2. In later sections of this study, we will delve deeper into analyzing the causal effects more extensively.

5.1.2 Summary Statistics: Plot Level

Table 5.3 provides an overview of key variables by STRV adoption status at the plot-level. The analysis reveals that most plots, accounting for 90% of the dataset, are cultivated under non-STRVs, while the remaining 10% represents cases with STRV adoption. Among the non-STRV plots, 34% come from 2014 round whereas 28 and 38 % come from 2017 and 2022 round respectively. Statistical tests demonstrate significant disparities in the distribution, including the average AUC, maximum and average inundation values, and average yield. Additionally, plots under STRVs have higher average yield and the variation of rice yield is statistically different from zero.

Table 5.3. Summary Statistics of Important Variables by STRV at Plot Level

	STRV Adoption			
	Non-STRV	STRV	Total	Test
N**	4,650 (90.0%)	517 (10.0%)	5,167 (100.0%)	
Year**				
2014	1,573 (33.8%)	72 (13.9%)	1,645 (31.8%)	<0.001
2017	1,309 (28.2%)	77 (14.9%)	1,386 (26.8%)	<0.001
2022	1,768 (38.0%)	368 (71.2%)	2,136 (41.3%)	<0.001
AUC*	2.78 (1.95)	2.45 (1.60)	2.75 (1.92)	<0.001
Max Flood*	0.33 (0.17)	0.29 (0.14)	0.32 (0.17)	<0.001
Mean Flood Value*	0.12 (0.08)	0.11 (0.07)	0.12 (0.08)	<0.001
Neighborhood flood*	0.31 (0.13)	0.28 (0.10)	0.31 (0.13)	<0.001
Average Yield (kgha)*	3,992.99 (1,597.91)	4,896.49 (1,432.87)	4,088.41 (1,605.36)	<0.001

**Mean (Standard deviation): p-value from Mann-Whitney test.*
***Frequency (Percent%): p-value from Pearson test.*

TABLE 5.4. Summary Statistics of Important Variables by Year at Plot Level

	Year			
	2014	2017	2022	Total
N(%)	1,645 (31.8)	1,386 (26.8)	2,136 (41.3)	5,167 (100.0)
Adoption				
Non-STRV (%)	1,573 (95.6)	1,309 (94.4)	1,768 (82.8)	4,650 (90.0)
STRV (%)	72 (4.4)	77 (5.6)	368 (17.2)	517 (10.0)
AUC	2.92 (2.01)	2.61 (1.89)	2.70 (1.86)	2.75 (1.92)
Max Flood	0.32 (0.17)	0.31 (0.18)	0.34 (0.16)	0.32 (0.17)
Mean Flood Value	0.13 (0.09)	0.11 (0.08)	0.12 (0.08)	0.12 (0.08)
Neighborhood flood	0.31 (0.14)	0.29 (0.14)	0.32 (0.12)	0.31 (0.13)
Average Yield (kgha)	3,960.61 (1,427.46)	3,798.57 (1,577.13)	4,362.50 (1,699.88)	4,088.41 (1,605.36)

Table 5.4 shows that the mean difference of some key variables based on different years. Specifically, the average AUC, maximum and mean flood value, and neighborhood flood differ across the years, suggesting variations in flood patterns in Bangladesh. Additionally, the average yield signifies the differences in agricultural productivity over the years. Like the results from household panel data, in this case, adoption of STRV increases over time refers to the increasing awareness among farmers.

Figure 5.2, depicts the kernel density plot of rice yield distribution over time and rice variety type. It is clear from the distribution that the yield of the STRV rice variety surpasses that of other varieties. This finding suggests that STRV rice exhibits enhanced crop efficiency and resilience than its counterparts towards environmental conditions that can impact yield. The distributional findings align with the descriptive results presented in Table 5.3 and 5.4. Also, the household panel data shows a similar pattern of yield distribution by rice type over time.

In summary, this section revels the distribution of key variables by rice variety type (STRV and Non-STRV) and year (2014, 2017, 2022). Also, we have discussed plot specific data along with household panel data. The data integration process is slightly different causing a marginal deviation from the household level descriptive statistics. We find, STRV adoption is increasing over time. Additionally, STRVs have a higher yield than Non-STRVs.

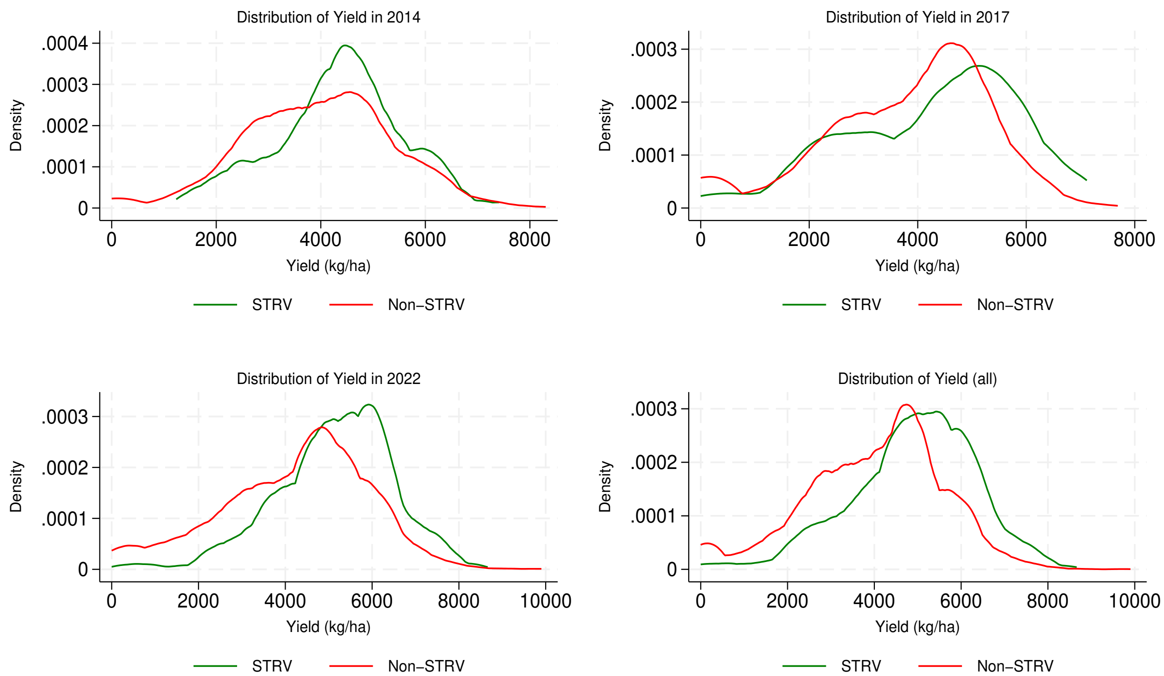


FIGURE 5.2. Distribution of Yield By Year and Rice Variety at Plot Level

5.2 Two-Way Fixed Effect (TWFE) Analysis

This section presents the results obtained from the TWFE analysis. This statistical method enables us to account for time-invariant factors by introducing fixed effects for households and time. By controlling for unobserved heterogeneity and time-specific shocks, we can discern the actual effects of the variables of interest on the outcome variable. The TWFE analysis offers valuable insights into the underlying dynamics and provides robust evidence for the impact of STRV adoption on rice yield. Table 5.5 reports the results from the TWFE model with household and time fixed effect.

To answer our research question we need to look closely to Table 5.6 where we summarize and present the point estimates and the linear combination of the independent variables. In Equation 4.2.1, the coefficient γ captures when farmers adopt STRV and face no flood. This measures the difference of average yields for adopters who experience no flood relative to non-adopter who experience no flood. Across three of the four models the coefficient

Table 5.5. TWFE Models (Equation 4.2.1)

Ln Yield	(1)	(2)	(3)	(4)
Max Flood	-1.646			
	[-2.58,-0.72]			
Adoption × Max Flood	0.293			
	[-0.43, 1.01]			
AUC		-0.244		
		[-0.40,-0.09]		
Adoption × AUC		-0.001		
		[-0.05, 0.05]		
Mean Flood Value			-5.611	
			[-9.11,-2.11]	
Adoption × Mean Flood Value			-0.029	
			[-1.14, 1.08]	
Neighborhood flood				-2.144
				[-3.19,-1.10]
Adoption × Neighborhood flood				0.963
				[0.09, 1.83]
STRV Adoption	0.021	0.126	0.126	-0.178
	[-0.24, 0.28]	[-0.04, 0.29]	[-0.04, 0.29]	[-0.45, 0.09]
Number of Observations	2874	2874	2874	2874
Log Likelihood	-4220.32	-4222.43	-4222.43	-4216.02
Number of Cluster	958	958	958	958
Fixed Effect		Household and Time		

All equations include intercept and dummy variable of year

Values in parentheses include 90% confidence interval. Std. Errors are clustered at household level

γ is positive. But these coefficients are not statistically significant, meaning that, the difference in average yield between adopter and non-adopter is not different from zero. In other words, there is no yield benefit or penalty for adopting STRV when there is no flood.

A second scenario of adoption and flood describes when the farmer does not adopt STRV but face some degree of flooding. From Equation 4.2.1, ω captures this effect. It measures the difference in average yields for non-adopters who experience a flood relative to non-adopters who do not experience a flood. The negative coefficient ranging between -0.24 and -5.61 reflects that there is a negative effect on average rice yield and the difference of yield are significantly different from zero. This result signifies the findings that, non-adopter farmer experience a loss in yield during a flood event.

A third scenario is when a farmer adopts STRVs and experiences. From our TWFE estimation, β captures the difference on yields for an adopting farmer who experiences a flood relative to a non-adopter who faces no flood. The coefficient has a mixed effect on rice yield, sometimes being positive or negative, but is only statistically significant in one of the four regressions. In words, when β is not significant it means adopters who experienced the flood had yields that were no different from non-adopters who did not experience a flood. Simply put, that β is not negative and significant means that farmers growing STRVs have yields that are resilient to flood because they obtained yields equal to those who had no flood at all.

We can also consider two "total effect" scenarios. First, $\gamma + \beta$ measures the overall impact of adoption regardless of flood status. We find all the coefficients are positive ranging between 0.09 to 0.78, and the linear combination when using neighborhood flooding is statistically significant too. This finding means that there would be a yield gain from adoption compared to non-adoption in any flood state. However, for other flood measures, this difference in rice yield are statistically insignificant. Because in this case we are comparing the results between adopters and non-adopters regardless of flood status. Second, $\omega + \beta$ measures the impact of flood regardless of adoption status. From our estimation we find that, for all flood measures, the effect of flood on rice yield regardless of adoption is negative. The coefficient is ranging between -5.63 to -0.25.

The final comparison to be made is between adopters and non-adopters when there is a flood. To answer our research question we need to know the difference between ω and β. We run a F-test to evaluate the mean difference between these two parameters. For all flood measures, this test is positive and significant, meaning that the average yields for non-adopters who experience a flood are significantly less than adopters who experience a flood. Hence, this finding demonstrates the effectiveness of STRV during flood events.

To understand the effect of adoption to different flood intensity, in Figure 5.3 we classify the predicted value of rice yield into different flood categories. The lowest category comprises households with flood values in the bottom 25% of the data whereas the medium and highest flood category consists of middle 50% and top 25% of the entire data set. We find that, in most of the cases, STRV poses a higher yield than the Non-STRVs. Only the highest flood segment for flood mean and area under the curve has slightly different insights, showing that Non-STRV have a better yield. The predicted value of rice yield has a similar pattern compared to the actual rice yield (Figure 7.4). So, our estimation is in line with the actual yield value.

Table 5.6. Summary of Parameters and Point Estimates of TWFE Model

Parameter	Description	Flood Max	Flood Mean	AUC	Neighborhood Flooding
γ	measures the difference in average yields for adopters who experience no flood relative to non-adopters who experience no flood.	0.02 [-0.24, 0.28]	0.12 [-0.04, 0.29]	0.12 [-0.04, 0.29]	-0.17 [-0.44, 0.08]
ω	measures the difference in average yields for non-adopters who experience a flood relative to non-adopters who do not experience a flood	-1.64 [-2.57, -0.71]	-5.61 [-9.11, -2.11]	-0.24 [-0.39, -0.09]	-2.14 [-3.19, -1.09]
β	measures the difference in average yields for adopters who experience a flood relative to non-adopters who experience no flood	0.29 [-0.43, 1.01]	-0.02 [-1.14, 1.08]	-0.001 [-0.05, 0.05]	0.96 [0.09, 1.83]
$\gamma + \beta$	measures the overall impact of adoption regardless of flood status.	0.31 [-0.17, 0.79]	0.09 [-0.007, 0.25]	0.12 [-0.88, 1.08]	0.78 [0.15, 1.41]
$\omega + \beta$	measures the overall impact of flood regardless of adoption status.	-1.35 [-2.14, -0.56]	-5.63 [-0.39, -0.09]	-0.25 [-9.02, -2.25]	-1.18 [-2.0, -0.36]
test $\omega = \beta$ or $\omega - \beta = 0$	measures the difference of average yield between the adopter and non-adopter who experience flood	4.76**	5.43**	5.43**	8.65***

*All models include year dummy and intercept. Values in parenthesis represents 90% confidence interval. Standard Errors are clustered at household level. *,**,*** means value is significant at 10%, 5% and 1% level*

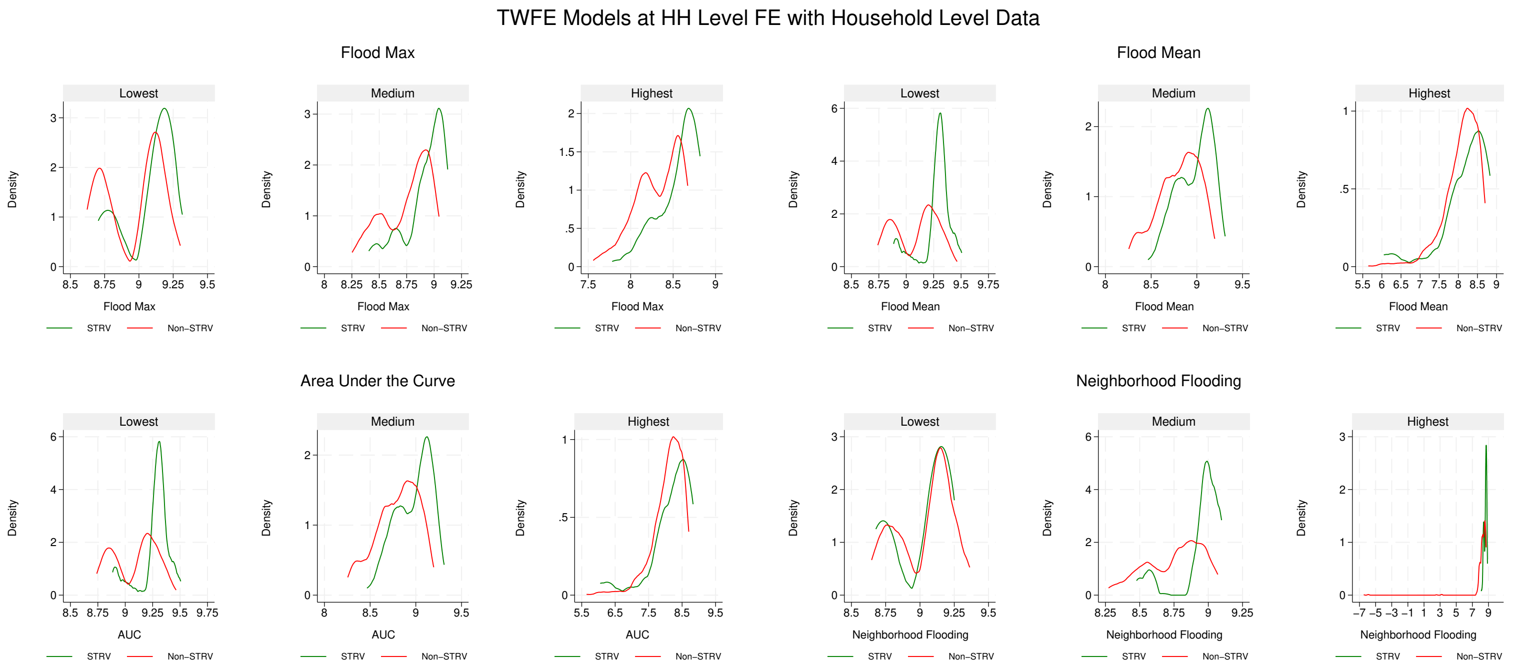


FIGURE 5.3. Predicted Value of Ln Yield from TWFE Models at Household Level

5.3 Two-Way Fixed Effect Instrumental Variable (TWFE-IV) Analysis

In this section, we delve into the results obtained from the TWFE-IV analysis. This approach tackles the endogeneity issue commonly encountered in econometric studies by employing instrumental variables to address potential biases caused by omitted variables or measurement errors. By accounting for the exogenous variation in the instrumental variables, we can establish causal relationships between the predictors and the outcome variable, further strengthening the validity of our findings

5.3.1 First Stage of TWFE-IV Model:

The results of the first stage of TWFE-IV approach is in Table 5.7. Following the Equation 4.2.2 we include the lag of all flood measures up to 13 years as the previous experience of flooding for each households. The selection of lag value is completely dependent on data availability. The main reason behind the inclusion of lag value is very intuitive. Farmers in Bangladesh use their previous years flooding experience (Yamano et al., 2018) and combine that experience with the land type, frequency and amount of rainfall of current year to predict the flooding potentiality in the current year. We have explained this kind of prediction and decision making in our conceptual framework in Section 4.1, Figure 4.1 as the "Appropriate context, prone to flood".

The analysis of the first stage equation reveals that previous flooding experience demonstrates a robust explanatory power in accounting for the observed variations in STRV adoption. Additionally, all the models exhibit high F-statistic values, exceeding the threshold of 10, commonly regarded as an indicator of a superior instrument for the second stage. The results lead to the conclusion that the lag values of flood measures provide strong explanatory power for the extent of variation in STRV adoption among the farmers.

TABLE 5.7. TWFE-IV model (First stage) (Equation 4.2.2)

	Flood max	Flood Mean	AUC	Neighborhood Flood
Lag 1	0.18	0.06	0.01	0.29
	[0.02, 0.34]	[-0.37, 0.49]	[-0.01, 0.02]	[0.10, 0.49]
Lag 2	-0.19	-0.04	0	-0.32
	[-0.34,-0.05]	[-0.43, 0.36]	[-0.01, 0.02]	[-0.49,-0.14]
Lag 3	-0.28	-0.98	-0.03	-0.29
	[-0.43,-0.14]	[-1.53,-0.42]	[-0.06,-0.01]	[-0.46,-0.12]
Lag 4	0.5	1.08	0.05	0.54
	[0.33, 0.67]	[0.63, 1.52]	[0.03, 0.07]	[0.34, 0.74]
Lag 5	0.26	0.22	0	0.28
	[0.08, 0.44]	[-0.27, 0.71]	[-0.02, 0.03]	[0.08, 0.49]
Lag 6	0.21	0.32	0.02	0.37
	[0.04, 0.38]	[-0.17, 0.81]	[-0.01, 0.04]	[0.16, 0.58]
Lag 7	0.12	0.61	0.03	0.21
	[-0.04, 0.28]	[0.19, 1.03]	[0.01, 0.05]	[0.01, 0.40]
Lag 8	-0.1	-0.3	-0.01	-0.14
	[-0.27, 0.07]	[-0.88, 0.28]	[-0.04, 0.01]	[-0.33, 0.06]
Lag 9	-0.53	-1.01	-0.04	-0.81
	[-0.71,-0.35]	[-1.46,-0.56]	[-0.06,-0.02]	[-1.01,-0.60]
Lag 10	0.43	1.01	0.04	0.61
	[0.27, 0.58]	[0.60, 1.42]	[0.03, 0.06]	[0.43, 0.79]
Lag 11	0.01	-0.41	-0.01	-0.01
	[-0.14, 0.16]	[-0.82, 0.00]	[-0.03, 0.00]	[-0.19, 0.16]
Lag 12	-0.12	-0.78	-0.03	-0.14
	[-0.28, 0.05]	[-1.25,-0.30]	[-0.05,-0.01]	[-0.34, 0.05]
Lag 13	0.3	1.18	0.05	0.36
	[0.21, 0.40]	[0.82, 1.54]	[0.04, 0.07]	[0.25, 0.47]
Number of Obs.	2874	2874	2874	2874
Log Likelihood	100.791	81.011	81.158	136.214
F Stat	12.508	11.105	11.194	15.235
Number of Cluster	958	958	958	958
Fixed Effect			Household & Time	

All models include year dummy and intercept.Values in parenthesis represents 90% confidence interval.
Standard Errors are clustered at household level

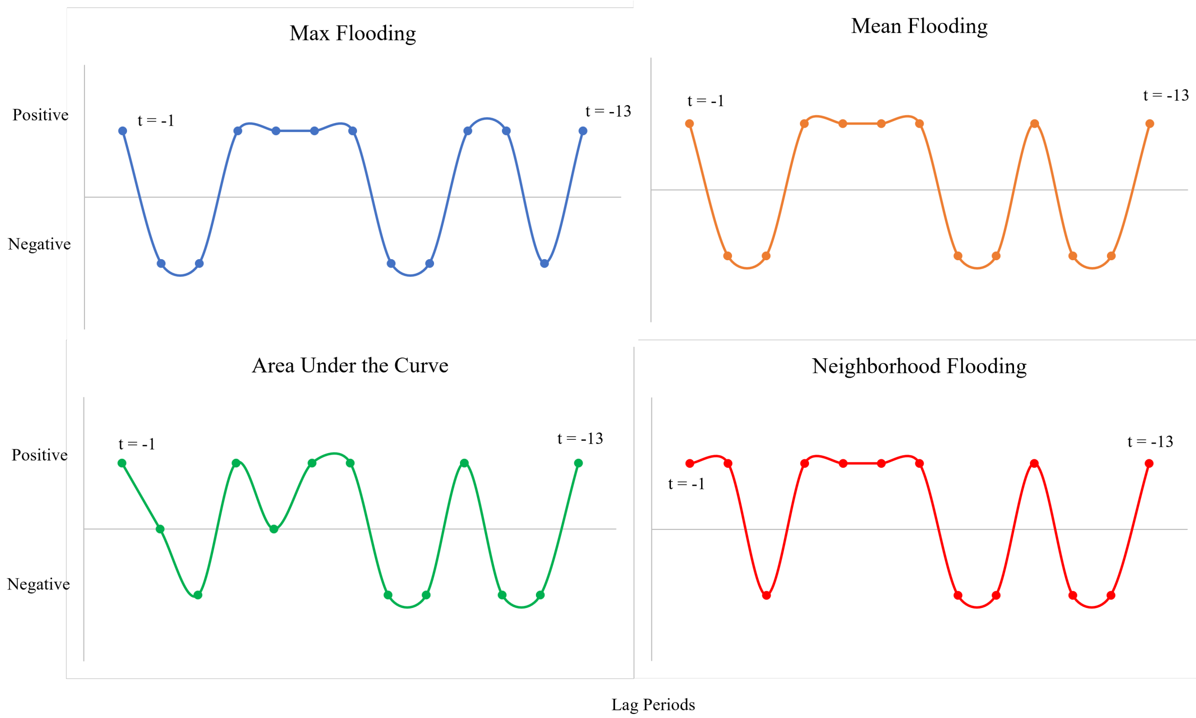


Figure 5.4. TWFE-IV First Stage Impact at Household Level *(not drawn to scale)*

Figure 5.4 demonstrates a non-linear relationship between the adoption of STRV and flooding measures. The x-axis represents the lag period, while the y-axis illustrates the impact of four flood measures. In each graph, points above the horizontal line indicate a positive effect of flood measure on STRV adoption, whereas the lower part signifies a negative impact. The findings from Figure 5.4 suggest that farmers are more inclined to adopt STRV based on the most recent flooding experience. In all first lag period the coefficients are positive. But in almost all second lag period, coefficients are negative or zero.As the lag period increases, farmers show an uinconsistent relationship between past flood experience and STRV adoption. Several potential reasons can account for this phenomenon.

First, STRVs represent a costlier alternative to traditional rice varieties. Consequently, it is commonplace for farmers to encounter financial constraints that hinder their ability to adopt STRVs every year. In the event of flooding during one year, farmers may adopt STRVs in the subsequent year. Furthermore, previous research findings and our own TWFE estimation have revealed no discernible yield benefit associated with STRV adoption during normal weather conditions. As a result, if farmers choose to adopt STRVs in a given year and subsequently experience a flood-free season, they will not observe any yield advantage resulting from their adoption - just increased costs. In contrast, their neighboring farmers who refrain from adopting STRVs may achieve comparable yields at lower costs. Considering the input and output aspects, this situation becomes disheartening for farmers who have embraced STRVs. Therefore, the observed tendency for farmers to adopt STRVs depending on short-run flooding experience can be attributed to a combination of factors, including financial constraints, variable soil conditions, and the absence of yield benefits under normal weather conditions.

5.3.2 Second Stage of TWFE-IV Model:

Estimation results from the second stage of the TWFE-IV model are presented in Table 5.8. As with the TWFE model, we focus our attention on the summarized results in Table 5.9.

Recall from Equation 4.2.3 θ_1 represents the difference in rice yield between adopters who experience no flood relative to non-adopters who experience no flood. All the coefficients for θ_1 are positive (for flood max, flood mean and area under the curve) and negative (neighborhood flooding) but insignificant. That means, the difference of rice yield between adopter and non-adopter who experience no flood is not different from zero. In words, there is no yield benefit or penalty for adopting STRV in a flood free season.

Next, ν measures the difference in average yields for non-adopters who experience a flood relative to non-adopters who do not experience a flood. From the TWFE-IV model we find that, for all flood measures, ν is negative and significant. This result shows that non-adopter farmers face yield loss due to flood, which is significantly different from zero.

θ_2 represents the difference in average yields for adopters who experience a flood relative to non-adopters who experience no flood. In our case, for flood max, flood mean and neighborhood flooding has negative but insignificant coefficient for θ_2. Only the AUC has a positive but insignificant result. This means that for all flood measures, the difference in average yield for adopters who experience a flood is no different than the average yield for non-adopters who do not experience a flood. In simple words, adopters who experience a flood had yields that were resilient to the flood and got yields equal to those who had no flood at all.

We can also look at $\theta_1 + \theta_2$, which measures the overall impact of adoption regardless of flood status. From Table 5.9 we can see that the coefficient is ranging between -1.82 to 0.28. Since both θ_1 and θ_2 are not different from zero, so the linear combination of these two parameters is also be zero. This is because the comparison group is non-adopters who experience no flood. So, this linear combination is not that informative because it compares adoption to the status quo of no flood non-adopters. Now, $\nu + \theta_2$ represents the impact of flood regardless of adoption status. We find that coefficients for all the flood measures are negative and statistically insignificant. This is because we are comparing everyone who experienced a flood to non-adopters who experienced no flood.

Finally, to answer our research question, we want to determine if yields for STRV adopters who experience a flood are significantly greater than the yields for non-adopters who also experience a flood. The test for a difference between ν and θ_2 turns up no significant difference in rice yield between these two groups. While our TWFE estimates showed a positive and signficant effect of STRV adoption on yields during floods, this result is not robust to the use of our IV. This may be due to several reasons. First, IV estimates have larger confidence intervals, meaning a difference might exist but we cannot measure it with precision. Second, our instrument may not be valid and therefore the TWFE-IV results are biased compared to our TWFE results. Third, our instrument may be valid, meaning the TWFE-IV is effectively controlling for endogeneity that is left uncontrolled for in the TWFE, meaning the null results of the IV estimates are to be believed. At this point we cannot determine which of these explanations is most likely.

TABLE 5.8. TWFE-IV model at Household level fixed effect

Ln Yield	(1)	(2)	(3)	(4)
Max Flood	-1.52			
	[-2.36,-0.68]			
Adoption × Max Flood	-1.88			
	[-6.92, 3.17]			
Mean Flood Value		-5.49		
		[-8.79,-2.20]		
Adoption × Flood Mean		-2.15		
		[-21.76,17.46]		
AUC			-0.24	
			[-0.39,-0.09]	
Adoption × AUC			0.10	
			[-0.48, 0.68]	
Neighborhood flood				-1.80
				[-2.80,-0.80]
Adopion × Neighborhood Flood				-1.85
				[-9.65, 5.95]
STRV Adoption	0.27	0.33	0.18	0.67
	[-1.05, 1.58]	[-0.91, 1.58]	[-0.69, 1.05]	[-1.29, 2.63]
Number of Observations	2874	2874	2874	2874
F Stat	1.550	1.597	1.587	1.600
Number of Cluster	958	958	958	958
Fixed Effect	Household and Time			

All models include intercept and dummy variable for year

Values in parenthesis represents 90% confidence interval. Std. Errors are clustered at household level

Table 5.9. Summary of Parameters and Point Estimates of TWFE-IV Model

Parameter	Description	Flood Max	Flood Mean	AUC	Neighborhood Flooding
θ_1	measures the difference in average yields for adopters who experience no flood relative to non-adopters who experience no flood.	2.65 [-1.04, 1.58]	0.33 [-0.91, 1.58]	0.18 [-0.69, 1.05]	0.67 [-1.29, 2.63]
ν	measures the difference in average yields for non-adopters who experience a flood relative to non-adopters who do not experience a flood	-1.51 [-2.35, -0.67]	-5.49 [-8.78, -2.19]	-0.24 [-0.38, -0.09]	-1.8 [-2.8, -0.8]
θ_2	measures the difference in average yields for adopters who experience a flood relative to non-adopters who experience no flood.	-1.87 [-6.92, 3.17]	-2.15 [-21.76, 17.45]	0.10 [-0.48, 0.68]	-1.85 [-9.65, 5.94]
$\theta_1 + \theta_2$	measures the overall impact of adoption regardless of flood status.	-1.61 [-5.51, 2.29]	-1.82 [-20.29, 16.64]	0.28 [-0.23, 0.79]	-1.18 [-7.09, 4.72]
$\nu + \theta_2$	measures the overall impact of flood regardless of adoption status.	-3.39 [-8.49, 1.71]	-7.65 [-28.97, 13.69]	-0.13 [-0.79, 0.52]	-3.65 [-11.17, 3.87]
test $\nu = \theta_2$ or $\nu - \theta_2 = 0$	measures the difference of average yield between the adopter and non-adopter who experience flood	0.01	0.09	1.12	0.00

*Values in parenthesis represents 90% confidence interval. Standard Errors are clustered at household level. *,**,*** means value is significant at 10%, 5% and 1% level*

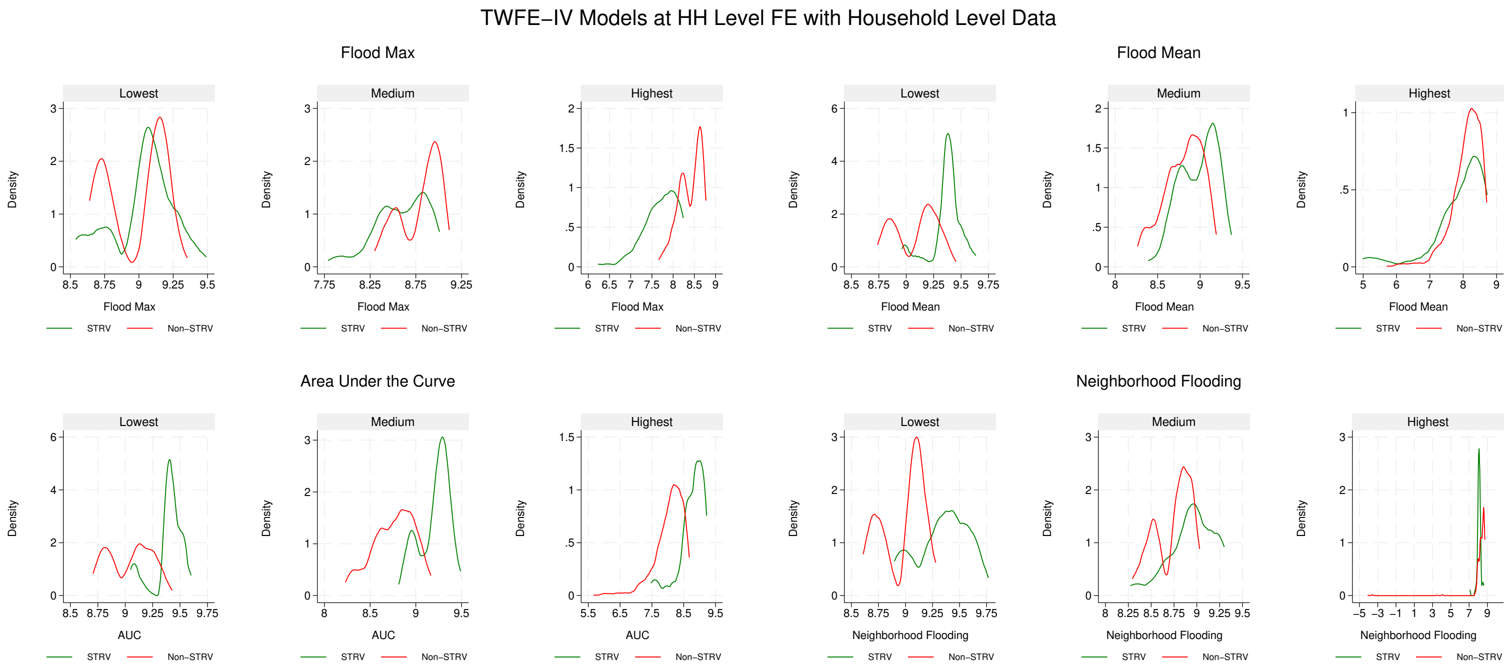


FIGURE 5.5. Predicted Value of Ln Yield from TWFE-IV Models at Household Level Fixed Effect

Figure 5.5, shows the predicted value of ln Yield from the above TWFE-IV model (equation 4.2.3) over STRV adoption status, classified as STRV and Non-STRV by different categories of flood measures. In this case, we categorize the flood measures into three parts, namely the lowest (bottom 25%), medium (middle 50%), and highest (top 25%) in terms of the value of each flood measure. It is evident that, in most of the cases, STRV shows a higher yield compared to the non-STRVs. But in terms of different segments of maximum flooding, non-STRVs do better.

5.4 Robustness Check:

In addition to the primary concern of TWFE and TWFE-IV models with household and time fixed effect from household panel data, we conduct another set of robustness checks with plot data from the households. The primary purpose of this analysis is to account for the fact that households do not adopt STRVs in all of their plots. And the data integration process for household panel data does not allow us to consider both STRV and Non-STRV plots at the same time. So, to understand the deviation coming from the data integration process we conduct the robustness check. In this case, we use the same estimation technique as in section 5.2 and section 5.3.

The results from the TWFE analysis with plot data, as presented in Table 7.3, demonstrate remarkable consistency with the household-level TWFE model. However, a noticeable deviation emerges when we try to measure the linear combination of parameters which is in Table 7.4. From this TWFE analysis we could not find any strong evidence to prove that STRVs are effective during flooding as the test for differences between ω and β is not significant. But flood is damaging the rice yield. β for TWFE and ν for TWFE-IV model (see Table 7.7) turns out as negative in some case whereas for other cases, its zero. Meaning that adopters who experienced the flood had yields that were 100% resilient to the flood and farmers got yields equal to those who had no flood at all. The reason behind these disparities can be attributed to plot specific heterogeneity inherent in the data used for the analysis and the data integration process. Individual plots possess unique attributes, such as diverse soil qualities, different drainage systems, and variations in land types. These plot-specific characteristics might influence the impact of STRV adoption on rice yield.

Chapter 6

Conclusion

Climate change is a pervasive threat to Bangladesh and many other parts of the world. In recent years, the country has experienced an increasing number of catastrophic floods (NASA Earth Observatory, 2022), which have caused substantial crop damage and rendered many poor households food insecure (Mishra et al., 2015). To counteract the effects of flooding, Bangladesh has introduced submergence-tolerant rice varieties. These varieties can withstand flooding, so farmers can still produce a crop even when their fields are submerged. This research uses three years of household panel data from rural Bangladesh to quantify the impact of stress-tolerant rice varieties (STRVs) adoption on rice yield. We extract the historical flooding experience by the farmer using Sentinel 2 and MODIS 500m jointly in CNN-LSTM algorithm in Google Earth Engine. We employ the Two-Way Fixed Effect (TWFE), and Two-Way Fixed Effect Instrumental Variable (TWFE-IV) approaches as a causal pathway.

We find that the STRV adoption has increased significantly over time, from around 8% in 2014 to 22% in 2022. This increase in adoption has led to a significant increase in average rice yields. From descriptive analysis we find that STRV adopter farmers have yields that are significantly higher than those of non-adopter farmers. Our causal effect analysis shows that all flood measures, including maximum flooding, mean flooding, the area under the curve (AUC), and neighborhood flooding, cause rice yield loss. From the TWFE estimation, we find strong evidence that STRVs are effective during any flood events compared to non-STRVs in terms of rice yield. But from the TWFE-IV model, we could not find any strong evidence supporting the same conclusion as the TWFE model. Our results are also not robust to when we use pooled plot-level data instead of household-level panel data.

In conclusion, our analysis of TWFE and TWFE-IV reveals no yield penalty for adopting STRVs during the flood-free season. Non-adopting farmers experience yield losses during flood events, whereas STRV adopters demonstrate resilient yields. Based on these findings, the government should encourage farmers to adopt STRVs to attain resilient yields. However, while the TWFE analysis supports the effectiveness of STRVs during floods, the TWFE-IV analysis needs more conclusive evidence, necessitating further research for solid policy recommendations. Hence, more investigation is required to ascertain the effectiveness of STRVs during flood events, ensuring well-informed decisions for sustainable agriculture and environmental conservation.

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Chapter 7

Appendix

7.1 Appendix A - Detail Tables and Figures

Table 7.1. Sampling Distribution of Households by Division and Year

	Year			
Division	2014	2017	2022	Total
Barishal	332	332	332	996
Chittagong	77	77	77	231
Dhaka	50	50	50	150
Khulna	134	134	134	402
Rajshahi	193	193	193	579
Rangpur	172	172	172	516
Total	958	958	958	2,874
Rate of Attrition		0.013	0.114	

Values represent frequency of households.
Rate of attrition represents before strongly balanced panel obs. count

Table 7.2. Sampling Distribution of Plots by Division and Year

	Year			
	2014	2017	2022	Total
Barisal	517	438	676	1,631
Chittagong	137	136	156	429
Dhaka	57	38	93	188
Khulna	221	202	316	739
Rajshahi	333	266	459	1,058
Rangpur	380	306	436	1,122
Total	1,645	1,386	2,136	5,167

Values represent number of plots

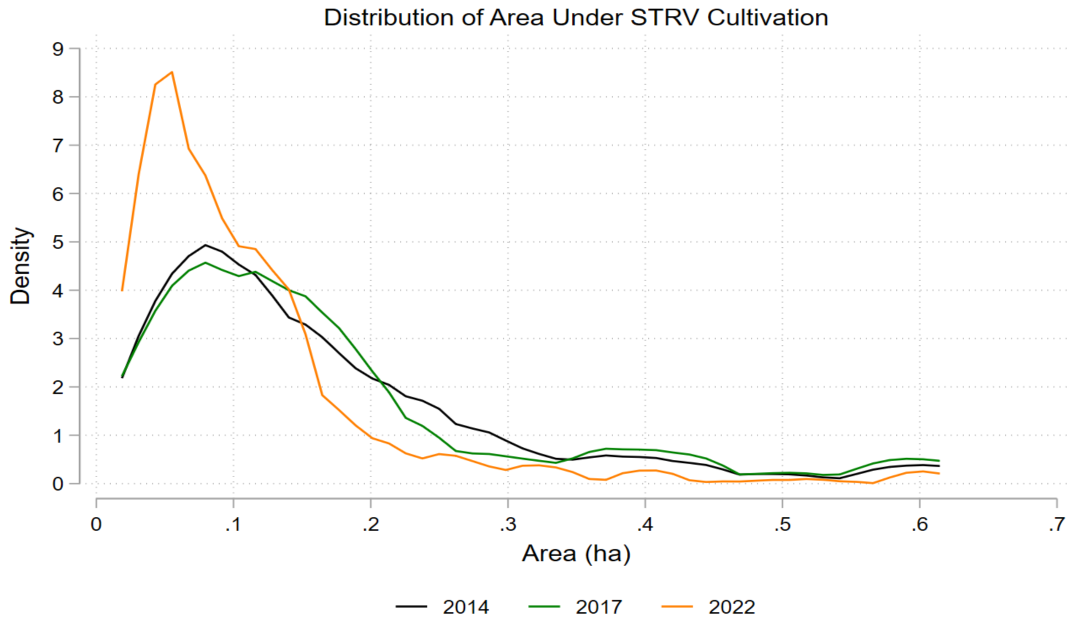

FIGURE 7.1. Area under STRV Cultivation by Year

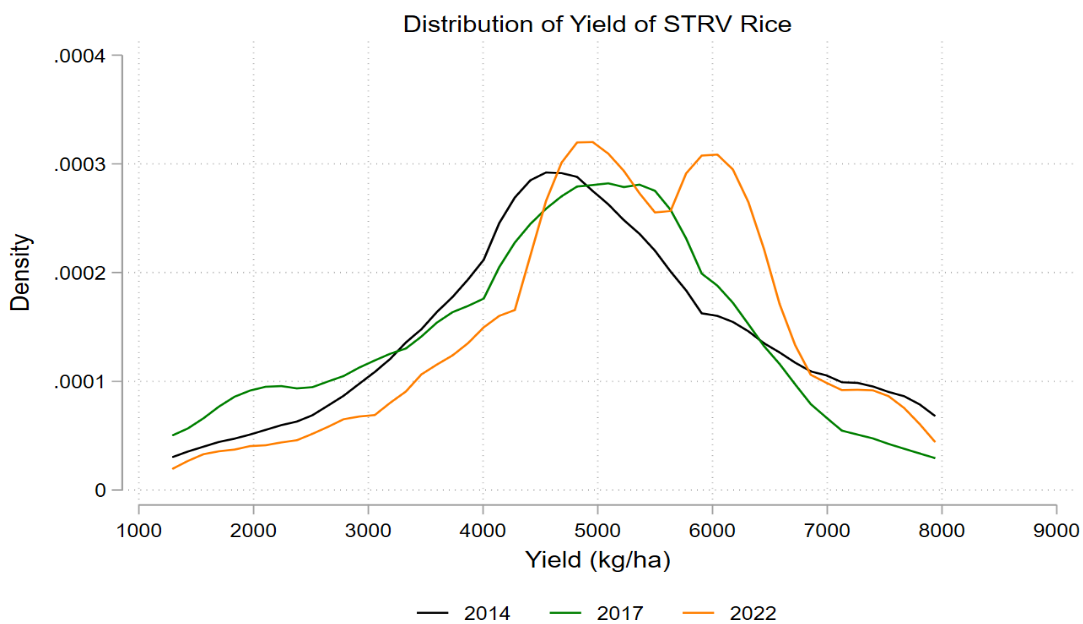

FIGURE 7.2. Average ln Yield Over Cultivated Area By Years

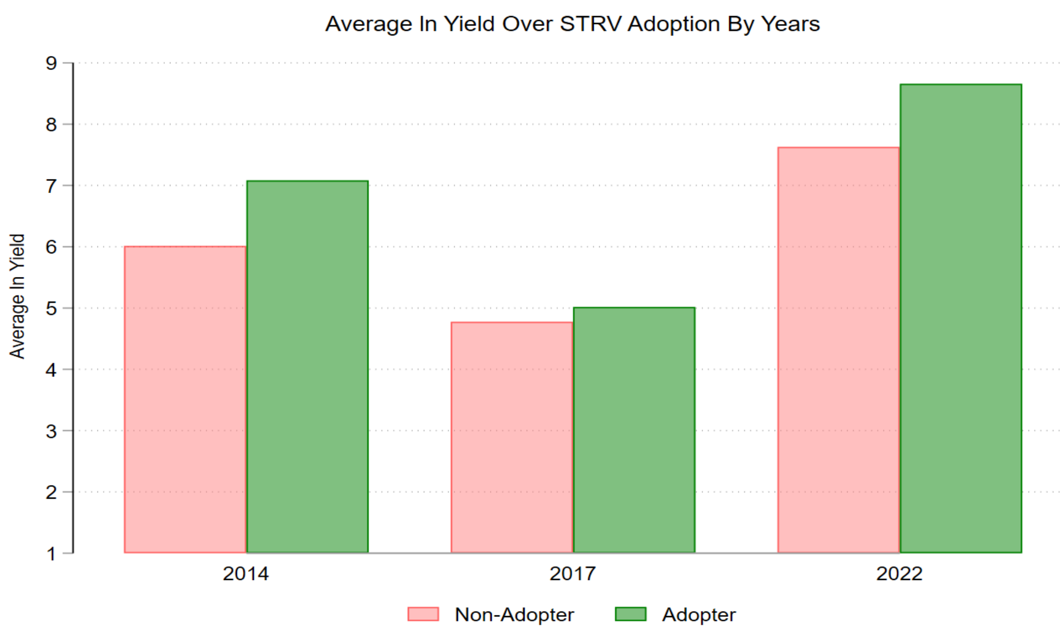

Figure 7.3. Average ln Yield Over Adoption Status By Years

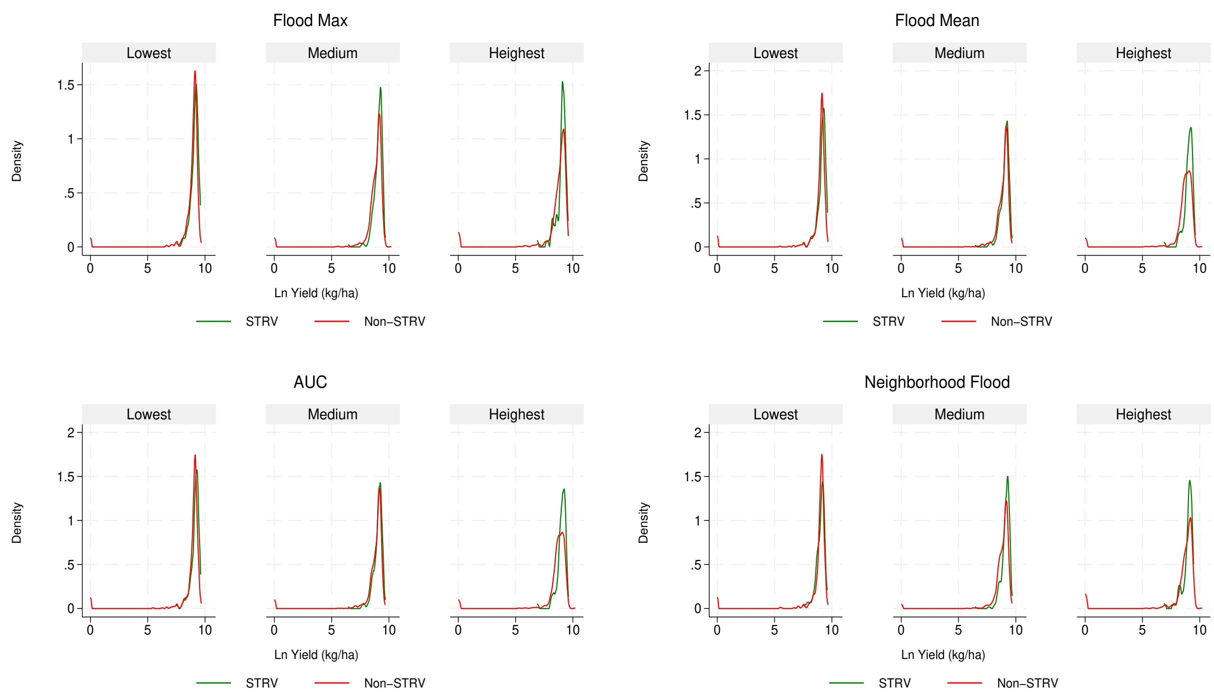

FIGURE 7.4. Actual Value of ln Yield with Household Panel Data

Table 7.3. TWFE Models with Plot Level Data (Equation 4.2.1)

Ln Yield	(1)	(2)	(3)	(4)
Max Flood	-0.939			
	[-1.72,-0.16]			
Adoption × Max Flood	0.401			
	[-0.42, 1.22]			
AUC		-0.088		
		[-0.16,-0.02]		
Adoption × AUC		0.012		
		[-0.04, 0.06]		
Mean Flood Value			-2.018	
			[-3.64,-0.39]	
Adoption × Mean Flood Value			0.265	
			[-0.90, 1.43]	
Neighborhood flood				-1.283
				[-2.44,-0.13]
Adoption × Neighborhood flood				0.093
				[-1.13, 1.32]
STRV Adoptiopn	0.098	0.211	0.211	0.180
	[-0.17, 0.36]	[0.00, 0.42]	[0.00, 0.42]	[-0.22, 0.58]
Number of Observations	4895	4895	4895	4895
Log Likelihood	-7605.41	-7610.07	-7610.07	-7604.84
Number of Cluster	922	922	922	922
Fixed Effects		Household & TIme		

All equations include intercept and dummy variable of year

Values in parenthesis represents 90% confidence interval. Std. Errors are clustered at household level

Table 7.4. Summary of Parameters and Point Estimates of TWFE Model

Parameter	Description	Flood Max	Flood Mean	AUC	Neighborhood Flooding
γ	measures the difference in average yields for adopters who experience no flood relative to non-adopters who experience no flood.	0.09[-0.16, 0.36]	0.21[0.001, 0.42]	0.21[0.001, 0.42]	0.18[-0.22, 0.58]
ω	measures the difference in average yields for non-adopters who experience a flood relative to non-adopters who do not experience a flood	-0.94[-1.72, -0.16]	-2.01[-3.64, -0.39]	-0.08[-0.15, -0.02]	-1.28[-2.43m -0.13]
β	measures the difference in average yields for adopters who experience a flood relative to non-adopters who experience no flood	0.40[-0.42, 1.22]	0.27[-0.90, 1.43]	0.01[-0.03, 0.06]	0.09[-1.12, 1.31]
$\gamma + \beta$	measures the overall impact of adoption regardless of flood status.	0.49[-0.122, 1.11]	0.47[-0.55, 1.51]	0.22[0.04, 0.399]	0.27[-0.59, 1.14]
$\omega + \beta$	measures the overall impact of flood regardless of adoption status.	-0.53[-1.39, 0.31]	-1.75[-3.17, -0.34]	-0.07[-0.13, -0.01]	-1.19[-2.52, 0.14]
test $\omega = \beta$ or $\omega - \beta = 0$	measures the difference of average yield between the adopter and non-adopter who experience flood	2.64	2.35	2.34	1.33

*All models include year dummy and intercept. Values in parenthesis represents 90% confidence interval. Standard Errors are clustered at household level. *,**,*** means value is significant at 10%, 5% and 1% level*

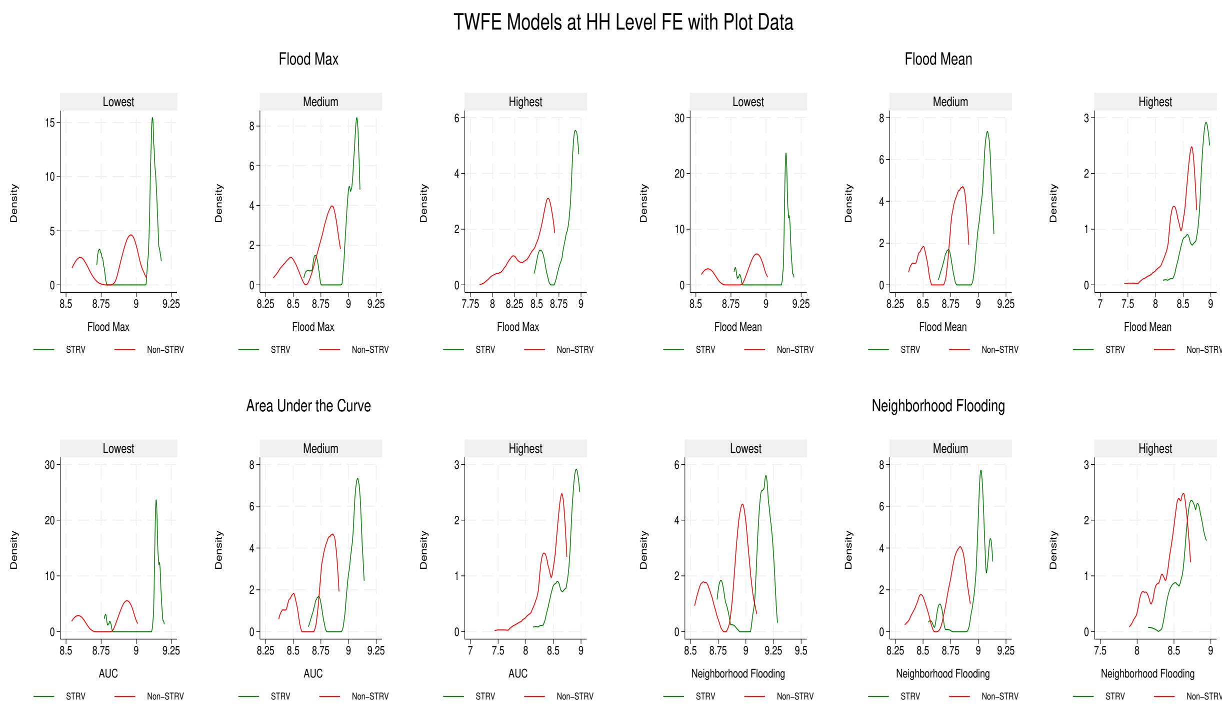

Figure 7.5. Predicted Value of Ln Yield from TWFE Models at Household Level Fixed Effect with Plot Data

Table 7.5. TWFE-IV model with Plot Level Data (1st stage) (Equation 4.2.2)

	Flood max	Flood Mean	AUC	Neighborhood Flood
Lag 1	0.05	0.08	0	0.17
	[-0.10, 0.19]	[-0.27, 0.44]	[-0.01, 0.02]	[-0.03, 0.37]
Lag 2	-0.09	0.01	0	-0.1
	[-0.19, 0.02]	[-0.27, 0.30]	[-0.01, 0.01]	[-0.25, 0.06]
Lag 3	-0.33	-0.99	-0.04	-0.44
	[-0.45,-0.20]	[-1.49,-0.50]	[-0.06,-0.02]	[-0.61,-0.27]
Lag 4	0.36	0.56	0.03	0.48
	[0.22, 0.50]	[0.20, 0.91]	[0.01, 0.04]	[0.30, 0.66]
Lag 5	0.29	0.42	0.01	0.39
	[0.14, 0.44]	[0.00, 0.83]	[-0.01, 0.03]	[0.20, 0.59]
Lag 6	0.19	0.45	0.02	0.48
	[0.06, 0.32]	[0.07, 0.83]	[0.00, 0.03]	[0.30, 0.66]
Lag 7	0.24	0.72	0.03	0.39
	[0.13, 0.36]	[0.40, 1.05]	[0.02, 0.05]	[0.23, 0.56]
Lag 8	-0.1	-0.07	0	-0.07
	[-0.23, 0.03]	[-0.54, 0.40]	[-0.02, 0.02]	[-0.27, 0.13]
Lag 9	-0.51	-1	-0.05	-0.74
	[-0.65,-0.37]	[-1.37,-0.63]	[-0.06,-0.03]	[-0.94,-0.55]
Lag 10	0.32	1.08	0.05	0.45
	[0.20, 0.44]	[0.73, 1.43]	[0.03, 0.06]	[0.28, 0.61]
Lag 11	-0.23	-0.87	-0.04	-0.24
	[-0.37,-0.10]	[-1.23,-0.51]	[-0.05,-0.02]	[-0.41,-0.07]
Lag 12	-0.1	-0.96	-0.04	0.04
	[-0.23, 0.02]	[-1.32,-0.59]	[-0.06,-0.02]	[-0.13, 0.21]
Lag 13	0.16	0.81	0.03	0.25
	[0.07, 0.25]	[0.50, 1.11]	[0.02, 0.05]	[0.14, 0.35]
Number of Observations	5167	5167	5167	5167
Log Likelihood	500.712	472.524	469.971	573.809
Number of Cluster	925	925	925	925
F Stat	9.938	8.692	8.65	11.881
Fixed Effects	Household & Time			

All models include year dummy and intercept. Values in parenthesis represents 90% confidence interval.

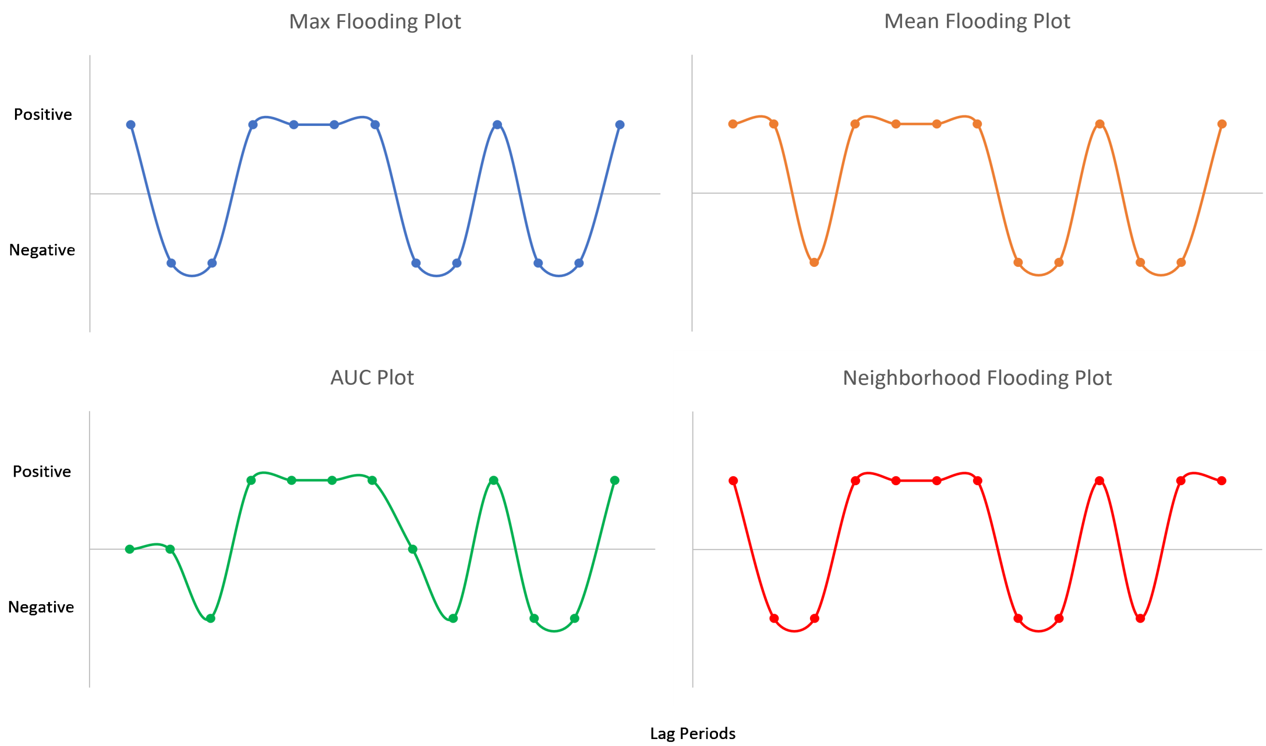

FIGURE 7.6. TWFE-IV First Stage Impact at Plot Level
(not drawn to scale)

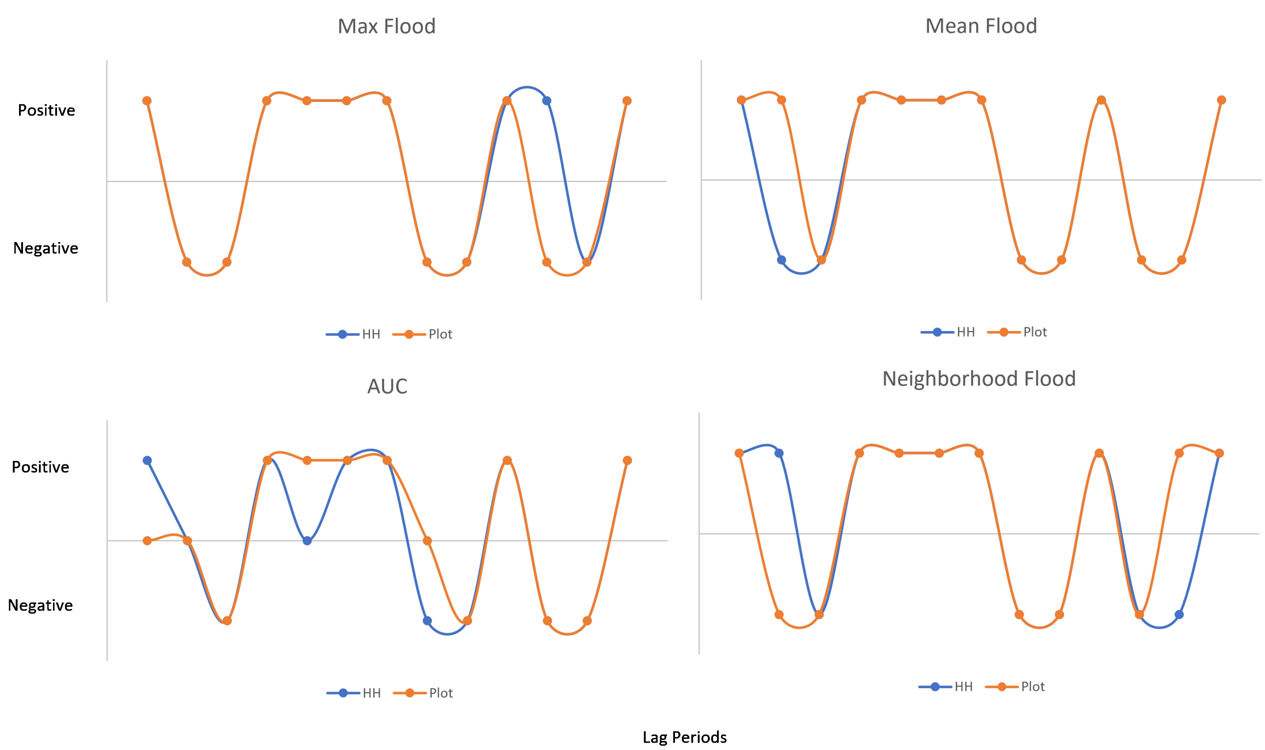

FIGURE 7.7. Comparison of TWFE-IV First Stage Impact Between Household Panel and Plot Data

(not drawn to scale)

TABLE 7.6. TWFE-IV model at HH level fixed effect with Plot Level Data (Equation 4.2.3)

Ln Yield	(1)	(2)	(3)	(4)
Max Flood	-0.91			
	[-1.68,-0.14]			
Adoption × Max Flood	-1.43			
	[-7.24, 4.38]			
Mean Flood Value		-2.13		
		[-3.85,-0.40]		
Adoption × Flood Mean		2.28		
		[-8.51,13.07]		
AUC			-0.09	
			[-0.17,-0.02]	
Adoption × AUC			0.14	
			[-0.32, 0.59]	
Neighborhood flood				-0.95
				[-2.22, 0.32]
Adoption × Neighborhood Flood				-7.06
				[-33.82,19.69]
STRV Adoption	0.20	0.18	0.34	1.94
	[-1.48, 1.88]	[-0.87, 1.24]	[-0.68, 1.36]	[-5.11, 8.99]
Number of Observations	4895	4895	4895	4895
F-Stat	2.784	2.820	2.800	2.716
Number of Cluster	922	922	922	922
Fixed Effects	Household & Time			

All models include intercept and dummy variable for year

Values in parenthesis represents 90% confidence interval. Std. Errors are clustered at household level

Table 7.7. Summary of Parameters and Point Estimates of TWFE-IV Model

Parameter	Description	Flood Max	Flood Mean	AUC	Neighborhood Flooding
θ_1	measures the difference in average yields for adopters who experience no flood relative to non-adopters who experience no flood.	0.19[-1.48, 1.87]	0.18[-0.87, 1.24]	0.34[-0.67, 1.36]	1.94[-5.10, 8.99]
ν	measures the difference in average yields for non-adopters who experience a flood relative to non-adopters who do not experience a flood	-0.91[-1.68, -0.14]	-2.12[-3.85, -0.40]	-0.09[-0.17, -0.02]	-0.95[-2.22, 0.32]
θ_2	measures the difference in average yields for adopters who experience a flood relative to non-adopters who experience no flood.	-1.43[-7.24, 4.38]	2.28[-8.51, 13.07]	0.13[-0.32, 0.59]	-7.06[-33.82, 19.69]
$\theta_1 + \theta_2$	measures the overall impact of adoption regardless of flood status.	-1.23[-5.54, 3.08]	2.46[-7.55, 12.47]	0.48[-0.27, 1.22]	-5.12[-24.86, 14.62]
$\nu + \theta_2$	measures the overall impact of flood regardless of adoption status.	-2.33[-8.10, 3.43]	0.15[-10.24, 10.51]	0.04[-0.38, 0.47]	-8.01[-34.04, 18.00]
test $\nu = \theta_2$ or $\nu - \theta_2 = 0$	measures the difference of average yield between the adopter and non-adopter who experience flood	0.02	0.40	0.60	0.13

*Values in parenthesis represents 90% confidence interval. Standard Errors are clustered at household level. *,**,*** means value is significant at 10%, 5% and 1% level*

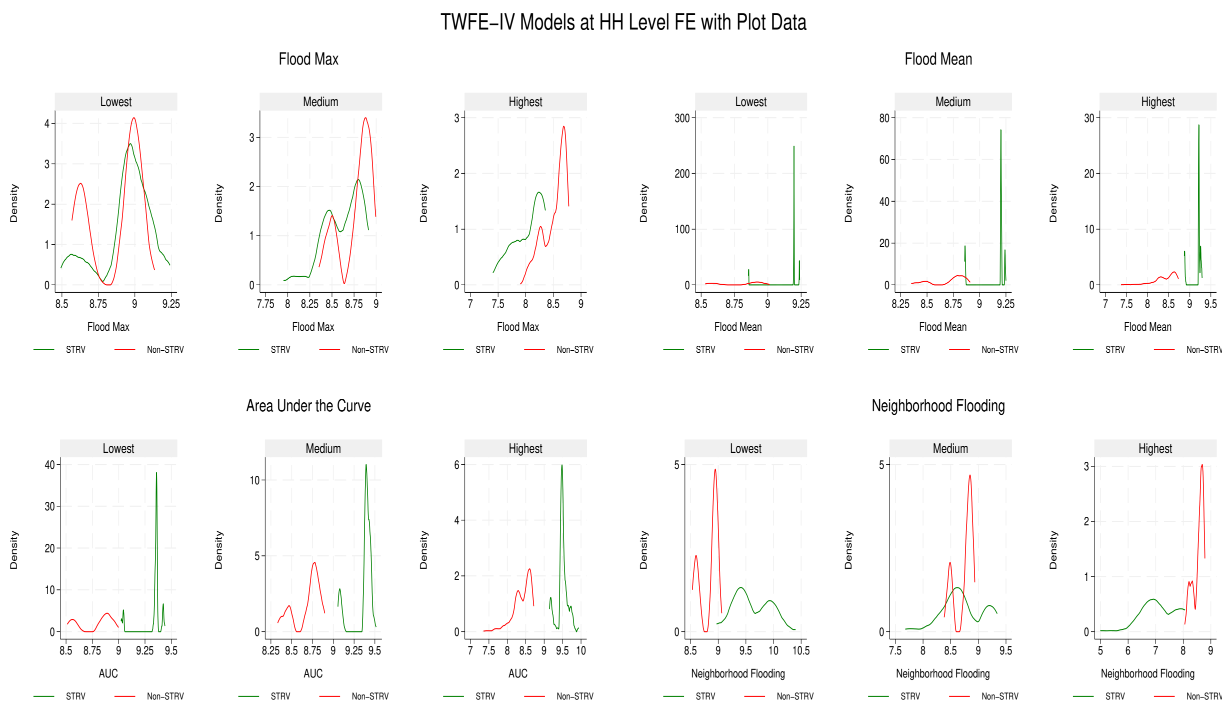

FIGURE 7.8. Predicted Value of Ln Yield from TWFE-IV Models at household Level Fixed Effect with Plot Data

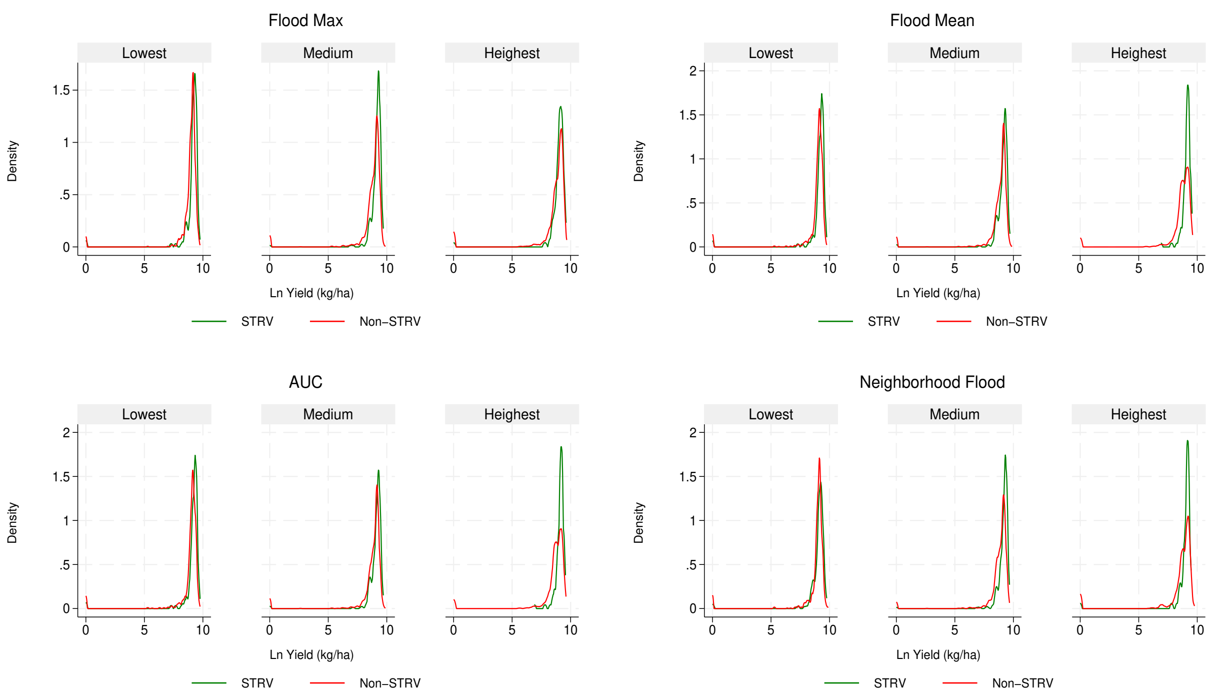

FIGURE 7.9. Actual Value of ln Yield with Plot Data