ADAPTATION TO NATURAL DISASTERS THROUGH THE AGRICULTURAL LAND RENTAL MARKET: EVIDENCE FROM BANGLADESH[*]

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We examine the effects of natural disaster on agricultural households who simultaneously make rent-in and rent-out decisions in the land rental market. Our econometric approach accounts for the effects of disaster-exposure both on the adjustments in the quantity of operated land (i.e. extensive margin) and agricultural income conditional on the land quantity adjustments (i.e. intensive margin), based on selectivity-corrected samples of rental market participants. Employing a household survey dataset from Bangladesh, we find that farmers were able to ameliorate their losses from exposure to disasters by optimizing their operational farm size through transactions in the land rental market. We also find that smaller farmers benefit more from these rental transactions. These results suggest that the land rental market may be an effective instrument reducing disaster risk, and post-disaster policies should take into account this role more systematically. Finally, our results are robust to alternative definitions of disaster-exposure and income. (JEL Q24, Q54, D13, D64, Q15).

Keywords: Bangladesh; Natural Disasters; Extensive and Intensive Margins; Land Rental Market.

I. INTRODUCTION

Agricultural households from low-income countries, where widespread poverty among rural households often limits their ability to invest in defensive measures especially when markets are incomplete or non-existent, are highly susceptible to exposure to climate-induced natural disasters such as floods and storms. Consequently, natural disasters often force rural households and farmers to adopt coping strategies such as cutting back on consumption of basic food and nutrients and selling of productive assets such as agricultural land (Duflo 2003; Jensen 2000).[1] Apart from selling agricultural land, the immediate response of many rural households is to seek off-farm employment (Banerjee 2007; Mueller and Quisumbing 2011). However, farmers might also have another coping mechanism, which is to adjust their operational farm size through participation in the land rental market (Banerjee 2010b; Ward

[1] For example, selling of arable land is among the coping strategies adopted by Bangladeshi farmers in response to disaster exposure (BBS 2010).

and Shively 2011). Through participation in the land rental market, some farmers facing exposure to disaster risks might choose to rent-in agricultural land, whereas others might rent-out land. These land rental transactions enable farmers to adjust their operational farm size, and thus indirectly, agricultural production. Literature has not yet addressed the revenue effect of this potential mechanism of farmers using the land rental market as a source of adaptation to natural disaster. Against this backdrop, we investigate the role of the land rental market in ameliorating the agricultural revenue effects of disaster exposure through a case study of Bangladesh.

Bangladesh is predominantly an agricultural country that experiences recurring damaging disaster events, such as floods and storms, with aggregate losses of US$ 114 million from 11 floods and US$ 2,570 million from 15 storms during 2006-11 (EM-DAT 2016). Most of these losses occur to agriculture, which employs around 44 percent of the labor force and accounts for 20 percent of gross domestic product (BBS 2010). In addition to farmer's apparent motive of maximizing profit from agricultural production, low average farm size and high incidence of rural poverty in Bangladesh necessitate the optimal management and utilization of the available land especially in response to a disaster.

We examine agricultural adaptation to natural disaster exposure via the land rental market using an econometric model of a farmer's rent-in and rent-out choices. For this purpose, we adopt the standard empirical model that accounts for both extensive margin, i.e., revenue-effect of disaster-induced adjustments in the quantity of operated land, and intensive margin, i.e. direct revenue-effect of disaster-exposure (e.g., Lee 1990; Moore, Gollehon, and Carey 1994; Pfeiffer and Lin 2012 and 2014). The extensive margin is estimated in a simultaneous equations model, in which the amounts of rent-in and rent-out land chosen by each farmer are censored by sample selection. On the other hand, intensive margin or the direct effect of disaster-exposure on agricultural income is conditioned on endogenously determined land rental transactions, and is estimated using a two-stage least squares regression model on the selectivity-corrected sample. We then calculate the total marginal effect as the sum of intensive and extensive margins of natural disaster exposure on agricultural revenue. Data comes from the Bangladesh Integrated Household Survey (BIHS) 2011-12, which is the most comprehensive source of household-level socioeconomic and agricultural data in Bangladesh (Ahmed 2013). This survey provides household-level information on exposure to natural disasters over the period 2006-11, which allows us to examine the effects of disaster-exposure in inducing variations in agricultural revenue (which indicates the direct effect of disaster-exposure on agricultural revenue) and land rental market transactions (which facilitates the indirect effect of disaster on agricultural revenue).

Existing literature focuses on the direct effects of natural disasters on agriculture (e.g., Deschenes and Greenstone 2007; Mendelsohn, Nordhaus, and Shaw 1994). In addition, Ward and Shively (2011) investigated the effects of covariate village-level income shocks on land market participation. They employed pooled cross-section instrumental variables probit and 3SLS estimates to identify that Chinese households engage in land rentals as a response to covariate shocks, but not in response to idiosyncratic shocks. To our knowledge, this is the only previous study of the role of the land rental market in facilitating adaptation to disasters. However, their analysis did not consider the indirect effects of land rental transactions in response to a disaster on agricultural outcome. We contribute in literature by estimating the resulting revenue effects of such agricultural land rental market transactions. In particular, we take into account the possibility that farmers might be able to mitigate or reduce the adverse effects of disaster on agricultural revenue through land rental market transactions (Banerjee 2010b). We find that an average Bangladeshi farmer exposed to a natural disaster have 7.61 percent higher crop revenue, which consists of -2.45 percent intensive margin and 10.06 percent extensive margin. That is, while the exposure to a disaster results in a 2.45 percent direct decrease in yield, those adjusting their operational farm size were able to overcome that loss due to a 10.06 percent indirect increase in revenue coming from the land rental market. In addition, we also find that smaller farmers benefit more from such disaster-induced increase in land rental transactions.

Our results have important implications for Bangladesh and other low-income countries in terms of the role of land management within a community for disaster risk reduction. In response to a natural disaster, if farmers in a rural community manage and utilize their land to increase their agricultural production, this coping strategy has been found to ameliorate adverse impacts and might even compensate for the losses from disaster-exposure (Sklenica *et al.* 2014; Deininger, Savastano, and Carletto 2012; Masterson 2007). In this paper, we show that access to a well-functioning land rental market might be a crucial part of the coping strategy that allows farmers to adjust their revenues, and thus improving and facilitating the functioning of such markets in rural areas should be an important component of government post-disaster risk reduction strategies.

The content of the remainder of this paper is as follows. Section II discusses the background information on land rental market and disasters during 2006-11 in Bangladesh.

Section III describes data and identification. Section IV specifies the empirical model. Section V reports and discusses empirical results. Finally, Section VI summarizes and concludes by discussing the key policy implications of the analysis.

II. BACKGROUND

II.A Disasters in Bangladesh: 2006-11

Geographic location and land characteristics make Bangladesh one of the most disaster-prone countries in the world: 26 percent of the population are affected by storms and 70 percent live in flood-prone regions (Cash *et al.* 2014). Wide-scale flooding has been the most recurrent type of disaster striking Bangladesh, and the country remains one of the worst affected by tropical storms globally. Large-scale natural disasters in Bangladesh include the 1970 cyclone, 1986 flood, 1991 cyclone, 1998 flood and 2007 cyclone. Our paper focuses on the series of natural disasters in Bangladesh that occurred from 2006 to 2011. Table A1 in the appendix lists all the floods and storms that took place during this period, alongside the associated numbers of deaths and affected people and economic damages.

Bangladesh experienced 11 floods and 15 storms during 2006 to 2011 (Table A1). These natural disasters resulted in around six thousand reported deaths, whereas more than 30 million people were affected, resulting in an estimated damages of US$ 2,648 million. However, note that the damage figures for many relatively smaller disasters are not reported in Table A1, implying that the actual economic damages from disasters over 2006-2011 are likely to be even higher.

In general, cyclonic storms primarily affected the coastal regions of Bangladesh whereas the northern regions were the primary victims of floods. Major such events during 2006-11 include the floods of 2007, the cyclone Sidr of 2007 and the cyclone Aila of 2009 (EM-DAT 2016). Two floods in June-July and July-September of 2007 covered 46 districts and affected around 13.3 million people including 6 million children. These back-to-back floods caused more than 1,200 deaths, in addition to 1.1 million damaged or destroyed homes and 2.2 acres of damaged croplands. Damages were estimated at US$ 100 million. Next, Cyclone Sidr struck the coastal regions of Bangladesh on November 15, 2007. The 240 km per hour winds destroyed 30 districts in Barisal and Khulna divisions, resulting in more than four thousand deaths and 55 thousand injuries in addition to 1.5 million damaged or destroyed homes and 2.5 acres of damaged croplands. Economic damages were estimated at US$ 2,300 million. Finally, cyclone Aila struck 14 districts on the south-west coast of Bangladesh on May 25,

2009. Aila affected around 4 million people and caused 190 deaths, in addition to an estimated US$ 270 million worth damages in infrastructures and livelihoods.

II.A Land Rental Market in Bangladesh

Common adaptation practices in response to disaster-exposure in Bangladesh include crop switching, migration, and increased labor supply (e.g., Moniruzzaman 2015; Penning-Rowsell, Sultana, and Thompson 2013; Banerjee 2007; Mueller and Quisumbing 2011). For example, Moniruzzaman (2015) employed a multinomial logit model to identify that farmers adapt to changing temperature and rainfall by switching to more climate-resilient crops. However, climatic extremes require immediate response to overcome the immediate harms, whereas a change in cropping patterns requires longer planning horizon and is more pertinent to continuous measures of climatic changes such as longer term variations in rainfall and temperature. In addition, Penning-Rowsell, Sultana, and Thompson (2013) found that permanent migration is an unlikely response of rural people who are less likely to migrate even in the face of extreme disasters, although they may temporarily migrate to safer places. This tendency is historically true for Bangladesh. For example, even the people affected by the 1970 great Bhola Cyclone did not migrate permanently (Sommer and Mosley 1972). However, since operational farm size is necessarily proportional to agricultural labor employment, our idea of using land rental market to adjust operational farm size is synonymous to increased labor supply in agriculture in response to disaster exposure. In related research, Banerjee (2007) identified that there can be increased supply of unskilled labor in the aftermath of floods, especially to plant agricultural lands.

Rural households in Bangladesh predominantly depend on agriculture for their livelihood and employment. Agriculture employs around 44 percent of the labor force in Bangladesh and contributes around 20 percent of its gross domestic product (BBS 2010). However, due to a high level of land fragmentation and increasing population, per-capita arable land declined from 0.174 ha in 1961 to 0.049 ha in 2013 (World Bank 2015), creating increased pressure on limited land resources to produce sufficient food and other commodities. Since Bangladesh has one of the lowest average farm sizes globally, estimated at 0.344 ha per rural household (BBS 2014), many farmers rely on the land rental market to better manage and utilize the available arable land.

Although rental arrangements do not change the land ownership structure, the presence of land rental market, mostly informal in Bangladesh like many other developing countries, is an effective way of redistributing the operational farm size among the farmers. Farmers often manage their agricultural plots to equalize the size distribution of the operating farms by either renting in additional land or renting out surplus land (Teklu and Lemi 2004; Rahman 2010). Typically, smallholders rent in land from larger farmers to increase their operational farm size. For example, in 2008, 33.8 percent of rural households in Bangladesh rented at least a part of their total operated land, whereas 24.2 percent operated a combination of owned and rented lands. In addition, 9.6 percent of them operated only rented lands (BBS 2014).

Common land rental categories in Bangladesh are (i) share-cropping arrangements, and (ii) cash-renting at a fixed predetermined rate. The Land Reform Act of 1984 fixed rents for share-cropping tenants at 33 percent of the harvest for the landlords (without input sharing) or 50 percent if inputs are shared at a 50 percent rate (GoB 1984; Rahman 2010). However, in absence of proper enforcement of existing laws, most of the agricultural land rental agreements take place without any documentation through informal land rental markets.

III. DATA AND IDENTIFICATION

III.A BIHS Data

Data for our analysis is from the Bangladesh Integrated Household Survey 2011-12 (BIHS) dataset, which was collected from October 2011 to March 2012. The USAID-funded survey was designed and supervised by the International Food Policy Research Institute (IFPRI), administered by Data Analysis and Technical Assistance, Dhaka, Bangladesh, and approved for publication by the Government of Bangladesh (Ahmed 2013). Statistically, BIHS is nationally representative of the rural areas of each of the seven administrative divisions of Bangladesh, with a sample size of 6,500 rural households from 325 primary sampling units. However, 5,491 of those households have agricultural activities, and therefore, forming our valid sample of rural agricultural households.

Table 1 describes and summarizes the variables we use in the empirical analysis of this paper. The BIHS dataset reports information on a household's exposure to any negative shock (e.g., death of main earner, loss of a regular job, loss of assets, crop loss, loss or decrease of remittances, natural calamities). We are particularly interested in household-specific reporting of exposure to natural disasters such as floods and storms, who, altogether, affect 15 percent households; whereas floods and storms, respectively, affect 6 and 9 percent of households. We use the self-reported household-level exposure to disaster from the BIHS in our subsequent analysis, therefore overcoming the limitations of using regional level disaster-exposure data.[2] In addition, we also use the severity of natural disasters, measured by the resulting monetary losses, as a continuous measure of exposure to disasters. Farmers experience an average monetary loss of US $113 from disaster-exposure.

BIHS dataset contains information on agricultural and total incomes, which are our outcome variables. On average, farmers receive US$ 426 in crop revenue, and their average total income, which combines crop revenue with non-agricultural income, is US$ 695. Table 1 also reports farmer's land rental market participation and transaction decisions. A total of 40 and 24 percent farmers, respectively, participate in the land rental market in order to, on average, rent-in 0.33 acres and rent-out 0.20 acres of agricultural land. These rental transactions increase operational farm size from 0.54 acres, which includes farmer's owned-operated and rented-out land, to 0.67 acres, which includes their owned-operated and rented-in land.

However, such rental transactions are conditional on a number of socioeconomic factors such as household-, farm-, plot- and regional-level attributes. First, the BIHS data includes information on household characteristics such as family size and employment status, age and education of the household head. Average household size is 4.29, and 21 percent households have at least one migrant member; whereas, household heads are 45 years old and have 3.46 years of schooling on average.

Second, BIHS also contains data on farm-level characteristics such as the ownership of farming assets (e.g., tractor or plough-yoke and irrigation pump), access to agricultural facilities (e.g., extension, subsidy and electricity) and agricultural diversification (i.e., fishing and livestock). Table 1 shows that 11 percent farmers own tractors or plough-yokes and 32 percent own irrigation pumps; whereas 7, 10 and 48 percent of farmers, respectively, benefit from agricultural extension services, agricultural subsidy, and electricity connections. In addition, the survey also includes information on the number of bovine animals owned and reared by the household and the amount of land area under fish cultivation. On average,

[2] For example, note from Table A1 that most of the disasters in Bangladesh during 2006-11 affected specific regions. In addition, certain regions experience recurring natural disasters, which make it difficult to identify random treatment and control groups at the regional level. Moreover, the EM-DAT database that is the source of Table A1 only reports a disaster if one of these four criteria is fulfilled: 1) 10 or more people are reported killed, 2) 100 or more people are reported affected, 3) declaration of a state of emergency, and 4) call for international assistance. However, in many cases, this is a highly restrictive definition to identify the number of affected people, and therefore, undermines the potential effects of disaster exposure at the household level.

households own 1.51 animals such as cow, goat and sheep and cultivate fish on 0.06 acres of land.

Third, we include average plot-level characteristics of rented-in and rented-out agricultural lands. In particular, we include soil type (clay, loam, sandy, clay-loam and sandy-loam soil) and distance (i.e., distance from homestead) of rented-in and rented-out agricultural lands. Table 1 reports that on average, rented-in and rented-out land plots, respectively, are 0.37 and 0.23 kilometers away from farmer's homestead. In addition, farmers transact land plots with all types of soil.

Finally, the BIHS contains information on the availability of local level infrastructure such as markets. Common survey proxies of such infrastructural access include distances of nearest market and paved road from the homestead. Table 1 reports that on average, households are located 2.21 and 1.77 kilometers away from the nearest paved road and market.

III.B Empirical Strategy

Since farmers are the primary victims of natural disasters in rural areas, investigation into the ways of agricultural adaptation to disaster exposure is important. For example, land rentals can serve as a risk coping strategy if rental decisions are made in response to shocks resulting in income losses (Ward and Shively 2011).[3] Farmers make livelihood decisions based on their owned land, and such decisions may often be motivated by exposure to extreme climatic events. The key idea behind quantity adjustment through a land rental market is that larger farmers rent-out their surplus lands to smaller farmers, who rent-in to optimize their operational farm size. We hypothesize that this phenomenon is accelerated when such transactions take place in response to exposure to a natural disaster.

We develop a conceptual model similar to Deschenes and Greenstone (2007).[4] For simplicity, we assume that the land rental market always clears irrespective of whether or not

[3] Ward and Shively (2011) employed pooled cross-section instrumental variables probit and 3sls estimates to identify that Chinese households engage in land rentals as a response to covariate shocks, but not in response to idiosyncratic shocks. To our knowledge, this is the only previous study of the role of the land rental market in facilitating adaptation to disasters. However, the authors did not consider the land rental market as a means of indirectly adapting land operation and yields to disasters, which is a key contribution of our paper.

[4] In case of US agriculture, Deschenes and Greenstone (2007) exploited the random year-to-year variation in temperature and precipitation to estimate whether agricultural profits are higher or lower in years that are warmer and wetter. Specifically, they estimated the impacts of temperature and precipitation on agricultural profits and then multiply them by the predicted change in climate to infer the economic impact of climate

a disaster takes place. However, this simplifying assumption implies that, in combination with high population density and low per-capita arable land, any increased rental transaction in response to disaster-exposure must be captured by observed heterogeneity in the socioeconomic and agricultural attributes associated to the transacted plots of land. Therefore, a representative farmer's optimal rent-in and rent-out amounts, respectively, are $l^i = l^i(\tau; \varpi^i)$ and $l^o = l^o(\tau; \varpi^o)$; whereas ϖ^i and ϖ^o are observed attributes associated to rented-in and rented-out land plots, respectively. $\tau = 1$ represents exposure to a natural disaster, and $\tau = 0$ indicates no such exposure.

We assume that the output and cost are functions of operational land, whereas price is normalized to unity. The representative farmer produces a given crop (or a given mix of crops) and is unable to switch crops in response to disaster-exposure. Therefore, capturing the effects of operational farm size adjustments on agricultural revenue requires maximizing the following profit function:

$$(1) \qquad \pi = (1 - \alpha\tau)q(l + l^i - l^o) - c(l + l^i - l^o) + (l^o - l^i)r,$$

where p, q, l, c and r, respectively, denote agricultural price, output, amount of owned land, cost of production and the pre-fixed rent per-unit of land. Total operational farm size is $l + l^i - l^o$. $\alpha \geq 0$ indicates the loss in agricultural revenue due to disaster exposure that results in lowering the productivity of operated land.

Although sharecroppers may have lower yield on rent-in land (Shaban 1987), we assume that the rent is pre-fixed by the government, which is independent of the occurrence of a disaster. Moreover, we focus on total agricultural revenue instead of per-acre yield, and since farmers are motivated by profit-maximization, this existence of pre-fixed rent allows us to normalize the productivity of each type of land.

Although price can be volatile, and it can be argued that an increase in agricultural revenue may largely be due to increased prices resulting from post-disaster production shortages, we normalize price to unity by taking the fact into account that potential relocation of agricultural operations through rental transactions to different plots of land might normalize price over regions in a specific production year. In absence of panel data, we cannot separate the price effect in our empirical analysis since farm-gate prices may not significantly vary across regions.

change in this sector. We differ by exploiting disaster-induced variations, other than continuous measures of climatic changes.

Since disaster-exposure affects rent-in and rent-out amounts as well as the output, we need to disentangle the direct and indirect effects of disaster exposure. The representative farmer's profit changes with disaster-exposure according to:

(2) $$\frac{\partial\pi}{\partial\tau} = -\alpha q + [(1-\alpha\tau)q' - c' - r]\left(l^{i\prime}(\varpi^i) - l^{O\prime}(\varpi^O)\right).$$

The first term, $-\alpha q$, accounts for the direct effect of a disaster on agricultural output, which, in general, implies that exposure to disaster lowers agricultural revenue since $-\alpha q < 0$. The second term, $[(1-\alpha\tau)q' - c' - r]\left(l^{i\prime}(\varpi^i) - l^{O\prime}(\varpi^O)\right)$, accounts for the indirect effect of a disaster on agriculture through the land quantity adjustment. It corresponds to the net effect of land quantity adjustment on agricultural revenue, which includes the agricultural income from rented-operated and owned-operated land, and money received from rented-out land, whereas deducts the money paid for rented-in land.

Table 2 summarizes our outcome variables by exposure to disaster. We find that disaster-affected farmers have higher agricultural income than their unaffected counterparts, i.e., $\frac{\partial\pi}{\partial\tau} > 0$. However, any conclusion drawn on these results may be misleading since the decomposition of the sources of agricultural revenue is important to understand whether the affected farmers have not experienced any loss from disaster or they have adapted effectively to overcome those losses. We explain this puzzle by exploiting the variations in participation and transaction in the agricultural land rental market. Table 2 also shows that disaster-affected farmers have higher participation and transaction in the agricultural land rental market than the unaffected farmers. Therefore, since $-\alpha q < 0$, we must have $[(1-\alpha\tau)q' - c' - r]\left(l^{i\prime}(\varpi^i) - l^{O\prime}(\varpi^O)\right) > \alpha q$, i.e., indirect effects through land rental transactions must offset the direct harmful effects of disaster, in order to get $\frac{\partial\pi}{\partial\tau} > 0$.

However, such rental transactions are conditional on a number of socioeconomic factors. In particular, since $\varpi^i = \varpi^O$ implies $l^{i\prime}(\varpi^i) = l^{O\prime}(\varpi^O)$ and invalidates the indirect beneficial effects of land rental transactions on the disaster-affected farmers, those attributes must exhibit sufficient heterogeneity across farmers' participating roles in the land rental market so that $\varpi^i \succ \varpi^O \Leftrightarrow l^{i\prime}(\varpi^i) > l^{O\prime}(\varpi^O)$. Table 3, which summarizes the control variables that we use in this paper, shows that socioeconomic attributes vary across farmers' rental market participating roles and, therefore, optimal adjustment of farm size through rental transactions must be conditioned on them. First, in terms of household-level attributes, summary statistics in Table 3 confirm that younger and less educated farmers with smaller landholdings, lower incidences of migrant member and larger families are more likely to rent-in than rent-out. In addition, farmers renting-in have higher tractor ownership, better access to extension and subsidy, and higher number of animals; whereas those renting-out have higher irrigation pump ownership, and better access to electricity connection. Finally, farmers renting-in have lower access to infrastructural facilities such as roads and markets: they are located far from these facilities than those renting-out. All these variables are important in determining the effects of disasters, and we include them in our econometric specifications in the following section.

IV. EMPIRICAL SPECIFICATIONS

We examine the effects of disaster-exposure on agricultural revenue, controlling for land quantity adjustment through farmer's participation and transaction in the land rental market, using an econometric approach that accounts for extensive and intensive margins. The intensive margin measures the direct effects of disaster on agricultural revenue, whereas the extensive margin considers the potentially mitigating effects of disaster-induced land quantity adjustments on the harms of disaster. Note that, we restrict our estimation to agricultural plots to avoid any potential bias that might arise from multiple use of land plots.

We estimate the effects of disaster exposure on land quantity adjustment through the rental market. However, as Figure 1 shows, both the rent-in and rent-out amounts are left-censored due to farmer's participation decisions: a positive amount of land brought into rental market for either renting-in or renting-out is observed only when a farmer decides to participate in the rental market. Thus, the participating samples are nonrandom, and are drawn from a wider population of farmers. Both the rent-in and rent-out choices must be modeled to avoid sample selection bias: Figure 1 confirms that both rent-in and rent-out amounts have better kernel density distribution from selected sample of participants. In addition, recent evidence indicates that such rent-in and rent-out decisions can be simultaneous in case of Bangladesh (Rahman 2010).[5] For example, 5.54 percent of farmers from our estimating sample make simultaneous rent-in and rent-out decisions on different plots of agricultural land (Table 3). Therefore, our determination of rental transactions must

[5] Rahman (2010) adopted a multivariate tobit structure to identify the joint determinants of simultaneously made rent-in and rent-out decisions by rural Bangladeshi farmers.

involve a simultaneous system of equations on the selectivity-corrected sample of agricultural land rental market participants.

Following Pfeiffer and Lin (2014), we use Lee's generalization of Amemiya's two-step estimator to a simultaneous equations model (Lee 1990), which is asymptotically more efficient than Heckman's selection model (Heckman 1978), when estimating a system of equations. At any point in time, the decision to participate in the land rental market and the optimal rent-in and rent-out amounts by each farmer can be estimated as a two-step process as outlined in equations (3) and (4). First, a farmer i participates in the land rental market according to:

$$\begin{aligned} L_{i1} &= f(w_i, x_i, z_i, \Delta, \varepsilon_{i1}) \\ L_{i2} &= f(w_i, x_i, z_i, \Delta, \varepsilon_{i2})' \end{aligned} \tag{3}$$

where $\varepsilon_{i1} \sim (0, \sigma_1^2)$, $\varepsilon_{i2} \sim (0, \sigma_2^2)$ and $cov(\varepsilon_1, \varepsilon_2) = \rho$. Binary outcome variables representing farmer's willingness to participate in the land rental market, L_{i1} and L_{i2}, are defined as $L_{i1} = 1$ if the farmer rents in land and 0 if not and $L_{i2} = 1$ if the farmer rents out land and 0 if not. Vectors w_i, x_i and z_i, respectively, contain the infrastructural variables, conventional controls and the measures of disaster-exposure; whereas, Δ is the vector of district dummies to control for any unaccounted regional effects.

Vector z_i includes our variables of interest defining disaster exposure of a household. We use three different definitions of disaster exposure. First, we define a binary measure of exposure to any disasters, which takes a value equal to 1 if the household was exposed to any flood or storm in last five years and 0 if it was not exposed. Second, we also use a continuous measure of the severity of disasters defined as the natural log of immediate monetary losses from exposure to natural disaster such as flood and storm in the last five years. Third, considering the fact that the effects may vary with disaster types, we use a third definition of disaster-exposure where the categorical exposure variable takes the value of 0 if not exposed to any disaster, 1 if exposed to storms and 2 if exposed to floods. In addition, since the amount of landholding influences the renting decisions in general (e.g., Rahman 2010), we interact our exposure variables with logged per-capita landholding in all three cases.

Our empirical approach to estimating (3) involves specifying the components of the vectors w_i and x_i based on the information available in the BIHS dataset. First, we include the infrastructural variables in w_i, which consists of logged distances of the farmer's homestead from the nearest market and paved road. Typically, distance from market measures the access to non-agricultural employment which might also have mitigating effects on the exposure to a natural disaster. Controlling for access to non-agricultural employment is important. For example, Kung (2002) found that Chinese households with active participation in off-farm labor markets have rented less land. On the other hand, both the distances from market and main road indirectly control for the non-agricultural and commercial use of a plot of land. Generally, better access to such infrastructural facilities lowers the dependency on agriculture, and, therefore, may affect rental market participation. Moreover, in absence of a direct measure of migration in response to disaster-exposure, they also control for farmer's likeliness to migrate to unaffected or urban areas.

We follow existing literature to specify generic determinants, x_i, of agricultural land rental decisions, which commonly include household- and farm-level characteristics (e.g., Taslim and Ahmed 1992; Deininger, Zegara, and Lavadenz 2003; Teklu and Lemi 2004; Deininger and Jin 2005; Rahman 2010). A household is defined to include the number of people that dine-in together from the same pot. Household characteristics include the age and years of schooling of the household head, household size, and whether the family has a migrant member. Farm-level characteristics include ownerships of tractor or plough-yoke and irrigation pump, diversification in farming structure and access to agricultural facilities. Diversification in farming structure is measured by the logged number of bovine animals owned and reared and logged acres of land under fish cultivation by the household. On the other hand, agricultural facilities include agricultural extension services (defined as 1 if the household has access to agricultural extension services and 0 if not), subsidy (defined as 1 if the household has received agricultural subsidy and 0 if not), and electricity (defined as 1 if the household has access to electricity connection and 0 if not).[6,7]

The purpose of the system of equations (3) is to select the sample of farmers participating in the land rental market either to rent-in or to rent-out land. Employing the bivariate probit estimation method, we simultaneously estimate the inverse mills ratios IMR_1 and IMR_2. We then include IMR_1 and IMR_2 as explanatory variables when estimating the optimal land quantity adjustment to correct the sample of land rental market participants and also to control for the information contained in the cross-equation correlations. Optimal rent-in and

[6] Bandyopadhyay and Skoufias (2015) identified ex ante occupational diversification, together with policy interventions such as access to market, credit and safety net, as an autonomous and proactive adaptation strategy in Bangladesh.

[7] Taslim and Ahmed (1992) found that farm size, number of workers or income earning members in the family and access to agricultural assets such as ownership of bullocks are important determinants of land rental market transactions in Bangladesh.

rent-out amounts for a participating farmer i are determined according to the system of equations:

$$(4) \qquad \begin{array}{l} L_{i1}^{*} = g(x_{1i}, z_i, \Delta, IMR_1, \xi_{i1}) \\ L_{i2}^{*} = g(x_{2i}, z_i, \Delta, IMR_2, \xi_{i2}) \end{array},$$

where L_{i1}^{*} and L_{i2}^{*}, respectively, denote the optimal rent-in and rent-out amounts, which are observed when $L_{i1} > 0$ and $L_{i2} > 0$, respectively. We empirically define the outcome variables L_{i1}^{*} as natural log of one plus acres of rent-in land by farmer i and L_{i2}^{*} as natural log of one plus acres of rent-out land by farmer i.

Both the vectors x_{1i} and x_{2i} include all the components of x_i. However, since rented-in and rented-out land plots may differ in their observable attributes, we also include distance from homestead and soil types of rented-in and rented-out plots of land. Both the distances and soil types are averaged across all the rented-in and rented-out plots separately, and then included in the corresponding vector in (4). In addition, since selection models are only identified by functional form assumptions without a plausible exclusion restriction and also since parameters in selection models are estimated with more precision if some regressors in the selection equation can be excluded from the outcome equation (Wooldridge 2010), we exclude the vector w_i, components of which affect the participation decision but not the optimal quantity adjustment decision.

Effects of disasters on agricultural revenue are conditional on rent-in and rent-out amounts, which are endogenously determined by equation (4). We employ following two-stage least squares (2SLS) model on the selectivity-corrected sample to estimate the effects of disaster on the agricultural income of a participating farmer i:

$$(5) \qquad Y_i = h\left(\widehat{L_{i1}^{*}}(x_{1i}, z_i, \Delta, IMR_1, \xi_{i1}), \widehat{L_{i2}^{*}}(x_{2i}, z_i, \Delta, IMR_2, \xi_{i2}), z_i, \epsilon_i\right),$$

where Y_i represents agricultural income, defined as natural log of one plus the market value of total harvested crops, minus the monetary value of the payments for rented-in land and plus the monetary value of the receipts from rented-out land. We consider all harvested crops and their local market prices reported by farmers when calculating total revenue. In fact, we adopt a modified Ricardian model in (5) where we use total crop revenue as our outcome variable instead of land value in order to capture the effects of disaster exposure in agriculture. The use of revenue is particularly appropriate in this set-up since land markets are often imperfect in Bangladesh like many other developing countries (Di Falco, Veronesi, and Yesuf 2011), and the use of land values requires fully functioning land markets so that land prices reflect the present discounted value of land rents into the infinite future (Deschenes and Greenstone 2007).

Estimated rent-in and rent-out amounts, i.e., $\widehat{L_{i1}^*}$ and $\widehat{L_{i2}^*}$, which are estimated simultaneously using (4), connect the coefficients of the components of z_i in (4) with the outcome variable in (5), and, therefore, yield the indirect effect or extensive margin of disaster-exposure through land rental transactions. On the other hand, coefficients of the components of z_i in (5) yield the direct effect or intensive margin of disaster-exposure on crop revenue. Following Moore, Gollehon, and Carey (1994), the marginal effect of disaster-exposure is the sum of the effects along the intensive and extensive margins from the selectivity-corrected sample of land rental market participants:

$$(6) \qquad \frac{dY}{dz} = \frac{\partial Y}{\partial z} + \frac{\partial Y}{\partial \widehat{L_1^*}}\frac{\partial L_1^*}{\partial z} + \frac{\partial Y}{\partial \widehat{L_2^*}}\frac{\partial L_2^*}{\partial z},$$

where $\frac{\partial Y}{\partial z}$ is the intensive margin, and $\frac{\partial Y}{\partial \widehat{L_1^*}}\frac{\partial L_1^*}{\partial z}$ and $\frac{\partial Y}{\partial \widehat{L_2^*}}\frac{\partial L_2^*}{\partial z}$ denote the extensive margins from rent-in and rent-out of agricultural land.

V. RESULTS AND ANALYSIS

V.A Disaster and Land Rental Market

Table 4 reports the determination of farmer's land rental market participation decisions. Participation choices, i.e., rent-in and rent-out, are estimated using a full information maximum likelihood bivariate probit model according to specification (3), where the binary dependent variables are rent-in (i.e., 1 if the farmer rent-in land and 0 if not) and rent-out (i.e., 1 if the farmer rent-out land and 0 if not). Statistically significant Wald test validates the use of bivariate probit model instead of separate regressions.

We find that disaster-exposure increases the probability of rent-in by 45.1 percent and decreases the probability of rent-out by 27.8 percent. However, disaster-affected farmers with 1 percent higher per-capita landholding are 1.6 percent less likely to rent-in and 3 percent more likely to rent-out than unaffected smaller farmers. These results are consistent when we use other definitions of exposure: Table 4 shows that the directions of these relationships are same in case of the continuous measure of the severity of disaster (columns 3 and 4), and in case of different types of disaster (columns 5 and 6). In addition, most of the other determinants of land rental market participation are statistically significant and exhibit same directions and similar magnitudes under all three definitions.

However, main purpose of equation (3) is to overcome the sample selection bias. We simultaneously estimate the inverse mills ratios from bivariate probit regressions, which are then used as additional regressors in corresponding estimations of equation (4). Table 5 reports the determinants of land rental market transactions from seemingly-unrelated regression estimates on selectivity-corrected samples of rental market participants. Due to missing data, we have 3,063 valid samples out of a maximum possible sample of 3,173 participating farmers.

We find that disaster-exposure increases the rent-in amount by 14.1 percent and decreases the rent-out amount by 18.2 percent. Also, disaster-affected farmers with 1 percent higher per-capita landholding have 0.55 percent lower rent-in and 1.18 percent higher rent-out amounts. These results are consistent when we use the continuous measure of the severity of disaster (columns 3 and 4), and different types of disaster (columns 5 and 6). Apart from confirming that disaster-exposure stimulates the land rental transactions, these results also confirm the stylized fact behind land quantity adjustment: larger farmers rent-out and smaller farmers rent-in to optimize their corresponding operational farm sizes.

In addition, a number of socio-economic factors affect farmers' participation in the land rental market but these work mostly in opposite directions regarding decision to rent-in or rent-out land. Most of them are statistically significant; however, we find that ownership of irrigation pump to have insignificant effects on renting-in decision, whereas ownership of tractor and access to extension services do not significantly affect rent-out decision.

Among the household characteristics, age of the household head represents an indirect, but commonly used, measure of farming experience. Since relatively experienced farmers may be more dependent on agriculture, our results quite fittingly show that older farmers have significantly higher rent-in and rent-out amounts. These results are consistent with literature (Kung 2002; Vranken and Swinnen 2006; Deininger and Jin 2005). Kung (2002) and Vranken and Swinnen (2006) found positive influence of age on renting-in land, whereas Deininger and Jin (2005) reported a negative influence.

We find that the households with better-educated heads rent-in less and rent-out more. Since schooling is an indicator of household's likeliness to have a non-agricultural source of income, and since education increases the opportunity cost of agricultural income (e.g., Teklu and Lemi 2004), better-educated households may rent-out land in order to substitute their time away from agricultural production (Deininger, Zegara, and Lavadenz 2003; Teklu and Lemi 2004; Rahman 2010). Another household-level indicator of access to non-agricultural income is having a migrant family member. Consistent with the effect of schooling, we also find that households with at least a migrant member have significantly lower rent-in and higher rent-out amounts. This result is consistent with the findings of Kung (2002) that Chinese households with active participation in the off-farm labor market rent-in less.

Family size represents subsistence pressure on the household (e.g., Rahman 2010; Teklu and Lemi 2004; Kung 2002), which necessitates higher operational farm size. Results show that larger families rent-in more and rent-out less amounts. That is, higher subsistence pressure increases operational farm size, and, therefore, results in increased dependency on agriculture. These results are consistent with the findings of Rahman (2010) and Teklu and Lemi (2004) that smaller families are more likely to rent-out, and the findings of Kung (2002) that that higher dependency ratio increases the likeliness to rent-in.

Among the farm-level characteristics, ownership of tractor or plough-yoke significantly increases rent-in, whereas ownership of irrigation pump significantly increases rent-out amount. Besides, access to agricultural extension services significantly increases rent-in amount, whereas access to agricultural input subsidy significantly increases rent-in and decreases rent-out amount. In addition, access to electricity significantly increases both the rent-in and rent-out amounts. In general, these results imply that the farmers with access to technological information and knowledge find it better to rent-in more to optimize their operational farm size.

Farmers with higher number of bovine animals rent-in more and rent-out less; whereas, those with higher amount of area under fishing have higher rent-in and rent-out amounts, with this effect being stronger for rent-in. Together, we infer that agricultural diversification results in farmers increasing the operational farm size through rental transactions.

Finally, average distance of plots from homestead significantly increases both the rent-in and rent-out amounts. However, effect of plot distance is slightly higher on rent-in, which implies that farmers overall try to lower the distance of their operated land plots. In addition, average soil types also have significant influences on rental decisions.

V.B Marginal effects of disaster

We are mainly interested in the total marginal effects of disaster-exposure on crop revenue, which can be calculated using the equation (6) as the sum of intensive and extensive margins. All the calculations are based on the coefficients of logged rented-in and rented-out amounts and the interaction between logged per-capita landholding and disaster exposure, all of which are statistically significant in all the regressions.

Table 6 reports the effects of disaster on crop revenue along the intensive margin conditional on land quantity adjustments. The coefficient of exposure is negative, and that of the interaction between exposure and logged per-capita landholding is positive. In particular, disaster-affected farmers have 19.4 percent significantly lower crop revenue; whereas disaster-affected farmers with 1 percent higher per-capita landholding have 1.21 percent significantly higher crop revenue than the unaffected smaller farmers. That is, while disasters cause direct harms to agriculture, the severity is lower for the larger farmers. Using these estimated coefficients, we calculate the intensive margin, defined as $\frac{\partial Y}{\partial z}$ in equation (6), as $-0.194 + 1.214 * \ln(landholding)$, which ranges from -0.0245 to 0.2553 (Table 7).

Next, we find that 1-percent increases in rent-in and rent-out amounts increase the crop revenue by 1.72 percent and 0.55 percent, respectively. These results are consistent with our definition of crop revenue, which includes the monetary value of receipts from rent-out and excludes the monetary value of payments for rent-in. Following equation (6), we multiply the estimated effects of disaster-exposure on land rental transactions from Table 5 with these estimated effects of rent-in and rent-out land on crop revenue to calculate the corresponding extensive margins. Total extensive margin, sum of extensive margin from rent-in calculated as $1.717 * [0.141 - 0.551 * ln(landholding)]$ and extensive margin from rent-out calculated as $0.546 * [-0.182 + 1.18 * \ln(landholding)]$, ranges from -0.4030 to 0.1427.

Finally, marginal effect of disaster-exposure, sum of intensive and extensive margins, ranges from -0.051 to 1.598. Together, average estimates of intensive and extensive margins and total marginal effect imply that although disaster-exposure lowers the crop revenue, an average farmer engaged in land rental transactions can successfully overcome the direct losses from disaster. In particular, Table 7 shows that an average direct loss in crop revenue by 2.45 percent can be compensated by an average 10.1 percent increase in crop revenue from land rental market transactions. In total, we identify that an average farmer transacting in the land rental market to optimize her operational farm size in the wake of a disaster ultimately experiences 7.61 percent higher crop revenue.

Our estimates of marginal effects of disaster-exposure are consistent when we use the continuous measure of the severity of disasters, which is defined as the natural log of immediate monetary losses from exposure to disasters in the last five years. Column 2 in Table 6 reports the effects of the severity of disasters on crop revenue along the intensive and extensive margins conditional on land quantity adjustments. In particular, farmers with 1-percent higher monetary loss have 0.039 percent lower crop revenue; whereas disaster-affected farmers with 1 percent higher per-capita landholding and 1-percent higher monetary loss have 0.195 percent higher crop revenue than unaffected smaller farmers. Using the coefficient estimates from tables 5 and 6 on the formulae outlined in equation (6), we calculate the intensive and extensive margins as $IM \in [-0.039, 0.314]$ and $EM \in [-0.0712, 0.0303]$, respectively. Consistent with our main results, we identify that farmers exposed to disasters were able to reduce their losses through land rental transactions. Estimates of marginal effects reported in Table 7 show that while on average a 1 percent increase in the losses from disaster directly reduces the agricultural income by 1.18 percent, average farmers adjusting their operational farm size were able to overcome that loss by 2.24 percent to ultimately have a 1.07 percent higher crop revenue.

Our third definition of disaster-exposure considers the fact that the effects may vary with disaster types, and, therefore, we redefine the disaster dummy as 0 if not exposed to any disaster, 1 if exposed to storms and 2 if exposed to floods. Column 3 in Table 6 reports the effects of different types of disaster on crop revenue along the intensive and extensive margins conditional on land quantity adjustments. In particular, storm-exposure decreases crop revenue by 22.2 percent; whereas storm-affected farmers with 1 percent higher per-capita landholding have 1.06 percent higher in crop revenue than unaffected smaller farmers. On the other hand, flood-affected farmers have 17.2 percent lower crop revenue; whereas flood-affected farmers with 1 percent higher per-capita landholding have 1.68 percent higher crop revenue than the unaffected smaller farmers. Together, intensive and extensive margins from storm-exposure are $IM \in [-0.222, 1.691]$ and $EM \in [-0.1592, 0.0998]$, respectively; whereas, those from flood-exposure are $IM \in [-0.172, 2.8659]$ and $EM \in [-0.7738, 0.2056]$.

Consistent with our main results based on the first definition, we identify that farmers were able to reduce their losses from storm and flood through participation in the land rental market. In both cases, farmers who transacted in the land rental market to optimize their operational farm size are better-off than non-participants. In particular, storm-exposure directly lowers crop revenue of an average farmer by 7.43 percent, which is then compensated by 7.98 percent increase in crop revenue from rental transactions, resulting in a net increase of 0.55 percent. On the other hand, flood-exposed average farmers do not experience any direct crop loss since the average intensive margin is positive, which might be a consequence of increased topsoil and open-access irrigation on the flooded plots of land in the following years. In related literature, for example, Banerjee (2010a) found that while severe flooding may lower agricultural yield in disaster months, they may also provide open-access irrigational input that lead to significant increases in post-flood productivity. However, smaller farmers, who have negative intensive margins, can benefit from rental transactions to increase their operational farm size. In particular, they can benefit from an average extensive margin of 13.37 percent and therefore can overcome the harms of floods.

Overall, our estimates of average marginal effect of disaster-exposure are consistent with the general findings of Mendelsohn (2008) that adaptation by farmers will partially offset some of the worst predicted damages to agriculture due to warming in developing countries over the next century. As panels A–D in Figure 4 demonstrate, our results suggest that the land rental market could enable farmers to more than overcome any agricultural income losses from disaster exposure. In addition, panels A–D in Figure 5 show that higher total marginal effects for larger farmers are mostly due to their intensive margins, which suggests that rental transactions in response to disaster-exposure benefit the smaller farmers more.

V.C Marginal effects of disaster on total income

We also investigate the role of land rental market transactions in mitigating the effects of disaster on total household income, which is the sum of crop revenue and non-agricultural income, employing the econometric specifications (3)–(6). Table 8 reports the effects of disaster-exposure on total income along the intensive and extensive margins conditional on land quantity adjustments, whereas Table 9 reports the estimated marginal effects for all three definitions of disaster-exposure.

Consistent with our estimate of total marginal effect for crop revenue, we find that land rental market transactions to optimize operational farm size also facilitate indirect adaptation to total household income. In particular, disaster-exposure directly lowers total income of an average farmer by 1.06 percent, which is then compensated by 9.88 percent increase in income from rental transactions, resulting in a net 8.82 percent increase in total income. Results are similar when using the continuous measure of exposure: an average farmer with 1 percent higher loss have 0.39 percent direct loss in income; whereas those adjusting their operational farm size were able to overcome that loss by 2.16 percent to ultimately have a 1.77 percent higher income.

However, disaster-specific effects are quite different on total income in comparison to those on agricultural income as described earlier. While average farmers do not experience any direct harms of floods on agricultural income, they experience lower total income from flood-exposure. On the other hand, storm-affected farmers have exactly opposite experience:

farmers experience direct loss in agricultural income but not in total income from storm-exposure. These results have two indirect implications. First, floods probably provide open-access irrigation coverage for the affected land plots in the subsequent cropping seasons (Banerjee 2010a), which may result in increased agricultural income of the flood-affected farmers. Second, storm probably creates higher structural change in terms of moving away from agriculture for income. However, the estimates of total marginal effects reported in Table 9 reconfirm that both the storm- and flood-affected farmers were able to benefit from land rental transactions. Therefore, our results are robust to different definitions of disaster-exposure and different definitions of income.

VI. CONCLUSIONS

We examine agricultural adaptation to disaster-exposure through simultaneously made rent-in and rent-out choices in the land rental market. We employ an econometric approach based on Lee (1990), Moore, Gollehon, and Carey (1994) and Pfeiffer and Lin (2014) that accounts for both the intensive and extensive margins. Evaluated at the mean value of (logged) per-capita landholding, we find that disaster-exposure results in 7.61 percent net increase in crop revenue: a 2.45 percent direct decrease in crop revenue is compensated by a 10.06 percent indirect increase through land rental market transactions. Therefore, farmers exposed to disasters appear to have successfully overcome the losses from disaster by adjusting their operational farm size through simultaneously made rent-in and rent-out decisions in the agricultural land rental market. These results are robust to alternative definitions of disaster-exposure and outcome variable, as shown in Section V.

Accounting for the effects of disaster exposure on adjustments in quantity of operated land and its impact on agricultural revenue is important since disaster-exposure results in losses in income (IPCC 2012). Such a relationship may be especially relevant when farmers actively participate in land rental markets (Figure 1). Our results have important implications for Bangladesh and other low-income countries in terms of land management, economic welfare and disaster risk reduction. In general, low-income countries have high degrees of land fragmentation, severe incidences of poverty and low per-capita arable land, contributing to increasing number of farms to increasingly depend on rented lands for managing operational farm size (Deininger, Savastano, and Carletto 2012; Jin and Jayne 2013; Masterson 2007; Sklenica *et al.* 2014). Here, we find another important function of the land rental market in poor rural areas, which is to assist farmers in adapting to the adverse impacts on agricultural income from natural disasters. Such a mechamism may become increasingly important as an adaptation response to climate change: since farmers appear to employ the land rental market to adjust the quantity of operational land to adapt to the losses of past disasters and to mitigate the potential losses of future disasters, the land rental market provides a useful mode of climate change adaptation relevant for any low-income agricultural country with recurrent disaster exposure.

As this paper suggests that access to a well-functioning land rental market might be a crucial part of the coping strategy that allows farmers to adjust their agricultural revenue, improving and facilitating the functioning of such markets in rural areas should be an important component of government post-disaster relief policies. Of particular concern is that the land rental market in rural areas of Bangladesh, as well as in many other low-income countries, is an informal institution. More research needs to be conducted on how well such informal land-rental markets function in the aftermath of natural disasters, and whether more formal markets would facilitate the role of the rental market in assisting farmers to adjust to the agricultural revenue impacts of disasters.

One important direction of future research is to address the effects of land quantity adjustment on the sustainability of land and soil resources in addition to the agricultural revenue effect explored in this paper. However, since adaptation increases food productivity (Di Falco, Veronesi, and Yesuf 2011), it may imply that farmers actually adapt to food scarcity and not to climatic extremes. This argument justifies the short-term nature of responses to disaster exposure such as adjusting operational land quantity as outlined in this paper. However, since weather extremes are noticed much earlier than changes in mean climate (Katz and Brown 1992), adaptation practices need to be incorporated in short-term investment decisions as well (Fankhauser, Smith, and Tol 1999). Therefore, although the debate will remain whether land quantity adjustment as adaptation to disasters is good for environmental sustainability, farmer's adoption of this channel of adaptation helps them at least to overcome the immediate harms of a disaster.

FIGURES

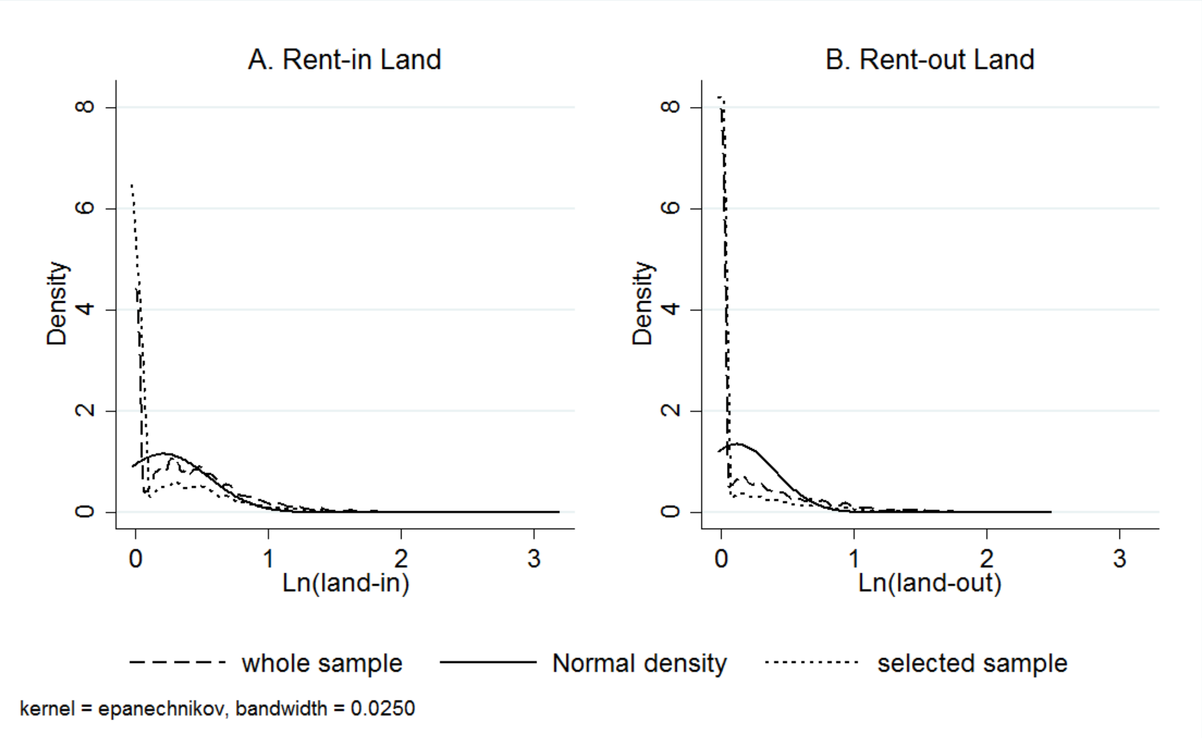

Figure 1 - Land rental transaction distributions

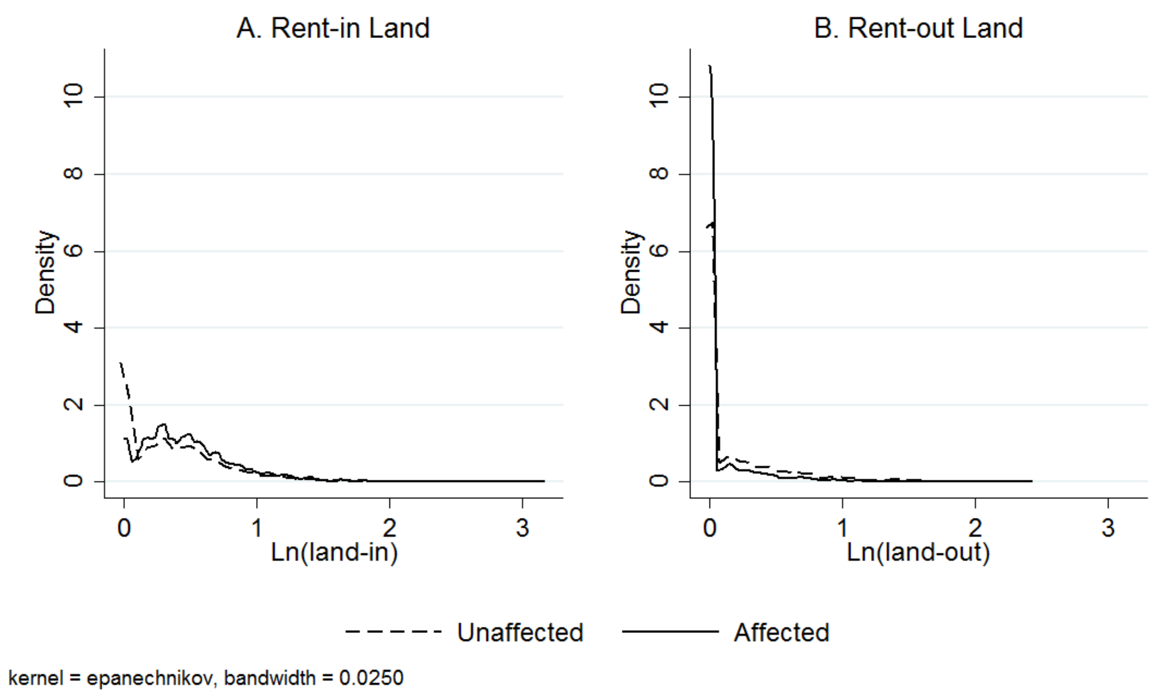

Figure 2 - Land rental transaction distributions by disaster-exposure

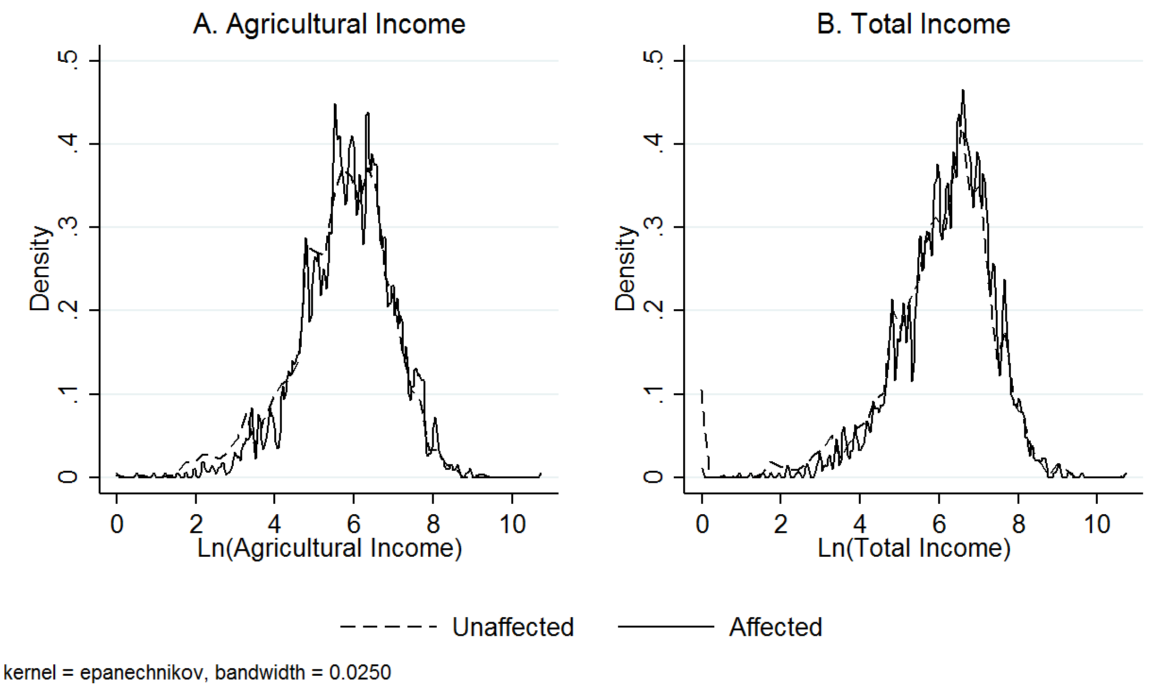

Figure 3 - Income distribution by disaster-exposure

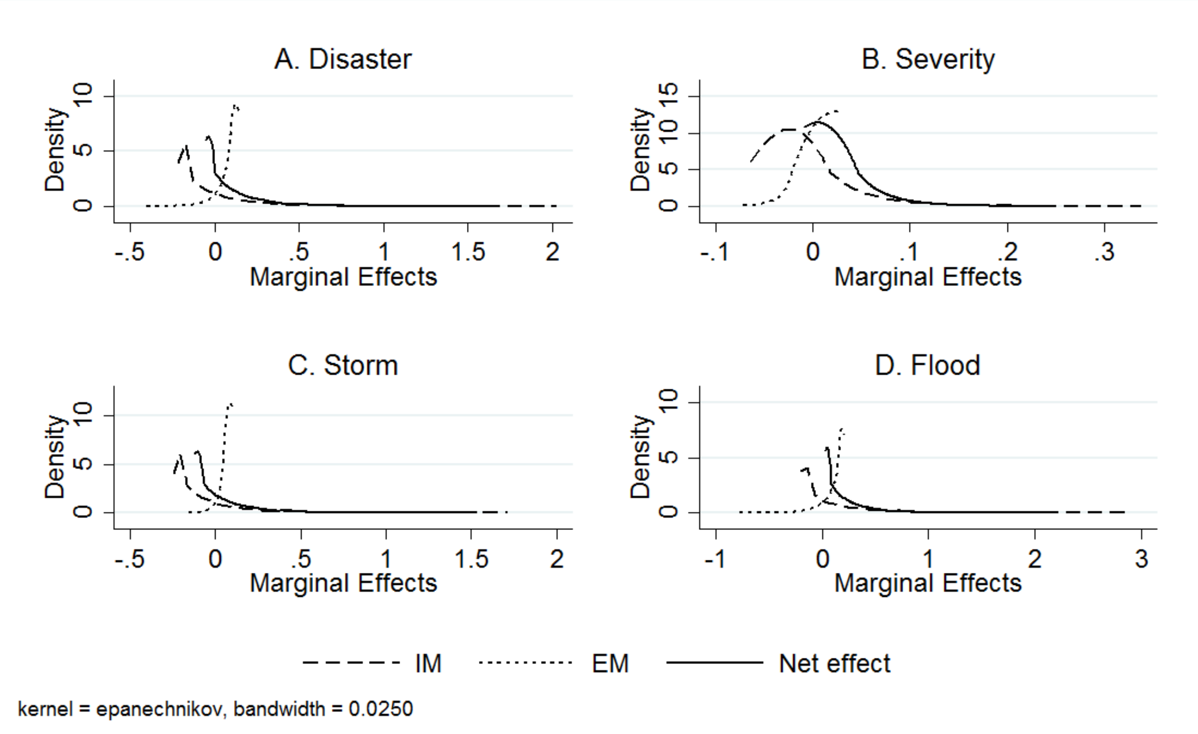

Figure 4. Marginal effects of disaster

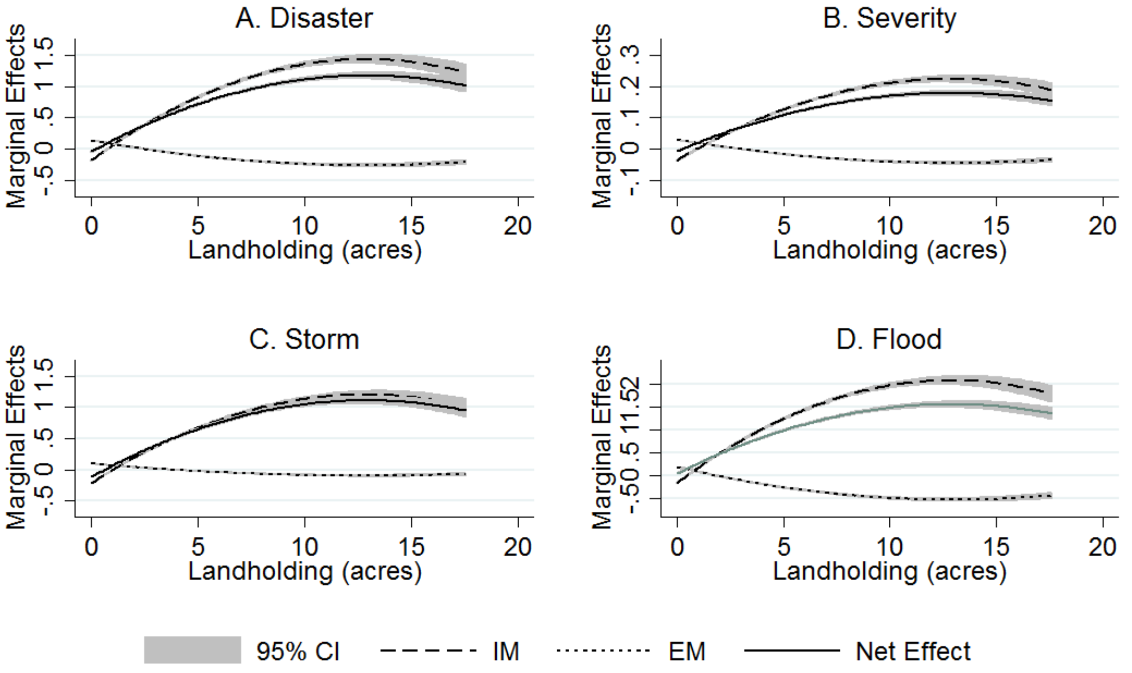

Figure 5 – Disaster-effects and landholding

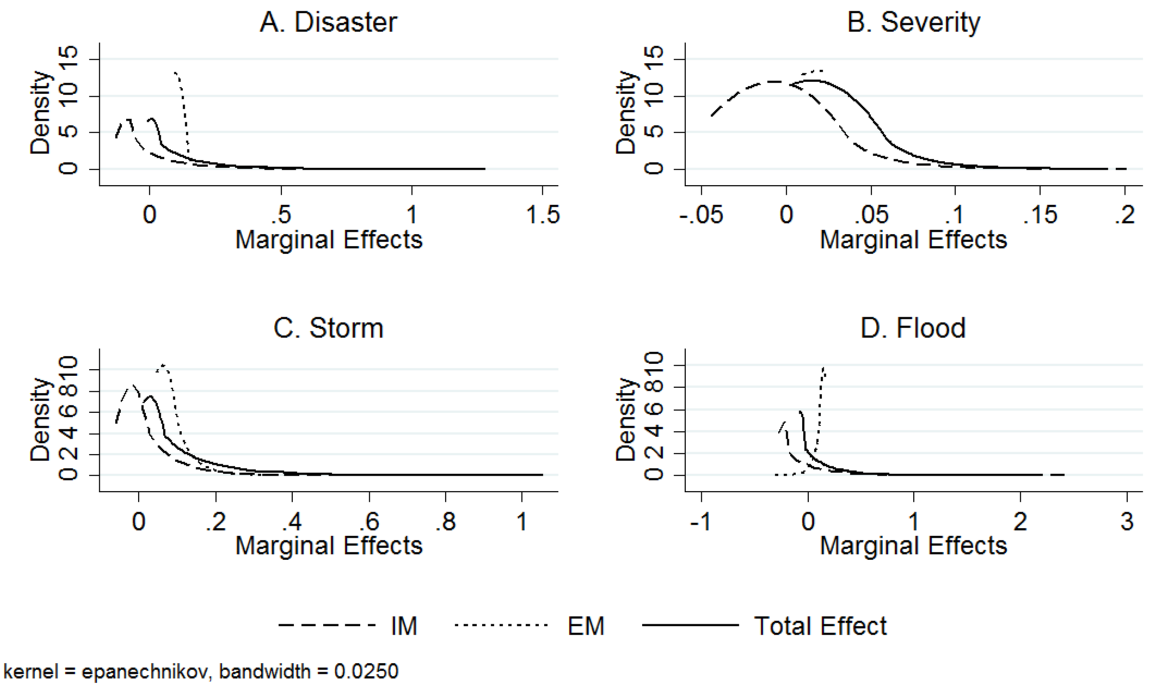

Figure 6 - Marginal effects of disaster on total income

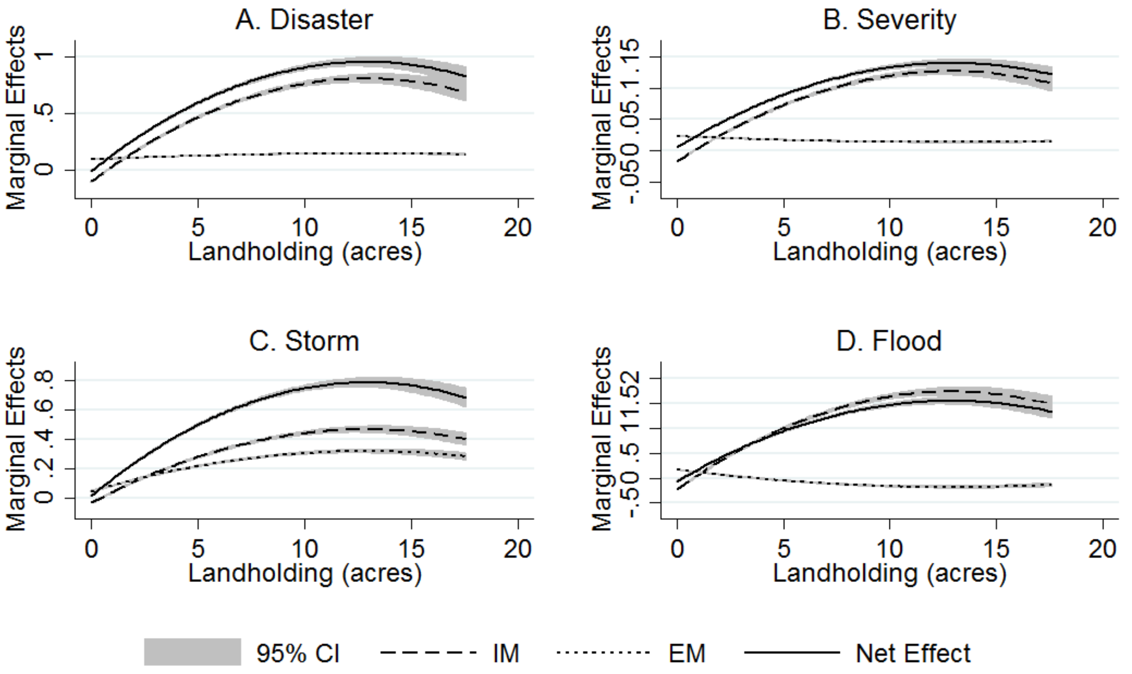

Figure 7 – Disaster-effects on total income by landholding

TABLES

Table 1 – Description and Summary Statistics

Variables	**Description**	**Mean**	**S.D.**	**Min**	**Max**
Disaster	Dummy: 1 if the household was exposed to any natural disaster in last 5 years, 0 if not.	0.15	0.36	0	1
Non-flood disasters	Dummy: 1 if the household was exposed to any non-flood disaster in last 5 years, 0 if not.	0.09	0.29	0	1
Flood	Dummy: 1 if the household was exposed to floods in last 5 years, 0 if not.	0.06	0.23	0	1
Severity of disaster	Monetary losses (US$) from exposure to natural disasters	112.96	789.34	0	24390.24
Rent-in	Dummy: 1 if the household rented in agricultural land, 0 if not	0.40	0.49	0	1
Rent-out	Dummy: 1 if the household rented out agricultural land, 0 if not	0.24	0.42	0	1
Land-in	Acres of rented-in agricultural land	0.33	0.78	0	22.59
Land-out	Acres of rented-out arable land	0.20	0.66	0	10.77
Landholding	Acres of owned agricultural land, includes rented-out lands	0.54	1.10	0	17.57
Farm Size	Acres of operated agricultural land, includes rented-in and owned-operated lands and excludes rented-out lands	0.67	1.12	0	25.18
Crop revenue	Market value of crops (US$), includes receipts from rented-out land and excludes payments for rented-in land	425.52	910.10	0.04	45829.33
Total income	Total income (US $), includes crop revenue and non-agricultural income	695.23	1142.87	0.04	45829.33
Age	Age of the household head	45.05	13.87	17	95
Household size	Number of family members	4.29	1.65	1	17
Education	Years of schooling of the household head	3.46	4.01	0	16
Tractor	Dummy: 1 if owns a tractor or a plough-yoke, 0 if not	0.11	0.31	0	1
Irrigation pump	Dummy: 1 if owns a pump or well for irrigation, 0 if not	0.32	0.47	0	1
Extension	Dummy: 1 if the household has access to agricultural extension services, 0 if not.	0.07	0.26	0	1
Subsidy	Dummy: 1 if the household has agriculture input subsidy card, 0 if not.	0.10	0.30	0	1
Electricity	Dummy: 1 if the household has electricity connection; 0 if otherwise	0.48	0.50	0	1
Animals	Number of bovine animals owned by the household	1.68	2.18	0	26
Fishing	Total area (pond/water-body) under fishing by the household (decimals)	0.06	0.49	0	23.83
Migrants	Dummy: 1 if the household has at least one migrant member, 0 if not	0.21	0.41	0	1
Road distance	Distance from the nearest paved road (in km)	2.21	4.11	0.05	60
Market distance	Distance from the nearest weekly/periodic market/bazaar (in km)	1.77	1.70	0.1	20
Distance (in)	Average distance of rent-in plots from homestead (km)	0.37	0.77	0	35
Distance (out)	Average distance of rent-out plots from homestead (km)	0.23	0.49	0	10
Clay (in)	Percentage of rent-in land with clay soil	0.04	0.18	0	1
Loam (in)	Percentage of rent-in land with loam soil	0.14	0.34	0	1
Sandy (in)	Percentage of rent-in land with sandy soil	0.06	0.23	0	1
Clay-loam (in)	Percentage of rent-in land with clay-loam soil	0.29	0.44	0	1
Sandy-loam (in)	Percentage of rent-in land with sandy-loam soil	0.16	0.36	0	1
Clay (out)	Percentage of rent-out land with clay soil	0.04	0.18	0	1
Loam (out)	Percentage of rent-out land with loam soil	0.07	0.25	0	1
Sandy (out)	Percentage of rent-out land with sandy soil	0.04	0.19	0	1
Clay-loam (out)	Percentage of rent-out land with clay-loam soil	0.19	0.38	0	1
Sandy-loam (out)	Percentage of rent-out land with sandy-loam soil	0.08	0.27	0	1

Notes. Number of observations is 5,491.

Table 2 – Summary Statistics of outcome variables by exposure to disaster

	Exposure to Disaster		Exposure to Non-flood Disaster		Exposure to Flood	
Variables	**Unaffected**	**Affected**	**Unaffected**	**Affected**	**Unaffected**	**Affected**
Rent-in	0.38	0.49	0.39	0.48	0.39	0.51
	(0.49)	(0.50)	(0.49)	(0.50)	(0.49)	(0.50)
Rent-out	0.23	0.26	0.23	0.27	0.23	0.24
	(0.42)	(0.44)	(0.42)	(0.45)	(0.42)	(0.43)
Land-in	0.30	0.51	0.31	0.48	0.32	0.56
	(0.65)	(1.28)	(0.73)	(1.13)	(0.71)	(1.49)
Land-out	0.19	0.23	0.19	0.26	0.20	0.18
	(0.63)	(0.80)	(0.63)	(0.92)	(0.67)	(0.55)
Crop revenue	408.23	521.39	422.01	459.02	413.33	623.07
	(941.06)	(707.34)	(939.02)	(562.71)	(910.25)	(885.99)
Total income	680.85	774.94	687.60	768.15	689.63	786.01
	(1180.44)	(903.19)	(1166.62)	(881.70)	(1154.13)	(938.48)
Number of Observations	4,652	839	4,971	520	5,172	319
	(84.72%)	(15.28)	(90.53%)	(9.47%)	(94.19%)	(5.81%)

Notes. Total number of observations is 5,491.

Table 3 – Summary Statistics by participation decisions

	Participation Decisions			
Variables	**No Participation**	**Rent-out Only**	**Rent-in Only**	**Both Rent-in and Rent-out**
Disaster	0.12	0.16	0.19	0.20
	(0.32)	(0.37)	(0.39)	(0.40)
Non-flood disaster	0.07	0.10	0.11	0.13
	(0.26)	(0.31)	(0.32)	(0.33)
Flood	0.04	0.06	0.08	0.07
	(0.20)	(0.23)	(0.26)	(0.26)
Severity of disaster	83.83	127.60	137.75	135.55
	(702.36)	(580.67)	(961.96)	(823.84)
Landholding	0.32	1.41	0.25	1.14
	(0.82)	(1.73)	(0.50)	(1.29)
Age	44.06	47.77	44.31	48.39
	(14.15)	(14.97)	(12.79)	(12.73)
Household size	4.13	4.09	4.56	4.54
	(1.60)	(1.75)	(1.61)	(1.64)
Education	3.17	5.67	2.54	4.21
	(3.83)	(4.53)	(3.38)	(4.27)
Tractor	0.06	0.10	0.15	0.21
	(0.24)	(0.30)	(0.36)	(0.41)
Pump	0.27	0.42	0.30	0.50
	(0.44)	(0.49)	(0.46)	(0.50)
Extension	0.04	0.07	0.10	0.18
	(0.19)	(0.25)	(0.30)	(0.38)
Subsidy	0.05	0.08	0.15	0.22
	(0.22)	(0.28)	(0.36)	(0.42)
Electricity	0.44	0.62	0.45	0.50
	(0.50)	(0.49)	(0.50)	(0.50)
Animals	1.25	1.41	2.20	2.74
	(1.90)	(2.07)	(2.36)	(2.43)
Fishing	0.02	0.06	0.06	0.28
	(0.11)	(0.20)	(0.35)	(1.83)
Migrants	0.21	0.31	0.15	0.27
	(0.41)	(0.46)	(0.36)	(0.45)
Road distance	2.26	1.95	2.30	2.18
	(4.29)	(3.79)	(4.10)	(3.78)
Market distance	1.77	1.56	1.86	1.85
	(1.80)	(1.43)	(1.71)	(1.65)
Number of Observations	2,326	989	1,872	304
	(42.36%)	(18.01%)	(34.09%)	(5.54%)

Notes. Total number of observations is 5,491.

Table 4 – Land rental market participation decisions

	(1)	(2)	(3)	(4)	(5)	(6)
	Definition 1		Definition 2		Definition 3	
Variables	Rent-in	Rent-out	Rent-in	Rent-out	Rent-in	Rent-out
Disaster	0.451***	-0.278***				
	(0.075)	(0.104)				
Ln(Landholding)*Disaster	-1.749***	2.406***				
	(0.342)	(0.453)				
Ln(loss)			0.082***	-0.039**		
			(0.014)	(0.019)		
Ln(loss)*Ln(Landholding)			-0.288***	0.340***		
			(0.053)	(0.083)		
Storm					0.360***	-0.349***
					(0.087)	(0.111)
Storm *Ln(Landholding)					-1.310***	3.108***
					(0.453)	(0.532)
Flood					0.611***	-0.216
					(0.124)	(0.146)
Flood *Ln(Landholding)					-2.468***	1.764***
					(0.550)	(0.591)
Age	0.010	0.021**	0.009	0.021**	0.009	0.021**
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Squared Age	-0.000*	-0.000	-0.000*	-0.000	-0.000*	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Education	-0.057***	0.083***	-0.058***	0.084***	-0.057***	0.083***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Family Size	0.232***	-0.092**	0.235***	-0.097**	0.236***	-0.088**
	(0.043)	(0.042)	(0.043)	(0.042)	(0.043)	(0.042)
Squared Family Size	-0.015***	0.006	-0.016***	0.006*	-0.016***	0.006
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Tractor	0.223***	-0.022	0.223***	-0.022	0.229***	-0.012
	(0.083)	(0.085)	(0.083)	(0.084)	(0.083)	(0.085)
Pump	-0.176***	0.288***	-0.176***	0.290***	-0.177***	0.291***
	(0.058)	(0.057)	(0.058)	(0.057)	(0.058)	(0.057)
Extension	0.288***	-0.034	0.285***	-0.029	0.284***	-0.040
	(0.086)	(0.091)	(0.086)	(0.091)	(0.086)	(0.091)
Subsidy	0.537***	-0.183**	0.535***	-0.178**	0.534***	-0.185**
	(0.080)	(0.089)	(0.080)	(0.089)	(0.080)	(0.089)
Electricity	0.021	0.282***	0.022	0.282***	0.021	0.280***
	(0.054)	(0.055)	(0.054)	(0.055)	(0.054)	(0.055)
Ln(Animal)	0.329***	-0.021	0.331***	-0.021	0.329***	-0.022
	(0.035)	(0.038)	(0.035)	(0.038)	(0.036)	(0.038)
Ln(Fish)	0.786***	0.491**	0.765***	0.513***	0.768***	0.480**
	(0.188)	(0.191)	(0.184)	(0.189)	(0.183)	(0.192)
Migration	-0.144**	0.296***	-0.144**	0.296***	-0.142**	0.297***
	(0.061)	(0.057)	(0.061)	(0.057)	(0.061)	(0.057)
Ln(Road)	-0.018	0.025	-0.017	0.024	-0.018	0.027
	(0.048)	(0.050)	(0.048)	(0.050)	(0.048)	(0.051)
Ln(Market)	0.065	-0.093	0.067	-0.095	0.065	-0.097
	(0.053)	(0.065)	(0.053)	(0.066)	(0.053)	(0.065)
Constant	-1.316***	-1.950***	-1.305***	-1.961***	-1.318***	-1.973***
	(0.269)	(0.284)	(0.268)	(0.284)	(0.269)	(0.286)
Observations	5,314	5,314	5,314	5,314	5,314	5,314
chi2_c	99.88	99.88	100.3	100.3	99.50	99.50

Notes: Standard errors clustered at the village level are shown in parentheses. ***,** and * represent statistical significance at 1, 5 and 10 percent levels, respectively. We do not report the district dummies; however, they are available upon request. Participation choices, i.e., rent-in and rent-out, are estimated using a bivariate probit model according to specification (3), where the binary dependent variables are rent-in (i.e., 1 if the farmer rent-in land and 0 if not) and rent-out (i.e., 1 if the farmer rent-out land and 0 if not). Statistically significant Wald test validates the use of bivariate probit model instead of separate regressions.

Table 5 – Land Rental Market Transactions

	(1)	(2)	(3)	(4)	(5)	(6)
	Definition 1		Definition 2		Definition 3	
Variables	Ln(land-in)	Ln(land-out)	Ln(land-in)	Ln(land-out)	Ln(land-in)	Ln(land-out)
Disaster	0.141***	-0.182***				
	(0.026)	(0.018)				
Ln(Landholding)*Disaster	-0.551***	1.180***				
	(0.105)	(0.079)				
Ln(loss)			0.027***	-0.029***		
			(0.005)	(0.003)		
Ln(loss)*Ln(Landholding)			-0.089***	0.172***		
			(0.017)	(0.012)		
Storm					0.119***	-0.191***
					(0.026)	(0.020)
Storm *Ln(Landholding)					-0.463***	1.192***
					(0.094)	(0.084)
Flood					0.167***	-0.148***
					(0.037)	(0.025)
Flood *Ln(Landholding)					-0.638***	1.012***
					(0.155)	(0.105)
Age	0.006***	0.004*	0.006**	0.004	0.006**	0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Squared Age	-0.000***	0.000	-0.000***	0.000	-0.000***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Education	-0.013***	0.038***	-0.013***	0.037***	-0.012***	0.035***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)
Family Size	0.037**	-0.057***	0.038**	-0.058***	0.035**	-0.053***
	(0.016)	(0.010)	(0.016)	(0.010)	(0.016)	(0.010)
Squared Family Size	-0.001	0.005***	-0.001	0.005***	-0.001	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Tractor	0.117***	-0.017	0.117***	-0.017	0.116***	-0.014
	(0.018)	(0.014)	(0.018)	(0.014)	(0.019)	(0.014)
Pump	0.010	0.134***	0.009	0.128***	0.011	0.125***
	(0.015)	(0.016)	(0.015)	(0.017)	(0.015)	(0.016)
Extension	0.097***	-0.009	0.096***	-0.006	0.095***	-0.009
	(0.022)	(0.016)	(0.022)	(0.016)	(0.022)	(0.016)
Subsidy	0.139***	-0.097***	0.140***	-0.090***	0.135***	-0.091***
	(0.028)	(0.016)	(0.028)	(0.017)	(0.028)	(0.016)
Electricity	0.023*	0.130***	0.024*	0.122***	0.023*	0.119***
	(0.012)	(0.016)	(0.012)	(0.017)	(0.012)	(0.016)
Ln(Animal)	0.083***	-0.012*	0.085***	-0.011	0.081***	-0.012*
	(0.017)	(0.007)	(0.017)	(0.007)	(0.017)	(0.007)
Ln(Fish)	0.608***	0.266***	0.600***	0.265***	0.602***	0.249***
	(0.045)	(0.033)	(0.044)	(0.034)	(0.045)	(0.032)
Migration	-0.032**	0.138***	-0.033**	0.130***	-0.031**	0.128***
	(0.014)	(0.017)	(0.014)	(0.017)	(0.014)	(0.016)
Ln(Distance)	0.147***	0.153***	0.146***	0.153***	0.147***	0.153***
	(0.023)	(0.024)	(0.023)	(0.024)	(0.023)	(0.024)
Soil type – Clay	0.488***	0.363***	0.488***	0.359***	0.488***	0.366***
	(0.030)	(0.028)	(0.030)	(0.028)	(0.030)	(0.028)
Soil type – Loam	0.413***	0.370***	0.414***	0.369***	0.413***	0.369***
	(0.020)	(0.022)	(0.020)	(0.022)	(0.020)	(0.022)
Soil type – Sandy	0.455***	0.323***	0.456***	0.325***	0.455***	0.322***
	(0.026)	(0.027)	(0.026)	(0.027)	(0.026)	(0.027)
Soil type – Clay-loam	0.454***	0.361***	0.454***	0.359***	0.453***	0.360***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Soil type – Sandy-loam	0.439***	0.349***	0.440***	0.352***	0.439***	0.349***
	(0.019)	(0.021)	(0.019)	(0.021)	(0.019)	(0.021)
Inverse Mills Ratio	0.266***	0.462***	0.271***	0.426***	0.256***	0.413***
	(0.073)	(0.056)	(0.072)	(0.059)	(0.074)	(0.052)
Constant	-0.935***	-0.904***	-0.942***	-0.833***	-0.915***	-0.799***
	(0.147)	(0.142)	(0.146)	(0.149)	(0.150)	(0.135)
Observations	3,063	3,063	3,063	3,063	3,063	3,063
R-squared	0.576	0.602	0.576	0.599	0.576	0.601

Notes: Standard errors are shown in parentheses. ***,** and * represent statistical significance at 1, 5 and 10 percent levels, respectively. We do not report the district dummies; however, they are available upon request. Extensive margins, i.e., indirect effects, of disaster exposure are estimated according to specification (4), where the dependent variables are Ln(land-in) (i.e., logged 1 plus the amount of rent-in land) and Ln(land-out) (i.e., logged 1 plus the amount of rent-out land).

Table 6 – Direct and Indirect Effects of Disaster on Agricultural Income

Variables	(1) Definition 1	(2) Definition 2	(3) Definition 3
Ln(land-in)	1.717***	1.736***	1.715***
	(0.095)	(0.095)	(0.095)
Ln(land-out)	0.546***	0.572***	0.546***
	(0.106)	(0.106)	(0.106)
Disaster	-0.194***		
	(0.069)		
Ln(Landholding)*Disaster	1.214***		
	(0.257)		
Ln(loss)		-0.039***	
		(0.012)	
Ln(loss)*Ln(Landholding)		0.195***	
		(0.041)	
Storm			-0.222***
			(0.084)
Storm *Ln(Landholding)			1.058***
			(0.293)
Flood			-0.172
			(0.107)
Flood *Ln(Landholding)			1.680***
			(0.450)
Constant	4.895***	4.888***	4.896***
	(0.055)	(0.055)	(0.055)
Observations	3,063	3,063	3,063
R-squared	0.163	0.163	0.164

Notes: Standard errors in parentheses. ***,** and * represent statistical significance at 1, 5 and 10 percent levels, respectively. We do not report the district dummies; however, they are available upon request.

Table 7 – Total Marginal Effects

Effects of Disaster-exposure	Mean	S.D.	Min	Max
Intensive Margin	-0.0245	0.2553	-0.1940	2.0013
Total Extensive Margin	0.1006	0.0635	-0.4030	0.1427
Total Marginal effect	0.0761	0.1918	-0.0513	1.5983
Effects of Disaster-severity	Mean	S.D.	Min	Max
Intensive Margin	-0.0118	0.0410	-0.0390	0.3136
Total Extensive Margin	0.0224	0.0118	-0.0712	0.0303
Total Marginal effect	0.0107	0.0292	-0.0087	0.2424
Effects of Storm-exposure	Mean	S.D.	Min	Max
Intensive Margin	-0.0743	0.2225	-0.2220	1.6912
Total Extensive Margin	0.0798	0.0301	-0.1592	0.0998
Total Marginal effect	0.0055	0.1924	-0.1222	1.5320
Effects of Flood-exposure	Mean	S.D.	Min	Max
Intensive Margin	0.0625	0.3533	-0.1720	2.8659
Total Extensive Margin	0.1300	0.1139	-0.7738	0.2056
Total Marginal effect	0.1925	0.2394	0.0336	2.0921

Notes: Marginal effects are estimated using the parameter estimates reported in Tables 5 and 6, and based on the formulae outlined in equation (6).

Table 8 – Direct and Indirect Effects of Disaster on Total Income

Variables	(1) Definition 1	(2) Definition 2	(3) Definition 3
Ln(land-in)	1.774***	1.787***	1.772***
	(0.095)	(0.096)	(0.095)
Ln(land-out)	0.862***	0.883***	0.858***
	(0.107)	(0.107)	(0.107)
Disaster	-0.105		
	(0.070)		
Ln(Landholding)*Disaster	0.676***		
	(0.260)		
Ln(loss)		-0.019	
		(0.012)	
Ln(loss)*Ln(Landholding)		0.108***	
		(0.042)	
Storm			-0.035
			(0.085)
Storm *Ln(Landholding)			0.373
			(0.296)
Flood			-0.247**
			(0.108)
Flood *Ln(Landholding)			1.463***
			(0.454)
Constant	5.240***	5.232***	5.242***
	(0.055)	(0.055)	(0.055)
Observations	3,063	3,063	3,063
R-squared	0.125	0.124	0.127

Notes: Standard errors in parentheses. ***,** and * represent statistical significance at 1, 5 and 10 percent levels, respectively. We do not report the district dummies; however, they are available upon request.

Table 9 - Marginal Effects of Disaster on Total Income

Effects of Disaster-exposure	Mean	S.D.	Min	Max
Intensive Margin	-0.0106	0.1422	-0.1050	1.1174
Total Extensive Margin	0.0988	0.0083	0.0933	0.1650
Total Marginal effect	0.0882	0.1505	-0.0118	1.2824
Effects of Disaster-severity	Mean	S.D.	Min	Max
Intensive Margin	-0.0039	0.0227	-0.0190	0.1763
Total Extensive Margin	0.0216	0.0015	0.0097	0.0226
Total Marginal effect	0.0177	0.0212	0.0036	0.1860
Effects of Storm-exposure	Mean	S.D.	Min	Max
Intensive Margin	0.0171	0.0784	-0.0350	0.6395
Total Extensive Margin	0.0752	0.0425	0.0470	0.4128
Total Marginal effect	0.0923	0.1210	0.0120	1.0523
Effects of Flood-exposure	Mean	S.D.	Min	Max
Intensive Margin	-0.0428	0.3077	-0.2470	2.3985
Total Extensive Margin	0.1323	0.0552	-0.3053	0.1689
Total Marginal effect	0.0896	0.2525	-0.0781	2.0933

Notes: Marginal effects are estimated using the parameter estimates reported in Tables 5 and 8, and based on the formulae outlined in equation (6).

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APPENDICES

Appendix A. List of Disasters

Table A1 – List of Natural Disasters in Bangladesh, 2004-2011

Disaster No	Disaster Type	Date started	Totals deaths	Total affected	Total Damage ('000 US$)	Affected Regions (Districts)
2006-0146	Storm	03/04/06	4	5899		Bagerhat, Khulna
2006-0262	Flood	05/31/06		76000		Sylhet, Sunamganj, Moulvibazar, Hobiganj
2006-0502	Flood	08/24/06		135775		Jessore, Khulna, Satkhira
2006-0510	Storm	09/18/06	115	9135		Noakhali, Bagerhat, Potuakhali, Borguna
2006-0737	Storm	04/05/06	9	1465		Dhaka
2006-0738	Storm	04/08/06	22	1500		Tangail, Sirajganj
2006-0739	Storm	04/22/06	4	150		Rajshahi, Khulna, Jessore
2007-0161	Flood	06/11/07	120	80060	14000	Chittagong, Cox's Bazar
2007-0227	Storm	05/15/07	41	225		Chittagong, Cox's Bazar
2007-0311	Flood	07/21/07	1110	13771380	100000	Bandarban, Feni, Comilla, Sirajganj, Manikganj, Rangpur
2007-0556	Storm	11/15/07	4234	8978541	2300000	Khulna, Barisal, Bagerhat, Patuakhali, Barguna, Pirojpur, Jhalokathi, Bhola, Madaripur, Gopalganj, Shariatpur, Satkhira
2008-0285	Flood	06/26/08	16	20002		Chittagong, Cox's Bazar
2008-0385	Flood	08/30/08	12	615638		Bogra, Sirajganj
2008-0644	Storm	03/22/08	12	200		
2008-0648	Storm	10/27/08	15	200		Barisal, Patuakhali
2009-0157	Storm	04/19/09	7	19209		Chittagong, Cox's Bazar, Noakhali, Bhola, Thakurgaon
2009-0204	Storm	05/25/09	190	3935341	270000	Khulna, Satkhira, Patuakhali, Barisal, Barguna, Pirojpur, Jhalokathi, Laxmipur, Jessore, Bhola, Noakhali, Chittagong, Cox's Bazar, Feni, Chandpur, Pirojpur
2009-0294	Flood	07/03/09	6	500000		Habiganj
2009-0304	Flood	07/29/09	10			Dhaka, Comilla, Rajshahi, Chittagong, Barisal, Khulna, Sylhet
2010-0171	Storm	04/13/10	8	247110		Rangpur, Dinajpur, Nilphamari, Lalmonirhat, Kurigram, Gaibandha, Sirajganj, Bogra
2010-0205	Storm	04/17/10	3	10000		Lalmonirhat
2010-0269	Flood	06/24/10		75000		Sylhet, Moulvibazar, Sunamganj, Habiganj, Netrokona, Kurigram, Gaibandha, Lalmonirhat
2010-0676	Flood	10/01/10	15	500000		
2010-0686	Storm	05/01/10	15	50		Mymensingh
2011-0262	Flood	07/21/11	10	1570559		Chittagong, Cox's Bazar, Satkhira, Jessore, Narail, Bagerhat, Chuadanga, Kustia, Bogra, Sirajganj, Pabna, Lalmonirhat, Thakurgaon, Kurigram, Sherpur, Netrokona, Bandarban, Rajbari, Manikganj, Gaibandha, Naogaon
2011-0591	Storm	04/04/11	13	121		Sherpur, Mymensingh, Rangpur, Thakurgaon, Jamalpur, Netrokona, Gaibandha, Pabna

Notes. All data come from the EM-DAT database (http://www.emdat.be/database), an emergency events database collected by the Centre for Research on the Epidemiology of Disasters (CRED).