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Migration and female labour supply as shock coping strategies after economic crises and natural disasters

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Eugenia Canessa

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Supervisor: Gianna Claudia Giannelli

Doctoral Committee:

- Prof. **Maria Luigia Segnana** (University of Trento)
- Prof. **Federico Perali** (University of Verona)
- Prof. **Agnese Romiti** (University of Strathclyde)

Abstract

The research project intends to investigate the responses of households to economic uncertainty and natural shocks and the coping strategies developed both in terms of growing migration rates and remittance inflows and of increasing labour supply.

In the first Chapter, we employ household survey data from the Indian State of Kerala to evaluate how transfers of remittances sent from overseas respond to heterogeneous sectoral employment shocks experienced by migrants in the host country during the 2008 crisis.

In the second chapter, migration and remittances have been investigated as coping strategies adopted by households after a dramatic flood that hit Bangladesh in August-September 2014. The combination of high-resolution satellite data to precisely measure our treatment variable and the difference-in-difference estimations allow us to causally identify the impact of the dramatic flooding on internal and international migration.

The same robust estimation technique is then applied to evaluate the effect of the 2014 flood in Bangladesh on female labour force participation rate and on the probability for unemployed women to enter the labour force. In addition, correcting for selection into employment, we estimate how the flood affects the probability for women working in the household farm to engage in independent wage-earning activities, evaluatiing whether the expected rise in female labour force participation - instrumented by the shock intensity they face - would help to increase their bargaining power within the households.

Keywords: Migration and remittances; Shock-coping strategy; Self insurance; Flood; Female labour force participation; Intra-household bargaining

Contents

Introduction

The purpose of this study is to generate a deeper understanding of the risk coping strategies developed by households in case of unexpected economic and natural shocks. There is a growing literature which seeks to explain the fallback mechanisms used by households in response to the shocks, highlighting the constraints on their effectiveness (Dercon, 2002). Increasing hours of work, raising temporary savings and selling assets and livestock are shown among the most common behaviours, together with inter-household transfers, developed to compensate exogenous income shortfalls, alleviate liquidity constraints and prevent large drops in consumption (Kochar, 1999; Paxson, 1992; Dercon, 2002).

Recent research w orks have focused on the role of increasing migration rates, both internal and international, and of the consequent growing inflows of remittances as post-shock coping strategies to smooth fluctuations in household income. The insurance role of migration appears to be particularly effective in case of diversified migration destinations and, above all, in case of destinations far from the country of origin and exposed to less correlated income shocks (Balli & Rana, 2015).

Many studies showed that natural shocks, such as hurricanes, drought or rainfall shocks lead to significant increases in remittance inflows for migrants' households, allowing them to have their consumption unchanged (Clarke & Wallsten, 2003; Gubert, 2002; Yang & Choi, 2007). However, natural disasters are also shown to partially reduce mobility because of the depletion of initial resources necessary to migrate and because of the increase in manpower needs in the affected areas (Gray & Mueller, 2012).

Fewer authors focused instead on the effect of income shocks in the destination countries of migrants. Shrinking GDP and higher unemployment rate would have a negative effect on money transferred home (Lin, 2011), while the appreciation of migrants' currencies is shown to boost remittances sent for investment purposes (Yang, 2008).

The literature on remittances has broadly examined which are the determinants of these flows both at the micro and macro level. Authors interpreted the increase in remittances sent in case of domestic shocks faced by relatives left behind as an altruistic behaviour. However, the higher saving rate observed among migrant workers and their increase in remittances sent home might reveal an insurance strategy against the greater level of economic uncertainty experienced in the host country. Periods of economic recessions, increasing unemployment rates and salary cuts at destination, paired with the likelihood of returning home, contribute to raise both the likelihood to remit and the amounts transferred by migrants. According to Amuedo-Dorantes and Pozo (2006), migrants would behave as risk-averse individuals, both paying *premiums* through periodic money transfers to family left behind to guarantee themselves their support in case of return, and self-ensuring through the accumulation of savings.

Increasing labour supply is shown to be another relevant coping strategy developed by households after idiosyncratic shocks to absorb their consequences on households income. Some studies evaluated the response of households in terms of labour force participation to political crisis and wars (Smith & Ward, 1985; Acemoglu, Autor, & Lyle, 2004; Goldin & Olivetti, 2013), while others focused on the coping strategies developed after unexpected and dramatic natural shocks (Mueller & Quisumbing, 2011).
In developing countries, and in particular in rural contexts, natural shocks are among the main drivers of female labor force participation. Long periods of drought, for example, are shown to lead to higher female labour supply (Attanasio, Low, & Sánchez-Marcos, 2005; Bhalotra & Umana-Aponte, 2010). Similarly, women labour force participation would act counter-cyclically increasing during periods of recession and slowing down with economic recovery (Priebe, 2010).

The research project intends to investigate the responses of households to economic uncertainty and natural shocks and the coping strategies developed both in terms of growing migration rates and remittance inflows and of increasing labour supply.
In the first Chapter, we employ household survey data from the Indian State of Kerala to evaluate how transfers of remittances sent from overseas respond to heterogeneous sectoral employment shocks experienced by migrants in the host country during the 2008 crisis. Since, according to the literature on the determinants of remittances, increasing income risk would lead migrants to remit more as a form of self-insurance, we analize whether a drop in employment in the sector of occupation of migrants is correlated to an increase in the probability to remit and in the amounts sent. In addition, we test whether the economic uncertainty experienced in the host country affects mainly monetary transfers sent to fulfil family consumption needs or the amounts intended for investment purposes. Controlling for different migrants' characteristics that might drive their remitting behaviour, we also evaluate the heterogeneous effect of income uncertainty in the host country according to the recipient households' position in the income distribution.
In the second chapter, migration and remittances have been investigated as coping strategies adopted by households after a dramatic flood that hit Bangladesh in August-September 2014. Following the methodology employed by Gröger and Zylberberg (2016), we use georeferenced data from high-resolution NASA satellite images for mapping the flooding, and we employ survey data for panel households for the period before and after the shock to estimate first of all the impact of the shock - measured as the share of inundated areas for each sampled village where households reside - on income and consumption. We then analyze the effect on household migration outcomes, evaluating the variation due to the shock both in their likelihood to have migrant members and to receive remittances, and in the amounts received.

Migration and remittances, as well as labour supply, are complex phenomena do be detected as re-

sponse of households to an exogenous factor and require a proper identification strategy. In the first chapter, we make advantage of panel data to isolate the effect of rising economic uncertainty from household time-invariant unobserved characteristics. In the second chapter, the combination of high-resolution satellite data to precisely measure our treatment variable, and the difference-in-difference estimations allow us to causally identify the impact of the dramatic flooding on internal and international migration. The same robust estimation technique is then applied to original outcomes in the third chapter, contributing to enrich the existing literature. In this chapter we estimate the effect of the 2014 flood in Bangladesh on female labour force participation rate and on the probability for unemployed women to enter the labour force. In addition, correcting for selection into employment, we evaluate how the flood affects the probability for women working in the household farm to engage in independent wage-earning activities, as well as the effect on their weekly working hours and average monthly income. Finally, in the second part of the analysis, we investigate whether the expected rise in female labour force participation and in particular women employment outside the household farm - instrumented by the shock intensity they face - would help to increase their bargaining power within the households.[1]

For the effect of increasing income uncertainty experienced by migrants in the country of destination, we find that a one percent drop in employment in the sector of occupation in which they are employed is correlated to an increase in the probability to send remittances by over 5 percentage points and to a growth in the amounts transferred by $137 PPP. After correcting for selection bias due to initial migration and to employment status in the host country, we observe that while remittances sent to fulfil family consumption needs slightly increase because of rising income risk, transfers sent for investment purposes increase significantly and, on average, by larger amounts. However, the impact of increasing uncertainty on remittances does not vary significantly with initial income of recipient households in case of transfers sent for family consumption. The amount of remittances sent for investment purposes, instead, are higher by $166 PPP if directed to high-income recipients compared to low-income ones.

The results of the second chapter show that the average income loss suffered by the most affected households after the shock amounts to approximately 60 percent compared to the previous period, while net consumption decreases by 30 percent. The emigration rate and the likelihood to receive remittances, however, rise significantly among affected households. The amount of remittances, in addition, increase by approximately $200 PPP and these monetary transfers are shown to compensate for 28 percent of the loss faced by migrants' families.

Finally, for the effect of the flood shock on female labour force participation, we find that both the likelihood to enter the labour market and to engage in independent wage-earning activities increase sig-

[1] Note that between the second and the third chapter there are similarities in the description of the data sources and of the treatment employed. These sections were necessary to be included for reasons of completeness since the three chapters were conceived as separate research works.

nificantly, respectively by 22 and 28 percentage points, for women residing in villages affected by the flooding. In addition, their average monthly income rises by around $24 PPP due to the shock. Finally, we find that the increase in female labour force participation - in particular in case of women working outside the household farm -, if instrumented by the severity of the flood shock that women faced, contributes to raise their bargaining power within the household.

The three empirical studies contribute to extend the existing literature on household risk coping strategies. The first Chapter enriches research on the determinants of migrants' remitting behaviour (Rapoport & Docquier, 2006), giving evidence of the correlation between economic crisis and employment shocks in the sector of occupation of migrants and their outflows of remittances. In addition, we further extend the analysis investigating the different impact of income uncertainty on remittances sent for family consumption or rather for investment and self-insurance purposes, and evaluating whether the effect is diversified according to the recipient households' position in the income distribution.

The second Chapter applies robust causal inference estimation methods to investigate the effect of the 2014 flood. While previous research on the effects of floods in Bangladesh has mainly employed self-reported information from household surveys on damages caused by these natural calamities (Alvi & Dendir, 2011), using georeferenced data the paper contributes to the field of research on the causal effects of natural disasters with a focus on both internal and international migration and remittances as shock-coping strategies.

Finally, the third Chapter contributes to the existing literature on the impact of natural shocks on labour supply, relating it to the strand of research on the determinants of female autonomy (Sell & Minot, 2018). We evaluate how not only women's labour force participation but also their monthly earnings and their probability to work outside the husband's farm are affected by this natural shock, employing fixed effect and difference-in-difference estimations to control for time-invariant unobserved individual and household heterogeneity. In addition, we apply instrumental variable techniques to identify the causal effect of labour force participation on women bargaining power, and using different comprehensive measures of female autonomy we test the hypothesis that only working for an independent income contributes to increase women's autonomy.

1

Remittances and overseas migrants' economic shocks: evidence from Kerala's recipient households after the 2008 global crisis

Abstract

Using household survey data from the Indian state of Kerala we investigate how transfers of remittances sent from overseas responded to heterogeneous sectoral employment shocks that migrants experienced in the host country during the 2008 crisis. According to the literature on the determinants of remittances, increasing income risk would lead migrants to remit more as a form of self-insurance. We find that a one percent drop in employment in the sector of occupation in which migrants are employed is correlated to an increase in the probability to send remittances by over 5 percentage points and to a growth in the amounts transferred by $137 PPP. After correcting for selection bias due to initial migration and to employment status in the host countries, we observe that while remittances sent to fulfil family consumption needs slightly increase because of rising income risk, transfers sent for investment purposes increase significantly and, on average, by larger amounts. Controlling for different migrants' characteristics that might drive their remitting behaviour, we also evaluate the heterogeneous effect of income uncertainty in the host country according to the recipient households' position in the income distribution.

Keywords: Migration and remittances; Shock-coping strategy; Self insurance

JEL Classification: Q12; F22 ; F24; D8;

1.1 Introduction

Our paper is related to the strands of literature that investigate the effects of rising economic uncertainty that migrants experience in the host country on their flows of remittances, focusing on overseas Kerala's migrants after the 2008 crisis. India, with around 10 million of its nationals - i.e. 1 percent of its population - living abroad, is in fact the first among developing countries for remittances received that amounted to $52 billion in 2008, representing 4.2 percent of its GDP. Among the other Indian States, Kerala is therefore an interesting studying case because of the high level of integration of its economy, due both to the number of its emigrants and to the large monetary inflows it receives, that makes it highly vulnerable to external shocks. Understanding the effect of overseas members' macroeconomic shocks on remittances is indeed important for any assessment of how international migration affects origin households.

Migrants in the sample are directed to over 40 different international destinations but around 82 percent of them reside in the Gulf region, like 45 percent of total Indian migrants. Destination countries were differently affected by the 2008 crisis - with the shock of oil price falling by more than 70 percent between 2008 and 2009, and involving mainly Indians employed in the construction sector in the Gulf - but the overall rising unemployment rate and the dramatic salary cuts had repercussions on migrants.
According to statistics from the Center for Development Studies (CDS, Kerala), around 61,000 migrants returned to Kerala after 2008, a number by far below the expectations and explained by the need for the majority to remain abroad, accepting worse labour conditions and lower wages. Similarly, even if a steep decline in remittances was expected, evidence showed instead a rise in monetary transfers sent by migrants to India. In Kerala, despite a high increase of unemployment among emigrants and salary cuts ranging between 10 to 30 percent of the pre-crisis levels, these flows increased by around 5 percent between 2008 and 2009 (Imai, Gaiha, Ali, & Kaicker, 2014).
The literature suggests many possible reasons to explain the resilience of remittances after shocks, among which the need to maintain the visa and to repay the debt incurred before migration, as well as the high level of unemployment at home - as in the case of Kerala - and the existence of networks of relatives and friends that are essential to share risks in the host countries (Ratha, Mohapatra, Xu, et al., 2008). At the same time, the increasing level of income risk faced abroad might contribute to boost the transfers sent for self-insurance motive.

Employing a panel survey for Kerala's households for the period before and after the 2008 economic crisis, we analyze its effect focusing in particular on the correlation between the increasing income uncertainty, proxied by the percentage drop in employment in the sector of occupation in which migrants

are employed, and remittances sent to recipient households. Since the destination countries and sector of employment were differently affected by the 2008 crisis, we exploit the variability in the employment shock that migrants faced to investigate its effect on remittances, employing a first-difference estimation strategy to eliminate time-invariant heterogeneous characteristics of migrants and their households that might affect both the choice of the host country and the choice of occupation - and consequently the intensity of the shock faced - as well as the outcomes considered.
We then test the impact of other factors, such as the undocumented work status of migrants and the number of years spent abroad, that are employed in the literature as proxies of income risk and that might contribute to increasing remittances sent for insurance reasons. Finally, we investigate whether the expected rise in remittances differ according to whether these transfers were sent for family consumption or for investment purposes, and we evaluate the heterogeneous effect of income uncertainty in the host country according to the recipient households' position in the income distribution.

Empirical findings show that migrants self-insure in case of rising economic uncertainty in the host country, remitting around $137 PPP more in case of a one percent drop in employment in the sector of occupation in which migrants are employed. We also observe that while remittances sent to fulfil family consumption needs slightly increase by $29 PPP because of rising income risk, transfers sent for investment purposes increase significantly by $279 PPP. In addition, the correlation between economic uncertainty and the increase in monetary transfers is higher if the migrant is the head of the household, if he or she often returns home to visit and resides in a relatively less geographically distant country. Finally, results show that both remittances sent for investment purposes and for family consumption decrease with the household income. However, while the impact of increasing uncertainty on remittances does not vary significantly with the initial income level of recipient households in case of transfers sent for family consumption, the amount of remittances sent for investment purposes are higher by $166 PPP if directed to high-income recipient households compared to low-income ones.

This paper contributes to the existing literature on the determinants of migrants' remitting behaviour (Rapoport & Docquier, 2006), giving evidence of the correlation between the employment shock in the sector of occupation and migrants' remittances to show the insurance motive behind these transfers. In addition, we further extend the analysis investigating the different impact of income uncertainty on remittances sent for family consumption or rather for investment and self-insurance purposes, and exploring the heterogeneous effect according to the recipient households' position in the income distribution.
The structure of the paper is as follows. After a review on the related literature (Section 1.2) and a description of the household survey data employed for the analysis (Section 1.3), we illustrate our research

strategy (Section 1.4) and we finally present our results (Section 1.5) and concluding remarks (Section 1.6).

1.2 Literature review

Literature on remittances has broadly examined which are the determinants of these flows both at the micro and macro level. In the context of intra-familial bargaining, migration and remittances are considered as agreements that are stipulated for the reciprocal benefit of migrants and their relatives. Migrants send regular payments to family left behind to fulfil a moral contract, expecting in return their support in the event of any failure in their experience abroad (Lucas & Stark, 1985; Stark & Lucas, 1988; Poirine, 1997). Risk diversification of migration strategies is shown to be fundamental as insurance against domestic shocks faced by relatives left behind. This mitigation effect is particularly strong when migrants' destinations are far from the origin country and subject to different economic cycles (Balli & Rana, 2015). Several research works on remittances have then tried to distinguish the motivations for these monetary transfers, focusing mainly on the relation between the economic performance of the origin country and the amounts remitted. In case of a period of recession at home, an increase in remittances has been interpreted as an altruistic behaviour, while if these flows are positively correlated with home country's GDP growth, self-interest has been addressed as main motivation to remit (Chami et al., 2008).

While a broad branch of literature starting from the early 2000's investigated upon possible consequences of economic shocks in the country of origin, and on the role that remittances inflows might have in mitigating the effects of the recession for families left behind (Clarke & Wallsten, 2003; Yang & Choi, 2007; Combes & Ebeke, 2011; Belasen & Polachek, 2013), fewer authors focused on the effect of shocks in the destination country. Those authors agree that macro variables that change during economic crisis in remitting countries might influence remittances, finding a negative effect of shrinking GDP and higher unemployment rate on money transfers (Lin, 2011), while the appreciation of migrants' currencies is shown to boost remittances sent for investment purposes (Yang, 2008).

Accumulated migrant earnings, however, might also reveal an insurance strategy. The greater level of economic uncertainty that migrants experience in the host country, paired with the likelihood of returning home, contribute to explain the higher saving rate observed empirically among migrant workers compared to natives (Paulson & Singer, 2000). Migrants would behave as risk-averse individuals when exposed to rising economic uncertainty overseas both paying *premiums* through periodic money transfers to family left behind to guarantee themselves their support in case of return, and self-ensuring through the accumulation of savings (Amuedo-Dorantes & Pozo, 2006).

1.3 Data sources and variables

We employ the 2008 and 2009 waves of the *Kerala Migration Surveys (KMS)*, a panel study conducted by Centre for Development Studies (Thiruvananthapuram, Kerala). The survey covers 5000 households and is representative of both urban and rural areas in all 63 administrative divisions of the State.

Besides data on household characteristics, the questionnaire includes information on remittances sent home by migrant members and on the end use of the these transfers.[1]

We restrict the sample to the 2,673 households surveyed in 2008 and re-tracked in 2009 who have at least one international migrant working in the host country. Table A1 shows the main destination countries for sampled migrants in 2008.

Table 1.1 presents the descriptive statistics for the panel sample of 1859 working migrants taken at baseline, in 2008. Interestingly, 90 percent of them declared to send remittances home and the average amount sent over a one-year period is around $2000 PPP. Among remitting migrants, 54 percent declared to send remittances to fulfil family consumption needs (such as *daily expenditures* or *payment of dowry*), while 45 percent remitted for investment motive (such as *buying land or house, starting a new business or accumulating savings in a bank account*).

Following the ILO classification the questionnaire records the industry sectors in which migrants are employed. We find that the largest share of them, 55 percent, were employed in the construction and mining sector. Our main explanatory variables, i.e. the percentage decrease in the number of employed workers per industry sector between 2008 and 2009, reveals that the mean decrease in employment was around 2 percent and that the highest drop in employment was registered in the construction and mining sector.

The fact that the larger share of migrants reside in the Gulf and are concentrated in the construction and mining sector might raise an issue of lack of heterogeneity, leading thus to a lower precision in the estimation of the coefficients of the main explanatory variable.[2] However, the employment shock within the same sector varied across the six Gulf states that have been differently affected by the shock. Given the different policy responses to the economic crisis, heterogeneous reactions are observed across these coun-

[1] As far as attrition is concerned, only 1.1 percent of households from 2008 could not be tracked in the following year, while at the individual level, 31 percent of 2008 emigrants could not be followed. However, we have to consider that the 2009 sample was meant to cover over 6,500 households previously surveyed in 2007 and 2008 (2,556 from the 2007 and 3,981 from the 2008 round), selecting in particular those families who reported to have at least one emigrant or one return migrant, so that only a part of the 2008 sample households has been intentionally selected by interviewers to be re-tracked in 2009.

[2] Indeed a high variation in the explanatory variables leads to a lower variance of the OLS estimate. When instead there is small variety in the regressors, their coefficients might be driven by the particular characteristics of the fewer observations that differ from the majority for their values of the explanatory variable.

tries bringing to different trends in GDP growth rate and in unemployment across the Council members. Saudi Arabia, for example, being the largest producer of hydrocarbon resources, suffered from stronger effects of the oil price shock with respect to the more diversified economies of U.A.E. and Qatar.

We have to consider, in addition, that these industries usually employ low-skilled migrant workers that remit on average lower amounts of remittances leading to a potentially negative selection bias and determining an underestimation of the effect of the shock on our dependent variable (Faini, 2007).

We then take into consideration the other variables proxying the level of income risk in the host countries. A significant share of migrants, 86 percent, declare to have a network of family and friends in the same destination country, 28 percent of them were undocumented and the average number of years spent in the destination country is around 8.

Introducing some driving factors that might explain the end use of remittances, we find that 26 percent of migrants were the head of their household and that 7 percent of them declared to regularly return home to visit.

Table 1.1 Descriptive statistics of the panel sample of working migrants in 2008

	N.	Mean	Std. Dev.	Min	Mdn	Max
Number of working migrants (panel dataset)	1,859*					
Proportion of migrants sending remittances		0.90				
Remittances received from migrant members per year ($ PPP)		2,013.717	1,943.61	140.98	1,691.79	28,196.61
(Rupees)		71,417.06	68,930.77	5,000	60,000	100000
Proportion of migrants sending remittances for family consumption		0.54				
Proportion of migrants sending remittances for investment		0.45				
Household size (excluding overseas members, 2008)		4.60	2.34	1.00	4.00	22.00
Number of return migrants per household		2.20	2.34	0.00	1.00	4.00
Proportion of married migrants		0.40				
Proportion of married migrants		0.02				
Proportion of migrants who completed secondary education		0.13				
Proportion of migrants with outstanding debt		0.41				
Unemployment rate of the district of origin		9.18	1.66	4.70	9.40	11.10
Industry sector: agriculture		0.01				
Industry sector: construction, mining, gas/electricity/water supply		0.55				
Industry sector: manufacturing		0.04				
Industry sector: services (trade, transportation, accommodation, etc.)		0.27				
Industry sector: public admin., community, social and other services		0.09				
Employment shock (Oct. 2008-Sept. 2009)		-0.0227				
Employment shock - agriculture		-0.0121				
Employment shock - construction, mining, gas/electricity/water supply		-0.0307				
Employment shock - manufacturing		-0.0650				
Employment shock - services (trade, transportation, accommodation, etc.)		-0.0020				
Employment shock - public admin., community, social and other services		- 0.0041				
Proportion of migrants with networks of family and friends in the host country		0.86				
Proportion of undocumented migrants		0.28				
Number of years spent abroad		7.95	8.07	0.00	5.00	45.00
Proportion of household head migrants		0.26				
Geographical distance from Kerala (Km)		3,043.64	1,425.17	1,952	3,059	11,750
Proportion of migrants returning home to visit		0.07				
Remittances received from migrant members per year - low-income hh ($ PPP)		3,432.68	2,582.99	2,030.15	2,819.65	28,196.61
Remittances received from migrant members per year - middle-income hh ($ PPP)		1,533.68	242.21	1,127.86	1,466.22	1,973.76
Remittances received from migrant members per year - high-income hh ($ PPP)		451.02	366.01	56.39	563.93	1,071.47

*Note:** The total number refers to the subsample of working migrants of panel households surveyed in 2008 and re-tracked in 2009. All monetary values are expressed in PPP-adjusted USD at constant prices.

1.4 Method

As already mentioned, we explore the relationship between the drop in employment in each sector of occupation of migrants residing in different host countries between 2008 and 2009 and their outflows of remittances employing a first-difference regression.

The benchmark specification we estimate is the following:

$$\Delta Y_{ijkt} = \beta_0 + \beta_1 EmpChange_{jk} + \beta_2 X_{iht-1} + \epsilon_{iht} \tag{1.1}$$

where ΔY_{ijkt} is the variation in the dummy for sending remittances and in the amount of remittances sent from migrant i of household h employed in sector j in country k between 2008 and 2009.[3] The amount of remittances is expressed in \$ PPP at constant prices with CPI 2012= 100.00 as reference period to remove effect of inflation.

$EmpChange_{jk}$ is the percentage change in the number of employed workers for each industry sector j in country k, measured as following:

$$EmpChange_{jk} = \frac{N.Empl_{jk2009}}{N.Empl_{jk2008}} - 1$$

where -0.05 corresponds to a 5 percent decline in the number of employed workers. We employ data from ILO Official Statistics for the number of employed workers in each economic activity, including both workers in paid employment and self-employed, disaggregated according to the latest version of the International Standard Industrial Classification of All Economic Activities (ISIC) available for 2008, 2009.[4]

X_{iht-1} represents pre-shock socio-demographic characteristics of migrants and their households.[5]

We control thus for migrants' features that might affect both the choice of the host country and the choice of occupation, as well as the outcomes of interest, employing first-difference regression that corresponds to including household fixed effects to remove the influence of time-invariant unobserved household characteristics.

For the purpose of our analysis we selected from the initial sample only households with at least one migrant member and, among them, only migrants working in the host country in 2008. We therefore need

[3] The amount of remittances are referred to transfers sent in the 12 months before the collecting period, meaning November 2007 - October 2008 for the first wave and October 2008 - September 2009 for the second wave.

[4] This data can be publicly accessed at *https://ilostat.ilo.org*.

[5] X_{iht-1} encompasses variables that might determine the remittance behaviour of migrants: household size; number of return migrants per household; gender indicator; an indicator for migrants' marital status; a dummy equal to one if migrants have completed secondary school; a dummy for migrants having outstanding debts; unemployment rate of the district of origin of migrants.

to include in the first-difference regression a correction term for selection bias due to the initial probability for households to have migrant members and due to the employment status of migrants. We follow the methodology employed by Tunali (1986) to estimate a double selection model, running a bivariate probit at baseline on all the individuals of the initial sample to estimate the two probabilities of migrating and of being employed overseas. This methodology takes into account the correlation between the errors of the two selection processes, as we assume that migration decisions and employment status in the host country are not independent ($\rho_{uv} \not\equiv 0$).

$$Migr._{ih} = \gamma Z_{ih} + u_{ih}$$

$$Migrant_{ihvr} = 1[Migr._{ih} > 0]$$

$$Empl.Mig_{ih} = \delta W_{ih} + v_{ih}$$

$$EmployedMigrant_{ih} = 1[Empl.Mig_{ih} > 0]$$

where Z_{ihvr} and W_{ih} are baseline characteristics of migrants and their households which influence, respectively, the probability of migrating and of being employed overseas. In addition, two exclusion restrictions have been added to the probit model that would influence the two probabilities at baseline, however being uncorrelated with their remittance behaviour in 2009: the percentage of migrants over total population in 2003, and the share of employed migrants for the same year for each district of origin of households.[6] The two covariates represent, respectively, the lagged propensity to migrate and to be employed overseas per district of origin, and are expected to affect positively and significantly the two probabilities of interest. From the bivariate probit we obtain two correction terms:

$$\lambda_{1ih} = \varphi(Z'_{ih}\hat{\gamma}) * \phi(\frac{W'_{ih}\hat{\delta} - \rho Z'_{ih}\hat{\gamma}}{(1-\rho^2)^{\frac{1}{2}}}) * \phi_2(W'_{ih}\hat{\delta}, Z'_{ih}\hat{\gamma}, \rho)$$

$$\lambda_{2ih} = \varphi(W'_{ih}\hat{\delta}) * \phi(\frac{Z'_{ih}\hat{\gamma} - \rho W'_{ih}\hat{\delta}}{(1-\rho^2)^{\frac{1}{2}}}) * \phi_2(W'_{ih}\hat{\delta}, Z'_{ih}\hat{\gamma}, \rho)$$

that are then inserted to correct the first-difference regression.

$$\Delta Y_{ijkt} = \beta_0 + \beta_1 EmpChange_{jk} + \beta_2 X_{iht-1} + \lambda_{1ih} + \lambda_{2ih} + \epsilon_{iht} \tag{1.2}$$

No selection for migrants sending remittances at baseline has been performed. In fact, also migrants not remitting in any of the two waves have been included since we are interested in evaluating the variation in the likelihood to remit and in the amounts remitted (shifting also from zero remittances to a

[6] Data source for the share of migrants over district population and for the share of workers over total migrants per district are official reports of the Kerala Migration Survey 2003 by the Center for Development Studies (Zachariah & Rajan, 2004).

positive amount) as a consequence of the variation in the explanatory variables.[7]
To prevent issues related to fitted regressors, we correct the variance-covariance matrix of the error terms to account for the heteroscedasticity and the correlation across the errors due to the inclusion of the Inverse Mills Ratio following the methodology employed by Greene (1981).

We then add to Equation 3.2 additional variables reported by the literature among the main proxies of income uncertainty borne by migrants in the host countries that would increase their outflows of remittances sent for insurance purposes (Amuedo-Dorantes & Pozo, 2006): the presence of a network of family and friends in the host countries that are expected to mitigate the consequences of income risk; the undocumented status of migrants that probably would lead them to accumulate larger savings in the event of a forthcoming return; the number of years spent in the destination country that are presumably correlated to working experience and thus to a higher level of economic stability; an indicator for the sector of occupation, since some sectors, such as agriculture, are more volatile and expected to lead migrants to self-insure through remittances.

We then perform an heterogeneity analysis: we distinguish migrants' motivation to remit employing a dummy variable for both 2008 and 2009 indicating whether remittances were sent to fulfil consumption needs of the recipient family or rather to accumulate savings in the country of origin for investment purposes. We evaluate the impact of our explanatory variables on the variation in monetary transfers sent for the two types of motivation, estimating Equation 3.2 separately on remittances sent for family expenditures and on remittances sent for investment, where remittance motives are exclusive and mixed motives are not allowed.[8]
However, we argue that some characteristics of migrants might drive their motives for sending international remittances, and that they might increase the likelihood that these transfers are employed for the intended final use, especially in case of remittances sent for investment purpose: if migrants are the head of the households we believe that they would have discretionary power in deciding how these transfers are employed. Similarly, if migrants' destinations are relatively close to the origin country and migrants often return home to visit, we suppose that their investment plans would be more likely to be realized.

[7] Due to the presence of zeros in the dependent variables, we estimated also a Tobit model. However, existing estimating techniques fit random-effects Tobit model. Honoré (1992) has developed a semi-parametric estimator for fixed-effect Tobit models that we employed. Nevertheless, unconditional fixed-effects estimates produced are likely to be biased.

[8] Since migrants were recorded by the survey to send transfers only for one of the two purposes mentioned, the amount of remittances sent for a specific reason correspond to the total amount sent by the migrant if the dummy for sending for those purposes is equal to one, allowing also the possibility of zero remittances in case of non-remitting migrants or if remittances were sent for other purposes. No selection for transferring money for family consumption or to invest at home is thus performed as we are interested in investigating the variation in the amounts remitted for a particular motive (shifting also from zero remittances to a positive amount) as a consequence of our explanatory variables.

We therefore interact our main explanatory variables with these migrants' characteristics to test our hypotheses.

Finally, to deepen the understanding of the determinants of remittances we investigate how the initial position of origin households in the income distribution would affect their migrants' remitting behaviour. While in fact we expect that belonging to lower-income quantiles would be correlated to larger inflows from overseas, a higher income of origin households would lead to larger remittances sent by self-ensuring migrants accumulating assets because of increasing economic uncertainty in the host country. According to Lucas and Stark (1985) in fact, remittances sent with insurance purpose would increase with the origin households' income since the recipients would provide a larger *insurance coverage* to migrants facing larger income risk in the host country and returning home. To assess this, we divide the sample into tertiles of households' income distribution at baseline and we explore the heterogeneous effects of increasing income risk in the country of destination according to whether origin households belong to low-, middle- or high-income groups.

1.5 Results

Table 1.2 contains the results of the bivariate probit estimation for the probability of migrating abroad and of being employed in the host country. The two exclusion restrictions included, i.e. the lagged propensity to migrate and to be employed overseas per district of origin, affect positively and significantly the outcome of interest. In addition, also being the head of household and having completed secondary education is positively correlated with the probability to migrate and to find employment in the host country. Residents of urban areas, then, are less likely to migrate and to be employed compared to individuals living in rural areas.

Our estimation confirms that there is a statistically significant relationship between the increase in economic uncertainty that migrants bear in the destination country and their likelihood to remit and, on average, the amount remitted for insurance purposes, as shown by results in Table 1.3.
In the first column, since the dependent variable is dichotomous, we employed a Linear Probability Model (LPM) to estimate the regression, assuming that the probability to send remittances is a linear function of the regressors. However, since linear equations are not bounded, this technique may lead to predict probabilities outside the 0-1 interval, and, given that the outcome is binary and that the explanatory variables are both binary or continuous, the regression line does not perfectly fit the data, generating a meaningful R-squared. In addition, this method generally raises issues of heteroskedasticity. Indeed, since

Table 1.2 Probit model for migrating abroad and for being employed in the host country

Prob. to have one migrant	Employed in the host country	
District unemp. rate	0.0281***	0.0137
	(0.00976)	(0.00939)
Hh size	-0.00305	-0.0195***
	(0.00576)	(0.00568)
Urban sector	-0.144***	-0.179***
	(0.0305)	(0.0295)
Educ. > secondary	0.162***	0.154***
	(0.00619)	(0.00591)
Head of hh	0.650***	0.673***
	(0.0256)	(0.0246)
District percentage of migrant popul. 2003	0.0229***	0.0242***
	(0.00150)	(0.00142)
District percentage of employed migrants 2003	0.684***	0.887***
	(0.216)	(0.105)
Constant	-2.185***	-1.864***
	(0.0729)	(0.0693)
Observations	15,000	15,000

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: The regression has been run on all households of the initial sample. All monetary values are expressed in PPP-adjusted USD at constant prices.

the actual values of the dependent variable is rather 0 or 1, but the predicted probabilities may vary between these two values, the size of the residuals grows with the predicted values. We therefore compute the White variance-covariance matrix to correct the errors.

A percentage drop in the sector of occupation of migrants overseas is correlated to an average increase in the probability to send remittances by over 5 percentage points and to a growth in the amounts transferred by $137 PPP, where the two coefficients are statistically significantly different from zero (at the 0.001 level). For households with migrants working abroad this represents an increase in the inflows received of approximately 8 percent.[9]

A higher number of return migrants per household, as expected, leads to a significant decrease in both the likelihood to receive money and in remittances received. Similarly, also coefficients on the dummies for migrants being married overseas and for having outstanding debt are negative and significant: migrants who are married and have their wife or husband in the host country, as well as migrants who need to repay the debt incurred before migration, as expected, are less likely to send part of their earnings to family left-behind in the country of origin. On the contrary, in case of an increase in the unemployment rate in their district of origin by one percentage point, remittances are shown to rise significantly by

[9] The percentage increase is calculated dividing the coefficient by the average yearly remittances of the pre-shock period, that is, 137.3/1838.6.

over $70 PPP and this is in line with the literature that supports the hypothesis of remittances sent for altruistic purposes in case of worsening economic conditions at home (Lucas & Stark, 1985; Faini, 1994; R. Agarwal & Horowitz, 2002).[10]

In addition, female migrants appear to remit on average larger amounts of money compared to males. Finally, the coefficients on the selection correction terms of initial migration and employment status overseas, $Lambda_1$ and $Lambda_2$, are jointly significant.

The amount of remittances received by recipient households might be certainly conditioned by the number of return migrants that in turn is influenced by the job loss experienced abroad. Migrants who returned between 2008 and 2009 are 628, around 14 percent of the initial sample of migrants (4,312). Since 47 percent of them have less than secondary education and 41 are employed in the agriculture and construction sectors, we could suppose that the subsample of working migrants surveyed in 2008 and re-tracked in 2009 that are still abroad in the second wave - on which we focus the analysis - are positively selected. This could represent a factor of potential selection bias for our analysis, since more educated migrants who are employed in more secure and remunerative employment sector, who therefore are less likely to return, may also send higher remittances home. However, as already mentioned, also migrants facing increasing income uncertainty and planning to return home may be induced to remit more in the event of a forthcoming return, compensating the above-mentioned selection effect.

Since our observations are nested within destination countries and industries, we estimated also a Multilevel Random Effect model assuming that the β coefficient might vary across groups. Results and comments are inserted in the Appendix, Section 1.A2.

Table 1.4 shows results of the first-differenced regression controlling for income risk factors. Differently from Amuedo-Dorantes and Pozo (2006), we find that documented migrants are not significantly different in their remitting behaviour compared to undocumented ones. Given the strict *Kafala recruitment system*, a sponsorship mechanism that is adopted for the majority of immigrant workers in the Gulf and that was designed to provide transient workforce in case of increasing labour demand (Khan & Harroff-Tavel, 2011), we could suppose that being documented under that system - as the majority of the 82 percent of workers residing in these countries - would not guarantee any employment stability in case of economic crisis.

On the contrary the variation in monetary inflows is significantly related to other risk factors: we observe that the likelihood to receive remittances and the amount of transfers decrease by $20 PPP with every additional year spent abroad by migrants and, as expected, remittances are lower by $250 PPP if migrants have social networks overseas. Income uncertainty is in fact mitigated by the longer working experience of migrants that might offer them more earning opportunities, as well as by the presence of relatives and friends to rely upon in the same host country. Our results are in line with existing research finding a neg-

[10] Data on unemployment rate in Kerala's districts were taken from Zachariah and Rajan (2010).

Table 1.3 First-differenced regression of change in remittances received on sector employment shock

	Remittance incidence	Amount of remittances
Sector emp. shock	0.0558***	137.4***
	(0.00151)	(15.15)
Hh size	-0.00968**	22.47
	(0.00373)	(16.02)
N. return migrants 2008	-0.0311***	-232.1*
	(0.00832)	(128.7)
Married marital status	-0.0755***	-266.0**
	(0.0128)	(110.6)
Female migrant	0.0218	717.6***
	(0.0636)	(180.5)
Migrants educ. > secondary	-0.00966	164.3
	(0.0221)	(242.5)
Dummy debt repayment	-0.159***	-348.5***
	(0.0173)	(43.02)
District unemp. rate	0.0167***	71.41**
	(0.00378)	(30.44)
$Lambda_1$	-0.587	-5,514***
	(0.387)	(1,184)
$Lambda_2$	1.014**	6,851***
	(0.377)	(1,298)
Constant	-0.257***	-1,629***
	(0.0512)	(444.3)
Observations	1,859	1,859

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

Note: The regression has been run selecting all household having one migrant employed in 2008. All monetary values are expressed in PPP-adjusted USD at constant prices.

ative relationship between migrants' employment contract duration and outflows of remittances (Batista & Umblijs, 2015).

In addition, the income vulnerability and the seasonality of employment in agriculture leads to higher transfers sent from migrants employed in this sector compared to all the other industries (*construction and mining, manufacturing; services; public administration, community, social and other services and activities*). The results illustrated above confirm the hypothesis of the insurance motive for the increasing remittances sent by migrants in case of higher earning risk overseas.

1.5.1 Heterogeneity analysis: differentiating by remittance motives

Results of the Equation 3.2 run separately on remittances sent for investment and for family consumption purposes are shown in Table 1.5 and confirm that in both cases an increase in income uncertainty due

Table 1.4 First-differenced regression of change in remittances received on sector employment shock controlling for income risk indicators

	Remittance incidence	Amount of remittances
Sector emp. shock	0.0621***	157.3***
	(0.00239)	(11.30)
Hh size	-0.00994*	-1.367
	(0.00548)	(11.41)
N. return migrants 2008	-0.0245***	-205.9
	(0.00867)	(132.8)
Married marital status	-0.102***	-390.6***
	(0.0176)	(125.1)
Female migrant	-0.0129	608.2***
	(0.0695)	(211.9)
Migrants educ. > secondary	-0.0528*	229.6
	(0.0304)	(232.7)
Dummy debt repayment	-0.186***	-442.7***
	(0.0197)	(81.34)
District unemp. rate	0.0165***	61.49
	(0.00376)	(38.07)
$Lambda_1$	-0.562	-5,263***
	(0.392)	(1,326)
$Lambda_2$	0.900**	6,233***
	(0.389)	(1,623)
Migration network	0.00475	-250.0*
	(0.0313)	(144.9)
Documented migrant	-0.0228	97.36
	(0.0563)	(83.76)
Years worked abroad	-0.00713***	-20.00***
	(0.000898)	(6.299)
Construction, mining, quarrying	-0.0848*	-2,518***
	(0.0430)	(516.5)
Manufacturing	-0.117	-2,739***
	(0.0964)	(686.2)
Services	-0.0700	-2,456***
	(0.0446)	(575.7)
P.A., community, social serv. etc.	-0.229*	-2,925***
	(0.122)	(482.6)
Constant	0.000343	1,490***
	(0.0990)	(489.3)
Observations	1,859	1,859

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

Note: The regression has been run selecting all household having one migrant employed in 2008. All monetary values are expressed in PPP-adjusted USD at constant prices.

to the drop in employment in the sector of occupation of migrants leads to larger remittances. However, in the first case we observe a significant increase by almost $280 PPP of the transfers received annually, while in the second case the increase is considerably lower and the coefficient has a larger p-value.

We could thus argue that transfers sent to accumulate assets as a form of investment (as already mentioned, in case of investment purposes migrants reply to send remittances to buy land, renovate houses, start a new business, etc.) represent a self-insurance strategy and increase with the economic uncertainty experienced in the destination country. Remittances sent for family consumption, instead, are part of the agreement stipulated with the household left-behind inducing migrants to send regular payments home as a form of repayment of the loan used to finance the expenses incurred for emigration (Rapoport & Docquier, 2006). Remittances sent for households daily expenditures, thus, are not expected to vary significantly with the unemployment faced overseas.

Column (2), however, shows that these transfers increase on average if the migrant is female and more educated. In addition, the need to repay the debt incurred before migration significantly reduces - by over $600 PPP - the transfers sent for family expenditures. Finally, the positive and significant coefficient on the unemployment rate of the district of origin suggests that the altruistic motivation - that leads to increasing monetary transfers in case of worsening economic conditions at home - prevails over the insurance purposes in case of remittances sent for family consumption needs.

1.5.2 Driving factors analysis

As mentioned above, migrants claim to have sent remittances to fulfil household consumption needs or to invest their savings at home, although they may not be able to monitor how these monetary amounts are used by the recipients families. We investigate some factors that might drive migrants choice on the purpose of remittances as well as their actual final use, interacting our sector employment covariate with three variables: a dummy equal to one if the migrant is the head of household; a dummy indicating whether the migrant periodically returns to visit the family; the log of the geographic distance in kilometres between Kerala (Thiruvananthapuram) and the capital city of the destination country.[11]

In line with the findings of Cai (2003) and Singh (2007), we find that only migrants who maintain strong ties with their home country and have decision-making power within the households accumulate savings to invest in their origin country, as shown in Table 1.6. Being the head of households increases the amounts transferred home in case of a drop in employment faced in the destination country. Also making regular visits home might represent a way to monitor their investments, thus we observe that in case of higher economic uncertainty, migrants who temporarily come back to the origin country send on average $51 PPP more compared to migrants who seldom return. Finally, a one percent increase in the distance from the country of origin decreases the amount of remittances sent in case of rising economic insecurity for investment purposes by around $280 PPP.

On the contrary, these factors do not significantly affect migrants' decision to send money for family con-

[11] Data on geographical distance between capitals were obtained from http://www.indo.com/distance.

Table 1.5 First-differenced regression of change in remittances received for family consumption and self-insurance

Amount of remittances	For investment	For family consumption
Sector emp. shock	279.5***	29.58**
	(21.75)	(12.23)
Hh size	5.294	56.91
	(12.50)	(44.81)
N. return migrants 2008	-117.9	-348.1
	(140.2)	(341.4)
Married marital status	-17.95	-319.9
	(96.94)	(208.1)
Female migrant	722.0**	429.8*
	(324.5)	(224.8)
Migrants educ. > secondary	-372.8	530.4*
	(302.4)	(283.9)
Dummy debt repayment	-66.83	-669.3***
	(60.90)	(123.9)
District unemp. rate	11.81	12.27***
	(27.06)	(12.27)
$Lambda_1$	-2,266*	-7,020***
	(1,206)	(1,842)
$Lambda_2$	2,416	7,964***
	(1,447)	(2,147)
Constant	-635.3	-921.9
	(431.8)	(977.6)
Observations	1,859	1,859

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

Note: The regression has been run selecting all household having one migrant employed in 2008 and distinguishing between migrants claiming to have sent remittances and for investment purposes and for family consumption needs. All monetary values are expressed in PPP-adjusted USD at constant prices.

sumption needs that results to be mainly driven by the altruistic behaviour of migrants, since, as shown in column (2), these amounts react to changes in unemployment rate in the district of origin but do not change with migrants' role within the household or with the geographical distance from the home country.

1.5.3 Differentiating by income groups

Table 1.7 shows the results of the heterogeneity analysis conducted to investigate whether the different correlations we find between income risk in the host countries and migrants' propensity to send remittances for different purposes vary in relation to the initial level of income of recipient households. We therefore classify sampled households by income tertiles - employing household income distribution in 2008 - and we interact our main covariate with a categorical variable indicating whether households

Table 1.6 First-differenced regression of change in remittances received for family consumption and self-insurance with driver analysis

Amount of remittances	For investment	For family consumption
Sector emp. shock	76.76*	2,372
	(41.08)	(3,500)
Head of household	143.1*	-95.52
	(80.46)	(129.5)
Head of household * Sector emp. shock	4,227*	382.3
	(2,367)	(2,058)
Temporary visit home	281.8*	140.6
	(154.3)	(110.5)
Temporary visit home * Sector emp. shock	59.41**	2,519
	(24.56)	(2,170)
Log. distance	-311.6	324.7
	(350.2)	(195.8)
Log. distance * Sector emp. shock	-277.8**	-1,338
	(114.85)	(1,990)
Hh size	7.386	12.21
	(16.97)	(29.61)
N. return migrants 2008	-34.84	-230.2
	(159.0)	(171.7)
Married marital status	24.98	-124.3
	(100.6)	(129.4)
Female migrant	874.3**	633.1***
	(401.7)	(217.6)
Migrants educ. > secondary	-380.6	-504.0
	(453.2)	(322.1)
Dummy debt repayment	-79.93	-203.4***
	(59.39)	(67.32)
District unemp. rate	16.58	60.51**
	(36.94)	(23.95)
$Lambda_1$	-1,934	-3,077**
	(1,626)	(1,194)
$Lambda_2$	2,052	3,396**
	(1,946)	(1,370)
Constant	-571.5	-1,081***
	(637.8)	(340.6)
Observations	840	1,019

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

Note: The regression has been run selecting all household having one migrant employed in 2008 and distinguishing between migrants claiming to have sent remittances and for investment purposes and for family consumption needs. All monetary values are expressed in PPP-adjusted USD at constant prices.

belong to the low-, medium-, or high-income group. As household income may be itself influenced by remittances received, causing an issue of reverse causality, we employ as measure for the classification the sum of the income of non-migrant household members excluding remittance receipts.

We find that both remittances sent for investment purposes and for family consumption decrease with

the level of household income.

The literature shows that remittance transfers are mainly directed to families belonging to the bottom of the income distribution, confirming the altruistic behaviour of migrants overseas and revealing an *equalizing* effect of these transfers (Straubhaar & Vâdean, 2006). However, the coefficient on the interaction with sector employment in the destination country reveals that the impact of increasing uncertainty on remittances does not vary significantly with initial income of recipient households in case of transfers sent for family consumption needs.

On the contrary, in case of higher income risk, the total amount of remittances sent for investment purposes rises by $166 PPP if directed to high-income recipient households compared to low-income ones. As expected, wealthier recipient households would be more adequate to assist migrants accumulating assets for self-insurance. Batista and Umblijs (2015) investigate how the employment status of recipient network members - proxying the availability of financial resources to support migrants in case of need - affects migrants' outflows of remittances. We employ instead the household income, including also unearned income, as an indicator of their capacity to provide financial assistance to migrants in case of return. The decision of migrants to invest their savings in the home country as a way to self-insure in case of return is thus shown to be a rational choice increasing both with the earning risk faced and with the economic well-being of recipient households.

Table 1.7 First-differenced regression of change in remittances received for family consumption and self-insurance - controlling for income tertile groups

Amount of remittances	For investment	For family consumption
Sector emp. shock	50.90***	52.66**
	(14.76)	(21.01)
Middle-income hh	-663.6***	-658.4***
	(100.3)	(147.8)
High-income hh	-1,821***	-1,651***
	(156.0)	(386.6)
Middle-income hh * Sector emp. shock	975.7	885.9
	(1,088)	(757.4)
High-income hh * Sector emp. shock	166.9***	666.5
	(23.96)	(2,621)
Hh size	20.05	31.23
	(17.50)	(38.34)
N. return migrants 2008	-139.0	-193.2
	(111.0)	(369.2)
Married marital status	-118.5	-153.9
	(98.89)	(161.0)
Female migrant	417.1**	320.1
	(161.5)	(218.4)
Migrants educ. > secondary	237.9	490.3*
	(214.5)	(272.5)
Dummy debt repayment	-75.33	-100.9
	(65.69)	(75.17)
District unemp. rate	-21.67	5.222
	(25.42)	(66.83)
$Lambda_1$	-5,137***	-6,934***
	(1,295)	(2,215)
$Lambda_2$	5,230***	7,262***
	(1,384)	(2,485)
Constant	859.7*	481.6
	(479.5)	(1,071)
Observations	840	1,019

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

Note: The regression has been run selecting all household having one migrant employed in 2008 and distinguishing between migrants claiming to have sent remittances and for investment purposes and for family consumption needs. All monetary values are expressed in PPP-adjusted USD at constant prices.

1.6 Concluding remarks

Previous literature has mainly investigated the consequences of economic or natural shocks in the country of origin on inflows of remittances sent from migrants overseas. However, since remittances represent a significant source of wealth in India, as in many developing countries, where they contribute to welfare enhancing and poverty reduction among recipient families, allowing for greater investment in education and health, as well as physical capital accumulation (Ratha, Mohapatra and Scheja, 2011), it is important to understand how these transfers are affected by migrants wage risk in the host countries.

After the 2008 crisis, the overall rise in unemployment and the cuts in salaries in the majority of the destination countries of Indian migrants were expected to lead to a significant increase in the number of returnees and to a drop in the inflows of remittances to Kerala where the share of migrant households is around 26 percent. However, in line with official statistics we find that these transfer increased on average between 2008 and 2009. Employing the Kerala Migration Survey we observe that a one percent drop in employment in the in the sector in which migrants are employed increases migrants' probability to remit by five percentage points and the amounts remitted by $137 PPP between 2008 and 2009. These amounts also increase by larger amounts if migrants are employed in volatile sectors, such as agriculture, while the need to self-insure against income risk through remittances appears to be mitigated by the increasing number of years spent abroad by migrants and by the presence of social networks overseas.

Our results are in line with Amuedo-Dorantes and Pozo (2006) confirming that there is a positive relationship between the increase in income uncertainty and the remitting behaviour of migrant. However, while the latter find that income risk in the host countries increases the proportion of migrants' labor earnings remitted both to fulfil family consumption needs and for investment purpose, our results show that the first type of transfers only slightly increase - by $29 PPP - as a consequence of a one percent drop in sectoral employment, while transfers sent for investment purposes increase significantly by $279 PPP. This result suggests that remittances sent for family consumption are part of the agreement stipulated with the household left-behind as a form of repayment of family loans used to finance the expenses incurred for emigration and these transfers do not change systematically with income uncertainty in the host countries. Differently, transfers sent to accumulate assets as a form of investment represent a strategy of self-insurance and increase with the economic uncertainty experienced in the destination country.

We also observe that the correlation between economic uncertainty and the increase in monetary transfers is higher if the migrant is the head of the household, if he or she resides in a relatively less geographically distant country and often returns to visit.

Finally, our results confirms the hypothesis of the altruistic model as we find that remittances increase with decreasing income of the origin family. However, while we do acknowledge that different motiva-

tions to remit home might coexist, investigating the relationship between economic income risk in the host country and remittances we find evidence of the insurance purpose of this transfers. In this case, the amounts sent to self-insure through investments would prevail over those sent for consumption and would increase with recipient household income. Wealthier recipient households would in fact represent a favourable financial environment for migrants' assets and their lower need for economic support would guarantee the actual realization of investment plans.

The results overall confirm how migrants' remitting decisions are rational choices of risk-averse individuals who diversify risk to alleviate future credit constraints and to boost local productive investments.

Appendix

1.A

1.A1 Tables

Table 1.A1 Destinations of international migrants, 2008

	N. migrants	percent of total
United Arab Emirates	817	43.95
Saudi Arabia	507	27.27
Oman	167	8.98
Qatar	109	5.86
Kuwait	98	5.27
Bahrain	95	5.00
USA	17	0.91
Malaysia	10	0.54
UE	10	0.54
South Africa	6	0.32
UK	5	0.27
Singapore	5	0.27
Australia	4	0.22
Others	8	0.43
Observations	1,859	

Note: The total number refers to the subsample of working migrants of panel households surveyed in 2008 and re-tracked in 2009.

1.A2 Multilevel random effect

Since our observations are nested within destination countries and industries, besides estimating a first-differenced regression with clustered standard errors, we estimated also a Multilevel Random Effect model. Migrants residing in the same country or working in the same employment sector may indeed have higher correlations in the outcome. The model, estimating residuals at each level of grouping, takes into account these correlation correcting for the heteroskedasticity of the standard errors of the regression coefficients that would be otherwise underestimated.The results of this estimation are displayed in table 1.A2 and show that the coefficients maintain the sign and are close to the results of the original specification. Being the standard errors higher, the t-statistic is lower with respect to Table 1.3 but the coefficients are still significant.

In addition, the likelihood ratio test conducted to verify whether the two models, the original estimation and the multilevel random effect regression, provide the same goodness of fit, was not significant, supporting the null hypothesis and thus suggesting to employ the former.

Table 1.A2 First-differenced regression of change in remittances received on sector employment shock

	Remittance incidence	Amount of remittances
Sector emp. shock	0.0560*	137.4
	(0.0308)	(75.91)
Hh size	-0.00979**	22.47
	(0.00401)	(29.91)
N. return migrants 2008	-0.0310*	-232.1**
	(0.0158)	(118.1)
Married marital status	-0.0755***	-266.0**
	(0.0172)	(128.1)
Female migrant	0.0217	717.6**
	(0.0439)	(328.2)
Migrants educ. > secondary	-0.00977	164.3
	(0.0246)	(184.0)
Dummy debt repayment	-0.159***	-348.5***
	(0.0171)	(127.8)
District unemp. rate	0.0163***	71.41*
	(0.00519)	(38.75)
$Lambda_1$	-0.584**	-5,514***
	(0.229)	(1,707)
$Lambda_2$	1.009***	6,851***
	(0.245)	(1,828)
Constant	-0.253***	-1,629***
	(0.0774)	(577.5)
Observations	1,859	1,859
R-squared	0.144	0.036

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

Note: The regression has been run selecting all household having one migrant employed in 2008. All monetary values are expressed in PPP-adjusted USD at constant prices.

2

Migration and remittances as risk copying strategy after natural disasters: rural Bangladeshi households' response to flood shock

Abstract

Using georeferenced data for mapping the strong flood that hit Bangladesh in August-September 2014, this paper aims at evaluating how rural households have coped with the consequences of this natural shock. Employing survey data for panel households for the period before and after the shock, we estimate the impact of flooding - proxied by the share of inundated areas for each village where sampled households live - on income, consumption and migration outcomes.

We find that, having experienced an average decrease in income of around 60 percent and a consequent drop in expenditure of 30 percent, affected households have a higher probability to migrate and to receive remittances. In addition, while the incidence of internal migration is similar across households with different initial incomes, the probability of international migration varies with the availability of initial assets. The findings suggest that migration, and in particular international migration, represents an insurance in case of natural disasters also for lower income households. International migrants' households among the latter, in fact, are shown to better differentiate risk, thus compensating more effectively the income shock with the amounts of remittances received.

Keywords: Flood; Migration and remittances; Shock-coping strategy; Bangladesh

JEL Classification: Q12; F22 ; F24; Q54

2.1 Introduction

Starting in the late 1990s, several research studies have investigated the risk-coping strategies developed by households in rural contexts where income is volatile and subject to seasonal shocks (Paxson, 1992; Gubert, 2002; De la Briere, Sadoulet, De Janvry, & Lambert, 2002; Udry, 1994; Fafchamps & Lund, 2003).

Just as crop shocks and health shocks are shown to increase the migration rate and the likelihood to receive remittances for affected households (De la Briere et al., 2002), similarly, after natural disasters migration and remittances are found to contribute to mitigating the economic losses for families left behind (Rapoport & Docquier, 2006; Yang, 2011).

Although migration after natural shocks represents in many situations a forced choice rather than a voluntary insurance mechanism (Clarke & Wallsten, 2003; Yang & Choi, 2007; Belasen & Polachek, 2013), the flows of remittances sent from migrants are shown to increase as an insurance mechanism for families left behind and to compensate for a large part of the income loss, thus smoothing the consequences of the shock on consumption behaviors of migrants' households (Yang and Choi (2007)).

Risk diversification of migration destinations is fundamental as an insurance against domestic shocks faced by relatives left behind, and this strategy is particularly effective when migrants' destinations are far from the origin country. Blumenstock, Eagle, and Fafchamps (2016) and Gröger and Zylberberg (2016) find in fact that the amount of internal remittances increases with the geographical distance from the origin country after a natural disaster. In particular, the latter study provides evidence on the failure of internal migration to close districts similarly exposed to the consequences of typhoon Ketsana in Vietnam, while long-distance migration appears to be a more effective coping strategy. Likewise, international migration to geographically distant countries and different economic areas represents a better risk-diversification strategy to support the origin family facing the shock.

For the types of migration, many studies in the field have focused on the consequences of natural shocks on international migration and international remittances (Ratha, 2011). This notwithstanding, the large majority of instances of migration, and of sending of remittances, take place internally, and several studies provide evidence in favour of the insurance hypothesis in this case as well (Gubert, 2002; De la Briere et al., 2002).

In this paper, we investigate the effects of the 2014 flood in Bangladesh on income, consumption and migration behaviour of households. Beginning in mid-August 2014, continuous monsoon rains hit the country together with overflows from the Brahmaputra and Ganges rivers, causing dramatic flooding that affected over 3 million people until the end of September. The flood was felt particularly strongly

in the northeastern part of the country, where water inflows from upstream hill areas across the border inundated large rural fields, damaging crops, in particular cultivations of paddy covering approximately 77 percent of the total crop area in Bangladesh.

We refer to the *new climate-economy literature* examining how weather variations over time within a given geographical area influence economic outcomes. This novel empirical approach combines panel survey data with high-precision satellite data to measure the impact of natural shocks at the local level, thus improving the robustness of the empirical estimates (Dell, Jones, & Olken, 2014).

This paper contributes to the field of research on the causal effects of natural disasters on household income and expenditure, with a focus on international and internal migration and remittances as shock-coping strategies adopted by households in the aftermath of dramatic economic losses. Previous research on the effects of the great 1998 floods in Bangladesh has mainly employed self-reported information from household surveys on damages caused by natural calamities (Alvi & Dendir, 2011). We instead follow Gröger and Zylberberg (2016) in using georeferenced data from NASA satellites that measure the impact of the flood as the share of inundated areas for each sampled village where households reside.

We match the high-resolution satellite imagery data with with data drawn from the *Bangladesh Integrated Household Survey*, a panel study conducted by IFPRI in two rounds, the first in 2011-2012 (October 2011-June 2012) and the second in 2015 (January-June 2015), exactly the period before and after the flooding.

For our research strategy, we adopt a difference-in-difference approach to identify the effects of flooding on agricultural income, revenues from paddy cultivations, wage income, food and non-food expenditure, propensity to migrate within and outside the country and the amount of remittance received from the two types of migration.

After conducting a balance test to compare treated and untreated areas at baseline, we estimate our models with OLS, also controlling for household fixed effects. To evaluate the robustness of our results, we control for potential endogeneity related to the likelihood of each village being inundated depending on village topographic characteristics, and we perform two parallel trend tests. Finally, we perform some heterogeneity analysis.

To our knowledge, this is the first study on this natural disaster in Bangladesh and the first one to use causal inference of this kind.

Our results show that the average income loss suffered by the most affected households after the shock - i.e., households where the share of inundated areas reached the maximum of 94 percent - amounted to approximately 60 percent with respect to the previous period, and was mainly due to damages to crop and livestock, while net consumption decreased by 30 percent. The emigration rate, however, increased by approximately 5 percent, as did remittance inflows, which show an increase of approximately $200 PPP. These monetary transfers compensate for 28 percent of the loss faced by migrants' families. These

empirical findings are robust to our testing procedure.

Assuming that the ability to cope with risk through migration strategies is different according to the position of households in the income distribution, as it depends on initial resource constraints, we investigate the migration and remittance response of households belonging to different income groups.

We find that, after the flooding, while internal migration incidence is similar across income tertiles, wealthier households have a higher likelihood of sending migrants abroad. However, among households with international migrants, the increase in monetary transfers received is by far higher for lower income households, representing approximately three times the variation of the middle-income group and compensating for approximately 85 percent of the losses that poorer households suffered if affected by flooding.

The paper is organized as follows. After the description of the georeferenced satellite data and of the household survey (Section 2.2), we illustrate our method (Section 2.3). We then present our results (Section 2.4) and discuss them (Section 2.5). Finally, we provide some concluding remarks (Section 2.6).

2.2 Data sources and variables

2.2.1 Georeferenced data

As already mentioned, in our analysis village exposure to inundation represents the treatment. To build a measure of this treatment we use the *NASA Flooding Map*, composed of satellite images obtained by applying the LANCE processing system to MODIS products.[1] In these 250-m resolution images, flooded areas are determined as water observations falling outside normal water levels, taking as reference another MODIS product, MOD44W. In particular, we employ composite images for an interval of 15 days between the end of August and mid-September, since, according to the Official Report of the *Bangladesh Water Development Board* of the National Government for 2014, rainfall reached the highest record in this period.[2] Figure 2.1 shows that in 2014 rainfall intensity during the monsoon season (measured as average tenth of millimetres of rainfall accumulated in a 15-day period among all the Bangladeshi villages) exceeded that of previous years and reached the maximum peak toward the end of August. We therefore define as treatment the share of flooded areas in the first days of September resulting from the accumulated rainfall of the last two weeks of August. Figure 2.A1 in the Appendix illustrates MODIS

[1] The data can be publicly accessed at https://floodmap.modaps.eosdis.nasa.gov.

[2] The NASA composite product for the period August 31st-September 15th, by combining information from daily images and "smoothing" high-frequency variations, overcomes the issue of sensing measurement errors due to clouds that prevent the satellite from obtaining a precise image, identifying a pixel area as "flooded" if it is recognized as such at least twice.

satellite images for the period before the flooding, July 2014 - already in the monsoon season - and for the period considered. Flood zones - coloured in orange, to be distinguished from normal surface water in blue - are clearly more numerous in the second picture, in particular in the northeastern part of the country.

The 318 surveyed rural villages that are nationally representative of the country's rural areas are the units of analysis for the natural shock. For each village in the sample we calculate the share of pixels (where pixel resolution is 250 m) identified as "flooded" in a 5-kilometre radius, where the average number of pixels in the calculated radius is approximately 3800.

To check for robustness, we also repeat our tests for 2- and 10-kilometre radiuses. This treatment variable corresponds to the probability of a "pixel area" in the village being inundated in the period considered. Figure 2.A2 in the Appendix shows the percentage of inundated areas during flooding with respect to normal periods. With the treatment specification of the 5-kilometre radius, the mean share of submerged area corresponds to 18 percent, with a maximum of 94 percent, while in normal periods, the mean is 8 percent and the maximum is approximately 45 percent. However, to understand the economic consequences of flooding, it is important to highlight that in some villages stream water did not flow away immediately after the flood, probably because of differences in soil absorption (see Figure 2.A2). In line with the literature, this measure of treatment proxies the village-level damage the flood caused to rural areas and cultivations. Figure 2.2 illustrates the geographic distribution and the intensity of the treatment variable during the flooding (August 31st-September 15th).

As previously anticipated, sampled villages may differ in some geographical characteristics that affect both the probability to be treated and the outcomes of interest. To take account of this endogeneity, we control for the village propensity to be submerged by water during normal times as measured by the percentage of water coverage in a 5-kilometre radius in July 2014. In addition, we include province and wave fixed effects and village topographic features, such as the proximity to a river or to the coast, to allow villages with differences in these features to have different trends.

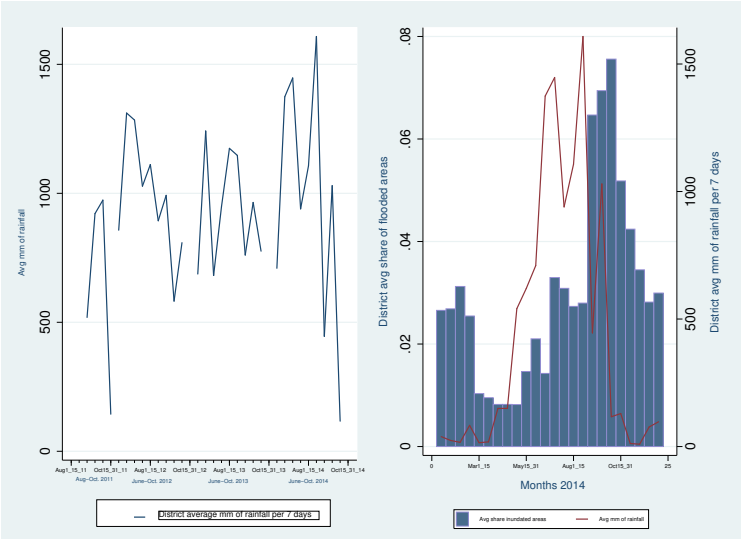
In addition to flooding data, we take advantage of multi-satellite information on rain gauge measurements for the same period.[3] An alternative treatment variable is the average millimetres of rainfall per day in the 5-kilometre radius around each village, cumulated for the 15 days of interest. This measure has the advantage of being exogenous and unaffected by the lay of the land. We also build a control measure for the average daily rainfall in normal periods, although this measure is less precise because of the lower resolution of the satellite images.

[3]The data source for rain gauge is the NASA Integrated Multi-satellite Retrievals for GPM (IMERG), which provides the Day-1 multi-satellite precipitation product at a resolution of 0.25 degrees.

2.2.2 Household survey

We employ the *Bangladesh Integrated Household Survey*, a panel study conducted by IFPRI in two rounds, the first in 2011-2012 (October 2011- June 2012) and the second in 2015 (January - June 2015). This survey has a national coverage and is representative of rural areas of all the seven divisions of the country. Besides data on production and food security, the questionnaire includes also detailed information on income, expenditures, savings, as well as specific sections on migration and remittances.
The survey follows approximately 6,500 households and 27,000 individuals. The attrition rate is 4.4 and 22 percent at the household and individual level, respectively.

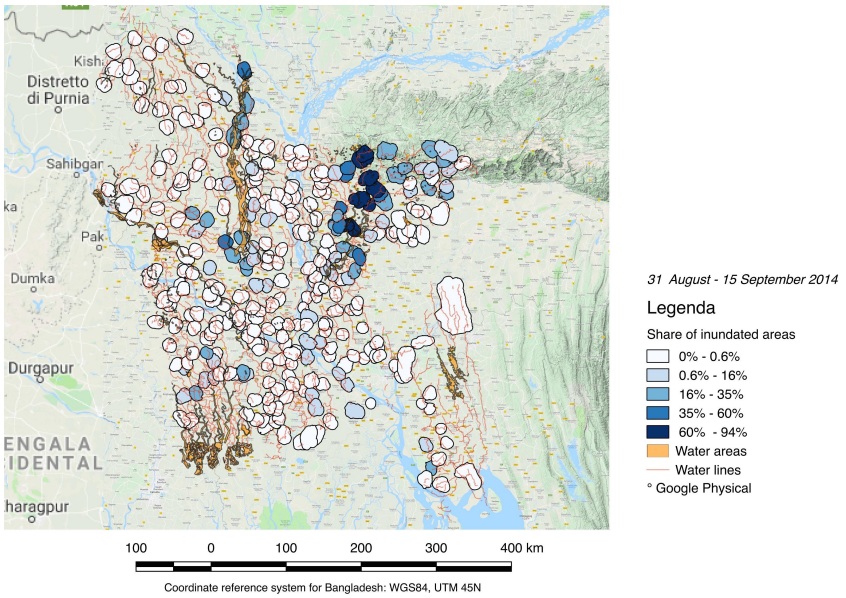
Figure 2.1 Two-week cumulated average millimiters of rainfall and share of flooded areas in the Bangladeshi villages for the period 2010-2014



Note: The figure shows in panel A the rainfall intensity for the monsoon periods between 2010 and 2014, measured as average tenth of millimetres of rainfall cumulated in a period of 15 days in all Bangladeshi villages and obtained from NASA Integrated Multi-satellite Retrievals for GPM. The same measure for rainfall is combined in panel B with average shares of inundated areas in all villages for 2014 calculated from NASA MODIS Satellite images.

A major concern is bias deriving from the possible correlation between the occurrence of flooding and the failure to track displaced households - according to national statistics, approximately 57,000 families were displaced between August and September 2014 (Ministry of Disaster Management and Relief, 2014) - and households that might have chosen to leave to avoid the dramatic consequences of the shock. To address this problem, we run a regression where the outcome variable is a dummy equal to one for each household tracked in the second wave, and the main explanatory variable is the treatment - i.e., the share of inundated areas in a 5-kilometre radius around each village. The coefficient of the treatment variable is not significantly different from zero, thus ruling out the possibility of this potential bias (see Appendix, Section 2.A1).

Figure 2.2 Geographical distribution of the treatment



Note: The map illustrates the share of inundated areas for each 5-km buffer built around the 318 villages in the sample. Author's calculations are based on products from NASA LANCE processing system applied to MODIS images from Terra and Aqua satellites with 250 m resolution, where flooding is determined as water observations falling outside normal water levels.

Table 2.1 presents the descriptive statistics for the panel sample at baseline (2012). The average number of household members, excluding migrants, is 4.8. Since the sample is mainly representative of rural areas, agriculture is the main sector of occupation, employing 48 percent of the labour force in farming and 26 percent in livestock jobs. With average monthly household earnings of approximately $305 (or 6,474 Taka; all monetary values are expressed in US$ PPP, CPI on the 2010 = 100 base period), agricultural revenues represent 40 percent of total household income net of transfers and remittances.

Household monthly income is the sum of monthly individual earnings of all household members in paid work. It comprises income from wage labour and income from self-employment in farming, namely, agricultural and livestock activities. Agricultural income comprises revenues from all types of cultivations, including paddies, which represent the main crop in Bangladesh. The survey also provides separately the total annual revenues from paddy cultivations, which we analyse in a distinct regression. Household monthly expenditure is on average $268, of which over 70 percent ($201) is for food consumption. Medical expenditures ($298 per year) amount to 9 percent of total consumption, while those for education ($124 per year) are only 3 percent.

Regarding migration, 20 percent of households have at least one migrant, and among them, 19 percent have more than one member overseas. The total number of migrants in 2012 is 1,663, and 31 percent of them live outside Bangladesh. Most importantly, 73.5 percent of families with at least one member overseas receive remittances, while 7 percent of total sampled households receive monetary transfers from

Table 2.1 Descriptive statistics of the panel sample in 2012

	N.	Mean	Std. Dev.	Min	Mdn	Max
HOUSEHOLD CHARACTERISTICS						
Number of households (panel dataset)	6,223*					
Household size (excluding overseas members, 2008)		4.83	1.83	1.00	5.00	17.00
Monthly income per hh ($PPP)		305.34	475.16	0	229.91	1,558.58
(Taka)		6,474.11	8,802.28	0	5,200	35,250
Monthly income per hh, wage labour ($PPP)		81.31	143.88	0	0	585.84
(Taka)		1,839.11	3,254.12	0	0	13,250
Monthly income per hh, farming/livestock ($PPP-adjusted)		113.73	184.91	0	44.21	733.96
(Taka)		2,572.41	4,182.19	0	1,000	16,600
Annual revenues per hh, paddy cultivation ($PPP)		289.22	1,571.93	0	0	4,443.61
(Taka)		6,541.36	35,551.91	0	0	100,500
Monthly expenditures per hh, food ($PPP)		201.67	137.05	0	169.18	1,820.86
(Taka)		4,436.79	3,015.14	0	3,722	40,059
Monthly expenditures per hh, non-food ($PPP)		65.69	218.02	0	39.54	454.81
(Taka)		1,445.35	4,796.49	0	870	10,006
Annual expenditures per hh, health ($PPP)		298.52	16,178.17	0	111.81	2,929.54
(Taka)		6,567.44	735.37	0	2,460	64,450
Annual expenditures per hh, education ($PPP)		124.52	240.62	0	27.72	1,029.09
(Taka)		2,739.58	5,293.72	0	610	2,2640
MIGRATION						
Proportion of hh with at least one migrant		0.20				
Proportion of international migrants		0.31				
Migrants' education level (internal)						
Illiterate/no educ.		0.10				
Primary school		0.35				
Upper-primary school		0.27				
Secondary		0.17				
Degree holders		0.05				
Others		0.06				
Migrants' education level (international)						
Illiterate/no educ.		0.06				
Primary school		0.36				
Upper-primary school		0.35				
Secondary		0.19				
Degree holders		0.03				
Others		0.01				
Proportion of migrant's households receiving remittances		0.73				
Remittances received from migrant members per year - migrant hh ($PPP)		2,765	4,252.02	4.54	1,363.63	22727.27
(Taka)		62,535.36	93,544.45	100	30,000	500000
Remittances received from non-household members per year - total hh ($PPP)		233.78	1,737.51	0	0	120,000
(Taka)		5,143.346	38,225.24	0	0	5,454.54
GEOREFERENCED VARIABLES						
Share of inundated areas per village, 1-15 September 2014		.18	.16	0.0002	.10	0.94
Share of inundated areas per village, 1-15 July 2014		.08	.09	0.0002	.02	0.45
Avg. mm rainfall, 15-31 August 2014		487.37	481.48	1.49	265.29	2,116.09

*Note:** The total number refers to the subsample of households surveyed in 2012 and re-tracked in 2015, that is, 6,223 households and 26286 individuals. All monetary values are expressed in PPP-adjusted USD at constant prices.

migrants who are not household members. The average gross amount received annually from members living abroad is $2765, while transfers received from non-family remitters are approximately $223.

For sampled migrants, the descriptive statistics show that among international migrants a lower share (6 percent) are uneducated with respect to internal migrants (10 percent), and that the proportion of those with secondary school is higher in the first group by two percentage points; migrants with higher education represent a small minority in both groups.

Internal migrants are mainly employed in private enterprises in the service sector (23 percent), while the majority of international migrants are construction and factory workers (48 percent).

For the main destinations of those overseas, 28 percent reside in Saudi Arabia, 22 percent in the United Arab Emirates, and less than 2 percent in the E.U. and U.S. Table 2.2 contains information on the characteristics of households distinguishing by income group (low-, middle- and high-income), a distinction that we use in our heterogeneity analysis.

As a first check for pre-treatment differences between treated and untreated (or rather between less and more treated) households, we perform a balance test at baseline.[4] Table 2.A2 in the Appendix confirms that the geographical position of some villages, correlated with a higher propensity to be inundated, may favour cultivations and harvest, and consequently lead to a higher level of some types of income and consumption outcomes for sampled rural households. Table 2.A2 also shows that there are no systematic differences at baseline in migration incidence and remittances received, while remittance incidence is significant at 10 percent.

Table 2.2 Descriptive statistics by income group

	Low income hh	Middle income hh	High income hh
Avg. monthly expenditures per hh, food ($PPP)	215.10	229.39	347.80
Proportion of hh with migrants in 2012	0.33	0.13	0.13
Proportion of hh with international migrants in 2012	0.13	0.04	0.04
Proportion of hh with migrants in 2015	0.37	0.20	0.23
Proportion of hh with international migrants in 2015	0.14	0.05	0.07
Remittances received from migrant members per year- only hh with migrants ($PPP)	2,631.82	2,369.43	3,444.71
Observations	2,198	2,121	1,904

Note: The sum of the three groups is the subsample of households surveyed in 2012 and re-tracked in 2015, that is, 6,223 households and 26,286 individuals.

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[4] We estimate an OLS regression at baseline, employing the continuous treatment as explanatory variable to check for its correlation with the different outcomes of interest.

2.3 Method

As already mentioned, we perform a difference-in-difference estimation, employing as treatment the continuous indicator for the share of inundated areas in a buffer of 5 kilometres around the villages where surveyed households live. The first specification we estimate is the following:

$$Y_{hvrt} = \beta_0 + \beta_1 T_v * t_{=2015} + \beta_2 T_v + \beta_3 t_{=2015} + \beta_4 P_v * t_{=2015} + \beta_5 P_v + \beta_6 X_{ht} + \beta_7 W_{rt} + \epsilon_{hvrt} \quad (2.1)$$

where Y_{hvpt} indicates the different outcome variables for each household h residing in village v of region r at time t; T_v is the treatment variable, namely, the share of inundated pixels for each village v; $t_{=2015}$ is the dummy for the second year; and β_1 is the difference-in-difference coefficient of the treatment. P_v is the propensity to be inundated within the same radius during normal times (July 2014); controlling for P_v allows us to identify the change in the outcome of interest over time due to the treatment for those villages that have the same propensity to be inundated, meaning the same percentage of area submerged in non-flooding periods. X_{ht} represents socio-demographic characteristics of the household.[5] W_{rt} are interactions between wave and region fixed effects to account for changes in regional characteristics over time. The errors, ϵ_{hvrt}, are clustered at the lower administrative level of divisions.

We first estimate the model with OLS on the observations common to the two waves (6,223 households over the total 6,503 of the initial sample). We then add fixed effects to control for time-invariant unobserved household characteristics α_h. The model thus becomes:

$$Y_{hvrt} = \beta_0 + \beta_1 T_v * t_{=2015} + \beta_2 P_v * t_{=2015} + \beta_3 X_h t + \beta_4 W_{rt} + \alpha_h + \epsilon_{hvrt} \quad (2.2)$$

All monetary values are expressed in $ PPP at constant prices.

To proxy the area where economic activities might have been damaged by flooding, we use information at baseline on land and pond or water bodies owned or under operation by households. Although the survey data show that the average distance from households' dwellings is less than 500 metres, we build this measure in a 5-km radius as in (Gröger & Zylberberg, 2016). However, we repeat the analysis in a 2- and a 10-km radius, finding very similar coefficients, although with higher standard errors with the 10-km radius.

When the regression is applied to dichotomous dependent variables, we employ a Linear Probability Model (LPM), assuming that the probability to send remittances is a linear function of the regressors. As mentioned in the previous Chapter, this empirical technique may lead to predict probabilities outside the 0-1 interval and may raise issues of heteroskedasticity since the predicted probabilities may vary

[5] Number of male and female adults in the family, number of elderly and children, and age and gender of the head of household.

between 0-1 and the size of the residuals increases with the predicted values. However, in order to employ a difference-in-difference approach with panel data and fixed effects, LPM is preferred to logit or probit models whose coefficients represent the differences in log odds and can not be directly interpreted as causal effect measures (Puhani, 2012). In addition, since the difference-in-difference method calculates the mean differences due to the treatment - comparing the mean of the dependent variables among differently treated units before and after the shock - if the predictive margins are between 0-1, the results represent an appropriate estimation of the differences in probabilities. However, including continuous covariates in the regression may lead to over-estimation in the predicted probabilities (Allison, 1999; Mood, 2010).

Propensity score methods are generally employed in difference-in-difference estimations to remove the bias due to the different distribution of some characteristics between treated and control groups that might contribute to affect the outcomes. In case of continuous treatment, the *Generalized Propensity Score* (GPS) (Hirano & Imbens, 2004) should be implemented. The latter relies on the *unconfoundedness assumption*, which implies that adjusting for differences in observed pre-treatment variables removes biases from comparisons by treatment level. As for the *Propensity Score Matching* (PSM) applied to binary treatment, this technique allows to control for self-selection among units into lower or higher level of treatment, ruling out the possibility that some of their characteristics may be positively related with the likelihood to be treated as well as with the outcomes. However, in our case the treatment is taken at village level so that self-selection might be related to the presence of some households' features that may lead them to locate in differently treated areas and that are at the same time correlated with our dependent variables. However, one of the main criticisms raised about matching is that the propensity score, making the treatment group orthogonal with respect to the covariates, is assimilated to a control that might pair observations with large differences in the covariates, thus not contributing to decrease confounder imbalance, but rather leading to biased estimations of the treatment effect (King & Nielsen, 2019). Therefore, in our case, since we assume that there is not selection bias due to the village of residence, introducing controls at village level such as the share of inundated areas in normal periods and other villages' topographic characteristics allow us to compare differently treated villages with similar propensity to be affected before the flood.

To deepen the understanding of the effects of flooding, we conduct some heterogeneity analyses. First, we investigate whether household outcomes differ in relation to the initial level of income. The literature reviewed in the introduction does not disentangle the natural shock effects according to the heterogeneity of household income. Gröger and Zylberberg (2016) partly touch on this issue looking at the effect of the typhoon on the variation in remittances normalizing them by household income, without explicitly differentiating by income groups. We therefore investigate the heterogeneous effects of flooding on our outcomes of interest by estimating our model separately by tertiles of the income distribution at baseline. Regarding the migration outcome, for example, we expect migration incidence to change after the flood,

as households might be induced to send more members away as a coping strategy to face the natural shock. Accounting for income heterogeneity allows us to test whether in our causal setting households that are initially worse off, and become even more so after the flooding, are more likely to have migrant members.

We also distinguish between internal and international migration, to test whether, for example, international migration would represent a more effective diversification strategy, with overseas destinations being exposed to different economic cycles and no flooding. This heterogeneity analysis aims at understanding whether remittance receipt is effective in compensating for the income loss, whether migration is also beneficial for lower income households, and whether the natural shock affects households with internal and international migrants differently.

Second, as the sample is representative of rural areas at the national level, it is interesting to disentangle the differences in household outcomes according to their position in the local market as net seller or buyer. We therefore estimate our benchmark specification dividing the sample between net food buyer and net food seller households.[6] Since net seller households rely on agricultural activities as their main source of income, for them we expect to find larger effects in terms of income loss and drop in expenditure, together with higher increases in migration incidence and remittances.

Turning to robustness checks, as already mentioned, the potential endogeneity in our empirical strategy derives from the fact that flooded villages may have particular layer characteristics, such as being flatter or being located close to water surfaces, which make them particularly vulnerable to flooding. In addition, these features might favour the harvest, consequently affecting income and consumption outcomes of households as well as migration and remittance choices, independent of the level of flooding. To control for this endogeneity issue, as in Gröger and Zylberberg (2016), we instrument the flooding treatment variable with rainfall, which represents a more exogenous indicator of village exposure to the shock. We therefore apply a two-stage least squares method:

$$T_{vt} = \beta_0 + \beta_1 R_{vt} + \beta_2 P_{vt} + \beta_3 P^R_{vt} + \beta_4 X_h t + \beta_5 W_{rt} + \alpha_h + \epsilon_{hvrt}, \tag{2.3}$$

$$Y_{hvrt} = \beta_0 + \beta_1 \hat{T}_{vt} + \beta_2 P_{vt} + +\beta_3 P^R_{vt} + \beta_4 X_h t + \beta_5 W_{rt} + \alpha_h + \epsilon_{hvrt}. \tag{2.4}$$

where R_{vt} are average tenth of millimetres of rainfall per day in the 5-kilometre radius around each village, cumulated for the 15 days of interest (as already mentioned, to explain flooded areas in the first days of September, we take as our rainfall intensity measure the cumulated average for the two weeks before that period). P^R_{vt} is a control for the average intensity of rainfall in normal pre-shock periods, again taking as reference July 2014.

[6] Using yearly information on kilograms of each food item cultivated and sold in the market and on the corresponding quantities purchased, we define net sellers as households for whom the total amount of items sold is higher than the amount purchased, and the sample of net buyers as households for whom the reverse is true.

However, the rain gauge estimation is much less precise than the flood measure because of the lower resolution of the satellite imagery. In addition, rainfall estimation might not always be highly correlated with flooding, especially in those villages that are close to mountainous areas and may be hit by water inflows from upstream hill zones independently of rainfall measures. This appears to be particularly true for the areas in the northern part of the country where snowmelt from the mountains results in soil erosion and a rapid increase in river discharge. It is therefore important to add a second robustness check controlling for the specific topographic characteristics of sampled villages. In a first specification, we therefore add control dummies indicating whether the village lies at the bottom of a valley, or stands on a hill or mountain, or rather if it is close to rivers or other water surfaces, which are all important factors influencing the propensity to be inundated.[7] In addition, we include in the estimation a control for *flows direction*, calculating for each pixel the main direction of water run-off over the geographic area of interest depending on elevation and cell height values, thus creating a dummy equal to one for the potential catchment areas where surface water would accumulate.

An alternative specification of this robustness check includes, among the controls of the benchmark regression, an interaction of wave fixed effects with average rainfall in the same period of interest (August-September) for the years 1970-2000. Finally, in the last specification of these robustness checks controlling for topographic features, we add a *vulnerability index* built for each village according to the distance from rivers, lakes, water surfaces and the nearest coastline. Calculating the Euclidean distance from these water areas and assigning each unit of observation to a category of *low, medium and high* risk based on this measure, we build a control variable interacted with wave fixed effects, to allow villages with different exposure to flooding to have different trends.

In addition, we include in the main specification a control for price variation at the local level to test whether this variation, which might be partially influenced by the flooding, drives the estimated coefficients of the treatment in the regressions for our outcomes of interest. If, after inserting this control, our estimated coefficients remain unchanged, we can conclude that the observed variation in these outcomes is only due to the shock.

As a third robustness check, we estimate a parallel trends test to assess whether differently treated villages would have followed similar trends in the absence of the flood. However, with only two available panel waves for the sample considered, we repeat the estimation as if the flood had occurred two years before, in 2012, employing as data for the pre-treatment period *night lights* data. As in Henderson et al. (Henderson, Storeygard, & Weil, 2012), we use the amount of light observed from outer space to proxy the level of economic activity in the absence of more traditional measures. We therefore employ the NOAA/NCEI products, obtained by collecting measures of night time light intensity at 750-metre

[7] In particular, employing georeferenced data on the Digital Elevation Model, we add two dummy variables for each village being close to a river line or water surfaces, and three other indexes for being located on plain areas, hills or mountains.

resolution from the Visible Infrared Imaging Radiometer Suite (VIIRS) - a NASA instrument providing detailed images with different bandwidths of light - and filtering them from the noise due to stray light, lightning, lunar illumination, and cloud cover.[8] In particular, we compute the yearly average of the monthly composite measure for the intensity of night lights in 2012 and 2013. We then regress the average light estimation in the 5-km radius around each village in the sample on the flooding treatment variable, adding as controls the propensity to be inundated in normal times and the region-wave fixed effects, to check whether there are ex-ante correlations between the treatment and trends in the outcomes. To prove the reliability of this test, we compare the results of the placebo with results obtained by regressing the same type of outcome on the treatment for the period when the flood actually hit, running the same difference-in-difference estimation for the years 2012-2015.[9]

In addition, to estimate an alternative placebo test using household information as outcomes, we perform a second parallel trends test employing as the data source for the pre-shock period another household survey, the Bangladesh Household Income and Expenditure Survey (HIES 2010), conducted by the Bangladesh Bureau of Statistics (BBS) and the World Bank.

The survey contains all information on the household income, expenditures and migration behaviour that we take as dependent variables in our benchmark specification, but the HIES sample is formed by different households with respect to our initial sample. However, since the unit of observation for our treatment are again villages, the aim of this robustness check is to prove that household outcomes aggregated at the village level would have followed similar trends in the absence of the shock. We repeat the placebo test as if the flood hit Bangladesh between 2010 and 2012, employing HIES for 2010 and the first wave of BIHS for 2012, taking the variables of interest as averages at village level. The specification for this difference-in-difference estimation, performed both as OLS and fixed effects, is:

$$Y_{hvrt} = \beta_0 + \beta_1 T_v * t_{=2012} + \beta_2 T_v + \beta_3 P_v * t_{=2012} + \beta_4 P_v + \beta_5 X_{ht} + \beta_6 W_{rt} + \epsilon_{hvrt} \tag{2.5}$$

However, the two surveys have in common only 55 out of the 318 villages for 2012. Therefore, we first perform the placebo test on the 55 common villages [10], aggregating household outcomes at the village level and running the fixed effects estimation on this subgroup of observations. We then employ the same sample to repeat the estimation for the period when the flood actually hit, namely, between 2012 and 2015, to test whether this subgroup is representative of the whole sample and to show the lack of effects in the placebo test and the consequences of the flood for the post-treatment estimation.

In addition, to also exploit information from the other non-common villages, we employ matching tech-

[8] These data can be publicly accessed at $https://www.ngdc.noaa.gov/eog/viirs/download_dnb_composites.html$.

[9] Since we do not have information at the household level, all the variables - dependent, explanatory and control - are taken at village level, the estimation being a test for pre-treatment differences across these units of observation.

[10] T-tests implemented show that the 55 villages common to the two samples are not significantly different from the whole initial BIHS sample in terms of georeferenced variables that may affect the likelihood of being inundated.

niques to pair the remaining villages with the closest unit from 2010 in terms of Mahalanobis distance calculated on the basis of common georeferenced characteristics (see Appendix, section 2.A5).

2.4 Results

Table 2.3 shows the results of the benchmark household-level specification. For each outcome, the table reports the difference-in-difference coefficients of the treatment estimated with both the OLS and fixed effects regression. Each coefficient indicates the variation in a particular outcome between the two waves in those villages totally inundated by flooding with respect to unaffected ones. As shown in the descriptive statistics, the highest share of inundation is 0.94, and the lowest is 0.01. Monetary values are expressed in PPP-adjusted US$ at constant prices (CPI on the 2010 = 100 base period). Table 2.A3 in the Appendix reports the coefficients for all covariates included in the baseline estimation for the impact of flooding on monthly income from wage labour.

Effects on income and expenditure

The results show that monthly income from agricultural activities declines after the flood for affected households, and that income from livestock in particular drops by $16. Monthly income from wage labour declines more consistently as an effect of the shock, dropping by $50 on average in villages where the share of inundated areas reached the maximum. It is important to highlight in fact that the majority of those working for pay - 68 percent of the labour force in the sample - are employed in agricultural activities, and 56 percent of them in the livestock sector. For households with rural workers this approximately amounts to an income loss that can reach a maximum of approximately 60 percent (or 11 percent for the average share of inundated areas per village).[11] Among the other dependent variables, income from paddy cultivation appears to decline by over $70 between the two waves. However, its coefficient is only slightly significant; this might be because since rice is cultivated in three farming seasons - summer, autumn and winter - the flooding might have damaged paddy cultivations only in autumn, so that this cumulative measure for annual sales also includes positive revenues from the other periods. Our estimates also show a statistically significant loss of about $69 per household in total monthly expenditures, representing an average decrease of 30 percent with respect to the pre-shock period. Interestingly, the majority of this loss is due to a drop in food consumption. Also annual health and education expenditures per family decrease significantly between the two waves, by approximately 290 and $110, respectively.

[11] The income loss is calculated by multiplying the coefficient by the maximum share of inundation, i.e., 0.94, and dividing it by the average monthly labour income of the pre-shock period, that is, $(0.94 * 0.54)/81$ or $(0.18 * 0.54)/81$.

Table 2.3 Impacts of the flood shock on household outcomes

Outcomes	OLS	FE
Income		
Monthly income, wage labour	-54.28***	-51.28***
	(10.95)	(6.513)
Annual income, paddy	-69.05	-108.8*
	(107.4)	(63.97)
Monthly income, farming/livestock	-16.03***	-16.00***
	(3.968)	(2.553)
Expenditures		
Tot. monthly expenditures	-62.08***	-68.94***
	(18.55)	(10.95)
Monthly expenditures, food	-50.67***	-48.29***
	(8.432)	(5.695)
Monthly expenditures, non-food	-11.41	-20.65**
	(15.60)	(8.968)
Health expenditures, yearly	-284.0***	-291.3***
	(79.11)	(61.23)
Education expenditures, yearly	-158.4***	-109.0***
	(25.68)	(16.59)
Migration outcomes		
Migration incidence	0.0500***	0.0635***
	(0.00892)	(0.00275)
Remittance incidence	0.00725	0.0117***
	(0.00769)	(0.00378)
Net remittances received yearly	133.5*	197.2***
	(77.77)	(50.40)
Observations	6,223	6,223

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Each cell contains the difference-in-difference coefficient of the treatment for each outcome. All monetary values are expressed in PPP-adjusted USD at constant prices.

Effects on migration

Both migration incidence and the likelihood of receiving remittances increase, and the value of these monetary inflows - net of outflows of other transfers sent from households - increases on average by $197. These increasing transfers might contribute to increasing savings, but on average, they cannot prevent a drop in consumption. Considering the income loss that salaried workers suffered over a year (obtained by summing the monthly income losses), the increase in remittances could only compensate for 28 percent of the loss faced by affected households.

2.4.1 Differentiating by income groups

As mentioned, we apply the difference-in-difference estimation separately for the three groups of low-, middle- and high-income households.

Effects on income and consumption

Since the number of low-income households mainly involved in agricultural activities is proportionally higher[12], it is reasonable to expect that damages caused by flooding to crops and agricultural equipment had larger consequences for this group. Table 2.4 shows that this is indeed the case: only the treated low-income households suffer from a significant drop in monthly revenues from agricultural activities and in annual revenues from paddy cultivation (monthly data for this variable is not available), which declined by approximately 29 and $129, respectively, in villages affected by flooding.

Monthly income from wage employment shows a significant drop only for households in the second and third income group, while lower-income households experience an increase in this outcome. Some members in this group, in fact, may have moved to the wage sector as a consequence of the shock. For expenditures, we observe a significant drop for low-income households, driven by a substantial decline in non-food expenditures that confirms *Engel's law*: food consumption of poorer households is generally inelastic to a drop in income, while non-food expenditures decrease via a substitution effect. Middle-income households do not show any substantial variation in their expenditure choices. High-income households show a significant drop in expenditure, driven by their decline in food consumption (taking as reference the average expenditure of the different income groups at baseline, we approximately calculate a 22 percent drop in expenditure for low-income households and a 25 percent drop for high-income households).

The different results concerning food consumption of low- and high-income households after the shock may be due to different reasons, such as, for example, the different composition of food consumed. The low-income households' diet is rich in staple foods - e.g., cereals and vegetables - that are typically less income-elastic, while the high-income households' diet contains more nutrient-rich foods - i.e., animal source food - that is more income-elastic. In addition, income elasticity may vary within the same type of good according to its quality, as shown by the literature in the case of maize: according to Arifin, Achsani, Martianto, Sari, and Firdaus (2018), income elasticity of maize is positive for high-income people who consume mainly sweet maize, but it is negative among lower-income households that use maize as a staple food.

[12] In 2012 the share of agricultural households in the low-income group amounts to 84 percent, to 77 percent in the low-income group and to 71 percent in the high-income group.

Effects on migration and remittances

Regarding the other outcomes of interest, the increase in migration incidence is similar among the three groups of households. If affected by flooding, household likelihood to send some members away rises by 6 to 7 percentage points. In particular, the effect concerns internal migration, since the initial economic resources needed to send a relative to other districts of Bangladesh are lower than those needed for international migration. Our results show that the change in likelihood of sending a member abroad is lower for low-income households with respect to the other two tertiles. However, the proportion of migrant households in the lower income group is not negligible: approximately 37 percent of families in the first tertile have at least one migrant in 2015, and those with members living overseas represent 14 percent in the second wave (Table 2.2).

The results also show that wealthier households, who have initial assets to diversify the risk by sending members away, are thus more likely to receive monetary transfers in case of need. Remittances received by high-income households, in fact, increase by approximately $290, more than double the $110 variation of the middle-income group. Households belonging to the first tertile instead experience a positive but non-significant increase in total remittances after the flood.

For the heterogeneous effects on the amount of remittances - sent by either internal or international migrants - the variation in flows sent from internal migrants is again not significant for households in the first tertile, while it is positive and significant for middle-income and high-income households. However, inflows sent from household members overseas show a different pattern: international remittances received by the latter - if affected by the shock - increase by over $300. Households in the second tertile show a smaller increase, approximately $122, while high-income households, if affected, receive $250 more in international remittances. The latter result could be explained by the variety in migration destinations. Migrant members of wealthier families have higher initial assets and are thus more likely to migrate to high-income countries and access, on average, better paid jobs. Nevertheless, the positive increase in international remittances that we find for the first tertile is lower with respect to the variation experienced by low-income households.

If we consider by how much an additional inflow of remittances offsets the losses that flooded households experience (where this compensation effect is obtained estimating the proportion of inflows received over the monthly loss from all economic activities of the family aggregated at the annual level), we observe that the variation in internal flows cannot compensate for the income drop suffered by low-income households, while it contributes to offsetting 8 and 4 percent of the loss suffered by middle- and high-income households, respectively. However, monetary transfers sent from overseas account for about 85 percent of the income drop of low-income households, a proportion by far higher with respect to the 20 percent of the other two groups.

Our results support the hypothesis that migration, in particular international migration, represents a

form of insurance against natural shocks, including for low-income households. If the latter, in fact, have initial assets to send migrants abroad, they receive increasing transfers after the flood that compensate for a large part of their income loss and thus have an equalizing effect with respect to households in the upper parts of the income distribution.

Table 2.4 Impacts of the flood shock by income group, FE estimations

	Low-income hh	Middle-income hh	High-income hh
		Income	
Monthly income, wage labour	40.52***	-45.64***	-116.4***
	(8.212)	(9.544)	(14.79)
Annual income, paddy	-129.2***	44.48	-160.3
	(33.08)	(49.39)	(163.0)
Monthly income, farming/livestock	-29.43***	-12.91***	-8.859
	(3.752)	(3.578)	(5.678)
		Expenditures	
Tot. monthly expenditures	-50.58***	-9.280	-92.76***
	(12.00)	(14.69)	(11.68)
Monthly expenditures, food	-10.54	5.863	-106.2***
	(10.78)	(7.958)	(10.62)
Monthly expenditures, non-food	-40.04***	-15.14	-7.582
	(4.907)	(11.57)	(21.61)
		Migration outcomes	
Migration incidence, total	0.0627***	0.0557***	0.0687***
	(0.00596)	(0.00443)	(0.00505)
Remittance incidence, total	0.0223**	0.0261***	0.00208
	(0.00935)	(0.00543)	(0.00575)
Net remittances received, yearly	183.4	110.2***	287.9***
	(122.0)	(42.24)	(102.1)
Internal migration incidence	0.0508***	0.0482****	0.0628***
	(0.00526)	(0.00420)	(0.00453)
Net remittances received from internal migr.	62.71	47.85***	68.57***
	(58.09)	(18.40)	(14.35)
International migration incidence	0.0106***	0.0162***	0.0140***
	(0.00359)	(0.00245)	(0.00293)
Net remittances received from international migr.	318.9***	122.5***	257.2***
	(31.04)	(17.07)	(43.69)
Observations	2,198	2,121	1,904

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

Note: Each cell contains the difference-in-difference coefficient of the treatment for each outcome. All monetary values are expressed in PPP-adjusted USD at constant prices. The sample is divided among low-, medium- and high-income households on the basis of total monthly income at baseline.

2.4.2 Differentiating between net buyers and net sellers

As mentioned above, we re-estimate our model distinguishing between net food buyer and net food seller households.

Table 2.5 shows that our treatment variable has a higher impact on incomes from agricultural activities and on wage labour for net seller households. We also see larger effects on expenditure, where the drop in total monthly consumption for the first group is approximately 47 percent, by far higher with respect to the 10 percent decline for the second group. In addition, households whose production activities have been largely hit by the flood are induced to decrease their expenditures on non-food items, while for net buyers, this type of consumption appears not to be significantly affected by the treatment, presumably because of their lower drop in total earnings with respect to net sellers. Remittance incidence then increases for the group of net sellers affected by flooding by 2 percentage points, almost double the variation for the group of net buyers.

2.4.3 Robustness checks

Rainfall as instrumental variable

As a first robustness check, we instrument the flooding treatment variable with rainfall, a possibly more exogenous indicator of village exposure to flooding, in order to overcome the issue of potential endogeneity due to particular layer characteristics that flooded villages may have and that make them particularly vulnerable to flooding.

Table 2.A4 in the Appendix illustrates the results obtained from the instrumental variable regression estimated using rainfall as exogenous factor with respect to flood; the instrument is measured as average tenth of millimetres of rain registered by satellite in the 5-kilometre radius around each village in the period considered (August 31st -September 15th 2014). The sign and significance of the coefficients are quite similar to those obtained in the baseline specification of Table 2.3, but the absolute values vary substantially. Monthly income from wage labour decreases by $32 as an effect of the flood for households residing in villages that are completely inundated with respect to the unaffected ones, and annual revenues from paddy cultivation drop by $3800 in a year. Expenditures, then, decline by $280. Migration incidence rises by 6 percentage points and remittances by approximately $600.

In line with (Gröger & Zylberberg, 2016), the difference with respect to the benchmark specification can be explained by the large heterogeneity in the correlation between rainfall and flooding areas. As already discussed, the topographic characteristics of some areas make them particularly vulnerable to flooding, independent of rainfall level, such as in the northeastern region of the country where the average share

Table 2.5 Impacts of the flood shock for net food buyers and net food sellers, FE estimations

Outcomes	Net food buyer	Net food seller
Income		
Monthly income, wage labour	-41.53***	-80.00***
	(8.919)	(11.05)
Annual income, paddy	-97.75***	-159.9
	(22.91)	(172.8)
Monthly income, farming/livestock	-9.413***	-34.32***
	(2.962)	(5.280)
Expenditures		
Tot. monthly expenditures	-32.47**	-132.1***
	(15.51)	(14.49)
Monthly expenditures, food	-44.90***	-63.33***
	(7.812)	(8.356)
Monthly expenditures, non-food	12.43	-68.76***
	(12.73)	(11.68)
Migration outcomes		
Migration incidence	0.0578***	0.0683***
	(0.00394)	(0.00431)
remittance incidence	0.0120**	0.0197***
	(0.00502)	(0.00548)
Net remittances received yearly	207.2***	176.6***
	(73.59)	(60.69)
Observations	3,953	2,270

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Each cell contains the difference-in-difference coefficient of the treatment for each outcome. All monetary values are expressed in PPP-adjusted USD at constant prices.

of inundated areas reached their maximum, despite the flooding being less correlated with rainfall with respect to other regions. Consequently, the concentration of flooded areas in the northeastern part of the country could be explained by its closeness to the two major river basins and position in valleys between hills and mountains, rather than by the amount of rainfall. This explanation would justify the low correlation between rainfall variation and flooding found in the first stage of the IV method. In fact, two units of observation with similar rain gauge measures might show different shares of flooded areas because of their distance from rivers or lakes, or location in a plain or up on a hill or mountain.

In addition, the areas that are more likely to be treated are on average richer in terms of agricultural revenues - as found in the balance test on villages at baseline. The coefficients in the benchmark specification, where the effects of topographic features are omitted, could be thus underestimated with respect to those found in Table 2.A4, where only variation in rainfall is employed as explanatory variable and is orthogonal to these layer characteristics. Therefore, given the low precision of rain gauge measure and given these particular features of floods delineation in Bangladesh, we argue that a robustness check

controlling for the topographic characteristics of the areas considered would be more appropriate than the two-stage estimation using rainfall as instrument.

Adding controls for topographic characteristics

Table 2.A5(A) in the Appendix illustrates the results obtained adding these topographic controls to the initial specification in order to allow villages with different characteristics in terms of distance from water areas or watershed basins and same elevation to follow different trends. The coefficients again show a decrease in both income and consumption for households in largely treated villages, even if of a smaller magnitude compared to Table 2.3. Moreover, affected households are 13 percentage points more likely to have migrant members and 18 percentage points to receive remittances.

In addition, results are also robust when including the interaction of wave fixed effects with the average rainfall during the same monsoon period for the years 1970-2000 (Table 2.A5, B). Finally, the third specification controlling for the *vulnerability index* - built for each village according to its distance from rivers, lakes and coastal lines - again reveals similar correlations between the treatment intensity and the variation in the outcomes considered (Table 2.A5, C). However, the coefficient for non-food consumption in these three specifications that employ topographic indicators is not statistically significantly different from zero; the change in total consumption that we observe for affected households is therefore driven by the significant drop in food expenditures.

Controlling for price changes

To control for the possible effects of flooding on food prices, we include among the controls the variation in average food prices at village level. Using information on price per unit of main food consumption items for sampled households, we build an index of average food prices adjusted for inflation and converted in $ PPP in order to investigate how its variation over time, partially correlated with the flooding (the correlation coefficient between our flooding treatment and price variation is in fact approximately 10 percent), would affect our difference-in-difference estimation. Table 2.A6 in the Appendix shows that the coefficients do not change significantly with respect to the benchmark specifications, thus indicating that the treatment effect on outcomes of interest is not driven by the indirect influence of changes in average prices at the local level. (The price coefficient is significant for all outcomes.)

Placebo tests

Results from the first placebo test run for the period preceding the occurrence of the flooding, namely, 2012 and 2013, confirm that differently treated villages would have followed, in the absence of the shock, parallel trends in the outcome of interest. In fact, coefficients for the correlation between the treatment and the variation in night lights over time are neither statistically significant in the OLS nor in fixed effects regressions (Table 2.A7 in the Appendix). Instead, running the same regression for the periods between 2012 and 2015, we do observe that the effect of the treatment would lead to a significant drop in night light intensity by 0.09 units, where the unit of measurement is nanowatts/cm^2/steradian (nw/cm^2/sr). Despite the limits of this estimation, where the more informative income, consumption and migration outcomes are substituted with the single indicator of night lights, the literature (Henderson et al., 2012) agrees on the potential of night lights to be a useful proxy for economic activity. Therefore, our estimation results would support the hypothesis of equality of pre-treatment trends in economic growth among differently treated villages. Given equality in economic trends, we could assume also that any significant difference among villages could be found in consumption and migration behaviour of households.

Regarding the check for pre-treatment differential trends conducted among villages from the 2010 and the 2012 surveys, the estimation performed over the 55 common villages supports the hypothesis of the lack of effects in the placebo test run two years before the flood (2010-2012); the regression conducted on the same subsample for the period of interest (2012-2015) instead confirms the significant treatment effect after the flooding, even if the high standard errors due to the small number of observations make the coefficients of the latter estimation less significant (Table 2.A8 in the Appendix).

In addition, the test conducted on the whole sample of villages including also those non-common to the two surveys - matched on the basis of their georeferenced features - shows that there are not significant correlations between the treatment and the dependent variables in the absence of the flood (Table 2.A9 in the Appendix).

Altogether, our results are robust to the checks performed and confirm the increase in international migration incidence due to the shock among the affected households and the role that migration and remittance transfers, in particular those sent from overseas, have in mitigating income losses for the left-behind households hit by the natural shock.

2.5 Discussion

Our analysis has allowed us to causally identify the impact of the dramatic 2014 flooding on internal and international migration and the consequent remittance flows in Bangladesh. In contrast to Gray and

Mueller (2012), who employ multivariate event history analysis without finding any effect of flooding on labour mobility, our empirical results show an increase in the likelihood of migrating for the affected households after the shock.

Unlike earlier studies, we account for the position of affected households in the income distribution at baseline, and examine differences in migration incidence and monetary transfers received in the three income groups. Even if not comparable, our findings are in line with those of a randomized control experiment conducted by Bryan, Chowdhury, and Mobarak (2014) that assigns a small monetary incentive (money for the journey to the town) for households in rural Bangladesh to migrate during the lean season. The experiment shows that the incentive induces 22 percent of households to send a seasonal migrant and their consumption increases significantly. The authors conclude that since migration is risky, and requires individual-specific learning, some households are so close to subsistence that failed migration is very costly and even a very small incentive is enough to help them to face this risk. In our case, households in economic hardship after the flood may be induced to overcome the risk of failed migration, thus learning that the choice is indeed effective.

In terms of the replacement rate of remittances received after the income shocks that households experience, we find an increase in remittances of 28 percent of the income loss, similar to what is found in Clarke and Wallsten (2003), which estimates an increase of 25 cents for every dollar of loss suffered by household hit by a hurricane in Jamaica. Differently from what we observe, Yang and Choi (2007) find a considerably higher replacement rate of about 60 percent that allows Philippine families to maintain their consumption unchanged after rainfall shocks.

One weakness of this study is that we are unable to conduct the natural parallel trend test because of the lack of another panel wave of the BIHS administered during the pre-shock period. If this additional wave were available, we would have been able to test whether the average change in outcomes estimated for the untreated group reflects the counterfactual change in the treated group had the treatment not occurred. In the absence of this additional panel wave, we have conducted two alternative tests. First, we have used all villages in the survey to conduct a placebo test using night lights data as outcomes for the pre-treatment periods, assuming that this alternative variable, taken at village level, is a valid proxy for local economic development. Although this proxy of outcomes is correlated with income and consumption expenditure, as shown in several studies, its effect on migration is less predictable; moreover, we cannot assume that, given parallel trends in economic growth of the more and the less treated units, villages would also have followed similar trends in migration incidence and remittances.

As a second alternative, we have matched the 2012 BIHS data with data drawn from the 2010 HIES survey. This strategy has the advantage that the two surveys contain the same outcomes of interest, so we can aggregate them at village level. However, this alternative placebo test has the disadvantage that we could run it only on the subsample of the 55 villages common to the two surveys, out of the 318

villages surveyed in the BIHS sample.

Among the strengths of the analysis, the use of georeferenced data that provide precise measures of the intensity of flooding for each village of residence of sampled households has allowed us to obtain robust estimates. Satellite data - compared to self-reported measures of the shock, which might depend on households' subjective perception and variable coping ability to deal with these natural events - are a great advantage for the analysis. In addition, the numerous robustness checks controlling for all the topographic features that may affect the likelihood of villages to be flooded show that our substantive conclusions remain unchanged when we estimate alternative specifications of our model.

2.6 Concluding remarks

We use high-precision satellite data and a panel survey to evaluate the response of households to a dramatic flood that hit Bangladesh between August and September 2014. Although floods are quite common during the monsoon season in South Asian countries, climate change and the progressive variation in timing and intensity of these natural phenomena make it extremely relevant to understand their effects on income, consumption, and migration behaviour of households. Since the sample is representative of households living in the rural areas of Bangladesh, we use as treatment the share of inundated areas at the village level to approximate the probability of household economic activities, mainly in the farming and livestock sector, being damaged by flood waters.

The results of our difference-in-difference estimation show that agricultural revenues from self-employment in farming are particularly affected by flooding. However, since most of the labour force is employed in agricultural activities, the flood also has a negative and significant impact on incomes of salaried workers. As a consequence, both food and non-food expenditures, such as those for health and education, considerably decrease for all households living in inundated villages.

Over time, households have developed risk-coping strategies to adapt to these repeated natural shocks, becoming resilient to their consequences. In fact, our results show that the increasing level of inundation determines a higher incidence for the treated households of having migrant members and receiving remittances (increasing, respectively, by 6 and 1 percentage points), as well as receiving larger amounts of remittances. These monetary inflows, however, account for about 28 percent of the income loss suffered by damaged households, thus not completely offsetting the observed drop in expenditure.

The results of the analysis by income groups are in line with previous literature showing an increase in internal migration incidence for households independently of their level of initial incomes. However, as shown in Gröger and Zylberberg (2016), long-distance migration represents a more effective insurance than short-distance migration. Our results confirm this evidence, since international migration appears

to better mitigate the effects of the shock for the sample of the treated, in particular for households at the bottom of the income distribution. For these households, remittances received from overseas have an effective role in compensating losses due to the natural shock.

From the policy point of view, investments in protective infrastructure, such as embankments and flood shelters, and government expenditures for reconstruction are particularly adequate for predictable monsoon seasonality. However, in case of unexpected natural shocks of the size described in our analysis, migration and remittances might represent an inevitable choice. In this case, policies supporting migration, such as small monetary transfers for internal migration or microcredit loans targeted to international migration, have proven to be effective tools that should be further developed.

Appendix

2.A

2.A1 Attrition analysis

As mentioned, the attrition rate is approximately 4.4 and 22 percent at the household and individual level, respectively. Since the possible correlation between the occurrence of flooding and the failure to track displaced households may lead to biased estimates, we regress the indicator for attrition - a dummy equal to one in case of households or individuals not tracked in the second year - on our flood shock variable. Table A1 shows the results from *probit* regressions estimated at the household and individual level on all the observations of the sample for the two years. The main explanatory variable is the measure of the treatment, i.e. the share of inundated areas in a 5-kilometre radius around each village, while regression controls include household characteristics and location fixed effects. The coefficients of the treatment are not significantly different from zero, thus ruling out the possibility of sample selectivity bias due to attrition.

Table 2.A1 Impact of the flood shock on household and individual attrition rates, 2012-2015

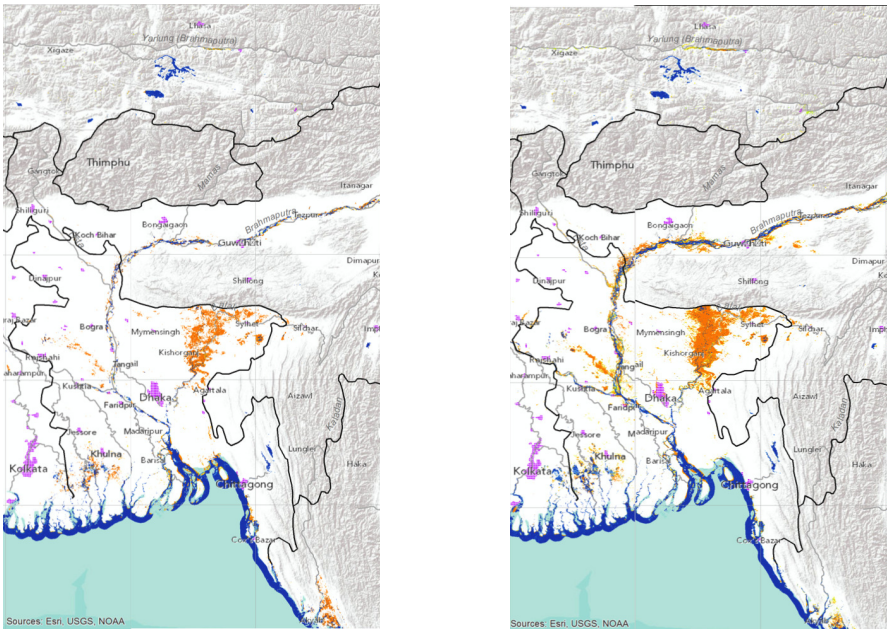
	Indicator of attrition
Household level	
	0.216
	(0.179)
Observations	6,223
Individual level	
	-0.0413
	(0.0530)
Observations	29,131

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: The table reports the coefficients of the treatment resulting from *probit* regressions estimated at the household and individual level, where the outcome is a dummy equal to 1 for households or individuals not tracked in the second year. Regression controls include household characteristics and location fixed-effects.

2.A2 Figures

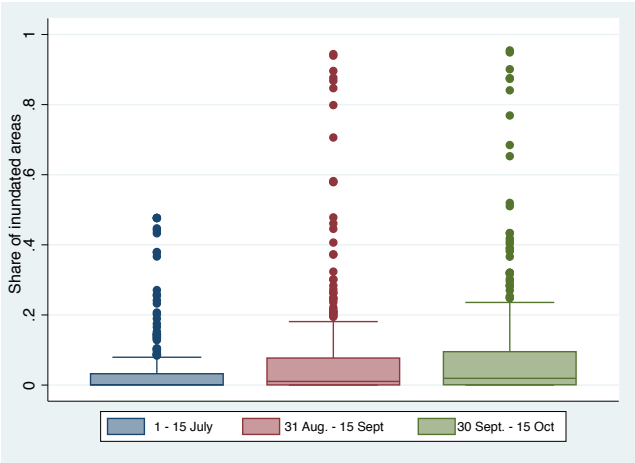
Figure 2.A1 NASA MODIS images, flood mapping



(a) July 2014 (b) September 2014

Note: NASA satellite image for non-flooding period, July 2014, compared to the period of interest, August 31st-September15th 2014.

Figure 2.A2 Share of inundated areas in a radius of 5km around each village



Note: The graph illustrates the box plot for inundated areas in a radius of 5 kilometers for each sampled village, before, during and after the flood.

2.A3 Tables

Table 2.A2 Balance test for the treatment at baseline

Outcomes	Share of inundated areas, 5km	St.error	P-value	Observations
	Income			
Monthly income, wage labour	65.77	7.932	0.000	6,223
Annual income, paddy	478.17	84.91	0.000	6,223
Monthly income, farming/livestock	-4.026	2.612	0.123	6,223
	Expenditures			
Tot. monthly expenditures	29.33	16.56	0.077	6,223
Monthly expenditures, food	42.55	7.244	0.000	6,223
Monthly expenditures, non-food	-13.22	14.15	0.350	6,223
Health expenditures, yearly	-29.99	42.81	0.484	6,223
Education expenditures, yearly	-71.56	13.44	0.000	6,223
	Migration outcomes			
Migration incidence	-.0203	.0208	0.331	6,223
remittance incidence	-.0300	.0181	0.098	6,223
Net remittances received, yearly	-82.57	173.09	0.633	6,223

Note: Each cell contains the difference-in-difference coefficient of the treatment for each outcome. All monetary values are expressed in PPP-adjusted USD at constant prices.

Table 2.A3 Impacts of the flood shock on monthly income from wage labour

	OLS	FE
VARIABLES	Monthly income, wage labour	Monthly income, wage labour
year 2015	-18.28***	-20.57***
	(3.155)	(1.914)
Tshare sept	65.18***	127.1
	(7.907)	(1,810)
year*Tshare sept	-54.28***	-51.28***
	(10.95)	(6.513)
share july	-55.82***	-498.5
	(16.99)	(3,953)
year*share july	92.35***	92.02***
	(24.77)	(14.82)
Eastern Bengal	-9.106***	
	(2.750)	
Central Bengal	-28.66***	
	(2.666)	
Southern Bengal	-26.10***	
	(2.869)	
year*Eastern Bengal	19.77***	21.53***
	(3.963)	(2.385)
year*Central Bengal	27.68***	27.06***
	(3.894)	(2.335)
year*Southern Bengal	24.64***	25.95***
	(4.198)	(2.517)
N. male adults	36.17***	26.01***
	(0.997)	(1.398)
N. femaleAdults	1.518	3.033**
	(1.119)	(1.348)
N children	0.848	4.181***
	(0.519)	(0.838)
N elderly	-4.361***	8.635***
	(1.379)	(2.220)
Age head Hh	-0.873***	0.185
	(0.0591)	(0.120)
Gender head Hh	-24.83***	-12.54***
	(2.189)	(3.221)
Constant	116.1***	49.81
	(4.424)	(166.8)
Number of HHid		6,223

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: The table shows results of the difference-in-difference estimations of the effect of flooding on monthly income from wage labour. All monetary values are expressed in PPP-adjusted USD at constant prices.

2.A4 Robustness checks

Table 2.A4 Robustness check using rainfall as instrument

Outcomes	Share of inundated areas (IVreg, 2nd stage)
Income	
Monthly income, wage labour	-32.27***
	(3.962)
Annual income, paddy	-3,768***
	(790.3)
Monthly income, farming/livestock	-62.77*
	(32.20)
Expenditures	
Tot. monthly expenditures	-283.2**
	(134.7)
Monthly expenditures, food	-135.5***
	(3.366)
Monthly expenditures, non-food	-346.0***
	(111.3)
Migration outcomes	
Migration incidence	0.0626***
	(0.00615)
remittance incidence	-0.00607
	(0.00816)
Net remittances received yearly	609.8***
	(104.9)
Outcomes	Rainfall instrument (IVreg, 1st stage)
Flood treatment	.0000702***
	(1.01e-06)
Cragg-Donald F statistic	335.87
Observations	6,223

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: All monetary values are expressed in PPP-adjusted USD at constant prices.

Table 2.A5 Robustness checks using topographic controls, FE estimations

	A	B	C
Outcomes	Share of inundated areas, 5km		
	Income		
Monthly income, wage labour	-40.63***	-51.76***	-41.77***
	(7.459)	(6.974)	(7.236)
Annual income, paddy	-44.66	-135.4**	-92.55
	(68.55)	(64.00)	(66.44)
Monthly income, farming/livestock	-14.34***	-17.96***	-18.86***
	(2.880)	(2.689)	(2.791)
	Expenditures		
Tot. monthly expenditures	-101.6***	-63.41***	-92.76***
	(12.04)	(11.25)	(11.68)
Monthly expenditures, food	-92.22***	-48.55***	-84.49***
	(6.284)	(5.895)	(6.101)
Monthly expenditures, non-food	-9.390	-14.86	-8.277
	(9.843)	(9.196)	(9.545)
	Migration outcomes		
Migration incidence	0.137***	0.0568***	0.0632***
	(0.0201)	(0.00675)	(0.00295)
remittance incidence	0.183***	0.00201***	0.0243*
	(0.0256)	(0.000755)	(0.0140)
Net remittances received, yearly	176.3	38.76	195.5***
	(347.3)	(116.7)	(51.04)
Observations	6,223	6,223	6,223

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

Note: All monetary values are expressed in PPP-adjusted USD at constant prices. The first column (A) contains the results of the first specification of the robustness check, estimated adding topographic controls (i.e. dummy variables for each village being close to a river line or water areas and to watershed basins, and other three indexes for being located on plain areas, low or steep hills or on mountains) interacted with wave fixed effects. The results of the second column (B) are obtained adding to the benchmark specification the interaction of wave fixed effects with average rainfall for the same monsoon period for the years 1970-2000. In the third column (C) we control for the *vulnerability index*, built for each village according to its distance from rivers, lakes and coastal line.

Table 2.A6 Impacts of the flood shock controlling for food prices

Outcomes	OLS	FE
Income		
Monthly income, wage labour	-53.41***	-55.10***
	(11.52)	(6.909)
Annual income, paddy	-89.28	-98.89
	(108.3)	(63.63)
Monthly income, farming/livestock	-16.25***	-16.93***
	(4.195)	(2.672)
Expenditures		
Tot. monthly expenditures	-62.15***	-67.47***
	(18.41)	(11.17)
Monthly expenditures, food	-49.45***	-47.32***
	(8.540)	(5.838)
Monthly expenditures, non-food	-12.70	-20.15**
	(15.36)	(9.138)
Health expenditures, yearly	-282.8***	-292.5***
	(82.34)	(63.34)
Education expenditures, yearly	-149.5***	-106.6***
	(26.48)	(17.08)
Migration outcomes		
Migration incidence	0.0489***	0.0643***
	(0.00873)	((0.00292)
Remittance incidence	0.0112	0.0160***
	(0.00744)	(0.00371)
Net remittances received yearly	173.3**	182.9**
	(77.87)	(48.65)
Observations	6,223	6,223

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Each cell contains the difference-in-difference coefficient of the treatment for each outcome. All monetary values are expressed in PPP-adjusted USD at constant prices.

Table 2.A7 Robustness checks with placebo test using night lights data for 2012-2013

Placebo test for 2012-2013		
Outcomes	OLS	FE
Night lights intensity	-0.0133	-0.0133
	(0.0455)	(0.00917)
Observations		318

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Treatment effect test for 2012-2015		
Outcomes	OLS	FE
Night lights intensity	-0.0769*	-0.0988***
	(0.0405)	(0.0231)
Observations		318

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: The two columns contain the difference-in-difference coefficient of the OLS and fixed effects regressions for the night light outcome at village level.

Table A8. Robustness checks using the HIES Survey for 2010 and the BIHS for 2012 (55 common villages)

.		.	
Placebo test for 2010-2012		*Treatment effect test for 2012-2015*	
Outcomes		Outcomes	
Income		*Income*	
Annual income, paddy	-1,036	Annual income, paddy	-594.5**
	(677.2)		(275.2)
Monthly income, farming/livestock	19.00	Monthly income, farming/livestock	-12.60
	(50.48)		(18.91)
Expenditures		*Expenditures*	
Tot. monthly expenditures	-178.7	Tot. monthly expenditures	-173.9*
	(171.9)		(89.40)
Monthly expenditures, food	-119.2	Monthly expenditures, food	-150.6*
	(116.1)		(84.09)
Monthly expenditures, non-food	-59.53	Monthly expenditures, non-food	-23.31
	(82.94)		(41.31.94)
Migration outcomes		*Migration outcomes*	
Migration incidence	0.0942	Migration incidence	0.0704***
	(0.489)		(0.0222)
Remittance incidence	0.298	Remittance incidence	0.228*
	(0.358)		(0.129)
Net remittances received yearly	155.6	Net remittances received yearly	3,842***
	(517.8)		(1,086)
Observations	55	Observations	55
Standard errors in parentheses		Standard errors in parentheses	
*** p<0.01, ** p<0.05, * p<0.1		*** p<0.01, ** p<0.05, * p<0.1	

Note: Each cell contains the difference-in-difference coefficient for the regressions on the different outcomes specified. All monetary values are expressed in PPP-adjusted USD at constant prices.

2.A5 Alternative parallel trends test

The aim of this test is to exploit information from all villages of the BIHS and the HIES surveys. As already mentioned, the two surveys have in common only 55 out of the 318 villages for 2012. We employ matching techniques to pair the other non-common villages with the closest unit from 2010 in terms of Mahalanobis distance calculated on the basis of their georeferenced characteristics. The matching covariates are georeferenced features that influence the "treatment", i.e. the likelihood of each village being inundated. They include dummy variables for each village being close to a river line or water areas, being located on plain areas, hills or mountains, and a control for potential catchment areas. In addition, as we want to match units that are not only similar in their characteristics but also in the intensity of treatment, we include our measures for the shares of inundated areas in normal times and in the period of interest. On the basis of these covariates we calculate the Mahalanobis distance using the *nearest neighbour* technique among villages from the two surveys. After excluding non-rural villages from the HIES, we manage to match all 318 villages. We aggregate the outcomes of interest as averages at village level and we estimate Equation 2.5 on paired villages.

Table A9 shows that there are not significant correlations between the treatment and the dependent variables in the absence of the flood.

Table A9. Robustness checks with placebo test using the HIES Survey for 2010 and the BIHS for 2012

Outcomes	OLS	FE
Income		
Annual income, paddy	1,210	1,146
	(791.1)	(770.2)
Monthly income, farming/livestock	11.55	13.78
	(19.27)	(19.41)
Expenditures		
Tot. monthly expenditures	-2.863	8.145
	(66.99)	(67.83)
Monthly expenditures, food	10.31	16.90
	(43.20)	(43.60)
Monthly expenditures, non-food	-13.17	-8.753
	(41.54)	(41.33)
Migration outcomes		
Migration incidence	0.111	0.114
	(0.0864)	(0.0809)
Remittance incidence	0.0521	0.0168
	(0.107)	(0.118)
Net remittances received yearly	1,036	1,046
	(659.0)	(651.6)
Observations	318	318

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Each cell contains the difference-in-difference coefficient for the regressions on the different outcomes specified. All monetary values are expressed in PPP-adjusted USD at constant prices. Non-common villages are paired with the closest unit from 2010 in terms of Mahalanobis distance calculated on the basis of their georeferenced characteristics.

3

Women's labour force participation and natural shocks

Abstract

We employ georeferenced data and longitudinal household survey data to investigate the impact of the dramatic flood that hit Bangladesh in August-September 2014 on female labour force participation. Development economics literature suggests that labour supply increases after an idiosyncratic shock to absorb its consequences and to prevent from a strong reduction in consumption.

The difference-in-difference estimations confirm these assumptions and reveal that female labour force participation raises by around 18 percentage points and that the probability for unemployed women to enter the labour force increases by around 22 percentage points after the flood. Correcting for selection bias due to initial employment status of women, we also find a significant rise in their probability to engage in independent wage-earning activities and in their average monthly income as a consequence of the shock. Moreover, we show that the greater involvement in the labour market - instrumented by the intensity of the flooding that women faced - contributes to raising their bargaining power within the household measured using the Women's Empowerment in Agriculture Index.

Keywords: Bangladesh; Flood; Shock-coping strategy; Female labour force participation; Intra-household bargaining

JEL Classification: F66; J16; Q12; Q54.

3.1 Introduction

A number of studies have investigated the impact of idiosyncratic shocks on households in developing countries, showing that labour supply would increase to absorb their consequences on household income and to prevent from a strong reduction in consumption. Some of these studies evaluate the consequences of earning shocks due to political crisis and wars (Smith & Ward, 1985; Acemoglu et al., 2004; Goldin & Olivetti, 2013), while others focus on coping strategies developed by households after natural shocks (Mueller & Quisumbing, 2011).

For women labour supply, previous research has seek to explain the determinants of female labour force participation focusing on education, fertility, social norms, etc. (Eckstein & Wolpin, 1989; Cullen & Gruber, 2000; Gaddis & Klasen, 2014). Klasen (2018) reviews the literature on the reasons for women's choice to work, comprehending both supply and demand side factors of the labour market.

Goldin (1994) and other authors conduct a macro-level analysis and hypothesize that female labour force participation has a U-shaped relationship with economic growth, and that it would drop at early stages of development and increase when the society shifts to a more industrialised and richer economy. This hypothesis has been tested by many studies, finding heterogeneous trends in female labor force participation according to countries, urban and rural sectors, policies and macroeconomic conditions (Luci, 2009; Tam, 2011; Gaddis & Klasen, 2014; Lahoti & Swaminathan, 2016). For the relation with economic development and households' wellbeing, Sarkar, Sahoo, and Klasen (2019) find that an increasing local economic development and a higher income of other members of the household would lead to a lower probability for women to work.

Among the drivers of female labor force participation rate (LFPR), natural shocks may lead to increasing women's participation rates as a coping strategy to reduce the uncertainty in earnings, as shown by Attanasio et al. (2005). Bhalotra and Umana-Aponte (2010) in their multi-country analysis for the developing world find evidence of raising LFPR in contexts of higher income volatility.

In addition, also women bargaining power in the household would be affected by idiosyncratic income shocks. Anderson and Eswaran (2009) find that women induced to work by economic hardship experience an increase their bargaining power, but only in case of employment outside their husbands' farms. Women's outside option, meaning the payoff they would get if they left their marriage, would be in fact higher, enhancing their decision power (Blumberg & Coleman, 1989; Rahman & Rao, 2004; Majlesi, 2016). Our paper is therefore related to the strands of literature that investigate the effects of women's ownership of production assets (B. Agarwal & Bina, 1994), access to credit programs (Hashemi, Schuler, & Riley, 1996; Anderson & Baland, 2002) and participation in wage-earning activities (Kelkar, Nathan, & Jahan, 2003) on their autonomy. According to these studies, new earning opportunities for women

have significant implications for their decision making power, as well as for their education, health status, fertility and investments in their children (Atkin, 2009; Jensen, 2012; Heath & Mobarak, 2015).

For the Bangladeshi context, data from the World Bank show how the progressive economic growth started in the 90's has been accompanied by an increase in female labour force participation rate from 23 to 33 percent in 2017 (Figure 3.1). This rise has been explained by numerous factors: the increase of agricultural yields brought by the *Green Revolution* that starting from the 60's, thanks to the introduction of new fertilizers, pesticides and modern irrigation equipments, brought to an increase in the harvest by around 150 percent (Headey & Hoddinott, 2016); the rapid decline of fertility rate from 4.4 in 1990 to 2.1 in 2016 (World Bank, 2018); and the diffusion of the garment industry that from the 90's has grown at a rate of 17 percent per year and where around 80 percent of the 4 million people employed in the sector are women. In addition, the rise in female education and in the enrolment rate that went from being half the rate of boys in 1970 to overcome it in recent years, contributed to boost women labour force participation. However, as shown in Figure 3.2, Bangladeshi women participation rate still remains far below the global average of 50 percent. According to World Bank data, male labour force participation rate was around 80 percent in 2017, a proportion considerably higher compared to the 33 percent of females.

As in the majority of South Asian countries, in Bangladesh flood phenomena are quite common during the monsoon seasons. The flood that hit Bangladesh starting from mid-August 2014 was particularly dramatic and affected over 3 million people until the end of September. The flood inundated large rural fields, especially in the northeastern part of the country where it severely damaged crops and in particular cultivations of paddy covering approximately 77 percent of the total crop area in Bangladesh.

Following the *new climate-economy literature* we combine data on flooding obtained from high-resolution satellite imagery with survey data for panel households drawn from the *Bangladesh Integrated Household Survey* for the period before and after the shock to examine its impact on female labor supply. While previous research on the effects of the great 1998 floods in Bangladesh has mainly employed self-reported information from household surveys on damages caused by natural calamities (Alvi & Dendir, 2011), we use georeferenced data from NASA satellites that measure the impact of the flood as the share of inundated areas for each sampled village where households reside, following the methodology employed by Gröger and Zylberberg (2016).

Using a difference-in-difference approach we estimate the effect of this continuous treatment on different outcomes for our sample of rural households: we investigate the impact on overall female labour force participation rate and on the probability for unemployed women to enter the labour force; for women that are employed at baseline, correcting for selection into the labour force, we evaluate how the flood

affects their weekly hours of work and their monthly income; finally, with a double-selection approach, we estimate how the probability for women working in the family business to engage in an independent wage-earning activities changes after the shock.

In the second part of the analysis we investigate whether the expected rise in female labour force participation and, in particular, their employment in independent wage-earning activities - instrumented by the shock - would help to increase women bargaining power within the households. Women decision making power is measured by the Women's Empowerment in Agriculture Index (WEAI) (Alkire et al., 2013), a survey-based index that employs individual-level data collected from the two primary male and female respondent adults of the household on the decision making process in different aspects of family life.

Note that we do not extend the investigation on the impact of the shock also to male labour supply. While we do acknowledge that an analysis comprehending also the effect on labour participation choices of male adults in the households would be relevant, in the rural context under analysis we find that the large majority of men are employed at baseline (around 91 percent of men over 15 years old) and we do not find significant changes in the share of men working outside the household farm between the two waves of the survey [1]. In addition, our estimations on female bargaining power, as will be outlined later, required a comparison with the male one in order to evaluate whether there have been improvements in women's autonomy.

Empirical findings show that female labour force participation increases by around 18 percentage points after the flood and that the probability for unemployed women at baseline to enter into employment raises by 22 percentage points. After correcting for selection bias due to initial employment status, we also find an increase in average monthly income by around $24 PPP due to the shock, while we do not observe any significant change in working hours per week. Weekly working hours are referred to the 7 days before the survey and, since the questionnaires were administered in two different cultivation seasons in 2012 and 2015, results might be biased by the seasonality of agricultural activities.

Interestingly, the probability for women working in the family business to engage in independent wage-earning activities outside the husband's farm increases after the flood by around 28 percentage points.

Finally, we find that the increase in female labour force participation, if instrumented by the severity of the flood shock that women faced, contributes to raise their bargaining power within the household by around 57 percentage points, even if this result is significant only in case of women working outside the household farm.

This paper contributes to the existing literature on the determinants of female autonomy (Sell & Minot, 2018), relating it to the strand of research on the impact of natural shocks on labour supply.

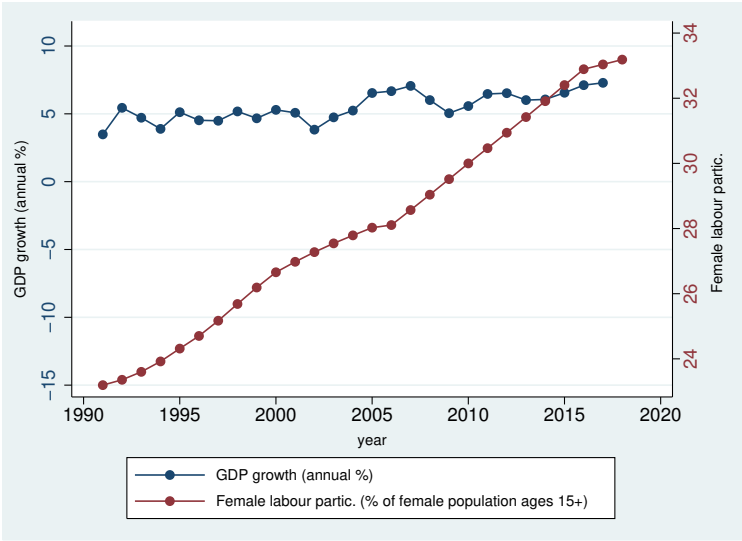
[1] The share of males not working on the household farm and working in the market is 42 percent in 2012 and 41 percent in 2015.

Female labour force participation is a potentially endogenous explanatory factor for women bargaining power, therefore we instrument it using the intensity of the flood that sampled women faced as an instrument.

Differently from Anderson and Eswaran (2009), we employ fixed effect and difference-in-difference estimations to control for time invariant unobserved individual and household heterogeneity, and to show how not only women's labour force participation but also their monthly earnings and their probability to work outside the husband's farm are affected by this natural shock. In the second part of the empirical estimation, we employ a comprehensive measure of female bargaining power, the Women's Empowerment in Agriculture Index, and we the test the hypothesis that only working for an independent income contributes to increase women's autonomy.

The structure of the paper is as follows. After illustrating a simple theoretical model (Section 3.2), we describe the georeferenced satellite data and the household survey employed for the analysis (Section 3.3). We then explain our research strategy and the robustness checks implemented (Section 3.4). We finally present our results (Section 3.5) and concluding remarks (Section 3.6).[2]

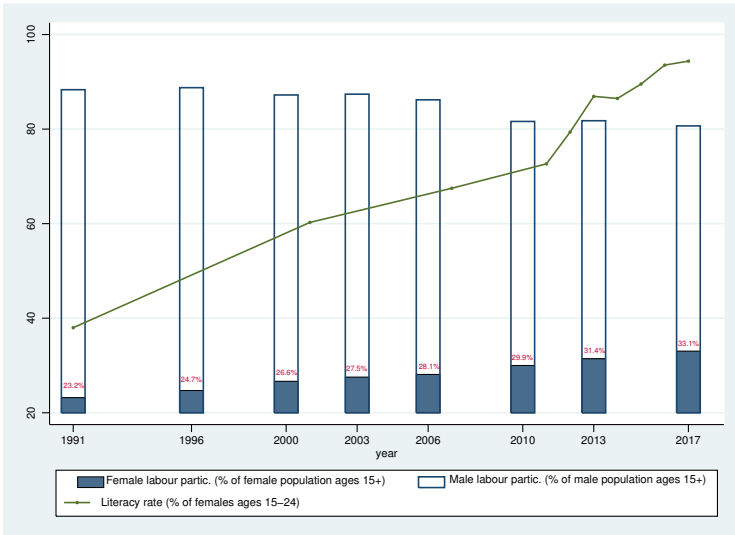
Figure 3.1 GDP per capita growth and female labour force participation rate



Note: Source: World Bank.

[2]As already mentioned, note that Section 3.3 has some similarities with Section 2.2 of the previous Chapter.

Figure 3.2 Labour force participation rate by gender



Note: Source: World Bank.

3.2 Theoretical model

Our simple theoretical model draws on the literature on *agricultural household models* (Huffman & El-Osta, 1997; Omamo, 1998; Key, Sadoulet, & Janvry, 2000) that describes farm and off-farm work participation choices of rural household members as functions of the local economic development, of the demand for off-farm goods and services and of the agro-ecological conditions.

In line with the *collective approach* (Apps & Rees, 1988; Chiappori, 1992) in our household model the partners have two distinct utility functions. Individual utilities depend on: leisure, l , private good purchased on the market, y, public good, Q^D - meaning domestic work that is assumed to be performed mainly by women -, and output of the household farm, Q^F.

In the cooperative scenario, the couple jointly maximises:

$$\alpha U_f + (1-\alpha)U_m \tag{3.1}$$

$$\alpha U_f(l_f, y_f, Q^D, Q^F) + (1-\alpha)U_m(l_m, y_m, Q^D, Q^F) \tag{3.2}$$

where $\alpha = f(\bar{U}_f, \bar{U}_m) = \frac{\bar{U}_f}{\bar{U}_f + \bar{U}_m}$ and $\bar{U}_f, \bar{U}_m$ are male and female utilities in the non-cooperative scenario. The weight given to female utility, α, is a proxy of her bargaining power and it is increasing in the reservation utility $\bar{U}_f$ she would obtain in case cooperation breaks down - where the more common scenario employed in the literature on developing countries is that of non-cooperative behaviour within marriage (see for example Lundberg, Pollak, and Wales (1997)) -, and decreasing in the reservation utility of her husband.

We assume that both the husband and the wife participate to the production of Q^F. The output Q^F depends on quantity of land, L, hours spent working on the farm, H^F, input factors, X, and location specific characteristics, ϕ, e.g., local climate and soil fertility (Huffman & El-Osta, 1997).

$$Q^F = f(L, H_f^F, H_m^F, X, \phi) \tag{3.3}$$

We distinguish two types of rural households, *net buyers and net sellers*, defining net sellers as households for whom the total amount of items sold is higher than the amount purchased, and net buyers as households for whom the reverse is true. This distinction is related to the size of the household farm since the empirical data for our sample shows that the average landholding size of net seller households is around 6500 squared metres, more than the double with respect to the 3000 of net buyers.[3]

For the first group of households the value of their production is higher than the value of the goods purchased, $P_Q^F Q^F > P_y Y$, while for *net buyers* the opposite is true.

For *net sellers* hired labour requires supervision and this implicit cost is increasing with the amount of land (Anderson & Eswaran, 2009). We assume therefore that family labour, inclusive of supervision costs, is cheaper and this would induce households to use more family labour on their farms.

At time 1 we assume that the husband of *net sellers* has two uses for his time: working on the farm, H_m^F, and leisure, l_m. The wife, instead, has four possible uses for her time: working on the farm, H_f^F, working in an activity that earns her income, H_f^M, producing the public good, H_f^D, and leisure, l_f.

$$\bar{T_m} = H_m^F + l_m, \; H_m^F > 0 \tag{3.4}$$

$$\bar{T_f} = H_f^F + H_f^M + H_f^D + l_f \tag{3.5}$$

where $\bar{T}$ is the daily time endowment of the husband and the wife.

Net seller households will maximise their utility subject to the budget constraint:

$$P_y Y = W H_f^M + P_Q^F (Q^F - C) + V \tag{3.6}$$

where $Q^F - C$ is the farm output net of own-consumption and V denotes the household non-labour income.

At time 1 the husband of *net buyers* has three uses for his time: working on the farm, H_m^F, working on the market H_m^M, and leisure, l_m. The wife has the same time allocation options of *net sellers*' ones.[4]

$$\bar{T_m} = H_m^F + H_m^M + l_m \tag{3.7}$$

[3]The average landholding size of the first group is around 75 *decimals* while the average of the second one is almost the double, 140 *decimals* (where decimals are among the most common units of measure used for land size in Southeast Asia and one *decimal* corresponds to around 40 squared metres).

[4]Our assumptions on the uses of time derive from the fact that, presumably, the larger the landholdings, the more likely is that the husband - that is generally the owner of the land - will devote all his working time to farming his own land instead of working in the market.

$$\bar{T}_f = H_f^F + H_f^M + H_f^D + l_f \tag{3.8}$$

Net buyer households will maximise their utility subject to the budget constraint:

$$P_y Y = WH_f^M + WH_m^M + P_Q^F(Q^F - C) + V \tag{3.9}$$

We then make two realistic assumptions, i.e. that female marginal productivity is lower than male one and that *net sellers* because of the larger size of their farm and therefore of their production, benefit from economies of scale due to cost reductions so that their marginal productivity, both for women and men, is higher. Figure 3.3 illustrates the labour supply and labour demand equilibria of the the *net buyers* market (market A) - points $E1_f^{NB}$, $E1_m^{NB}$ -, and of the *net sellers* market (market B) - points E_f^{NS}, E_m^{NS}. Since the four points represent full-employment equilibria, even if the wage in the *net sellers*' market is higher than in the *net buyers*' one (for both men and women), the workers could not move from market A to market B.

Given our sample of dual-earner households in which, independently from the wage level of the husband, women are required to work, in both markets there exist a female *survival wage*, w_{surv}, that represents a minimum value of female marginal productivity, under which the household could not produce the necessary output for survival, $Q_{surv.}^F$, and women would be forced to find employment elsewhere.

At time 2 an exogenous shock would change the production function of both *net sellers* and *net buyers*. Figure 3.4 shows the production function of *net buyers* where the input on the horizontal axis for the production of Q^F is the time spent working on the farm by the wife, H_f^F, (while the input for the production of domestic work is H_f^D and Q_m is the output of the time spent working on the farm by the husband). H_f^D represents the fixed share of time devoted to housework and leisure.[5] The production function of farm work would shift down after the shock becoming $Q^F = g(H_f^F)$ where $g^{'}(H_f^F) < f^{'}(H_f^F)$. Given the equality between the marginal productivity of labor and the wage rate, any new equilibrium of market B is assumed to remain above the equilibrium of market A at a higher wage.

For *net sellers*, given that all the working time of the husband is already devoted to the farming activity, in order to produce $Q_{surv.}^F$, the wife will curtail the amount of time she works on the market and all her working time will be spent on the farm ($H_f^F = T - H_f^D - l_f$).

For *net buyers*, as a consequence of the shock, the labour demand would contract from D^{NB} to D'^{NB}. For equal shifts of the demand curve for both females and males, we assume that the new equilibrium for the husband, $E2_m^{NB}$, would still be above the equilibrium for the wife, $E2_f^{NB}$. Given this scenario, at $E2_f^{NB}$ all working women would face a wage equal or lower than w_{surv} so that they would benefit from moving to work in market B.

[5] We do not consider the hypothesis of a change of this time share due to the shock since we consider domestic work as a fixed share of female time allocation and we do not expect that the correlation between our shock and time devoted to housework would be different in the two groups of *net sellers* and *net buyers*.

In market B the drop in marginal productivity would imply a downward shift of the demand function from D^{NS} to D'^{NS}. The labour supply curve would instead increase. If we hypothesize a larger shift of the supply curve with respect to the demand curve, the new equilibrium in our example would be $E2_f^{NS}$ where w is lower than $E1_f^{NS}$ - because of the drop in marginal production - but higher with respect to $E1_f^{NB}$. The number of employed women, n, is then increased with respect to time 1. Market B will employ female workers first, as they are remunerated with a lower wage with respect to males, satisfying its labour demand with the number of women coming from market A.

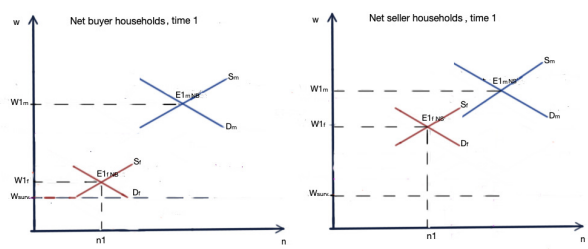
Section 3.A1 in the Appendix deepens the analysis of the response of labour supply and demand functions of market B to the shock.

Moving from market A to market B represents for the wife a shift from working on the husband's farm to engaging in an independent wage-earning activity. The higher wage rate she receives in market B[6] - represented in Figure 3.4 by the tangency point between female indifference curve and the new budget constraint given the wage received in market B, $W2_f^{NS}$ -, as in Anderson and Eswaran (2009), induce her to work more outside the husband's farm. As a consequence, the wife will curtail the share of her time devoted to farm work. Since H_f^F and H_m^F are assumed to be substitutes in the production of a minimum $Q_{surv.}^F$ (represented in Figure 3.4 by the sum of Q_m^F and Q_f^F), to maintain this output unvaried the husband will increase his working time devoting a larger part of it to working on the farm. The drop in the husband utility, due mainly to a drop in l_m and in the consumption of the private good, y_m, would decrease his threat utility $\hat{U_m}$. In a non-cooperative scenario $\hat{U_f}$ would raise - because of the wife's increased earning capacity and consumption of the market goods y_f and increased leisure l_f - leading thus to an increase in the indicator of her autonomy, α.

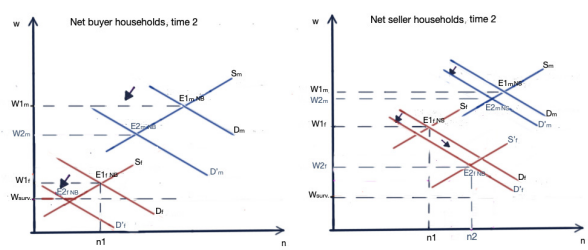
Our theoretical model employs working hours spent on on-farm and off-farm activities to show women labour force participation decisions. In our empirical estimation, however, due to the over-mentioned issues related with working hours recorded in the survey, we mainly employ dummies for participating to the labour force taking the dummy equal to zero at the corner solution where working hours equal zero.

[6] It is worth noting that in our empirical analysis women employed in the husband's farm work unpaid, while they earn an independent income only if they get employed in the local labor market. Therefore, our conjectures on the impact of increasing wage rate on female autonomy are applicable to the impact of the shift from unpaid to paid work in the empirical estimations.

Figure 3.3 Labour market equilibria for net buyers and net sellers



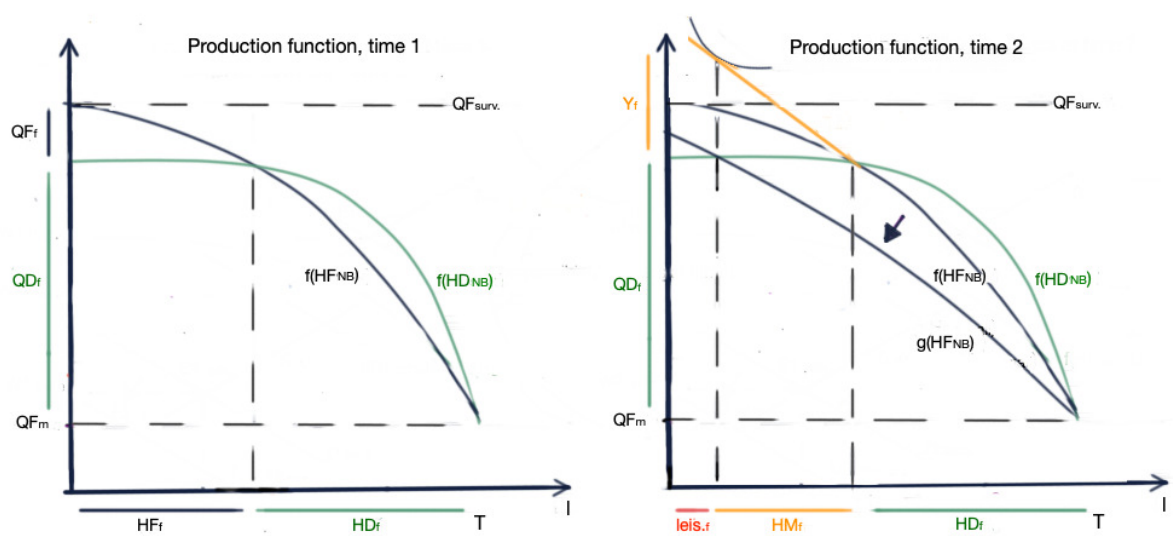
(a) Time 1



(b) Time 2

Note: Note that w in the graph represents the unpaid value of marginal productivity of labour in both markets, and only at time 2 w indicates the paid salary received from women shifting from market A to market B.

Figure 3.4 Labour productivity before and after the shock



Note: The figure shows the production functions of farm work before ($f^{'}(H_f^F)$ and after the shock ($g^{'}(H_f^F)$ of *net buyers*.

3.3 Data sources and variables

3.3.1 Georeferenced data

To measure the impact of natural shocks at the local level, we employ village exposure to inundation as continuous treatment for our analysis. For this purpose, we use the *NASA Flooding Map*, composed of 250-m resolution images obtained by applying the LANCE processing system to MODIS products.[7] The satellite images determine flooded areas as water observations falling outside normal water levels, taking as reference another MODIS product, MOD44W.

According to the Official Report of the *Bangladesh Water Development Board* of the National Government for 2014, rainfall intensity during the monsoon season exceeded that of previous years and reached the maximum peak toward the end of August, as shown in Figure 2.1 of Chapter 2. Therefore, we employ composite satellite images for an interval of 15 days between the end of August and mid-September.[8]

We define our treatment as the share of areas, in each village where sampled households reside, that were recognized as flooded in the first days of September resulting from the accumulated rainfall of the last two weeks of August. The unit of analysis for our treatment are the 318 surveyed rural villages that are nationally representative of the country's rural areas. For each village in the sample we calculate the share of pixels (where pixel resolution is 250 m) identified as "flooded" in a 5-kilometre radius, where the average number of pixels in the calculated radius is approximately 3800. To check for robustness, we also repeat our tests for 2- and 10-kilometre radiuses.

As in Gröger and Zylberberg (2016), the 5-kilometre radius presumably represents the area where rural households have their agricultural activities. The treatment variable corresponds thus to the probability of a "pixel area" in the village being inundated in the period considered and to the village-level damage caused to households' agricultural activities. Figure 2.2 of Chapter 2 illustrates the geographic distribution and the intensity of the treatment variable during the flooding (August 31st-September 15th).

A potential problem of endogeneity stems from the fact that villages may differ in some geographical characteristics that affect both the probability to be treated and the outcomes of interest. To take account of this issue, we control for the village propensity to be submerged by water during normal times as measured by the percentage of water coverage in the 5-kilometre radius in July 2014. In addition, we include province and wave fixed effects and village topographic features, such as the proximity to a river or to the coast, to allow villages with differences in these features to have different trends.

[7] The data can be publicly accessed at https://floodmap.modaps.eosdis.nasa.gov.

[8] The NASA composite product for the period August 31st-September 15th, by combining information from daily images and "smoothing" high-frequency variations, overcomes the issue of sensing measurement errors due to clouds that prevent the satellite from obtaining a precise image, identifying a pixel area as "flooded" if it is recognized as such at least twice.

MODIS satellite images for the period before the flooding, July 2014 - already in the monsoon season - and for the period considered are displayed in Figure 2.A1 of Chapter 2. Figure 2.A2 of Chapter 2 shows the percentage of inundated areas during flooding with respect to normal periods. With the treatment specification of the 5-kilometre radius, the mean share of submerged area corresponds to 18 percent, with a maximum of 94 percent, while in normal periods, the mean is 8 percent and the maximum is approximately 45 percent.

3.3.2 Household survey

We employ the *Bangladesh Integrated Household Survey*, a panel study conducted by IFPRI in two rounds, the first in 2011-2012 (October 2011- June 2012) and the second in 2015 (January - June 2015). This survey has a national coverage and is representative of rural areas of all the seven divisions of the country. The survey follows longitudinally around 6,500 households and 27,000 individuals, and for each of them reports information on employment status, working hours, monthly income, etc. In addition, the questionnaire includes a specific section intended to measure women's empowerment via the Women's Empowerment in Agriculture Index.

The attrition rate is 4.4 and 22 percent at the household and individual level, respectively. We run attrition analysis to address the possible bias due to the correlation between the occurrence of flooding and the failure to track displaced households - according to national statistics, approximately 57,000 families were displaced between August and September 2014 (Ministry of Disaster Management and Relief, 2014) - and households that might have chosen to leave to avoid the dramatic consequences of the shock. We run a regression where the outcome variable is a dummy equal to one for each household tracked in the second wave, and the main explanatory variable is the treatment - i.e., the share of inundated areas in a 5-kilometre radius around each village. The coefficient of the treatment variable is not significantly different from zero, thus ruling out the possibility of this potential bias (see Section 2.A1, Chapter 2).

Of the 14,292 women tracked in both waves, for our analysis we employ the subsample of 7,666 women older than 15 years in 2012.[9]

Table 3.1 presents the descriptive statistics for this panel subsample at baseline (2012). With a mean age of 37 years, the high majority of sampled women (81 percent) are married, but only 4 percent report to be the head of the household. In addition, being the sample mainly representative of rural areas, we find that 45 percent of women are uneducated, 27 percent completed secondary school and only 6 percent have tertiary education.

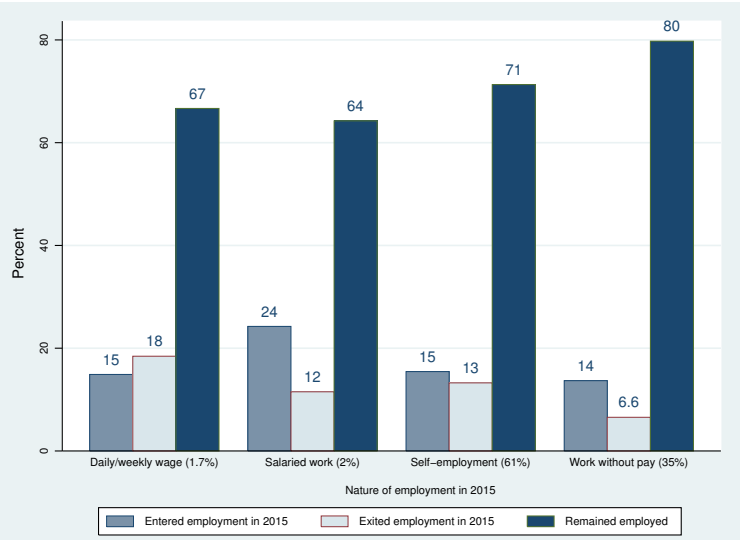
For the aim of our analysis, women are considered to be employed if they reported working for pay (salary, wage, or self-employed workers), working without pay (as apprentices or in family business), or

[9] World Bank statistics on labour force participation in Bangladesh refer to people ages 15 and older.

rather looking for a job. Contributing family workers, instead, are not considered among employed women in line with the ILO classification. According to this definition, we find that 57 percent of women are employed in both waves, while 16 percent remain unemployed. Over 16 percent of women shifted from being unemployed to employment, while only 10 percent exited the labour force. Accounting for the fact that women may carry on more than one economic activity, we find that around 93 percent of them are employed in agriculture in at least one of these activities and that their average monthly income - cumulated over the different activities - is around $22 PPP. The average number of working hours is 14 but, as previously anticipated, this measure is referred only to the 7 days before the survey and it might be biased by the seasonality of agricultural activities.

Figure 3.5 shows the percentage of women entering and exiting employment according to the nature of the employment they have in 2015 (while in case of those exiting the labour force the category of employment is that of 2012). It is interesting to observe that the share of women entering the labour force as salaried workers is higher with respect to the share of daily or weekly wage workers and with respect to the share of women working without pay in family business.

Figure 3.5 Employment entry and exit per category of employment in 2015 (for employed women 15+)



Source: Author's calculation from BIHS data.

The Women's Empowerment in Agriculture Index

The Women's Empowerment in Agriculture Index (WEAI) is a survey-based index designed to assess women's empowerment in agriculture in households for which we have a primary male and a primary female respondent. This index was initially developed as an evaluation tool for the Feed the Future

Program of the United States Agency for International Development (USAID) by Oxford Poverty and Human Development Initiative (Alkire et al., 2013) and the International Food Policy Research Institute (IFPRI), but it has been then largely applied in the literature (Sraboni, Quisumbing, & Ahmed, 2013; Sell & Minot, 2018) as it represents an integrated measurement of women's empowerment.

The index consists of two components: the so-called *5DE score* and the *Gender Parity Index* (GPI), whose weights in the final index are respectively 90 and 10 percent. The first component is a weighted average of 10 indicators of women adequacy that are grouped in the following five domains: (1) decisions over agricultural production, (2) access to and decision making power over productive resources, (3) control over use of income, (4) leadership in the community, and (5) time allocation.[10] For each indicator women are considered *adequate* if they reach or exceed the specified threshold for that domain.

The second component requires that *5DE score* is measured for both the principal male and female respondents in dual-adult households.[11] Women are defined as empowered in the GPI dimension if their achievements in terms of *5DE score* are equal or higher than the score of the primary male respondent of their households. Table 3.A1 in the Appendix reports the five components of the *5DE score* and their sub-components with their relative weights used to construct the index, and the percentage of women in the sample that are considered *adequate* in each dimension for the two years.

[10] See Alkire et al. (2013) for a complete description of the index.

[11] In our sample, for 4083 women - around 53 percent of our initial sample of working-age females - we have information for all the dimensions of the *5DE score* and we could calculate the GPI index, having data also on the primary male respondent in the same household.

Table 3.1 Descriptive statistics of the panel sample in 2012

	Obs.	Mean	Std. Dev.	Min.	Max.
Age (years)	7,666*	37.80	14.82	16	99
Marital status: Married	7,666	.81	.388		
Household head	7,666	.046	.21		
No formal education	7,666	.45	.49		
Primary educated	7,666	.25	.43		
Secondary educated	7,666	.27	.44		
Tertiary educated	7,666	.065	.24		
Household size	7,666	4.46	1.78	1	17
Number of children < 10	7,666	1.70	1.24	0	10
Avg. monthly mm rainfall in 2011	7,666	10.62	10.64	0	88.70
Avg. monthly night-time light intensity 2011	7,666	457.75	107.80	255.473	846.43
First factor for joint decision making	7,666	.0136503	1.29236	-2.452099	2.89546
First factor for sole decision making	7,666	.0168163	1.550332	-2.697159	5.583851
Employed in both rounds (n.4379)	57.12				
Employed in 2012 but not in 2015 (n.779)	10.16				
Not employed in 2012 but employed in 2015 (n.1,258)	16.41				
Not employed in both rounds (n.4,379)	16.29				
Among women employed at baseline (n. 5,158)					
Employed in agriculture (employed)	5,158	.93	.23		
Avg hours per week (employed)	5,158	14.11	13.46	0.5	122.5
Avg monthly income $ppp (employed)	5,158	22.04	56.99	0	12,60.12
(Taka)	5,158	492.72	1281.37	0	28,500
Empl. outside hh farm (employed)	5,158	.20	.40		

*Note:** The total number refers to the subsample of women older than 15 years surveyed in 2012 and re-tracked in 2015. All monetary values are expressed in PPP-adjusted USD at constant prices.

3.4 Method

As already anticipated, in the first part of the analysis we estimate the impact of the flood shock on female labour outcomes through a difference-in-difference estimation employing as treatment the share of inundated areas in a buffer of 5 kilometres around the villages where surveyed households live. The first specification we estimate is the following:

$$Y_{ihvrt} = \beta_0 + \beta_1 T_v * t_{=2015} + \beta_2 T_v + \beta_3 t_{=2015} + \beta_4 P_v * t_{=2015} + \beta_5 P_v + \beta_6 X_{iht} + \beta_7 W_{rt} + \epsilon_{ihvrt} \quad (3.1)$$

where Y_{ihvrt} indicates the different outcome variables for each female individual i of household h residing in village v of region r at time t; T_v is the treatment variable, namely, the share of inundated pixels for each village v; $t_{=2015}$ is the dummy for the second year; and β_1 is the difference-in-difference coefficient of the treatment. P_v is the share of inundated areas within the same radius around the villages during non-flooding period (July 2014). Controlling for P_v allows us to identify the change in the outcome of interest over time due to the treatment for those villages that have the same propensity to be inundated in normal times. X_{iht} represents socio-demographic characteristics of sampled women and their households.[12] Finally, W_{rt} are interactions between wave and regions fixed effects to account for changes in regional characteristics over time. The errors ϵ_{ihvrt}, instead, are clustered at the lower administrative level of divisions.

We first estimate the model with OLS on the observations common to the two waves (7,666 female individuals). We then add fixed effects to control for time-invariant unobserved females' and households' characteristics α_{ih}, as follows:

$$Y_{ihvrt} = \beta_0 + \beta_1 T_v * t_{=2015} + \beta_2 P_v * t_{=2015} + \beta_3 X_{iht} + \beta_4 W_{rt} + \alpha_{ih} + \epsilon_{ihvrt} \quad (3.2)$$

The same reasoning made in the second Chapter regarding the application of the Linear Probability Model as well as of the Generalized Propensity Score is applicable in this case.

For our first estimation we run Equations 3.1 and 3.2 on the whole sample of women older than 15 years to evaluate the impact of the shock on the dummy for female labour force participation, where the dummy is equal to one if the respondent reports being employed according to the definition specified above (Estimation 1).

In the second estimation we investigate how the probability to enter the labour force for women unemployed at baseline increases after the flood (Estimation 2). Selecting only the 2,507 women who are unemployed at baseline, we include in the difference-in-difference regression a correction term for selection

[12] X_{iht} comprehends variables reported by the literature among main determinants of female labour force participation (Klasen, 2018): the number of children in the family, the total household income excluding the woman's own income and a dummy equal to one for women with tertiary education.

bias due to initial employment status. Employing the Heckman's two-step procedure[13], we run a probit regression to estimate the probability for all sampled women in working age to be employed in 2012, as following:

$$Unemp_{ihvr} = \gamma Z_{ihvr} + u_{ihvr} \;\; with \; u_{ihvr} \sim N(0,1) \tag{3.3}$$

$$Unemployed_{ihvr} = 1 \; if \; Unemp_{ihvr} > 0 \; ; \; Unemployed_{ihvr} = 0 \; if \; Unemp_{ihvr} \leq 0 \tag{3.4}$$

where Z_{ihvr} are the different baseline characteristics of women which influence their probability to work. Following Klasen (2017), we add to female controls of our main regression two exclusion restrictions: the average monthly millimeters of rainfall accumulated in the 5 kilometers radius built around each village where women reside in 2011, and the average monthly night-time light intensity at the village level for the same year.[14] Since the literature shows that periods of drought lead to a higher female labour force participation (Bhalotra & Umana-Aponte, 2010), the level of rainfall in 2011 is expected to influence women's choice to work in 2012 without affecting their labour status in 2015. Similarly, according to Henderson et al. (2012), more intense night-time lights would indicate an higher level of local economic activity in 2011 and this would be correlated to a lower female labour force participation rate in the next year - following the *Feminization U-hypothesis* - being however uncorrelated with their labour entry in 2015.

From the first stage we obtain an Inverse Mills Ratio to be included in the difference-in-difference estimation.

$$Y_{ihvrt} = \beta_0 + \beta_1 T_v * t_{=2015} + \beta_2 P_v + \beta_3 X_{iht} + \beta_4 W_{rt} + \alpha_{ih} + \lambda_{Unemp_{ihvr}} + \epsilon_{ihvrt} \tag{3.5}$$

Including the fitted correction term in our main regression, we correct the variance-covariance matrix of the error terms to account for the heteroscedasticity and the correlation across the errors due to the inclusion of the Inverse Mills Ratio following the methodology employed by Greene (1981).

Similarly, we could use the same Z_{ivrt} controls - including the two exclusion restrictions - to estimate the probability to be employed in 2012. The correction term of employment at baseline is then inserted in our estimations - run on the 5,158 employed women at baseline - on the effect of the shock on the variation in monthly income (expressed in $ PPP at constant prices with CPI 2010= 100.00 as reference period to remove effect of inflation) and weekly hours worked between the two waves (Estimation 3, 4). For these

[13] Following Amuedo-Dorantes and Pozo (2002), the Heckman's two-step procedure is preferred to Tobit model because of the latter producing inconsistent estimates in the presence of heteroskedasticity and for the possibility to include different regressors in the two-steps estimation of the Heckman.

[14] Data source for rain gauge is the NASA Integrated Multi-satellite Retrievals for GPM (IMERG) that provides the Day-1 multi-satellite precipitation product at a resolution of 0.25 degrees; for night-time light data we employ the NOAA/NCEI products, obtained collecting measures of night-time light intensity at 750-meter resolution from the Visible Infrared Imaging Radiometer Suite (VIIRS) - a NASA instrument providing detailed images with different bandwidths of light - and filtering them from the noise due to stray light, lightning, lunar illumination, and cloud-cover. These data can be publicly accessed at $https://www.ngdc.noaa.gov/eog/viirs/download_dnb_composites.html$.

estimations we sum both hours and earnings across all of the economic activities that women report.
In addition, as already mentioned, we aim to test the hypothesis suggested by Anderson and Eswaran (2009) that female autonomy would increase women bargaining power, in particular in case of women engaging in independent wage-earning activities (Estimation 5).
In our sample, among employed women over 15 years old, 40 percent work exclusively in the household business, which is generally a farm given the sample of rural households (98 percent of households in the sample are engaged in agricultural activities on their land, and in 92 percent of the cases the land belongs to the husband). This share drops to 25 percent in the second wave. We therefore investigate how the probability to have a job outside the household farm increases between the two waves because of the shock. However, for this purpose we need to correct for double selection bias since this estimation is run on 4,069 women who are employed and work in the family business in 2012.
We follow the methodology employed by Tunali (1986) to estimate a double selection model. We run a bivariate probit regression to estimate the two probabilities of being employed and working in the household business at baseline to take into account the correlation between the errors of the two selection processes since we assume that the decision to work and the choice of the type of activity are not independent ($\rho_{uv} \not\equiv 0$).

$$Emp_{ihvr} = \gamma Z_{ihvr} + u_{ihvr} \tag{3.6}$$

$$FamilyFarm_{ihvr} = \delta W_{ihvr} + v_{ihvr} \tag{3.7}$$

From the bivariate probit regression we obtain two correction terms:

$$\lambda_{1ihvr} = \varphi(Z'_{ihvr}\hat{\gamma}) * \phi(\frac{W'_{ihvr}\hat{\delta} - \rho Z'_{ihvr}\hat{\gamma}}{(1-\rho^2)^{\frac{1}{2}}}) * \phi_2(W'_{ihvr}\hat{\delta}, Z'_{ihvr}\hat{\gamma}, \rho) \tag{3.8}$$

$$\lambda_{2ihvr} = \varphi(W'_{ihvr}\hat{\delta}) * \phi(\frac{Z'_{ihvr}\hat{\gamma} - \rho W'_{ihvr}\hat{\delta}}{(1-\rho^2)^{\frac{1}{2}}}) * \phi_2(W'_{ihvr}\hat{\delta}, Z'_{ihvr}\hat{\gamma}, \rho) \tag{3.9}$$

that are then inserted in the difference-in-difference regression.

$$Y_{ihvrt} = \beta_0 + \beta_1 T_v * t_{=2015} + \beta_2 P_v + \beta_3 X_{iht} + \beta_4 W_{rt} + \alpha_{ih} + \lambda_{1ihvr} + \lambda_{2ihvr} + \epsilon_{ihvrt} \tag{3.10}$$

In the second part of the estimation we investigate the impact of the shock on female bargaining power - measured by the WEAI - using a two-stage least squares (2SLS) method where the increase in female labour force participation is estimated using the different intensity of the flood shock as instrument, following the methodology employed by Lechtenfeld and Lohmann (2014) (Estimation 6). Female labour force participation rate is in fact a potentially endogenous estimator of female autonomy, being related to unobserved characteristics, such as individual and household attitudes towards female condition which would influence both women employment status and their decision making power, leading thus to biased

estimates. The different intensity of the flood shock serves as an exogenous source of variation in labour force participation in the following IV approach estimation[15]:

$$\begin{cases} Lab.Outcomes_{ihvrt} = \beta_0 + \beta_1 T_v * t_{=2015} + \beta_2 P_v * t_{=2015} + \beta_3 X_{iht} + \beta_4 W_{rt} + \alpha_{ih} + \epsilon_{ihvrt}, \\ WEAI_{ihvrt} = \beta_0 + \beta_1 Lab.\hat{Outcomes}_{ihvrt} + \beta_2 P_v * t_{=2015} + \beta_3 X_{iht} + \beta_4 W_{rt} + \alpha_{ih} + \lambda_{1ihvr} + \lambda_{2ihvr} + \epsilon_{ihvrt} \end{cases} \tag{3.11}$$

In the first stage we employ the labour outcomes that we already described to check whether it is the increase in female labour force participation, the expected rise in monthly income (for employed women at baseline) or rather engaging in an activity that earns her income (for women working in the household business) that determines an improvement in female autonomy.

Turning to robustness checks, as already mentioned, particular layer characteristics of villages, such as being located in valleys or in plains or close to water surfaces, affect both their likelihood to be *treated* and their type of cultivations, consequently influencing households' agricultural revenues and labour supply of their members.

To address this potential issue, we run the difference-in-difference estimation controlling for the specific topographic characteristics of sampled villages. In a first specification, we add control dummies indicating the altitude level of the village and its closeness to water surfaces.[16] In addition, controlling for *flows direction* - calculating for each pixel the main direction of water run-off over the geographic area of interest depending on elevation and cell height values - allows us to create a dummy variable indicating for each village whether there are potential catchment areas where surface water would accumulate.

In an alternative specification of this robustness check, we add among the covariates an interaction between wave fixed effects and average rainfall in the same monsoon season (August-September) for the previous decades (1970-2000). Finally, in the last specification of these robustness checks controlling for topographic features, we build a *vulnerability index* for each village calculating its Euclidean distance from rivers, lakes and the nearest coastline and assigning each unit of observation to a category of *low, medium and high* risk on the basis of this measure. We interact the index with wave fixed effects, to allow villages with different exposure to flooding to have different trends.

As a second robustness, we estimate a parallel trends test to assess whether differently treated villages would have followed similar trends in the absence of the flood. However, due to the lack of a third wave for the same panel sample, we run a placebo test as if the flood had occurred two years before, in 2012,

[15] Note that the two correction terms, λ_{1ihvr} and λ_{2ihvr}, are not inserted when the estimation is run on the whole sample to investigate the variation in overall female labour force participation.

[16] In particular, employing georeferenced data on the Digital Elevation Model, we add two dummy variables for each village being close to a river line or water surfaces, and three other indexes for being located in, hills or mountains.

employing as outcome variable for the pre-treatment period *night-time light* data. Given that the unit of analysis are villages, by construction the technique employed and the results we obtained are equal those displayed in the previous chapter (see Chapter 2, Section 2.4.3). Finally, in our third robustness check we employ an alternative measure of female bargaining power to rule out the possibility that the results obtained from the two-stage least squares estimation might be driven by the construction of the WEAI. We employ one module of the questionnaire where women reply additional questions about decision making and they report who normally takes decision within the households on different aspects of family life. For each type of decision we build a dummy equal to one if women decide alone on that aspect and another dummy equal to one if they decide jointly with other members of the family.

Following Seymour and Peterman (2017), we distinguish sole and joint decision making, since aggregating the two into one single estimator would assume that they are equally empowering for women. We aggregate responses across two groups of domains, meaning productive-agricultural decisions and non-economic decisions[17], and we convert these variables into indexes using the first factor extracted from factor analysis. First factor is then employed as dependent variable in the second stage estimation as a latent construct for women autonomy.

3.5 Results

3.5.1 Impact of the flood shock on labour force participation

Table 3.2 shows the results of the benchmark regression for female labour force participation estimated at individual level by OLS and including fixed effects (Estimation 1). The difference-in-difference coefficient indicates the variation in the outcome between the two waves in those villages totally inundated by flooding with respect to unaffected ones.[18] Without any selection of the sample at baseline we find that female labour force participation increases by 18 percentage points between the two waves as an effect of the shock. As in previous literature (Sarkar et al., 2019), we observe that a higher level of education

[17] The first group of decisions comprehends: agricultural production; purchase of agricultural inputs; types of crops to grow; household member who takes crops to market and when; and livestock raising. The second group includes: health care issues; means of protection form violence; expression of religious faith; time allocation to different daily tasks; family planning and birth control methods.

[18] The coefficients represent the impact on the outcomes for a shift in the continuous treatment from 0 percent to 100 percent. However the maximum share of inundated areas is 94 percent so that multiplying the regression coefficients for 0.94 we obtain the difference-in-difference impact between the most and least affected households.

is significantly correlated to a lower probability of being unemployed, and also the number of children has a negative, though not significant, coefficient. In addition, as expected, the coefficient on the level of income of the rest of the households is negative and significant.

3.5.2 Impact of the flood shock on the probability of entry into the labour force

We investigate then the factors that affect the probability for women to work at baseline. Table 3.3 reports the coefficients on the variables that influence the probability of being employed in 2012 in panel A and of being unemployed in panel B. The covariates' coefficients of the two panels are in fact the same but with opposite sign. Female education and household income once again negatively affect labour force participation, while the number of children does not impact significantly the outcome. For the exclusion restrictions, consistently with our hypothesis, we find that an higher level of rainfall, meaning a lower vulnerability to drought, as well as an higher local economic growth - proxied by night-time light intensity -, are correlated to a lower probability of female labour force participation. Figure 3.6 shows the negative relationship between local economic development and female employment in the cross-sectional data, obtained from baseline probit regression on employment. As our sample comprehends only rural households, the second increasing segment of the U-shaped relationship, that represents the shift to an industrial and service-based formal economy, is not observed from our data (Sarkar et al., 2019).
Table 3.4 shows that for women who are unemployed at baseline, the probability of entering the labour force increases by 22 percentage points in villages inundated by the flood (Estimation 2). The correction term $\lambda_{Unemp,i}$ has a significant and positive effect on the outcome.

3.5.3 Impact of the flood shock on monthly income and working hours

Focusing instead on the sample of women who are employed at baseline, Table 3.5 shows results of the estimation on the impact of the shock on labor supply at the intensive margin (Estimation 3, 4). As already mentioned, rural households were surveyed in two different cultivation season of the year. Therefore we do not find any significant effect of flooding on the variation in the number of hours between the two waves. For monthly income, we observe that the earnings of employed women increase by around $24 PPP. Multiplying the coefficient by the maximum share of inundation, i.e. 0.94, and dividing it by average monthly income of the pre-shock period (around $22.04 PPP), we could estimate that female earnings increase by over 100 percent after the flooding. As mentioned, we can not relate this average monthly income (referred to the whole year period before the survey) to working hours in the seven days before

Table 3.2 Impact of the flood shock on female labour force participation

	OLS Labour part. dummy	FE Labour part. dummy
year 2015	0.0825***	0.0779***
	(0.0272)	(0.0248)
Treat. share sept.	-0.119**	-159.5*
	(0.0497)	(85.12)
year*Treat. share sept.	0.182***	0.184***
	(0.0701)	(0.0638)
share July	0.105	
	(0.103)	
year*share July	-0.256*	-0.240*
	(0.146)	(0.133)
Eastern Bengal	-0.172***	
	(0.0224)	
Central Bengal	-0.0829***	
	(0.0213)	
Southern Bengal	-0.0587**	
	(0.0230)	
year*Eastern Bengal	-0.0845***	-0.0828***
	(0.0315)	(0.0286)
year*Central Bengal	-0.0131	-0.0100
	(0.0301)	(0.0274)
year*Southern Bengal	-0.0409	-0.0391
	(0.0325)	(0.0296)
Higher educ.	-0.173***	-0.223***
	(0.0165)	(0.0251)
N. children	0.0110***	-0.00492
	(0.00346)	(0.00818)
Household income excluding own income (ln)	0.00193	-0.0117***
	(0.00205)	(0.00412)
Constant	0.744***	16.92*
	(0.0222)	(8.637)
Observations	7,666	7,666

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: The regression has been run on all women ages 15 and older. All monetary values are expressed in PPP-adjusted USD at constant prices.

the interview. However, we could suppose that the increase in income observed is partially due to a shift from unpaid work in family business to paid work outside the household, as shown in the next subsection (as already mentioned, females working on the household farm are included in the sample of employed women at baseline but they work unpaid). As expected, female monthly income is positively affected by a higher level of education and negatively by the level of income of the rest of the family.

Table 3.3 Probability of employment in the baseline (2012)

	A Prob. employment 2012	B Prob. unemployment 2012
Age	-0.00313***	0.00313***
	(0.00101)	(0.00101)
Higher educ.	-0.541***	0.541***
	(0.0599)	(0.0599)
N. children	-0.000459	0.000459
	(0.0122)	(0.0122)
Household income excluding own income	0.0164**	-0.0164**
	(0.00760)	(0.00760)
Night-time lights 2011	-0.00658***	0.00658***
	(0.00137)	(0.00137)
Rainfall in 2011	-0.000534***	0.000508***
	(0.000140)	(0.000140)
Constant	0.832***	-0.832***
	(0.0917)	(0.0917)
Observations	7,666	7,666

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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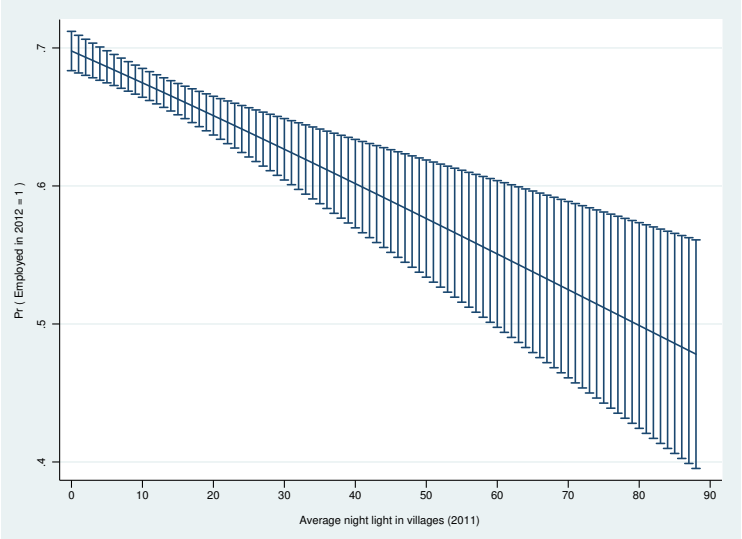
3.5.4 Impact of the flood shock on the probability to engage in an independent wage-earning activity

Correcting then for double selection bias due to employment in the household business, we observe that the probability to engage in an independent wage-earning activity increases by around 28 percentage points in those villages where the share of inundated areas reached the maximum (Estimation 5). To check, then, whether the assumptions made in our theoretical model are plausible, we add to our difference-in-difference estimation a variable for the farm size (where the variable for land size, reported in *decimals* is referred only to the cultivated land). In table 3.A2 in the Appendix the negative and significant coefficient of the triple interaction suggests that the impact of the shock over time on the probability to work autonomously is lower for net seller households with larger landholdings, thus confirming our theoretical conjecture that women belonging to net buyer households with relatively smaller farms would be more likely to find employment outside the household business.

Figure 3.6 Relationship between employment of women at baseline and local economic development proxied by night-time lights



Source: Author's calculation from BIHS data and NASA Integrated Multi-satellite Retrievals for GPM for rainfall data.

3.5.5 Driving factors analysis

To investigate the transmission channels that lead to increasing labour supply after the shock, we include in our estimation other household time-varying variables that are themselves correlated with the shock to check whether this could affect our difference-in-difference coefficients.

The variation in household income and production assets value (where the latter is calculated as the sum of agricultural implements and other production assets owned by households multiplied for their current value reported in the questionnaire) over time is partially correlated with the flooding.[19] These two variables, even if endogenous, are inserted in our regression run on the four different outcomes illustrated above: labour force participation, labour entry for unemployed women at baseline, monthly income and probability to shift from unpaid family work to independent wage-earning activities. Table 3.A3 in the Appendix shows that the difference-in-difference coefficients do not change significantly with respect to the benchmark specifications, thus indicating that the treatment effect on outcomes of interest is not driven by the indirect influence of drop in household income and production assets value.

As part of the analysis on the factors driving the variation in female labour choices, we also include additional controls for migration experience of the households and for the variation in average food prices at village level. For the first group of controls we add two time-varying dummies equal to one, respectively, if the household has at least one migrant member and if it receives remittances. The variation in both these

[19] Previous estimations (see Chapter 2) revealed that the shock brought a decline in monthly income from wage labour by over $50 PPP.

Table 3.4 Impact of the flood shock on entry into employment

	OLS Entry into empl.	FE Entry into empl.
year 2015	0.0342	-0.00857
	(0.106)	(0.106)
Treat. share sept.	-0.00555	
	(0.0668)	
year*Treat. share sept.	0.216**	0.225**
	(0.0943)	(0.0933)
share July	0.000726	
	(0.145)	
year*share July	-0.500**	-0.519**
	(0.205)	(0.203)
year*Eastern Bengal	-0.187***	-0.182***
	(0.0462)	(0.0457)
year*Central Bengal	-0.107**	-0.103**
	(0.0453)	(0.0448)
year*Southern Bengal	-0.0925*	-0.0877*
	(0.0497)	(0.0492)
$Lambda_{Unemp}$	0.000283	-0.584***
	(0.0767)	(0.187)
year*$Lambda_{Unemp}$	0.516***	0.554***
	(0.0870)	(0.0867)
Higher educ.	-0.000248	-0.202***
	(0.0250)	(0.0516)
N. children	0.00520	0.000469
	(0.00445)	(0.0111)
Household income excluding own income (ln)	0.00283	-0.00645
	(0.00261)	(0.00582)
Observations	2,507	2,507

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: The regression has been run on all women ages 15 and older that are unemployed in 2012. All monetary values are expressed in PPP-adjusted USD at constant prices.

two variables might in fact influence women labour force participation as well as their choice to work outside the household. Table 3.A4 in the Appendix shows in fact that while having a migrant member in the household mildly discourages unemployed women at baseline to enter the labour force if affected by the shock, receiving remittances decreases significantly women labour force participation by 5 percentage points and their probability to enter the labour force - if previously unemployed - by 9 percentage points. However, migration experience does not have a significant impact neither on the variation of monthly income over time, nor on the probability to engage in independent wage-earning employment. In addition, we do not observe any significant change in the difference-in-difference coefficients with respect to our benchmark specification.

Table 3.5 Impact of the flood shock on weekly working hours and average monthly income

	OLS Weekly working hours	FE Weekly working hours	OLS Monthly income PPP	FE Monthly income PPP
year 2015	-3.669*	-3.669**	-41.64***	-30.33***
	(2.183)	(1.794)	(11.32)	(11.71)
Treat. share sept.	3.568***		8.420	479.2
	(1.332)		(7.447)	(46,946)
year*Treat. share sept.	-1.848	-1.848	24.37**	24.51**
	(1.884)	(1.548)	(10.86)	(11.57)
share July	-12.81*		-59.67	
	(6.697)		(38.59)	
year*share July	19.73**	19.73**	49.89	55.50
	(9.471)	(7.782)	(54.43)	(56.12)
Eastern Bengal	-3.565***		-6.684*	
	(0.821)		(3.670)	
Central Bengal	-2.194***		0.565	
	(0.753)		(3.333)	
Southern Bengal	0.00402		4.028	
	(0.787)		(3.504)	
year*Eastern Bengal	0.700	0.700	5.729	4.390
	(1.162)	(0.954)	(5.192)	(5.494)
year*Central Bengal	2.401**	2.401***	4.509	6.782
	(1.064)	(0.875)	(4.682)	(4.853)
year*Southern Bengal	-0.220	-0.220	5.728	6.731
	(1.113)	(0.914)	(4.919)	(5.202)
Higher educ.	1.260	4.722*	43.30***	83.51***
	(1.071)	(2.462)	(6.201)	(22.14)
N. children	-0.246*	-0.557**	-1.080	-2.559
	(0.130)	(0.282)	(0.685)	(1.955)
Household income excluding own income (ln)	-0.450***	-0.574***	-2.496***	-3.445***
	(0.0773)	(0.142)	(0.401)	(0.948)
$Lambda_{Emp}$	6.408**	19.16***	102.6***	297.8***
	(2.754)	(5.925)	(14.26)	(44.46)
year*$Lambda_{Emp}$	2.890	2.890	69.28***	47.70**
	(3.894)	(3.200)	(20.89)	(21.53)
Constant	11.82***	3.650	-22.41***	-160.1
	(1.544)	(3.150)	(7.778)	(3,347)
Observations	5,158	5,158	5,158	5,158

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: The regression has been run on all women ages 15 and older employed in 2012. All monetary values are expressed in PPP-adjusted USD at constant prices.

To control for price changes at the local level, using information on price per unit of main food consumption items for sampled households, we build an index of average food prices adjusted for inflation and converted in $ PPP in order to investigate how its variation over time, partially correlated with the flooding (the correlation coefficient between our flooding treatment and price variation is in fact approximately 0.10), would affect our difference-in-difference estimation. Table 3.A5 in the Appendix shows that, while price variation has a positive and significant effect in increasing female participation (excluding the regression on monthly income where the coefficient on price variation is, as expected, negative and slightly significant), the difference-in-difference coefficients do not change significantly with respect

Table 3.6 Impact of the flood shock on independent wage-earning employment

	OLS Empl. outside hh farm	FE Empl. outside hh farm
year 2015	0.883***	0.854***
	(0.185)	(0.183)
Treat. share sept.	-0.0111	
	(0.0830)	
year*Treat. share sept.	0.288**	0.297***
	(0.117)	(0.114)
year*Eastern Bengal	0.0792*	0.0803*
	(0.0479)	(0.0467)
year*Central Bengal	0.216***	0.217***
	(0.0461)	(0.0449)
year*Southern Bengal	0.117**	0.117**
	(0.0494)	(0.0481)
share July	0.0134	
	(0.170)	
year*share July	-0.538**	-0.534**
	(0.240)	(0.234)
Higher educ.	-0.0168	0.0671
	(0.0364)	(0.0925)
N. children	0.00286	-0.0122
	(0.00528)	(0.0133)
Household income excluding own income (ln)	0.00557*	0.00759
	(0.00330)	(0.00752)
$Lambda_1$	0.0237	-0.174
	(0.185)	(0.423)
year*$Lambda_1$	0.345	0.306
	(0.252)	(0.247)
$Lambda_2$	-0.0214	0.187
	(0.256)	(0.533)
year*$Lambda_2$	-0.486	-0.433
	(0.340)	(0.334)
Constant	-0.0322	-0.0601
	(0.144)	(0.287)
Observations	4,069	4,069

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: The regression has been run on all women ages 15 and older working on the household farm in 2012. All monetary values are expressed in PPP-adjusted USD at constant prices.

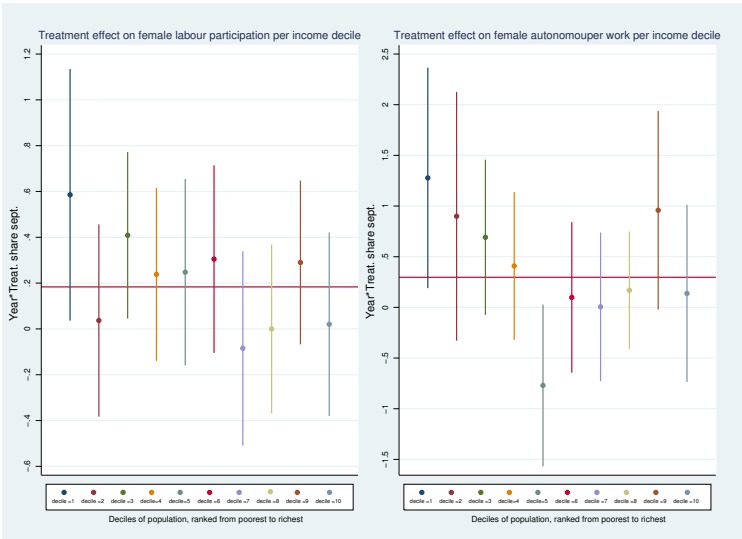
to the benchmark specifications, thus indicating that the treatment effect on outcomes of interest is not driven by the indirect influence of changes in average prices at the local level.

3.5.6 Heterogeneity analysis

Differentiating by income groups

To deepen the understanding of the effects of flooding, we conduct some heterogeneity analyses. First, we investigate whether female labour supply response differs in relation to the initial level of household income, by estimating our model separately by tertiles of the income distribution at baseline. Since, as already mentioned in the previous Chapter, the number of households mainly involved in agriculture is proportionally higher in the low-income group, we expect to find for them a stronger impact on the increase in female labour force participation as a coping strategy to face the natural shock. Table 3.A6 in the Appendix shows indeed that for women of treated low-income households the probability to be employed significantly increases by 26 percentage points after the shock as well as their probability of entering the labour force that rises by 40 percentage points. Female labour force participation increases also for households in the second tertile, while for high-income ones we do not observe any significant effect after the flooding. In addition, Figure 3.7 shows the distribution of the estimated impacts of the shock (measured by the coefficient *year*Treat. share sept*) for female individuals arranged by decile groups according to the level of households income at baseline. Both the coefficients of the impact of the shock on female labour force participation and on the probability to engage in independent wage-earning employment are indeed decreasing with the level of income of the households at baseline.

Figure 3.7 Impact of the flood shock by income deciles



Source: Author's calculation from BIHS data.

Differentiating by net buyers and net sellers

For the second type of heterogeneity analysis, we evaluate the differences in female labour supply outcomes according to the households' position in the local market as net seller or buyer. We therefore estimate our benchmark specification differentiating the sample between net food buyer and net food seller households.[20]

It is interesting to observe that female labour force participation increases significantly (by around 28 percentage points) only for women in net seller households. Women belonging to net buyers, instead, experience a significant increase in the probability to shift from working in the family business to an independent wage-earning employment outside the household (Table 3.A7). In line with the assumptions made in our theoretical model, results suggest in fact that the first group of households increases its farm-labor demand after the shock to raise their productive activities and compensate the economic losses suffered, while women of net buyer households raise their off-farm labour supply to boost family income and face economic challenges.

3.5.7 Impact of the flood shock on female bargaining power

As mentioned, we employ an instrumental variable estimation technique using different labour outcomes in the first stage in order to investigate which form of labour force participation contributes to increase female bargaining power (Estimation 6).

Table 3.7 shows that using flood intensity to instrument female labour force participation we do not find significant changes in the WEAI. However, it is interesting to observe that the increasing probability for women to engage in an independent wage-earning activity leads to a rise in the WEAI by 57 percentage points (where the Index ranges between 0-1) with a significant coefficient at the 0.05 level (Table 3.8). These results suggest that income idiosyncratic shocks might lead to an increase in labour supply among rural households - either to increase the productive activities in the farm or to enlarge the earning possibilities of their members working off-farm - and that female labour force participation acts as an insurance mechanism to absorb the consequences of these shocks. However, only in case women get a job outside the family business their decision making power increases. This result is consistent with the conclusions drawn in our theoretical mode.

Since working for an independent income implies also shifting from unpaid family business to paid work, our results are in line with previous studies that found that increasing women control over resources also contributes to strengthen their bargaining power (Adato, De la Briere, Mindek, & Quisumbing, 2000).

Table 3.9 shows the results of the two-stage least squares estimation run on the whole sample of employed

[20] Using yearly information on kilograms of each food item cultivated and sold in the market and on the corresponding quantities purchased, we define net sellers as households for whom the total amount of items sold is higher than the amount purchased, and the sample of net buyers as households for whom the reverse is true.

women at baseline for which an increase in female monthly income by $1 would imply a significant increase in the WEAI by 2 percentage points.

Table 3.7 IV-2SLS estimation for the impact of labour force participation on female bargaining power, FE estimations

	(1st stage) Labour part. dummy	(2nd stage) WEAI
year 2015	0.0764***	0.177***
	(0.0231)	(0.0223)
Treat. share sept.	0.162***	
	(0.0621)	
Labour part. dummy		0.212
		(0.204)
year*share July	-0.320**	-0.0407
	(0.129)	(0.0499)
year*Eastern Bengal	-0.0914***	-0.0156
	(0.0273)	(0.0243)
year*Central Bengal	-0.00817	-0.0182
	(0.0254)	(0.0138)
year*Southern Bengal	-0.0271	0.0368**
	(0.0279)	(0.0174)
Higher educ.	0.120	-0.0862
	(0.106)	(0.0612)
N. children	0.00511	0.00329
	(0.00851)	(0.00466)
Household income excluding own income (ln)	0.00287	0.000535
	(0.00401)	(0.00219)
Constant	0.737***	0.324**
	(0.0245)	(0.151)
Observations	7,666	7,666
F-statistic (1st stage)	7.91	

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: The regression has been run on all women ages 15 and older. All monetary values are expressed in PPP-adjusted USD at constant prices.

3.5.8 Robustness checks

Adding controls for topographic characteristics

Table 3.A8 in the Appendix shows the results of the first robustness check performed adding the topographic controls to the fixed effect difference-in-difference regression (Panel A). Controlling for villages characteristics in terms of distance from water surfaces or altitude, we find again an increase in both

Table 3.8 IV-2SLS estimation for the impact of independent wage-earning activity on female bargaining power, FE estimations

	(1st stage) Empl. outside hh farm	(2nd stage) WEAI
year 2015	0.741***	-0.393
	(0.232)	(0.276)
Treat. share sept.	0.297**	
	(0.124)	
Empl. outside hh farm		0.574**
		(0.282)
year*share July	-0.627**	0.123
	(0.262)	(0.170)
year*Eastern Bengal	0.0657	0.0159
	(0.0522)	(0.0392)
year*Central Bengal	0.205***	-0.0762
	(0.0495)	(0.0639)
year*Southern Bengal	0.110**	0.0451
	(0.0535)	(0.0396)
Higher educ.	0.170	-0.00253
	(0.193)	(0.152)
N. children	-0.0156	0.0142
	(0.0161)	(0.0125)
Household income excluding own income (ln)	0.00337	-0.0100*
	(0.00825)	(0.00609)
year*$Lambda_1$	0.260	-0.161
	(0.308)	(0.232)
year*$Lambda_2$	-0.303	0.239
	(0.420)	(0.312)
Constant	0.00299	0.526***
	(0.0504)	(0.0370)
Observations	4,069	4,069
F-statistic (1st stage)	280.91	

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: The regression has been run on all women ages 15 and older employed in the household farm in 2012. All monetary values are expressed in PPP-adjusted USD at constant prices.

labour force participation, labour entry and monthly income for women in largely treated villages, even if of a smaller magnitude than those found, respectively, in Table 3.2, Table 3.4 and Table 3.5. In addition, female adults of affected households are 26 percentage points more likely to have an independent wage-earning employment outside the household farm.

Results are also robust in the second specification, obtained including the interaction of wave fixed effects with the average rainfall during the same monsoon period for the years 1970-2000 (Table 3.A8, B), and in the third one, where we control for the *vulnerability index* - built for each village according to its distance

Table 3.9 IV-2SLS estimation for the impact of monthly income on female bargaining power, FE estimations

	(1st stage) Monthly income PPP	(2nd stage) WEAI
year 2015	-1.303	0.140***
	(3.137)	(0.0356)
Treat. share sept.	12.49**	
Monthly income PPP		0.0269**
		(0.0107)
year*share July	-1.303	0.140***
	(3.137)	(0.0356)
year*Eastern Bengal	3.635	0.0124
	(3.711)	(0.0581)
year*Central Bengal	2.099	0.000817
	(3.452)	(0.0429)
year*Southern Bengal	0.814	0.0336
	(3.797)	(0.0377)
Higher educ.	24.96*	-0.727
	(14.42)	(0.476)
N. children	-0.283	0.0115
	(1.157)	(0.0317)
Household income excluding own income (ln)	-1.563***	0.0344
	(0.541)	(0.0227)
Constant	23.83***	0.00673
	(3.249)	(0.279)
Observations	5,158	5,158

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: The regression has been run on all women ages 15 and older employed in 2012. All monetary values are expressed in PPP-adjusted USD at constant prices.

from rivers, lakes and coastal lines (Table 3.A8, C).

Placebo test

Results from the placebo test run for the period preceding the occurrence of the flooding, namely, 2012 and 2013, confirm that differently treated villages would have followed, in the absence of the shock, parallel trends in the outcome of interest (See Chapter 2, Section 2.4.3).

Factor analysis for women bargaining power

Finally, results obtained employing factor analysis as alternative measure to the WEAI confirm that increasing female labour force participation contributes to enhance women decision making power within

the household.

Interestingly, Table 3.A9 in the Appendix shows that engaging in independent wage-earning activities leads to an increase in the first factor for joint decision making by 4 units. Moreover, if investigating the impact of the same labour supply variables on sole decision making, we find a positive and higher effect (Table 3.A10).

The WEAI does not distinguish for joint and sole decision making, considering women *adequate* if they could participate to household decisions "to at least a medium extent". This robustness check is thus relevant to show that female labour market activity and their control over financial resources allow them to be more involved into family decisions, increasing also their probability to have full decision making power on economic and non-economic aspects of household life. However, the factor loadings of the different variables reveal that the economic aspects - and in particular decisions on agricultural production, purchase of agricultural inputs and types of crops to grow - are more relevant in defining the decision making power dimensionality (the first three economic items have in fact the strongest relationship with the unobserved factor). These results are in line with Anderson and Eswaran (2009) who find that women involvement in market work impinges on their autonomy in the economic sphere without affecting however their bargaining power in the non-economic spheres.

3.6 Discussion and concluding remarks

We evaluate the response of female labour supply to a dramatic flood that hit Bangladesh between August and September 2014 combining panel household survey with high-precision satellite data.

Although floods are quite common during the monsoon season in South Asian countries, shifting from lack of water during the lean season to strong flooding and cyclones in the peak one might severely harm the productive capacity of rural households. It is therefore extremely relevant to understand the effects of these natural phenomena on household behaviour. Literature has shown that over time households have developed risk-coping strategies to adapt to these repeated natural shocks, among which changes in labour force participation choices. Similarly to what found in Attanasio et al. (2005) who employ a life-cycle model to investigate women labour supply response to a period of agricultural shock due to lower rainfall, we find that earnings uncertainty increases female participation rates.

The results of our difference-in-difference estimations confirm indeed that after the shock female labour force participation rises by around 18 percentage points and that the probability for unemployed women to enter the labour force increases by around 22 percentage points. After correcting for selection bias

due to initial employment status, we observe also a significant raise in average monthly income by $24 PPP. Interestingly, the probability for women working on the household farm to engage in independent wage-earning activities increases by around 28 percentage points.

In addition, our findings are in line with those found by Sarkar et al. (2019), where the average marginal effect of night-time lights, employed as a proxy of local economic growth, on female labour force participation is negative suggesting that in rural areas women tend to participate less in the labour market when the intensity of economic activities in the region grows.

In the second part of the analysis we find that this increased involvement of women into the labour market - instrumented by the intensity of the flood shock that they faced - contributes to rise their bargaining power in the household, measured using the WEAI, by around 57 percentage points.

Consistently with our theoretical model, this significant change is observed only for women who find an employment outside the household farm. Our results therefore would confirm the evidence found by Anderson and Eswaran (2009) that wage labour has a more significant effect on women's autonomy than unearned income. However, employing comprehensive indicators of female autonomy that allows us to disentangle the different impact of women engagement in wage-earning activities on sole and joint decision making processes - considering both economic and non-economic aspects of family life -, we find that their work activity affects their probability to have full decision making power on economic and non-economic aspects of household life. The economic aspects, however, are shown to be more relevant in defining women bargaining power.

Previous literature as largely employed decision making on minor and major household expenditures as measures for women autonomy (see, for example, Acharya, Bell, Simkhada, Van Teijlingen, and Regmi (2010); Li and Wu (2011); Heath and Tan (2018)). However, women decision power on household expenses could merely reflect the fact that females engaging, after the shock, in independent wage-earning activities are able to decide on how to spend their earned income. The WEAI, instead, is an indicator for a more comprehensive and larger dimension of women autonomy, measuring their inclusion in the agricultural sector, their decision making over agricultural production, access to productive resources and control over use of income.[21] The latter is particularly relevant as shown by Kantor (2003) who find that for Indian women employed in the garment industry being employed in wage-earning activities does not directly influences their autonomy, while only the direct control over financial resources - without males as financial intermediaries - significantly improves their bargaining power.

Our exercise is not without limitations. As already outlined, we are unable to conduct the natural parallel trend test because of the lack of another panel wave of the BIHS for the same subsample. The alternative test we performed employing night-time light data as outcome relies on the assumption that this satellite

[21] In 60 percent of the cases women find autonomous employment in the agriculture sector. This contributes to improve their bargaining power within the household farm, since a large share of them (around 20 percent) continue working also in the household farm.

product is a valid proxy for local economic growth and that the observed parallel trends in local development would imply similar trends also in female labour force participation.

Among the strengths of the analysis, our results are proven to be robust to the numerous checks implemented, controlling for all the topographic features that may affect the likelihood of villages to be flooded and employing alternative indicators for female bargaining power to rule out the possibility that the particular construction of the WEAI could bias the estimations. In addition, the use of georeferenced data, employed both as treatment variable, exclusion restrictions, instruments and control variables, allow us to obtain robust estimates.

From the policy point of view, we have seen that in rural areas women working on the household farms in most cases do not own the land and do not have any decisional power on the economic activities performed. However, the natural shocks and the consequent larger participation of women in the labour market may alter this equilibrium. Women engaging in independent wage-earning activities are in fact shown to have higher decision making power not only on the use of household income and time allocation but also on productive activities of the farm. However, only women with working skills are likely to be employed in the labour market. Therefore, based on our findings, policies that encourage female labour force participation in the market - such as the training programs designed by the Bangladesh Rural Advancement Committee (BRAC) and the Grameen Bank to advance women's skills and reduce their economic dependency - should be further implemented.

As shown by Anderson and Eswaran (2009), if women acquire the skills to work autonomously in the market this would guarantee them a higher level of autonomy. In addition, many research works have demonstrated that increasing female autonomy and control over household financial resources would have beneficial repercussions for the whole household, such as improving food security and health status of its members (Dyson & Moore, 1983; Caldwell, 1986; Mason, 1987), as well as children school attendance (Luz & Agadjanian, 2015).

Appendix

3.A

3.A1 Theoretical model: labour supply and labour demand response to the shock

As in Buchenrieder and Mollers (2006) and Demeke and Zeller (2012), where farm households are shown to shift to market work because of weather and crops shocks, we could hypothesise how the labour supply and demand functions of market B vary after the shock affecting the off-farm labour supply of workers from market A (in our case the *net sellers*' market represents the receiving market of workers from the *net buyers*' one). The labour supply function to the off-farm labour market is:

$$H_f^F = f(W, P_y, P_{Q^F}, E, G) \tag{A-1}$$

where E are workers' characteristics and G are labour market characteristics.
Wages received off the farm depend on workers and market characteristics, on the local demand for labour D^M (which in turn is function of the demand for the off-farm goods, D_y) and on the labour supply S^M. Therefore, the wage equation can be expressed as by:

$$W = f(E, G, D^M, S^M) \tag{A-2}$$

D_y depends on the local economic development and therefore it is affected by the performance of the agricultural sector and by weather shocks represented by ϕ.
We can thus rewrite the labour supply function to the off-farm labour market as:

$$H_f^F = f(W\{E, G, D^M[D_y(\phi, R)], S^M(\phi, N))\}, P_y, P_{Q^F}, E, G) \tag{A-3}$$

Where R and N are other factors that might impact, respectively, D_y and S^M.

The first order condition of $H_f^F(.)$ with respect to D^M and S^M shows the effect of the weather shock on the supply of labour to the off-farm market:

$$\frac{\delta H_f^F}{\delta \phi} = \frac{\delta H_f^F}{\delta W}\,[\frac{\delta W}{\delta D^M}\frac{\delta D^M}{\delta D_y}\frac{\delta D_y}{\delta \phi} + \frac{\delta W}{\delta S^M}\frac{\delta S^M}{\delta \phi}] \tag{A-4}$$

The quantity of labour supplied depends on changes in local wage levels that in turn is the sum of the

responses to the changes in the demand and in the supply of labour, both reacting to the weather shock. The change in ϕ affects farm production negatively thus reducing the demand for off-farm goods and services. This leads to a drop in the demand for off-farm labour and to a consequent decline in off-farm wage levels (represented by the equilibrium $E2_f^{NS}$ in Figure 3.3).

At the same time households affected by the shock increase their off-farm labour supply, leading to a decrease in the off-farm wage rate. The overall effect on the wage rate depends on the elasticities of the labour demand and supply functions to the shock. In the case illustrated in Section 3.2, the wage rate in market B drops after the shock but remains above $E2_f^{NB}$, thus attracting workers from market A.

3.A2 Tables

Table 3.A1 The domains and proportions of the Women's Empowerment in Agriculture Index

DOMAIN	Indicator	Weight	Proportion of *adequate* women in 2012	Proportion of *adequate* women in 2015
Production	Input in production decisions	1/10	0.46	0.59
	Autonomy in production	1/10	0.57	0.80
Resources	Ownership of assets	1/15	0.71	0.99
	Purchase, sale or transfers of assets	1/15	0.77	0.80
	Access to and decisions about credit	1/15	0.47	0.53
Income	Control over use of income	1/5	0.59	0.68
Leadership	Group member	1/10	0.27	0.66
	Speaking in public	1/10	0.32	0.58
Time	Workload	1/10	0.75	0.72
	Leisure	1/10	0.70	0.75
Observations			4,083	4,083

Note: The table reports the five domains, the ten indicators and their weights used to construct the WEAI. The proportions of *adequate* women found for each indicator are similar to those reported by Alkire et al. (2013) in the pilot study for Bangladesh.

Table 3.A2 Impact of the flood shock and land size on independent wage-earning employment

	OLS Empl. outside hh farm	FE Empl. outside hh farm
Land size 2012	-2.01e-05	
	(8.74e-05)	
year 2015	0.895***	0.864***
	(0.182)	(0.184)
year*Land size	-0.0193	-0.0173
	(0.0305)	(0.0304)
Treat. share sept.	-0.0139	
	(0.0973)	
Land size*Treat. share sept.	0.00321	
	(0.131)	
year*Treat. share sept.	0.265**	0.277**
	(0.134)	(0.133)
Land size*year*Treat. share sept.	-4.08e-05	-0.00101**
	(0.000316)	(0.000430)
year*Eastern Bengal	0.00132	-0.0790*
	(0.0342)	(0.0468)
year*Central Bengal	0.000912	-0.218***
	(0.0326)	(0.0450)
year*Southern Bengal	-0.000701	-0.118**
	(0.0349)	(0.0482)
share July	-0.528***	
	(0.171)	
year*share July	0.0170	0.541**
	(0.171)	(0.234)
Higher educ.	-0.0178	0.0670
	(0.0371)	(0.0925)
N. children	0.00221	-0.0117
	(0.00541)	(0.0133)
Household income excluding own income (ln)	0.00585*	0.00768
	(0.00337)	(0.00754)
$Lambda_1$	0.0186	-0.175
	(0.186)	(0.423)
year*$Lambda_1$	0.365**	0.133
	(0.183)	(0.426)
$Lambda_2$	-0.0117	0.189
	(0.256)	(0.534)
year*$Lambda_2$	-0.502**	-0.248
	(0.251)	(0.530)
Constant	-0.0385	0.0442
	(0.145)	(0.290)
Observations	4,069	4,069

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: The regression has been run on all women ages 15 and older employed in the household farm in 2012. All monetary values are expressed in PPP-adjusted USD at constant prices.

Table 3.A3 Impact of the flood shock controlling for household income and value of production assets, FE estimations

	A	B	C	D
	Labour part. dummy	Prob. of entry into employment	Monthly income PPP	Empl. outside hh farm
	(no selection)	(unemployed in 2012)	(employed in 2012)	(working on the hh farm in 2012)
year 2015	0.0789***	-0.0302	-33.16***	0.832***
	(0.0252)	(0.109)	(11.68)	(0.184)
year*Treat. share sept.	0.203***	0.233**	22.00*	0.326***
	(0.0645)	(0.103)	(11.53)	(0.116)
year*share July	-0.302**	-0.581***	73.24	-0.644***
	(0.135)	(0.220)	(46.25)	(0.239)
year*Eastern Bengal	-0.0859***	-0.175***	3.586	0.0768
	(0.0291)	(0.0420)	(5.406)	(0.0473)
year*Central Bengal	-0.0136	-0.105**	4.664	0.210***
	(0.0278)	(0.0439)	(4.363)	(0.0455)
year*Southern Bengal	-0.0369	-0.0812*	5.529	0.123**
	(0.0300)	(0.0468)	(4.753)	(0.0487)
Higher educ.	-0.226***	-0.207***	82.77**	0.0786
	(0.0251)	(0.0541)	(35.85)	(0.0945)
N. children	-0.00635	-0.00583	-2.731*	-0.0204
	(0.00859)	(0.0126)	(1.531)	(0.0137)
Household monthly income (ln)	0.0320***	0.0226***	17.25***	0.0163*
	(0.00475)	(0.00613)	(1.959)	(0.00866)
Household asset value (ln)	0.0342***	0.0622***	-2.302**	0.0494***
	(0.00653)	(0.00966)	(1.124)	(0.0115)
year*$Lambda_{Ump}$		0.576***		
		(0.0905)		
year*$Lambda_{Emp}$			52.47**	
			(23.66)	
year*$Lambda_1$				0.273
				(0.249)
year*$Lambda_2$				-0.391
				(0.335)
Constant	3.163	0.707***	87.49	-0.0235
	(1.996)	(0.205)	(85.21)	(0.288)
Control for income and asset variation	YES	YES	YES	YES
Observations	7,666	2,507	5,158	4,069

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: The regression has been run on all women ages 15 and older in panel A, selecting unemployed women in panel B, employed ones in panel C and women working in the household farm in panel D. All monetary values are expressed in PPP-adjusted USD at constant prices.

Table 3.A4 Impact of the flood shock controlling for migration experience, FE estimations

	A	B	C	D
	Labour part. dummy	Prob. of entry into employment	Monthly income PPP	Empl. outside hh farm
	(no selection)	(unemployed in 2012)	(employed in 2012)	(working on the hh farm in 2012)
year 2015	0.0785***	0.139	8.369	0.755***
	(0.0249)	(0.0989)	(17.54)	(0.141)
year*Treat. share sept.	0.183***	0.227**	26.32**	0.284**
	(0.0638)	(0.0999)	(13.17)	(0.114)
year*share July	-0.241*	-0.523**	49.95	-0.528**
	(0.133)	(0.205)	(39.13)	(0.234)
year*Eastern Bengal	-0.0838***	-0.176***	5.642	0.0740
	(0.0286)	(0.0469)	(5.750)	(0.0471)
year*Central Bengal	-0.00892	-0.0889*	7.228*	0.213***
	(0.0274)	(0.0470)	(4.279)	(0.0450)
year*Southern Bengal	-0.0396	-0.0786	6.484	0.114**
	(0.0296)	(0.0522)	(4.844)	(0.0481)
Higher educ.	-0.225***	-0.191***	84.91***	0.0801
	(0.0250)	(0.0558)	(30.95)	(0.0922)
N. children	-0.00516	0.00241	-2.870*	-0.00808
	(0.00821)	(0.0118)	(1.541)	(0.0135)
Household income				
excluding own income (ln)	-0.0131***	-0.00762	-3.951**	0.00940
	(0.00421)	(0.00591)	(1.625)	(0.00761)
Migrant hh	0.0130	0.0571	-14.13*	0.0924
	(0.0371)	(0.0533)	(7.896)	(0.0611)
Remitt. recipient	-0.0572**	-0.0919**	-1.955	-0.0220
	(0.0279)	(0.0420)	(6.054)	(0.0464)
year*$Lambda_{Ump}$		0.408***		
		(0.0891)		
year*$Lambda_{Emp}$			12.33	
			(14.05)	
year*$Lambda_1$				0.206
				(0.171)
year*$Lambda_2$				-0.279
				(0.234)
Control for migr. dummies	YES	YES	YES	YES
Constant	3.169	0.604***	131.0	-0.0275
	(2.002)	(0.212)	(79.96)	(0.247)
Observations	7,666	2,507	5,158	4,069

Standard errors in parentheses

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

Note: The regression has been run on all women ages 15 and older in panel A, selecting unemployed women in panel B, employed ones in panel C and women working in the household farm in panel D. All monetary values are expressed in PPP-adjusted USD at constant prices.

Table 3.A5 Impact of the flood shock controlling for food prices, FE estimations

	A	B	C	D
	Labour part. dummy	Prob. of entry into employment	Monthly income PPP	Empl. outside hh farm
	(no selection)	(unemployed in 2012)	(employed in 2012)	(working on the hh farm in 2012)
year 2015	0.0766***	0.0165	34.97	0.915***
	(0.0248)	(0.107)	(21.37)	(0.176)
year*Treat. share sept.	0.189***	0.229**	26.70**	0.305***
	(0.0639)	(0.100)	(12.48)	(0.114)
year*Eastern Bengal	-0.0878***	-0.190***	5.315	0.0630
	(0.0290)	(0.0496)	(5.947)	(0.0469)
year*Central Bengal	-0.00987	-0.0967**	6.948*	0.201***
	(0.0273)	(0.0459)	(4.026)	(0.0453)
year*Southern Bengal	-0.0392	-0.0815	6.685	0.106**
	(0.0295)	(0.0530)	(4.417)	(0.0483)
year*share July	-0.242*	-0.540**	47.25	-0.596**
	(0.134)	(0.215)	(41.80)	(0.235)
Higher educ.	-0.226***	-0.203***	53.60*	0.0658
	(0.0250)	(0.0509)	(31.76)	(0.0918)
N. children	-0.00400	0.00376	-2.458	-0.0141
	(0.00824)	(0.0114)	(1.617)	(0.0133)
Household income				
excluding own income (lnln)	-0.0118***	-0.00400	-3.581**	0.00814
	(0.00414)	(0.00591)	(1.531)	(0.00751)
Village food prices (ln)	0.0124***	0.0209***	-1.793*	0.0220***
	(0.00384)	(0.00589)	(0.994)	(0.00644)
year*$Lambda_{Ump}$		0.523***		
		(0.0917)		
year*$Lambda_{Emp}$			36.41**	
			(16.59)	
year*$Lambda_1$				0.417*
				(0.235)
year*$Lambda_2$				-0.570*
				(0.317)
Constant	3.154	0.650***	223.2**	-0.103
	(1.999)	(0.204)	(104.8)	(0.279)
Control for price variation	YES	YES	YES	YES
Observations	7,666	2,507	5,158	4,069

Standard errors in parentheses

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

Note: The regression has been run on all women ages 15 and older in panel A, selecting unemployed women in panel B, employed ones in panel C and women working in the household farm in panel D. All monetary values are expressed in PPP-adjusted USD at constant prices.

Table 3.A6 Impact of the flood shock by income group, FE estimations

	A			B		
	Low-income hh	Middle-income hh	High-income hh	Low-income hh	Middle-income hh	High-income hh
	Labour part. dummy	Labour part. dummy	Labour part. dummy	Prob. of entry into employment	Prob. of entry into employment	Prob. of entry into employment
	(no selection)	(no selection)	(no selection)	(unemployed in 2012)	(unemployed in 2012)	(unemployed in 2012)
year 2015	0.0796	0.0607	0.0858**	-0.0868	-0.313	0.288*
	(0.0507)	(0.0388)	(0.0423)	(0.201)	(0.202)	(0.166)
year*Treat. share sept.	0.265**	0.239**	0.0771	0.401**	0.0942	0.123
	(0.116)	(0.111)	(0.106)	(0.157)	(0.192)	(0.174)
year*share July	-0.276	-0.597**	0.0828	-0.893***	-0.395	-0.277
	(0.238)	(0.234)	(0.220)	(0.336)	(0.463)	(0.354)
year*Eastern Bengal	-0.125**	-0.0308	-0.0774	-0.271***	-0.171**	-0.0967
	(0.0550)	(0.0466)	(0.0502)	(0.0888)	(0.0759)	(0.0851)
year*Central Bengal	-0.0228	-0.00830	0.00137	-0.167**	-0.0973	-0.0540
	(0.0541)	(0.0436)	(0.0469)	(0.0846)	(0.0706)	(0.0805)
year*Southern Bengal	-0.00175	-0.0272	-0.0818	-0.125	-0.0413	-0.115
	(0.0576)	(0.0482)	(0.0502)	(0.0972)	(0.0827)	(0.0860)
Higher educ.	-0.167***	-0.359***	-0.193***	-0.231**	-0.263***	-0.187**
	(0.0470)	(0.0503)	(0.0364)	(0.0998)	(0.102)	(0.0838)
N. children	0.0173	-0.00627	-0.0217	0.00249	0.00684	-0.00389
	(0.0144)	(0.0150)	(0.0134)	(0.0185)	(0.0208)	(0.0233)
Household income						
excluding own income (ln)	-0.00446	-0.0338***	-0.00654	0.0123	-0.0325***	-0.0223
	(0.00562)	(0.00856)	(0.00939)	(0.00802)	(0.0121)	(0.0160)
$Lambda_{Ump}$				-0.570*	-0.323	-0.671**
				(0.330)	(0.374)	(0.289)
year*$Lambda_{Ump}$				0.671***	0.836***	0.236
				(0.158)	(0.170)	(0.144)
Constant	0.634***	3.472	0.761***	0.589	0.539	0.911***
	(0.0294)	(2.124)	(0.0606)	(0.363)	(0.425)	(0.330)
Observations	2,623	2,526	2,517	944	745	818

Standard errors in parentheses

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

Note: The regression has been run on all women ages 15 and older in panel A and selecting unemployed ones in panel B. All monetary values are expressed in PPP-adjusted USD at constant prices.

Table 3.A7 Impact of the flood shock for net food buyers and net food sellers, FE estimations

.	A		.	B
	Net food buyer	Net food seller	Net food buyer	Net food seller
	Labour part. dummy	Labour part. dummy	Empl. outside hh farm	Empl. outside hh farm
	(no selection)	(no selection)	(working on the hh farm in 2012)	(working on the hh farm in 2012)
year 2015	0.0782**	0.0840**	0.666***	1.495***
	(0.0344)	(0.0357)	(0.209)	(0.408)
year*Treat. share sept.	0.0830	0.286***	0.375***	0.154
	(0.0833)	(0.102)	(0.142)	(0.197)
year*Eastern Bengal	-0.0969**	-0.0335	0.0979*	0.0471
	(0.0379)	(0.0459)	(0.0568)	(0.0842)
year*Central Bengal	-0.00644	-0.0136	0.243***	0.181**
	(0.0374)	(0.0399)	(0.0566)	(0.0746)
year*Southern Bengal	-0.0546	-0.00570	0.173***	0.0227
	(0.0400)	(0.0440)	(0.0601)	(0.0817)
year*share July	-0.232	-0.284	-0.831***	0.0888
	(0.164)	(0.228)	(0.277)	(0.446)
Higher educ.	-0.211***	-0.261***	0.0319	0.222
	(0.0305)	(0.0435)	(0.111)	(0.191)
N. children	-0.00197	-0.0166	-0.0136	-0.0167
	(0.00994)	(0.0146)	(0.0154)	(0.0265)
Household income				
excluding own income (ln)	-0.0176***	-0.00245	0.0120	-0.0104
	(0.00504)	(0.00769)	(0.00873)	(0.0152)
$Lambda_1$			-0.00767	-0.0624
			(0.472)	(1.314)
year*$Lambda_2$			-0.0175	1.339**
			(0.284)	(0.528)
$Lambda_2$			0.00900	-0.133
			(0.575)	(1.856)
year*$Lambda_2$			-0.0275	-1.769**
			(0.380)	(0.734)
Constant	0.775***	3.335	-0.0368	0.365
	(0.0327)	(2.116)	(0.302)	(1.072)
Observations	4,935	2,731	2,603	1,493

Standard errors in parentheses

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

Note: The regression has been run on all women ages 15 and older in panel A and selecting women working in the household farm in panel B. All monetary values are expressed in PPP-adjusted USD at constant prices.

3.A3 Robustness checks

Table 3.A8 Robustness checks using topographic controls, FE estimations

Outcomes	A	B	C	Obs.
Labour part. dummy	0.249***	0.178***	0.202***	7,666
(no selection)	(0.0695)	(0.0645)	(0.0678)	
Prob. of entry into employment	0.222**	0.212**	0.153	2,507
(unemployed in 2012)	(0.0984)	(0.0868)	(0.101)	
Monthly income PPP	17.05	27.57**	22.22*	5,158
(employed in 2012)	(11.58)	(12.21)	(11.88)	
Empl. outside hh farm	0.263**	0.324***	0.182	4,069
(working on the hh farm in 2012)	(0.120)	(0.112)	(0.118)	

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Each cell contains the difference in difference coefficient of the treatment for each specification and for each outcome. All monetary values are expressed in PPP-adjusted USD at constant prices.

Table 3.A9 Robustness check using factor analysis: IV-2SLS estimation for the impact of independent wage-earning employment on joint decision making, FE estimations

	(1st stage) Empl. outside hh farm	(2nd stage) Joint dec.-making
year 2015	0.757***	-2.365
	(0.229)	(2.296)
Treat. share sept.	0.275**	
	(0.123)	
Empl. outside hh farm		4.352*
		(2.546)
year*share July	-0.540**	0.357
	(0.256)	(1.247)
year*Eastern Bengal	0.0785	-0.463
	(0.0515)	(0.317)
year*Central Bengal	0.210***	-0.590
	(0.0491)	(0.541)
year*Southern Bengal	0.108**	0.00686
	(0.0529)	(0.312)
Higher educ.	0.158	-1.486
	(0.194)	(1.183)
N. children	-0.00828	0.0668
	(0.0155)	(0.0895)
Household income excluding own income (ln)	0.00590	0.0127
	(0.00814)	(0.0481)
year*$Lambda_1$	0.242	0.234
	(0.306)	(1.794)
year*$Lambda_B$	-0.301	-0.532
	(0.416)	(2.417)
Constant	-0.0214	-0.304
	(0.0493)	(0.286)
Observations	4,069	4,069

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: The regression has been run selecting women women ages 15 and older working on the household farm in 2012. All monetary values are expressed in PPP-adjusted USD at constant prices.

Table 3.A10 Robustness check using factor analysis: IV-2SLS estimation for the impact of independent wage-earning employment on sole decision making, FE estimations

	(1st stage) Empl. outside hh farm	(2nd stage) Sole dec.-making
year 2015	0.757***	-3.941
	(0.229)	(3.029)
Treat. share sept.	0.275**	
	(0.123)	
Empl. outside hh farm		6.040*
		(3.358)
year*share July	0.0785	-0.183
	(0.0515)	(0.419)
year*Eastern Bengal	0.0785	-0.463
	(0.0515)	(0.317)
year*Central Bengal	0.210***	-0.732
	(0.0491)	(0.713)
year*Southern Bengal	0.108**	0.0196
	(0.0529)	(0.412)
Higher educ.	0.158	-2.501
	(0.194)	(1.561)
N. children	-0.00828	0.0444
	(0.0155)	(0.118)
Household income excluding own income (ln)	0.00590	-0.0291
	(0.00814)	(0.0635)
year*$Lambda_1$	0.242	-0.852
	(0.306)	(2.366)
year*$Lambda_B$	-0.301	0.633
	(0.416)	(3.188)
Constant	-0.0214	-0.0236
	(0.0493)	(0.377)
Observations	4,069	4,069

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: The regression has been run selecting women women ages 15 and older working on the household farm in 2012. All monetary values are expressed in PPP-adjusted USD at constant prices.

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