Deepening inequalities? Evidence from floods in Bangladesh

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Abstract

Do climate-related shocks increase intra-household inequalities by instigating the redistribution of household resources? I study this question in the context of flood shocks in Bangladesh, a region vulnerable to the effects of climate change and where prevailing gender norms can disadvantage women within the household. Specifically, I investigate whether exposure to a flood diverts household resources away from women in favor of men, thereby establishing a direct link between intra-household inequality and climate-induced shocks.

I apply a structural model of collective households to estimate the share of total household resources – i.e., the fraction of the total household budget – that is devoted to men, women and children in households that experienced a flood relative to comparable households that did not. I apply this model in a dynamic setting that allows me to study how resource shares evolve over time after the shock. Using household data from the Bangladesh Integrated Household Survey and flood maps from the Global Flood Database, I find that, initially, exposure to a flood results in a 4.4 percentage point decrease in women's share of household resources, which is redistributed among men and children within the household. Over time, this gendered disparity intensifies, with women experiencing a 16.2 percentage point decrease in resource share four years post-flood, while men witness an increase of 16.3 percentage points. In terms of intra-household welfare, four years post-flood, women in affected households had an estimated average daily consumption value of $4.47 (in 2010$), which is roughly half of that for men in flooded households and women in unflooded households.

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1 Introduction

Conventional methods of evaluating individual material well-being within households often rely on per-capita consumption, assuming an equal distribution of resources among household members. While this assumption is reasonable in more egalitarian regions, it is less likely to hold in areas where prevailing cultural norms disadvantage certain types of household members. For instance, Jayachandran and Pande (2017) discuss the role of prevailing gender norms and son preference in determining the health status of children in India. In such contexts, it becomes important to study how resources are divided across members, and how these resource shares respond to various shocks.

In this paper, I investigate how the intra-household sharing rule and, by extension, the material well-being of individuals under the same roof, changes due to a negative climate shock. I study this question in the context of flood shocks in Bangladesh, where floods are likely to increase in intensity and frequency in the years to come. I seek to answer whether flood events divert resources away from certain household members in favor of others, and if certain household members are likely to become poorer than others as a result. A recent study by Brown, Calvi, and Penglase (2021) shows that the average resource share of women in Bangladesh is less than men's by 8 percentage points. I would like to go a step further and see if exposure to a negative and temporary shock like a flood can deepen existing intra-household inequalities in the short and longer-run and shift resources away from women towards men and children.

I expect women to be disproportionately impacted by climate shocks, specifically floods in the case of this paper, primarily due to the cultural context. Ethnographic studies in South Asia show that women are likely to experience a greater strain of household responsibilities, increased incidence of domestic violence, and a decrease in labor force participation after a flood (Memon 2020; Rezwana and Pain 2020). These factors may reduce the capacity of women to advocate for themselves within the household, manifest in a reduction of the share of total household resources allocated to them, and ultimately reduce the value of their consumption, i.e. their material well-being, relative to other household members.

Although this is a policy relevant question, it remains unanswered partly because we cannot observe how household members divide the total household budget between themselves. Therefore a framework is needed to model the allocation decisions of individuals within the household. I apply a structural model (grounded in economic theory pertaining to collective households [Chiappori 1988, 1992]) that extrapolates limited information on individual-level consumption to estimate an individual's share of total household consumption – i.e., it estimates the fraction of the total household budget that is devoted to men, women and children in the household. This methodology – which involves comparing the slopes of Engel curves for a private assignable good[1] across different

[1] A good consumed exclusively by a known member of the household

types of household members – has gained traction since the seminal paper by Dunbar, Lewbel and Pendukar (2013) who developed this approach to identify resource shares of men, women and children in a cross-section. I build on this approach and extend it in a longitudinal setting to estimate how resource shares change up to four years after a flood.

To estimate this structural model, I require longitudnal data on observable individual-level consumption data for at least one private good, while consumption of all other goods can be observed at the household-level. The Bangladesh Integrated Household Survey (BIHS), which is a panel survey conducted in 2011/12, 2015 and 2018/19 in 275 villages, fulfils these requirements. Through estimation of this structural model, I am able to identify differences in intra-household resource distribution in households that were exposed to a flood (tretaed households), relative to comparable households that had a similar probability of flooding but were not exposed (control households). By exploiting the panel dimension of the data, I am able to identify the evolution of resource shares over time.

Between the first and last rounds of the household survey, which I consider the study period, Bangladesh experienced 20 floods that exposed 99 of the 275 villages in my sample. Among villages that had a similar probability of experiencing a flood, there is randomness in the timing a village experienced its first flood since the start of the study period, creating cohorts of villages that were flooded for the first time in different years. Given the timing of the household surveys coupled with the randomness in the timing of the first flood, I can estimate the change in resource shares at different points on the event timeline. For example, for the cohort of villages that experienced their first flood in 2014 since the baseline household survey in 2011, I observe them six months after the shock in the 2015 round of the BIHS, and then again four years later in the 2018 round of the BIHS. Since this is the largest cohort of villages in my sample, my results will exclusively focus on this cohort. In future iterations of this paper, I will also include the 2016 and 2018 cohorts.

To estimate the causal effects of floods on intra-houseold resource allocation in the 2014 cohort of villages, I limit my sample to households that are located in villages that were actually flooded and comparable villages that had a similar probability of flooding but were not exposed. Estimates from the structural model show that, for an average household, experiencing a flood is associated with a decrease in women's resource share by 4.4 percentage points six months after the flood and this decrease is absorbed by men and children in the household. However, these effects are statistically insignificant. Over time, this gendered disparity intensifies, with women experiencing a 16.2 percentage point decrease in resource share four years post-flood, while men witness an increase of 16.3 percentage points. These effects are significant at 5% level. Children's resource share decreases by 0.1 percentage points which is both statistically and economically insignificant.

Subsequently, I calculate the material well-being of individuals within the household by multiplying estimates for the share of the total household budget allocated to men, women, and children with observed total household expenditure. This product, known as the shadow budget, represents the budget assigned to a household member to maximize their individual utility.

Four years after the flood, I find that in treated households women have an average daily shadow budget of \$4.47 (in 2010\$), relative to men that have an average shadow budget of \$8.94 per day. In untreated households, men and women, have a daily shadow budget that is \$7.03 and \$8.53, respectively. Therefore, men in treated households have are more materially well-off than men in untreated households. Interestingly, this is despite the fact that exposure to the flood decreased total household expenditures by around 12% both in the short and longer run. Taken together, this implies that even though the overall household budget decreases after a flood, men in these households actually become better off while the women are worse off relative to households in the untreated group. This occurs because of the redistribution of resources away from women towards men in the households.

This approach to studying the heterogeneous effects of a climate-related shock *within* the household is unprecedented and offers a unique data-driven method to determine the direction in which household resources are reallocated. Existing papers in the climate-economy literature investigate the effects of climate shocks on consumption and income for the household as a unit (e.g. Noy, Nguyen, and Patel 2021), but overlook the intra-household dimension. To the best of my knowledge, this is the first paper to analyze the individual-level impacts of a climate shock on consumption within the same household.

The rest of this paper is organized as follows: Section 2 will discuss background and contribution of this study to the existing literature. Section 3 will outline the structural model for identification of resource shares over time and important assumptions. I describe the household and flood data I use in Section 4 along with evidence for variation in the timing of treatment across villages in my sample. In Section 5, I predict the ex-ante probability of flooding at the village level, use this to select villages that have a similar probability of flooding, and show that for the selected sample, exposure to flooding can be considered as good-as-random. Preliminary results from the structural model are presented in Section 6, and Section 7 provides evidence against mechanisms such as male migration and changes in fertility. Finally, Section 8 concludes.

2 Background

In recent years, the collective household model has become the main framework through which household allocation decisions are studied (see, for example, Browning, Chiappori, and Weiss 2014). This model characterizes the allocation problem for a collection of individuals, all of whom have their own objective functions and interact with each other to yield Pareto efficient allocations (Chiappori 1988, 1992). A few studies have developed methods based on this model to estimate the proportion of the total household budget allocated to each individual, i.e. the resource share.

Lewbel and Pendakur (2008), Browning, Chiappori, and Lewbel (2013)[2], and Dunbar, Lewbel, and Pendakur (2013) (hereafter DLP) are some prominent studies in this area. The first two studies identify resource shares in a child-less setting, whereas the DLP model allows for nuclear families.

Specifically, the DLP model identifies individuals' resource shares by using Engel curves of private assignable goods and imposing semi-parametric restrictions on preferences of household members. This model has been extended in recent years to allow for complex household types (Calvi 2020), linear re-framing of the originally non-linear model (Lechene, Pendukar and Wolf 2022), and relaxed restrictions on preferences (Brown, Calvi, and Penglase 2021; Sokullu and Valente 2021).

Most of the aforementioned papers use resource shares as a means to estimate individual-level poverty at a point in time.[3] A few studies utilize resource share estimation as a way to evaluate the effects of policies that improve the status of women in the household. Calvi (2020) found that strengthening women's inheritance rights in India increased the share of resources devoted to them. Similarly, Tommasi (2019) found that access to a conditional cash transfer program targeted towards women redistributed resources away from fathers towards mothers in beneficiary households in Mexico.

Sokullu and Valente (2021) is the only other paper that studies the evolution of resource shares in a panel data setting to evaluate the effects of PROGRESA in Mexico. However, they only study effects over 13 months. Contrary to Tommasi (2019), they find that roughly one year after the program started, mother's share of household resources declined in treated households and there is a reallocation of resources away from mothers towards children of the household.

Although the approach in Sokullu and Valente (2021) relaxes some restrictions on preferences present in DLP, it require some degree of price stability over the study period. This constraint makes it less suitable for analyzing resource share evolution over several years, as in my study. Therefore, I adopt a different set of identifying assumptions that I argue are better suited for longer-term analyses. This paper represents the first attempt to investigate the reallocation of household resources in response to a climate shock, spanning a period of four years.

Qualitative field research in South Asia suggests that floods could disproportionately affect the status of women in the household. Cultural norms in the region dictate that women are responsible for household work such as providing clean drinking water and food in any climate stressed situation. Memon (2020) interviews women in flood prone areas of Pakistan and finds that when women are unable to fulfil their household duties in a satisfactory manner after a flood, they can be met with

[2]Intra-household resource distribution not only gives us insight into the consumption dynamics within a household, but also informs us of the bargaining power of individuals. Browning, Chiappori, and Lewbel (2013) show that there is a monotonic correspondence between the fraction of total household expenditure allocated to an individual (i.e. their resource share) and their bargaining power.

[3]For example, in their seminal paper, Dunbar, Lewbel, and Pendakur (2013) use data from Malawi to show that children have higher rates of poverty than their parents.

emotional or physical violence. In Bangladesh, Rezwana and Pain (2020) discuss how women's household work and responsibilities increase after a flood, making it difficult for them to search and take-up new jobs. This increases their dependence on other household members. In other cases, women report that men marry additional wives for dowry money to help address poverty. These findings insinuate that flood shocks could change the relative bargaining power of household members.

The new climate-economy literature is limited in its ability to characterize distributional impacts of climate-indiced shocks, such as floods, within the household. Therefore most studies are unable to address any disproportionate impacts on women. Existing papers study the effects on consumption and income at the household level (Anttila-Hughes and Hsiang 2013; Poaponsakorn, Meethom, and Pantakua 2015) rather than for individuals. A few studies look into how effects could vary by sector of economic activity (Noy, Nguyen, and Patel 2021) and time since the flood shock (De Alwis and Noy 2019; Mueller and Quisumbing 2011). Some papers delve into risk-coping strategies employed by affected households. For example, Gianelli and Canessa (2022) find an increase in male migration in households exposed to a flood.

To my knowledge, Gianelli and Canessa (2021) is the only paper that is tangentially related to my study. The authors focus on the 2014 monsoon flood in Bangladesh and find that women increase their labor supply as a coping strategy and self-report higher levels of bargaining power. While this paper explores a connection between floods and bargaining power, it does not extend its analysis to how floods affect the distribution of household budgets among members, thus omitting insights into changes in the material well-being of household members. Secondly, the authors use self-reported measures of decision-making as a proxy for bargaining power, which can suffer from subjective biases. I argue that resource allocation as a measure of bargaining power does not suffer from such biases, as they are estimated solely from observing family characteristics and consumption of goods.

3 Intra-household allocation of resources

This section outlines the theory and estimation strategy for identifying the fraction of total household expenditure allocated to men, women and children in the household – i.e. their resource share. As we cannot observe how household members divide the household budget amongst themselves, there is a need to model the allocation problem of the household to estimate the share of the total household budget consumed by an individual household member or different types of household members (for example men, women and children).

In this section, I will describe the structural model developed in Dunbar, Lewbel, and Pendukar (2013) to identify resource shares in the cross-section and extend it to identify resource shares in a panel data setting. For simplicity, I focus on households that have one man, woman, and child. The model can be generalized to nuclear households with multiple children and extended households.

It is important to note that households differ in terms of observable characteristics such as composition, socio-economic attributes, and exposure to the "treatment", i.e. a flood. These differences could affect preferences, bargaining power, and how resources are allocated within the household. However, these covariates are not *required* for identification of resource shares, so I omit them from the model below to simplify notation and convey what drives the identification of resource shares. These covariates will enter into the model in the empirical estimation to allow for some flexibility in preferences and resource shares across households.

3.1 The efficient collective household model

In this model, in any time period t, all household members J come together to purchase K goods at market prices $p_t = (p_t^1, ..., p_t^K)$. The vector of total observable quantities of goods purchased by the household is $z_t = (z_t^1, ..., z_t^K)$, and the unobservable quantities of goods consumed by household member j is given by $x_{jt} = (x_{jt}^1, ..., x_{jt}^K)$.

A linear "consumption technology" transforms household-level purchased goods z_t to individual-level consumption x_{jt}. This consumption technology is represented through a $K \times K$ matrix A such that $z_t = A \sum_{j=1}^{J} x_{jt}$. Therefore, if there is one man, one woman and one child, $z_t = A(x_{mt} + x_{wt} + x_{ct})$. Matrix A also allows us to express the unobserved shadow prices of goods as $A'p_t$. This means that for shared goods with economies of scale like gasoline or heating, the shadow price of that good will be less than the market price. If goods are not shared by members, then the shadow price should equal to the market price.[4] Intuitively, if we could solve for the bundle of goods x_{jt} and price it at shadow prices $A'p_t$, we will get the value of total consumption for individual j. Dividing by the total household expenditure would give us the share of total household resources allocated to that individual.

Following the literature, I assume an efficient collective household model in which every household member j has their own utility function $U_{jt}(x_{jt})$, and within-household allocation of goods is Pareto efficient. $U_{jt}(x_{jt})$ is twice continuously differentiable, monotonically increasing and strictly quasi-concave over the vector of goods x_{jt}.The household maximizes a joint social welfare function U_{ht} in which the preferences of each individual are weighted. These weights are called "Pareto weights"

[4] A is a block diagonal matrix that allows for sharing or jointness of consumption for all good except a private assignable good – a good that is consumed exclusively by a known member of the household. For any private assignable good, there will be a 1 in the elements corresponding to this good and all off-diagonal rows and columns for this good will be 0. This is because these goods do not have any economies of scale in consumption (since they are not shared). The off-diagonal elements being 0 implies that there are no complementarities in consumption for these goods. For any shared goods, like shelter or gasoline, there are no restrictions on complementarities and economies of scale.

and denoted as μ_{jt} below:

$$U_{ht}(U_{jt}(x_{jt}), ..., U_{Jt}(x_{Jt}), p_t, y_t) = \sum_{j=1}^{J} \mu_{jt} U_{jt}(x_{jt}) \tag{1}$$

where y_t is total household expenditure and J is the total number of members. Broadly speaking, these weights are measures of intra-household bargaining power: the larger the weight, the greater the bargaining power. Browning, Chiappori, and Lewbel (2013) show that there is a one-to-one correspondence between resource shares and bargaining power.

The household solves the following optimization problem in any time period t:

$$\begin{aligned} \max_{z, x_1, ..., x_N} \quad & U_{ht}(U_{jt}(x_{jt}), ..., U_{Jt}(x_{Jt}), p_t, y_t) \\ \text{s.t.} \quad & z_t = A \sum_{j=1}^{J} x_{jt} \\ & y_t = z_t' p_t \end{aligned} \tag{2}$$

The solution of this optimization problem gives the private quantities for the vector x_{jt} for each member j. Pricing x_{jt} at shadow prices $A'p_t$ and scaling by y_t yields the resource share of individual j at time t, which is denoted as η_{jt} below. This is the parameter of interest.

Assuming an efficient collective model implies that the solution to the household's allocation problem above can be equivalently represented as a two-step process: In each time period, (1) household members allocate resources so that the shadow budget constraint $\eta_{jt} y_t$ for each household member can be determined; and then (2) each member j chooses bundle x_{jt} that maximizes their utility subject to shadow prices $A'p_t$ (which are the same for all members), and a shadow budget constraint $\eta_{jt} y_t$ (which are different across members).

We can express the household's demand for a good k as follows:

$$z_t^k = A^k \sum_{j=1}^{J} h_{jt}^k(\eta_{jt} y_t, A' p_t) \tag{3}$$

where $h_j^k(\eta_j y, A'p)$ is individual j's Marshallian demand for good k subject to the shadow price and their shadow budget constraint.

For example, if a household had one man, one woman, and one child, the household demand for good k would be:

$$z_t^k = A^k (h_{mt}^k(\eta_{jt} y_t, A' p_t) + h_{jt}^k(\eta_{wt} y_t, A' p_t) + h_{jt}^k(\eta_{ct} y_t, A' p_t)) \tag{4}$$

If a good j is privately consumed by only person j, then the household's demand for that good simplifies because there are no economies of scale and good j factors into only the utility function for person j.

$$z_t^j = h_{jt}^j(\eta_{jt}, y_t) \tag{5}$$

In what follows, to simplify notation, the Marshallian demand for a good consumed exclusively by person j is represented as $h_{jt}(\eta_{jt}, y_t)$.

3.2 Identification of resource shares

Dunbar, Lewbel, and Pendukar (2013) show that resource shares for a person j where $j = m, w, c$ can be identified in the cross-section by comparing the slopes of the household's Engel curves for a private good that is assignable to each person j. An Engel curve captures the relationship between the share of total household budget spent on a good and total household expenditure, holding prices fixed. A private assignable good (PAG) is a good that is not shared and is consumed exclusively by a known member of the household. Examples include food, clothing or footwear, among others. The PAG in this paper is the food consumption of person j. Food is private in the sense that a unit of food eaten by one person cannot also be consumed by someone else. It is also assignable because the Bangladesh Integrated Household Survey (BIHS) – the household data I am using for this analysis – has information on food consumption of each household member.[5]

The Marshallian demand for a private good j that is assignable to person type j can be derived from that individual's indirect utility function. Following Dunbar, Lewbel and Pendukar (2013) I assume that η_{jt} is independent of y_t in poor households[6] and that each person j has their own PIGLOG indirect utility function:

$$V_{jt}(p_t, y_t) = \psi_{jt}\left[ln\left[ln\Big(\frac{y_t}{G_{jt}(p_t)}\Big)\right] + F_{jt}(p_t), \tilde{p_t}\right] \tag{6}$$

where p_t is the price of all goods including the PAGs, $\tilde{p_t}$ is the price of all goods except the PAGs. G_{jt} is an individual-specific expenditure deflator function, that is non-zero, differentiable and homogenous of degree 1. F_{jt} is also individual-specific, differentiable, and homogenous of degree 0. ψ_{jt} is differentiable and strictly monotonically increasing. The price of the PAG for person j is p_{jt}.

[5]If the BIHS did not have information on individual level food consumption, food would still have been a private good but not assignable and could not have been used for estimation.

[6]This assumption implies that if a household's total expenditure increases, resource shares across household members would not change. This is quite a strong assumption, but there is some empirical support for it (Menon, Perali, and Pendakur 2012). Note that this restriction does not apply to variables closely related to expenditure, such as measures of wealth.

To derive person j's Marshallian demand for the PAG in a given time period, apply Roy's identity, i.e. $h_{jt}(p_t, y_t) = -\frac{\partial \psi_{jt}(.)}{\partial p_{jt}} / \frac{\partial \psi_{jt}(.)}{\partial y_t}$.

This gives the following expression (surpressing arguments of G_{jt} and F_{jt} for conciseness):

$$h_{jt}(p_t, y_t) = y_t \left(\frac{G'_{jt}}{G_{jt}} + F'_{jt}\, lnG_{jt} \right) - F'_{jt}\, y_t\, lny_t, \tag{7}$$

where G'_{jt} and F'_{jt} are first derivatives with respect to p_{jt}.

As an individual makes a consumption decision based on their shadow budget constraint $\eta_{jt} y_t$, and shadow prices $A' p_t$, $h_{jt}(p_t, y_t)$ can be expressed as :

$$h_{jt}(A' p_t, \eta_{jt} y_t) = \eta_{jt}\, y_t \left(\frac{G'_{jt}}{G_{jt}} + F'_{jt}\, lnG_{jt} \right) - F'_{jt}\, \eta_{jt}\, y_t\, ln(\eta_{jt}\, y_t) \tag{8}$$

To express as budget shares of the PAG, multiple both sides by $\frac{p_{jt}}{y_t}$:

$$W_{jt} = h_{jt}(A' p_t, \eta_{jt}\, y_t) \frac{p_{jt}}{y_t} = p_{jt}\, \eta_{jt} \left(\frac{G'_{jt}}{G_{jt}} + \; F'_{jt}\, lnG_{jt} \right) - p_{jt} F'_{jt}\, \eta_{jt}\, ln(\eta_{jt}\, y_t) \tag{9}$$

where W_{jt} is the share of the total household budget that is spent on good j that is assignable to person j.

Rearranging terms:

$$W_{jt} = p_{jt}\, \eta_{jt} \left(\frac{G'_{jt}}{G_{jt}} + \; F'_{jt}\, lnG_{jt} \right) - p_{jt} F'_{jt}\, \eta_{jt}\, ln\eta_t - p_{jt} F'_{jt}\, \eta_{jt}\, lny_t \tag{10}$$

To simplify equation (9), let $\alpha_{jt} = p_{jt} \left(\frac{G'_{jt}}{G_{jt}} + \; F'_{jt}\, lnG_{jt} \right)$ and $\beta_{jt} = -p_{jt}\, F'_{jt}$. This simplifies the Engel curve for a PAG for person j in time t to:

$$W_{jt} = \; \eta_{jt}\, \alpha_{jt} + \beta_{jt}\, \eta_{jt}\, ln\eta_{jt} + \beta_{jt}\, \eta_{jt}\, lny_t \tag{11}$$

An Engel curve describes the relationship between the budget share of person j's PAG and total household expenditure, keeping prices constant. With PIGLOG preferences, this curve is linear in ln$y$[7], and α_{jt} and β_{jt} can be interpreted as preference parameters because they determine the intercept and slope of this curve. β_{jt} can be loosely interpreted as the marginal propensity to consume the PAG as household expenditure increases.

To estimate the resource shares of person j at any given time t, I would ideally like to estimate a

[7] A popular example of such Engel curves is the "Almost Ideal" demand system of Deaton and Muellbauer (1980).

system of Engel curves, one for each person j:

$$\begin{aligned}
W_{wt} &= \left[\eta_{wt}\alpha_{wt} \ + \beta_{wt}\eta_{wt}\, ln\eta_{wt}\right] \ + \eta_{wt}\beta_{wt}\, lny_t, \\
W_{mt} &= \left[\eta_{mt}\alpha_{mt} \ + \beta_{mt}\eta_{mt}\, ln\eta_{mt}\right] \ + \eta_{mt}\beta_{mt}\, lny_t, \\
W_{ct} &= \left[\eta_{ct}\alpha_{ct} \ + \beta_{ct}\eta_{ct}\, ln\eta_{ct}\right] \ + \eta_{ct}\beta_{ct}\, lny_t.
\end{aligned} \tag{12}$$

With data on budget shares and total household expenditure, we could regress W_{jt} on y_t, and the slope would estimate $\eta_{jt}\beta_{jt}$, while the constant would estimate the term in the brackets. However it is not possible to identify η_{jt} from this system, as there are only 6 moment conditions (3 slopes and 3 intercepts) and 9 unknowns for any period t. If we account for the restriction that $\eta_{mt}+\eta_{wt}+\eta_{ct} = 1$, it brings the number of unknown parameters down to 8, but the model is still under identified.

Therefore further restrictions are needed on the unknown parameters to identify η_{jt}. One possible assumption is that $\beta_{jt} = \beta_t$, which implies the marginal propensity to consume the private assignable good varies across time, but is the same across individuals.

Recall that $\beta_{jt} = -p_{jt}\, F'_{jt}$. Therefore, for $\beta_{jt} = \beta_t$, both p_{jt} (i.e. the price of the private assignable good for person j) and the derivative of $F_{jt}(p_t)$ with respect to p_{jt} must not vary with j. The private assignable good in my setting is food, therefore the price of this good must be the same across individuals, since food prices do not vary based on who is consuming the good.

Similarly, I require that $F'_{jt} = F'_t$. This restriction implies that the shape of the Engel curves for the PAG will be the same across j.[8] It is important to note that it does *not* imply that preferences for the PAG are *identical* across j, as they can still vary across j through an intercept shift (i.e. through the α_{jt}). In the Appendix, I provide a fully specified example of an indirect utility function that satisfies this requirement.

With $\beta_{jt} = \beta_t$, the number of unknown parameters reduces to 6 in a given time period t and matches the number of moment conditions, allowing the identification of η_{jt} by taking the ratio of the slopes and solving for η_{jt}. If the slope of the Engel curve is steeper for men relative to women, then it means they have a higher share of household resources devoted to them.

3.3 Illustration of identification of resource shares from Engel curves

Figure 1 demonstrates the intuition behind identification of resource shares at a time period t. Recall that information on floods or any other household socio-economic attributes (except for

[8] This restriction is tantamount to applying the Similarity Across People (SAP) restriction in Dunbar, Lewbel, and Pendukar (2013) for each time period t.

their total household expenditure and budget shares on a private assignable good) is not required for identification of η_{jt} for a set of households in time t. Identification of η_{jt} comes from the slopes of Engel curves of a private assignable good and the identifying assumptions in section 3.2.

For simplicity, I only consider households with one man and one woman in this example, therefore $\eta_{mt} + \eta_{wt} = 1$. The horizontal axis plots the logarithm of total household expenditure and the vertical axis plots the budget share spent on a private assignable good, such as food consumed, for men and women denoted as W_{mt} and W_{wt}. If the budget shares for a private assignable good and total household expenditure are observable, then we can draw these Engel curves for a hypothetical homogeneous set of households.

The slopes for men and women are $\eta_{mt}\beta_{mt}$ and $\eta_{wt}\beta_{wt}$ (system 12), and these will be estimated as the coefficients on ln$y$ when it is regressed on W_{mt} and W_{wt}, respectively. Under the shape-similarity assumption that $\beta_{mt} = \beta_{wt} = \beta_t$, resource shares can be backed out by taking the ratio of the slopes of men and women, setting it equal to the ratio of the coefficients on ln$y$ and solving for η_{wt} and η_{mt}. After the cancellation of the β_t terms, two unknown parameters remain, along with two equations: the ratio of the slopes and the condition that resource shares sum to one (i.e., $\eta_{mt} + \eta_{wt} = 1$). This results in a situation where the model is just identified.

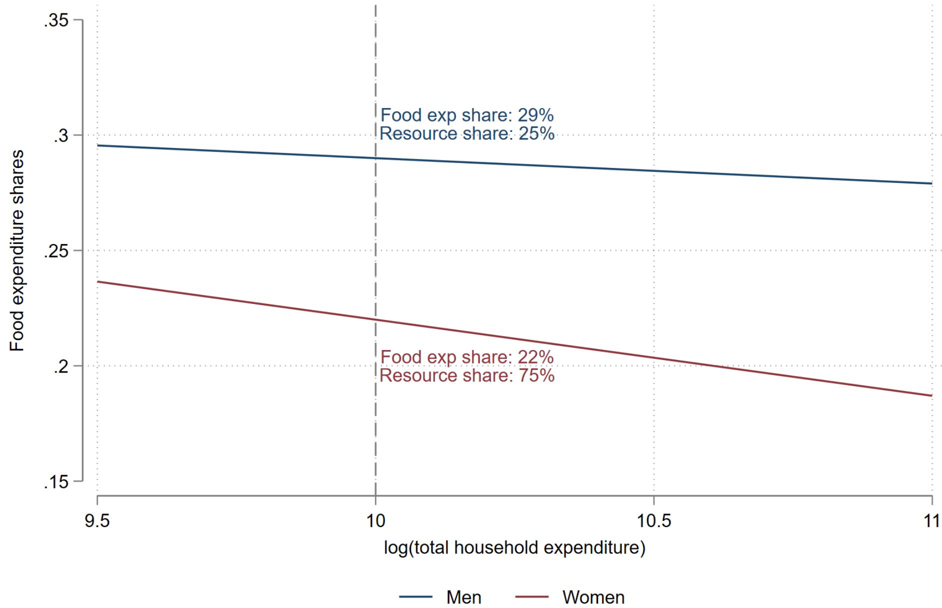
Note that Figure 1 also shows that budget shares for a private assignable good are not necessarily indicative of the share of total household resources allocated to that individual. In this hypothetical example, men have a higher food budget share which could reflect their tastes, different calorie requirements, etc. However, the *slope* of their Engel curve is one third that of women, therefore women have a higher resource share than men.

In the next subsection, I will introduce floods explicitly in the estimation of the system of Engel curves in (12) that will allow me to compare the distribution of household resources in households that are randomly "treated" by a flood verses untreated households.

3.4 Estimation of resource shares

I apply Nonlinear Seemingly Unrelated Regression (NLSUR) to estimate the set of Engel curves (12) because there might be correlated errors across equations. To allow preferences and resource shares to vary flexibly across households, I model each unobservable parameter—η_{jt}, β_t, and α_{jt}—as a linear combination of observable household socioeconomic characteristics, time variables, and exposure to flooding.

Figure 1: Example of Engel curves for men and women



Notes: This figure shows hypothetical Engel curves for a private assignable good (food in this case) for men and women at a time period t across a group of households that is homogeneous except for their total household expenditure and food expenditure shares. Children are excluded from this example. The Engel curve for women is three times as steep as that for men. Both Engel curves are downward sloping in accordance with Engel's Law.

More specifically, the resource share η_{jt} for person type $j = m, w, c$ are modeled as:

$$\eta_{jt} = \eta_{0j} + \eta_{1j} Flood_h + \eta_{2j} Survey2 + \eta_{3j} Survey3 + \eta_{4j} Flood_h \times Survey2 + \eta_{5j} Flood_h \times Survey3 + \eta_{6j}(X_{ht} - \overline{X}_{ht}), \tag{13}$$

where $Flood_h$ is an indicator variable for whether the household was exposed to a flood, $Survey2$ and $Survey3$ are indicator variables referring to the second and third rounds of the BIHS survey (baseline survey conducted in 2011/12 is the reference period), and X_{ht} refers to the numbers of men, women and children in the household, and the age of the youngest child. For the 2014 cohort, the parameters η_{4j} and η_{5j} indicate if resources move away or towards type j with exposure to a flood in the short and longer-run, respectively. Household composition variables are centered around the mean, so that estimates of the constant term $\hat{\eta}_{0j}$ reflect the resource share for person type j for the average household at baseline (2011). The β_t, and α_{jt} terms are modelled similarly.

Appendix A1 provides a graphical illustration of how the parameters η_{4j} and η_{5j} are identified in the Engel curve framework.

4 Data

4.1 Flooding data

My primary source for flood maps is the Global Flood Database (GFD)[9] which uses daily satellite imagery at 250-metre resolution to estimate flood extent for 913 large flood events documented by the Dartmouth Flood Observatory (DFO) from 2000 to 2018 (Tellman et al. 2021). For each flood event, the GFD provides a map that shows the maximum observed surface-water extent, the start and end date of the flood, as well as an estimate for the the population that was exposed. It is important to note that the DFO catalogue is compiled largely from news reports, so event maps provide a lower bound of maximum flood extent.

From the GFD, I map 97 floods that affected Bangladesh between 2000 to 2018.[10] I remove permanent surface water from these maps to be able to better distinguish flood water. As an example, Appendix Figure B2 shows the flood map for one event that occurred from August 20 to September 8 in 2014 that impacted around 11 million people.

The GFD also allows me to generate a satellite-based flood plain that outlines all areas that have experienced a flood from 2000 to 2018. This is one of the variables I use to predict the probability of flooding in villages that described in more detail in Section 5.

4.2 Household level data

I use all three waves of the Bangladesh Integrated Household Survey (BIHS), which is a household panel survey nationally-representative of rural Bangladesh conduced by International Food Policy Research Institute (IFPRI) in 2011/12, 2015, 2018/19 covering around 5,500 households (Akhtar, 2013; IFPRI, 2016; IFPRI, 2020).[11] Households are located in all of Bangladesh's 64 districts and in 275 villages. It contains detailed information about socio-econoic characteristics of the household, including demographics, household expenditures, employment, agricultural activities, and migration. Most importantly, unlike typical household panel surveys, it contains information on food intake of each individual household member. As explained in Section 3, this disaggregated information, even if it is just for the food module, provides crucial information on a private assignable good (PAG) – a good consumed exclusively by a known member of the household – that is necessary for estimating resource shares.

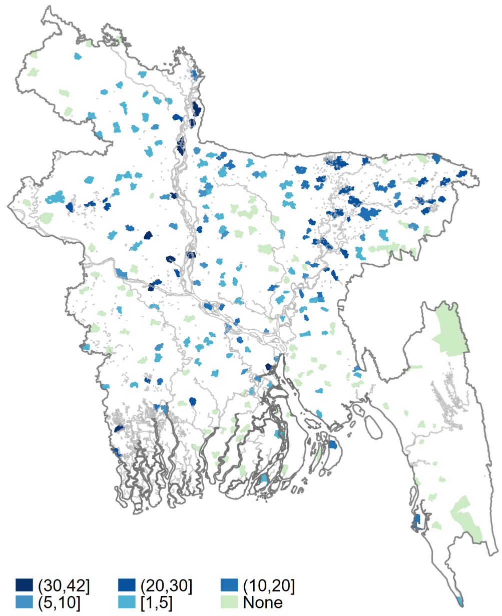
To my knowledge, the BIHS is the only publicly-available household survey in a developing country

[9] https://global-flood-database.cloudtostreet.ai/

[10] 91 of these floods were due to heavy rain, 2 due to dams, and 4 due to a tropical storm.

[11] The BIHS defines a household as a group of people who live together and take food from the "same pot". If two brothers stay in the same house with their families but they do not share food costs and they cook separately, then they are considered two separate households.

Figure 2: Cumulative number of floods across villages from 2000 - 2018



Notes: The unions in which the villages are located are presented in this graph instead of village GPS coordinates, to protect the identity of individual villages. Shades of blue indicate the number of times each village has been hit by a flood from 2000 to the final round of the BIHS survey in 2018/19. Villages in green-shaded unions did not get hit by any floods from 2000 to 2018. Gray lines show inland perennial water.

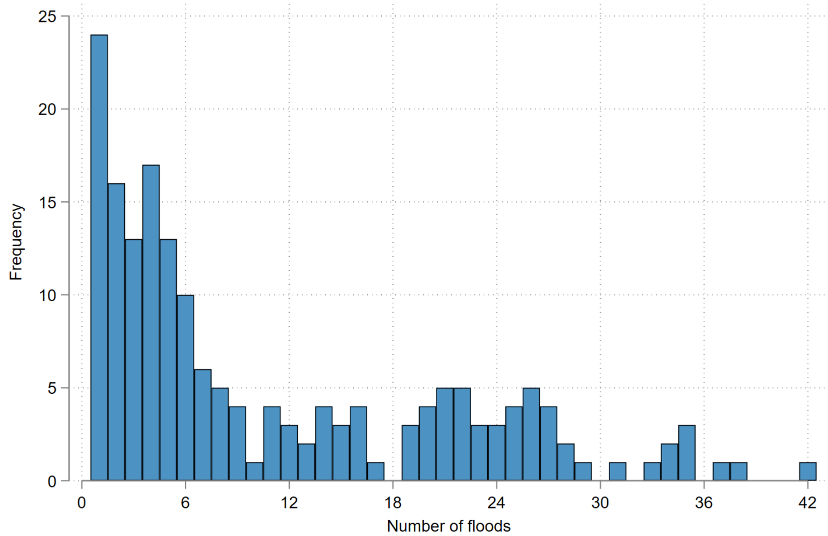
that contains disaggregated information on the PAG for each household member. This means that I can estimate resource shares by gender, age, or any other observable characteristic. For this analysis, I estimate resource shares of adult men, adult women and children.[12]

Utilizing all three rounds of the BIHS, I initially had a baseline sample of 5,543 households, of which 4,603 were surveyed across all three rounds. Around 8% of the baseline sample was lost after either round 1 or round 2, 1.6% of the baseline sample was interviewed in rounds 1 and 3 but missing in round 2, and 7.7% of households in round 1 split into different households by time of the last survey. After removing outliers, such as households with more than five children and those with total household expenditures above the 99th percentile, as well as dropping households with missing values for food budget shares – which will be the left hand side variable when estimating the system of Engel curves in (12) – the sample reduced to 3,010 households located in 275 villages. From this subset, I focus on the 1,596 households containing at least one man, one woman, and one child.

To determine whether villages in my sample were exposed to floods, I use data from IFPRI on village GPS coordinates which have been randomly displaced by up to 5km to protect the confidentiality

[12]I define adult as any individual of 16 years or above at the time of the baseline survey in 2011. A child is anyone 15 years or below during the 2011 survey.

Figure 3: Frequency of flooding from 2000 - 2018



Notes: Frequency of floods in the 179 villages that experienced at least one flood from 2000 to the third round of the BIHS survey in 2018/19. The mean number of floods for these"treated" villages is 11.02.

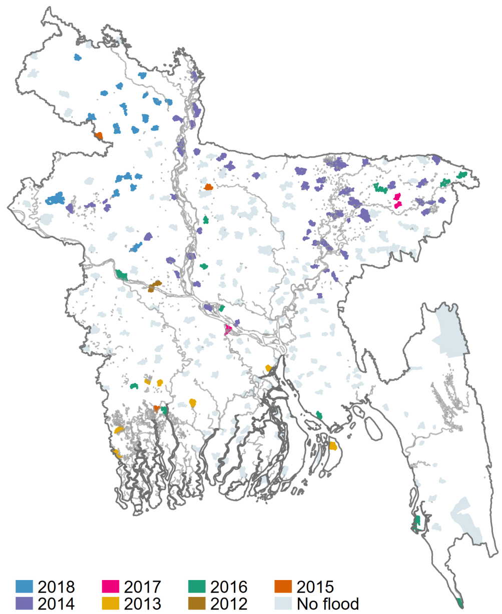
of surveyed households. I create a buffer of 5km around these village GPS coordinates, overlay it with each of the 97 flood maps for Bangladesh from 2000 to 2018, and compute the share of area within 5km of the village that was inundated during each flood event. I binarize this treatment as equal to 1 if more than 15% of the area around the village is flooded and 0 otherwise. Treatment is assigned at the village level, and all households in the village are considered treated (or untreated).

Figure 2 illustrates the frequency of floods experienced by villages from 2000 up to the last survey conducted in 2018/19. To protect the identity of individual villages, the graph depicts the union (a level 4 administrative boundary) in which each village is located. Villages within green-shaded unions indicate areas that remained unaffected by flooding. Approximately 35% of the villages within my sample (96 villages) did not encounter any flooding.

Figure 3 shows the distribution of the number of floods experienced by the 179 villages that were exposed to at least one flood between 2000 to 2018. Around 60% of these villages experienced less than 5 floods. About 40% of the villages (71) experienced 10 floods or more. The average number of flood occurrences per village stands at 11.02.

Of the 97 floods in Bangladesh between 2000 and 2018, 20 occurred after the initial round of the BIHS survey. These floods affected 99 villages in my sample at various points in time. Figure 4 depicts the group of villages that encountered their *first* flood since the baseline BIHS survey was conducted. Among them, 84 villages faced their initial flood event in 2014, 2016, or 2018.

Figure 4: Cohorts of villages flooded from 2012-2018



Notes: The unions in which the villages are located are presented in this graph, to protect the identity of individual villages. 99 villages were hit by floods from 2012-2018 at different times. The figure shows the year they were hit by their first flood since the baseline BIHS survey.

Specifically, in 2014, 51 villages were exposed to their primary flood event since the baseline BIHS survey, forming the largest cohort of treated villages.

5 Sample selection

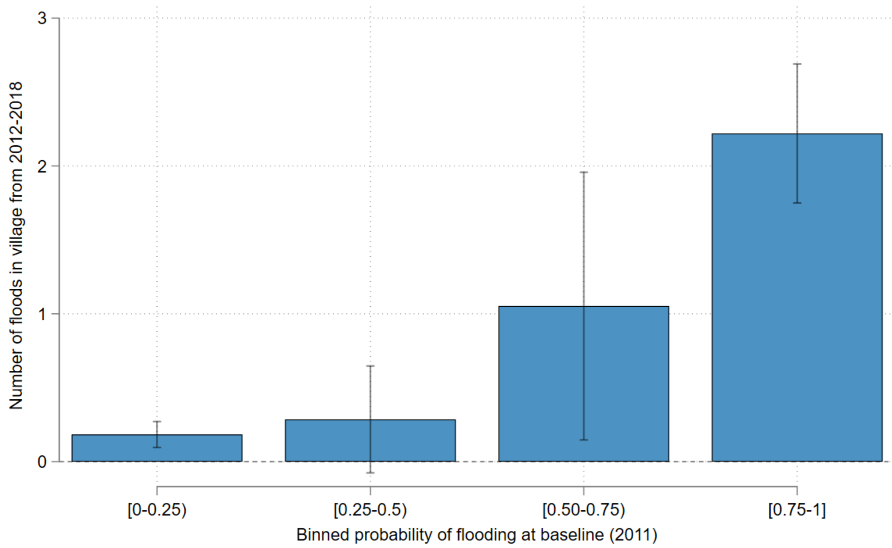
5.1 Determining probability of flooding

Figure 2 suggests that villages located in certain parts of the country may be more prone to flooding. For example, villages closer to inland waterbodies experienced a higher frequency of flooding relative to areas further away. Other characteristics such as topography, rainfall and vegetation cover, among others, could also help determine the probability flooding.[13]

Appendix Figure B3 covers four main climatic and geographic features relevant to flooding, to show the variation in these factors across the country. Panel A depicts the average annual rainfall at the village level using data over 20 years (2000 to 2020). Villages on the eastern side of the country experience relatively higher rainfall per year. Rainfall data were collected from the Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) database that combines satellite and station-level information to provide measures of rainfall over a 5km grid. As a measure of vegetation cover,

[13]https://www.usgs.gov/faqs/how-are-floods-predicted

Figure 5: Actual floods in 2012-2018 vs. ex-ante probability of flooding



Notes: Figure shows the average number of times villages in each bin were treated during 2012-2018. Error bars indicate 95% confidence intervals.

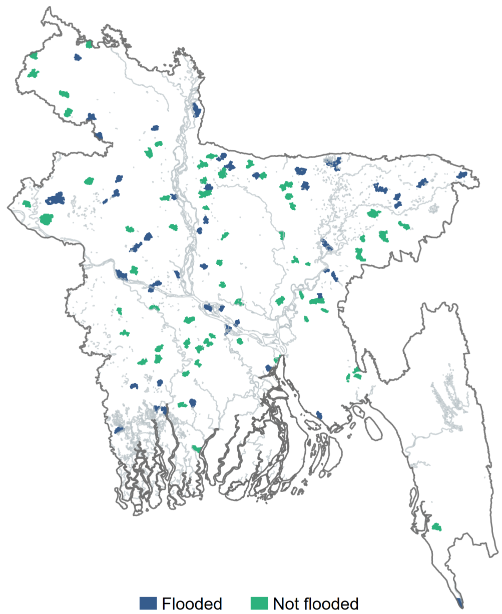
average monthly Normalized Difference Vegetation Index (NDVI) at the village level is presented in panel B of Appendix Figure B3. The NDVI is a measure of greenness, so a higher NDVI should correspond to areas with greater agriculture and vegetation. Monthly NDVI was collected using satellite imagery from January 2000 to December 2018 at 5km resolution from the NOAA AVHRR Surface Reflectance product.[14]

Panel C shows the elevation in meters.[15] The relatively lower elevation of the northeastern region compared to surrounding areas is of particular importance as it forms a saucer shaped shallow depression, making it prone to flash flooding. This geographic feature could explain why this region appears flooded in Appendix Figure B2. Lastly, panel D shows a flood risk map developed by the Bangladesh Agricultural Research Council (BARC) which outlines the areas prone to river flooding, flash flooding or tidal flooding. The map also details whether this risk is high, medium or low.[16]

To predict the probability of flooding at the village level, I estimate a probit model where the outcome variable is one if a village had experienced a flood by the time of the 2011/2012 BIHS survey and zero otherwise. The village-level regressors include a combination of time variant and invariant characteristics. The former category includes village-level trends for annual rainfall, NDVI, and

[14] https://developers.google.com/earth-engine/datasets/catalog/NOAA_CDR_AVHRR_NDVI_V5#description
[15] Obtained from https://data.humdata.org/dataset/bangladesh-contour-lines
[16] Obtained from https://data.humdata.org/dataset/bangladesh-hazards

Figure 6: Selected treated and untreated villages



Notes: Dark blue markers represent villages that actually experienced a flood in 2012-2018 and were successfully matched to control villages shown in green. To protect village confidentiality, unions in which villages are located are depicted instead of village GPS coordinates to protect village confidentiality.

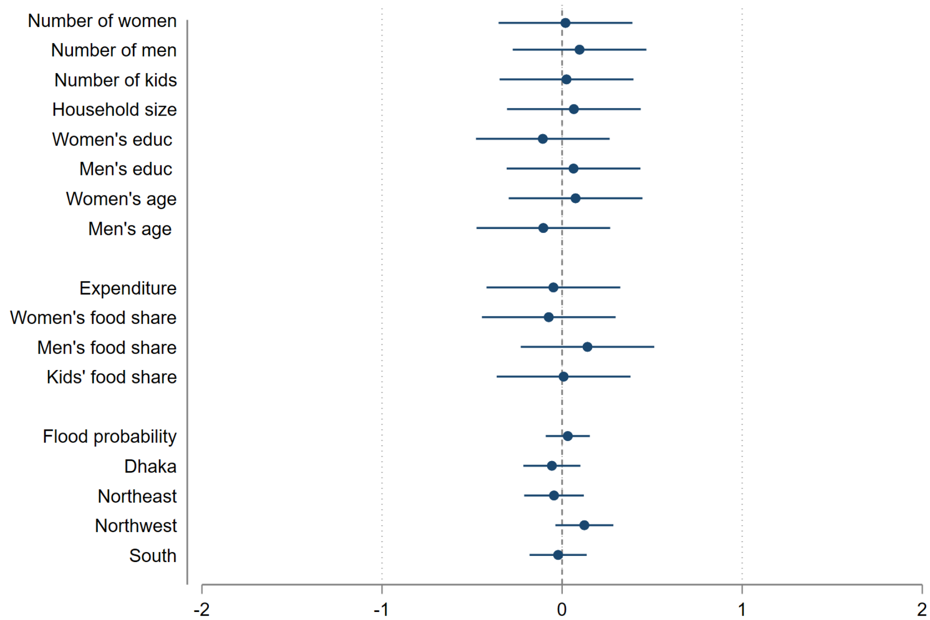
land surface temperature from 2001 until 2011. Time invariant characteristics include the village's elevation, climate zone, distance to inland surface water, administrative division, whether the village is located in a flood plain, is within 15km of a major river or stream, or is in a tidal/flash/river flooding zone as specified by the BARC. I use this model to predict the probability of flooding at baseline, i.e. 2011.

Figure 5 demonstrates the positive relationship between the ex-ante probability of flooding in 2011 and the subsequent number of floods experienced by a village from 2012 to 2018, indicating that villages with higher ex-ante probabilities are more likely to experience flooding during this period.

5.2 Selection of control villages

To estimate the causal effects of floods on intra-household allocation of resources, I need to limit my analysis to households in villages that have a similar geographic characteristics and ex-ante probability of being exposed to a flood. I accomplish this, within each cohort, I match treated villages with upto three untreated villages having an ex-ante probability of flooding within 0.3 and located within the same 100km grid. The former ensures a comparison of flooding effects between villages with similar likelihoods of flooding, differing only in treatment status, while the latter ensures geographic similarity among villages.

Figure 7: Household characteristics in treated and control villages



Notes: This figure shows the coefficient of the binary treatment variable (flooding in 2012-2018) from a series of regressions of the outcome variables listed on the vertical axis on the treatment variable. Household-level are continuous and have been standardized. Error bars indicate 95% confidence intervals.

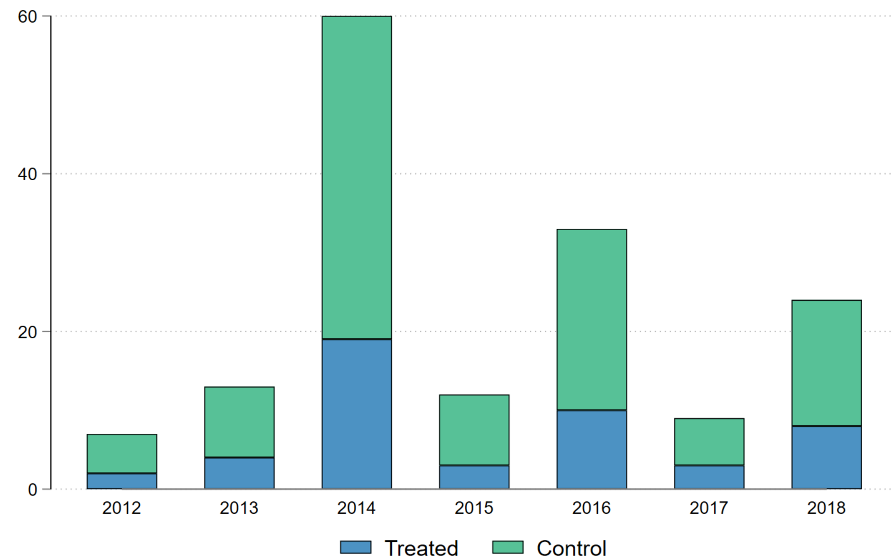
Based on this selection criteria, 49 of the 99 treated villages from 2012-2018 were matched to 69 control villages. Figure 6 shows the the geographic location of the selected treated and control villages. The dark blue colored villages actually experienced a flood in 2012-2018, i.e. more than 15% of the area around the village was inundated by flood water, and the green colored villages are comparable untreated villages based on the aforementioned selection criteria.

Figure 7 shows that households in treated and untreated villages are balanced in various socio-economic characteristics, such as household size, household composition, completed years of education, total household expenditure, and food expenditure shares at baseline. They are also balanced in terms of flood probability and geographic region. Furthermore, these covariates are not jointly significant in determining treatment status.[17] Figures B4, B5, and B6 depict event study graphs illustrating village-level rainfall, NDVI, and land surface temperature for the six years preceding the flood and the four years following it. These graphs demonstrate that there are no significant pre- or post-trends for this group of villages, reinforcing the idea that flooding can be construed as good-as-random.

Figure 8 shows the number of treated villages in each cohort that were successfully matched to

[17] F statistics: 0.47; pvalue 0.95

Figure 8: Number of villages matched across cohorts



Notes: Figure plots the number of treated villages in each cohort that were successfully matched to control villages. A total of 49 treated villages are matched to 69 unique control villages.

control villages. The 2014, 2016 and 2018 cohorts together make up 75% of all treated villages in this subsample, which is expected since 84 of the 99 treated villages belonged to these cohorts (Figure 4). Therefore, I will be focusing on these three cohorts because of their relatively larger sample size. For this paper, however, I will be focusing exclusively on the 2014 cohort which is the largest, and future iterations of this paper will include estimates from the 2016 and 2018 cohorts.

Descriptive statistics of the 391 households in the 59 villages for the 2014 cohort across all three rounds of the survey are in Table 1. On average, households had around 1 woman, 1 man and 2 children. The average nominal total household expenditure at baseline was Taka 1,13,000 which rose over time. The average share of the total household budget spent on men's food is 18.9% , 15.7% for women and 17.8% for children at baseline. The average budget share spent on non-food items is 47.6% at baseline.

6 Preliminary estimates of resource shares

Before delving into the results of the structural model, I first estimate the causal impact of flood exposure on total household expenditure. As previously mentioned, my analysis focuses on the cohort of villages that encountered their initial flood in 2014, as this group constitutes the largest cohort in my sample (see Figure 8). I observe these households in the baseline survey conducted in 2011/2012, then six months after the 2014 flood (corresponding to the second survey), and finally,

Table 1: Summary statistics for 2014 cohort only

	(1) Survey 1	(2) Survey 2	(3) Survey 3
Number of women (age 16+ in 2011)	1.212	1.199	1.174
	(0.462)	(0.431)	(0.430)
Number of men (age 16+ in 2011)	1.189	1.161	1.120
	(0.459)	(0.426)	(0.383)
Number of kids (age ≤15 in 2011)	2.026	2.199	2.263
	(0.982)	(0.956)	(0.969)
Max age of kids	9.051	11.65	14.01
	(4.200)	(4.198)	(4.357)
Min age of kids	5.077	6.586	7.926
	(3.762)	(4.513)	(5.461)
Flooded (0/1)	0.320	0.320	0.320
	(0.467)	(0.467)	(0.467)
Women's food share	0.157	0.167	0.143
	(0.0730)	(0.0782)	(0.0686)
Men's food share	0.189	0.188	0.163
	(0.0853)	(0.0758)	(0.0745)
Children's food share	0.178	0.238	0.225
	(0.106)	(0.105)	(0.100)
Total HH expenditure (10,000 Taka)	11.30	18.17	24.10
	(7.621)	(11.27)	(13.94)
Observations	391	391	391

Notes: Standard deviations in parentheses. Computed from the 2011/12, 2015, and 2018/19 BIHS surveys for households in selected treated and control villages.

four years post-flood, corresponding to the final BIHS survey conducted in 2018/19. Estimates from the second and third surveys enable me to assess the short-term impact and the impact four years later, respectively.

Table 2 illustrates the causal effect of exposure to the 2014 flood on the logarithm of total household expenditures. In Column 1, there are no statistically significant differences in total household expenditures between treated and untreated villages two years before the flood. However, Column 2 indicates a roughly 12% decrease in total household expenditures six months after the flood. Notably, these negative effects endure over time. Standard errors are clustered at the village level since that is the level of treatment assignment.

Table 2: Effect of floods on total household expenditure

	(1) Survey1	(2) Survey2	(3) Survey3
Flood	0.045	-0.128*	-0.121*
	(0.083)	(0.075)	(0.072)
Observations	391	391	391

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Sample size: 391 households in 59 villages that have similar ex-ante probability of experiencing a flood. Standard errors are clustered at the village level.

The household Engel curves for the private assignable goods for men, women and children are estimated based on the estimation strategy in Section 3.4. Table 3 presents the results of the structural model for the average household, where the household covariates in equation 13 are at the mean. At baseline, the resource shares for women, men and children are 13.2%, 57.5% and 29.3%, respectively. The gap between men and women's resource shares at baseline is 44.3 percentage points. It should be noted that this stark divide is not necessarily representative of rural Bangladesh, as the sample of villages considered in this structural estimation had very high flood risk.[18] Over time, there is trend of more gender equality between adult men and women in the household.

In treated villages, six months after the flood, the average resource share of women was 33.7%, which is 6.6 percentage points lower than the corresponding resource share for women in comparable untreated villages at this time. This drop is absorbed by men and children in the household. Men had a resource share of 45.2% in treated villages, which is 3.8 percentage points higher than men in untreated villages. Within treated households, there is a gender disparity of 11.5 percentage points, on average, in favor of men. While these effects are economically meaningful, they lack statistical significance.

Four years post-flood, this divide increases. Women's resource share in treated households, on average, is 28.2% which is 18.1 percentage points lower than the corresponding resource share for women in untreated villages. Men's resource share on the other hand is 55.8% which is 17 percentage points higher than the average resource shares for men in untreated villages. The intra-household gender disparity between men and women increases to 27.6 percentage points in favor of men, as resources get redistributed away from women. These effects are statistically significant at 5%. Put a different way, these results show that women's resource share, on average, would have been 18 percentage points higher in a counterfactual world where their village had not been flooded, and men's resource shares would have been 17 percentage points lower.

[18]The average ex-ante probability of flooding in these villages is 0.95.

Figures 9 and 10 illustrate this further. They depict the distribution of women's and men's resource shares in treated and untreated households at the time of the second household survey, when treated households had experienced a flood 6 months prior. Figure 9 shows that the distribution for women's resource shares in flooded households lies to the left of that of women in unflooded households. The opposite is seen in the distribution of men's resource shares in Figure 10.

Figures 10 and 11 plot the same distributions at the 4 years mark and show that the distribution for women's resource shares in flooded households moves further to the left, while Figure 11 shows that the distribution for men's resource shares in treated households moves further to the right. No significant changes are seen in the distribution of the predicted resource shares of children shown in Appendix Figure B7.

Table 3: Resource shares of representative household

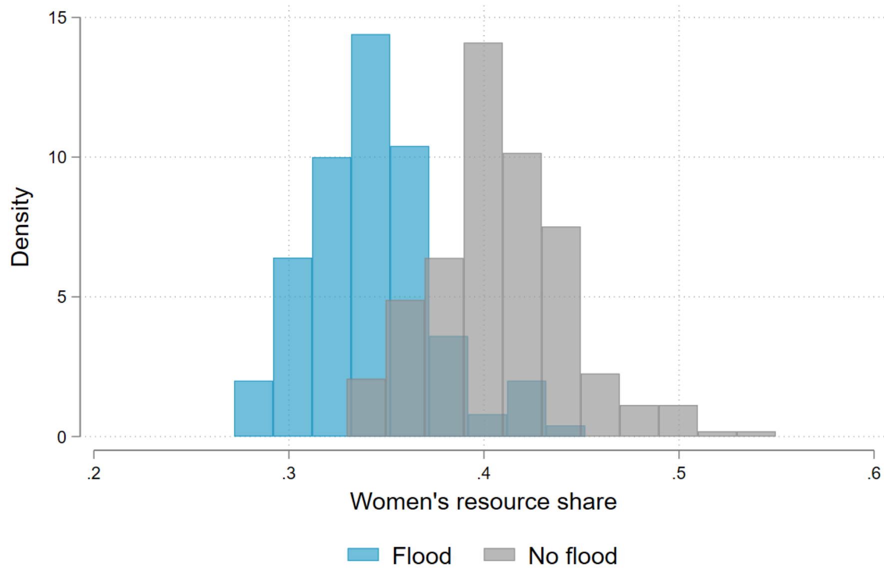
	(1) Women	(2) Men	(3) Children
Constant	0.132^{***}	0.575^{***}	0.293^{***}
	(0.007)	(0.000)	(0.000)
Survey2	0.272^{***}	-0.161^{**}	-0.111^{***}
	(0.000)	(0.011)	(0.002)
Survey3	0.331^{***}	-0.187^{***}	-0.144^{***}
	(0.000)	(0.003)	(0.000)
Flood×Survey2	-0.067	0.038	0.029
	(0.450)	(0.640)	(0.241)
Flood×Survey3	-0.181^{**}	0.170^{***}	0.011
	(0.011)	(0.005)	(0.582)

p-values in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Sample size: 391 households in 59 villages. Results are from estimation of system of Engel curves from section 3.2, controlling nonlinearly for exposure to the 2014 flood (1/0), time fixed effects, interactions of the binary flood variable with post-treatment dummies, household composition, and the age of the youngest child, as explained in equation 13. Standard errors are clustered at the village level.

To put these results in context, Calvi (2020) found that an inheritance policy for women in India improved women's resource share by 0.8-2.3 percentage points depending on whether the household had any children. Similarly, Tommasi (2019) found that access to PROGRESA in Mexico increased the resource share of mothers by 2.6 percentage points. While these papers do not look at the evolution of resource shares over time, in relative terms, the redistribution effects of a single flood are a lot stronger compared to the above mentioned programs.

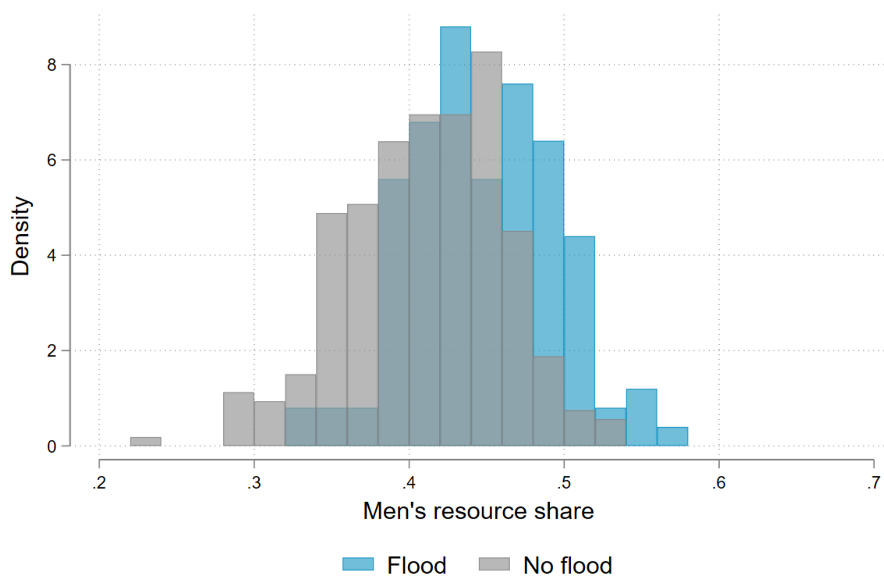
Given these estimates of the share of household resources devoted to men, women, and children in flooded and unflooded households, we can go a step further and compute their shadow budget by multiplying the estimates of resource shares within the household with the observed total household expenditure at time t– i.e. $\eta_{jt}\, y_t$. Figures 13 and 14 plot the distributions of the shadow budget

Figure 9: Distribution of women's resource share (short run)



Notes: This figure shows the distribution women's resource share in treated and untreated households at the time of the second BIHS survey, 6 months after the 2014 flood.

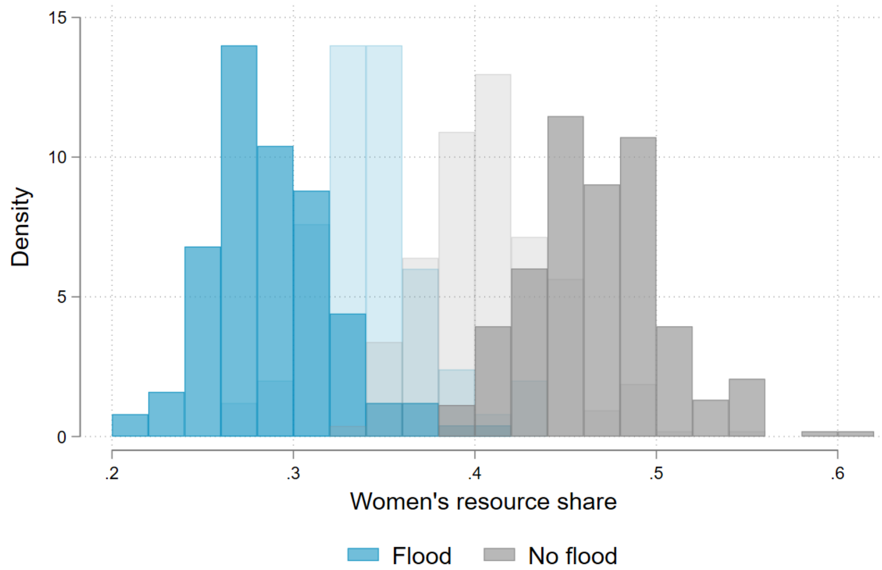
Figure 10: Distribution of men's resource share (short run)



Notes: This figure shows the distribution men's resource share in treated and untreated households at the time of the second BIHS survey, 6 months after the 2014 flood.

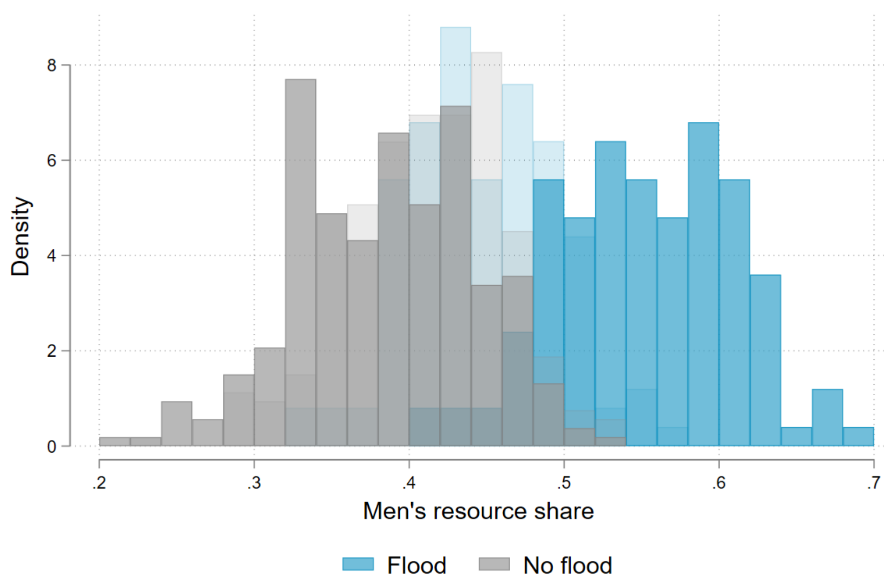
per day for men and women in treated and untreated households, respectively, four years after the

Figure 11: Distribution of women's resource share (long run)



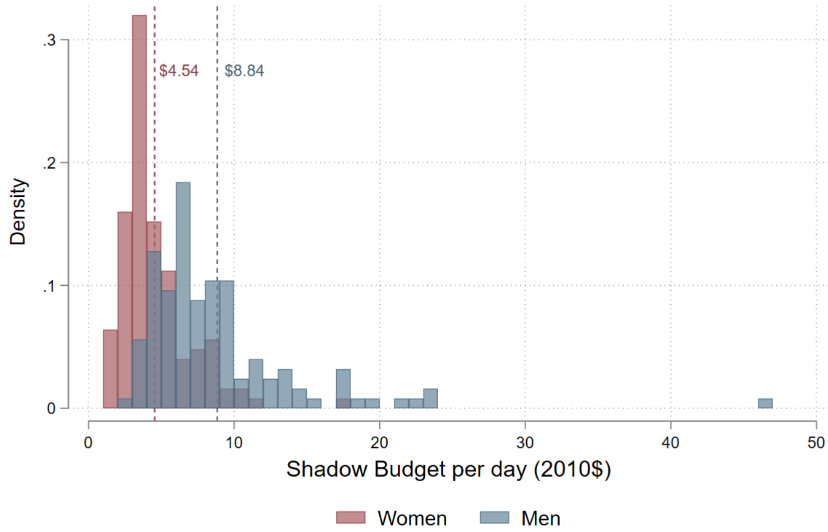
Notes: This figure shows the distribution women's resource share in treated and untreated households at the time of the final BIHS survey, 4 years after the 2014 flood. Faded bars are the distribution of women's resource shares in the short-run.

Figure 12: Distribution of men's resource share (long run)



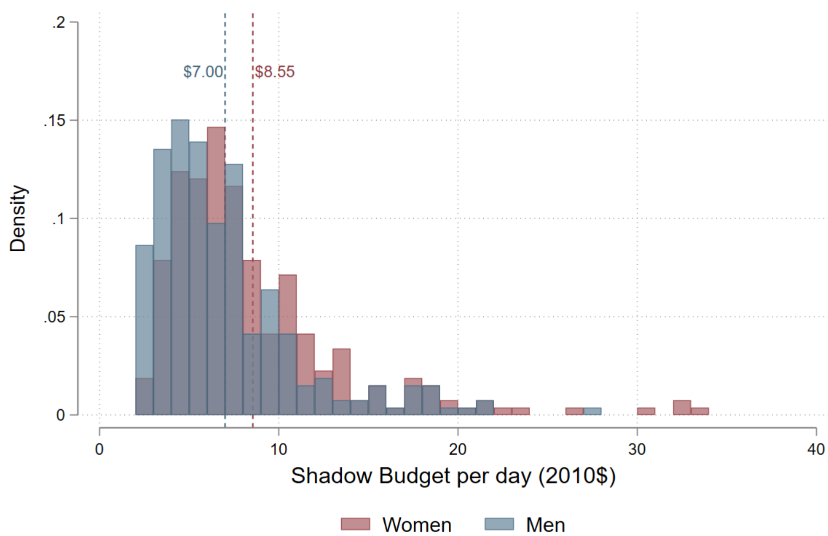
Notes: This figure shows the distribution men's resource share in treated and untreated households at the time of the final BIHS survey, 4 years after the 2014 flood. Faded bars are the distribution of men's resource shares in the short-run.

Figure 13: Distribution of the shadow budget in treated households



Notes: This figure shows the distribution of the shadow budget of men and women in households exposed to flooding. The shadow budget is computed by multiplying the estimated resource share of men, women, and children in the household with the observed total household expenditure. Vertical dashed lines denote the means of the distributions.

Figure 14: Distribution of the shadow budget in untreated households



Notes: This figure shows the distribution of the shadow budget of men and women in households not exposed to flooding. Vertical dashed lines denote the means of the distributions.

flood. All shadow budgets are represented in real 2010$.

7 Mechanisms

8 Conclusion

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