UNIVERSITY OF GOTHENBURG
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Master's Thesis in Economics

# Climate Change, Making Poor People Poorer?

## An assessment of climatic shocks on household income in Bangladesh.

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## Abstract

As global average temperatures are increasing due to climate change, economic impacts are increasingly palpable. A major concern is that these impacts are likely disproportionally concentrated in developing countries, and in turn poor communities within these countries. This thesis aims to quantify the distributional impact of climate shocks in Bangladesh. We analyze the effects of weather shocks such as floods, droughts and extreme temperature on household income. For this purpose, we combine climate data with data from the Bangladesh Household Income and Expenditure Survey (HIES) and use a fixed-effect regression analysis. To further assess the vulnerability on households of different income levels an unconditional quantile regression approach is additionally applied. Our results indicate that higher income households are most vulnerable to climate shocks. We find that extremely cold temperature days negatively affect income. Our estimates show that floods effect households in multiple ways, negatively for small and high magnitude floods, yet positively for floods of medium magnitude. These effects are solely regarding higher income households. We find that different sectors are most likely affected differently from climate events. A modern and agricultural sector might be affected to different extents and directions when exposed to climate events.

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# List of Abbreviations

| | |
|---|---|
| BBS | Bangladesh Bureau of Statistics |
| BMD | Bangladesh Meteorological Department |
| CQR | Conditional Quantile Regression |
| DFO | Dartmouth Flood Observatory |
| HIES | Household Income and Expenditure Survey |
| IPCC | Intergovernmental Panel on Climate Change |
| RIF | Re-centered Influence Function |
| SPEI | Standardized Precipitation- Evapotranspiration Index |
| UQR | Unconditional Quantile Regression |

# 1. Introduction

Over the past decades, the topic of climate change has become increasingly important, both in research and policy communities. It is a well-established fact that human activities are a major cause of climate change occurring across the globe. Climate change is causing temperatures to steadily increase, sea-levels to rise, and increasing occurrences of climatic events and extreme weather, such as floods and droughts (Hansen et al. 1981, IPCC 2014). Within the economics literature, the research estimating the economic impacts of climate change and the corresponding implications for climate change policy has also rapidly expanded over the past three decades and grown in prominence. The recent acknowledgement of William Nordhaus, who was awarded the Nobel Prize due to his work on integrated assessment models (Nordhaus 1977, 1992, 2010 & 2017), is a clear example of that.

Within this literature, the costs as a consequence of human-induced climate change are typically characterized as an externality cost; a negative by-product of economic activity. Greenhouse gases are emitted in the atmosphere during production processes and accumulates in the atmosphere over time. The accumulated stock of greenhouse gases traps heat which cause global warming. This climate change is expected to have adverse effects on economic activities, specifically by changing the setting of which economic agents acts. As such, greenhouse gas emissions constitute a negative externality cost. This implies that there exists a discrepancy between privately and socially optimal production and consumption decisions. Such externalities could, for example, be floods or droughts that destroy production factors and decreases yield. (Stern 2008).

Countries that are expected to be most affected by climate change are mainly developing countries close to the equator (GCRI, 2015). One such country is Bangladesh, a poor developing country situated in South Asia. Bangladesh is an interesting case study for the following reasons. The country has recently experienced some of the highest rates of economic growth in the world. With the aid of a large influx of foreign capital and large investments in infrastructure and industry, Bangladesh has been able to increase the living standards of millions of its citizens in the past decade (World Bank 2019a). Additionally, consumption has increased in particular due to a growing middle class, which further drove the GDP growth (World Bank 2019b). However, the recent economic successes for Bangladesh have also been threatened by the impacts of climate change. Bangladesh is a lowland country that has the world's largest river delta, where rivers such as Ganges and Brahmaputra run out in the Bay of Bengal. While these features have been a geographical and ecological gift to the region, providing fertile lands for an agricultural sector with higher yields, they also come with the constant risk of floods due to the low-lying land. Floods often impose significant damage to infrastructure, household and other productive assets, which in turn reduces the capacity for economic growth. Due to climate change, extreme weather such as extreme precipitation and droughts are expected to increase in frequency. The IPCC recognizes rising sea levels, cyclones and floods to be the main threats to Bangladesh in the future. Especially the agricultural sector, with its high exposure to the climate, is expected to be adversely affected by an increase in extreme weather events. Droughts and floods can additionally cause shortages of drinking water due to salinization (IPCC 2014). And as a lowland country with over 160 million inhabitants, Bangladesh is one of the most densely populated areas expected to fall below sea-level as the sea-level rises (Huq 2001).

This thesis assesses the economic impacts of climatic shocks and events on a regional level in Bangladesh. We first put forward a stylized theoretical framework, which captures the effect of climate shocks on household income. This framework allows us to formulate hypotheses about possible effects we might observe in our data. In turn, we combine data on weather, floods, and droughts, with household income data, and estimate the impacts of weather shocks on household income. We first estimate the overall effect of floods, droughts and extreme temperature on household income. There are, however, good reasons to expect that households at different income levels may be affected by weather shocks to different extents. To allow for such heterogeneity, we subsequently use an unconditional quantile regression approach to assess the difference in vulnerability to climatic shocks for households at different income levels. Our results do not support the hypothesis that low-income households are more vulnerable to climate shocks than high-income households. Rather, we find that high income households are more adversely affected to certain events such as floods of high and low magnitude as well as extreme cold temperature, while the impact on poorer households is statistically insignificant. Different explanations are presented regarding the results and further why the magnitude of floods showed to have ambiguous effects, with adverse effects for floods of lower and higher magnitude yet positive effects for floods of medium magnitude.

Even though there exists substantial literature estimating the effects of weather shocks on economic outcome, literature that focuses specifically on Bangladesh is rather scant. Previous work by Brouwer et al. (2007) and Rabbani et al. (2013) does show that climatic shocks often hit poor communities the hardest, as typically a greater share of their income comes from sectors heavily exposed to climate change, such as agriculture, forestry and fishing. Nevertheless, the research mentioned focuses on either qualitative data or a quantitative analysis on a macro-scale, with little regard to quantitative measures on a household scale. The effects caused by climate change on a more micro-level scale are thus not extensively researched, although this aspect can have significant importance and relevance. Putting a price tag on the cost of climate change for households is important for policymakers in particular, as this allows them to identify vulnerable regions and households and target adaptation efforts to mitigate adverse effects.

The remainder of this thesis is structured as follows. Section 2 and 3 discuss relevant literature and present an institutional context of Bangladesh. In Section 4 we put forward a stylized theoretical framework and formulate hypotheses. Sections 5 and 6 discuss the data and empirical approach. Results are presented in Section 7, followed by a discussion in Section 8. Section 9 concludes and discusses future research avenues.

## 2. Literature Review

There exists much literature estimating the economic effects of climate change. The literature that more specifically considers distributional implications primarily uses cross-country comparisons to link climate change impacts to poverty. Examples of such studies are Angelsen et al. (2014) and Wunder et al. (2018). Angelsen et al. (2014), which assess the dependence of poor, rural households on environmental income i.e., income originating from non-cultivated sources such as natural forests, grasslands, and wild plants and animals. Using 33 regions around the globe they find that poor households rely more on environmental income. Wunder et al. (2018) contribute to this debate by examining rural household's dependence on crop income, focusing on developing countries across the tropics. Their results indicate that optimal temperature and rainfall for crop production is 21° C and 2000 mm per annum. Furthermore, they find that crop production is more sensitive to temperature and rainfall perturbations than forestry. This represents a potential for labor to reallocate to the latter sector in response to climate change as part of a mitigation strategy.

Literature which examines how climate change and climatic events interact with economic activities such as how temperature impact economic growth, how floods effect crop production or how other natural disasters impact economic activities is well-researched. Dell et al. (2012), Padli et al. (2009), Hsiang & Jina (2014) and Toya & Skidmore (2007), examine different channels where climate change impact economic activities. Dell et al. (2012) estimate the relationship between local temperature and economic activities. Dividing countries into poorer and richer, they find that a rise of 1° C reduces economic growth by 1.3 percentage points on average. Instead of temperature, Padli et al. (2009) examine natural disasters in over 73 countries. Their results indicate that wealthier nations are better prepared for natural disasters, and are also more prepared to minimize the aftermath of disasters in the aspect of economic impacts. As our research considers temperature and disasters, we build on the work by Dell et al (2012) and Padli et al. (2009). Contrary to these papers, however, we examine the impacts on a household level rather than a cross-country study. Hsiang & Jina (2014) investigate how climate catastrophes affect economic growth. They use a simulation model that estimates the causal effects of cyclones on long run growth by adopting a difference-in-difference approach. They find evidence that countries frequently affected by cyclones have 1-7.5 percentage points lower annual average growth, as compared to a situation where no cyclones have occurred. Using their results, they additionally compute the global average annual growth rate in a world without cyclones and establish that cyclones reduced the global growth rate from 3.8% to 2% between the years 1970-2008.

The examination of natural disasters impact on countries on a macro-level is also researched by Toya & Skidmore (2007), who, compared to Hsiang & Jina (2014), do not solely focus on one type of natural disaster. They examine the degree to which natural disasters effect economic development at a country level, examining 151 countries. Their results indicate that the cost for safety measurement implementations which would reduce the impacts of natural disasters exceeds the expected benefits for poorer people. Due to the cost exceeding the benefits, a consequence might be that no implementation is executed. Furthermore, their findings show a negative relationship between schooling and damages per GDP, implying that other aspects besides income are important in reducing the number of deaths and damages per GDP. The above-mentioned articles focus on natural disasters and its macro-level impacts. Our research measures the impacts of natural disasters such as floods and droughts on a household level.

The reviewed literature above are all cross-country analyses. A growing number of qualitative micro-level studies have also been conducted to investigate the effects of natural disasters within countries, especially Bangladesh. Due to the limited availability of detailed data in developing countries, a large portion of these micro-level studies use customized surveys implemented by the researchers. Examples of such studies established in Bangladesh are Brouwer et al. (2007), Islam et al. (2013), Rabbani et al (2013), Akter & Mallick (2013) and Sen (2003). Brouwer et al. (2007) investigate the relationship between environmental risk, poverty and vulnerability in a severely flood-prone area southeast of the capital Dhaka. They conduct interviews with 700 residents and show a positive relationship between poverty, vulnerability and environmental risk. More specifically, they find that poorer respondents live closer to the river, which increases their vulnerability to floods. Additionally, they find that people who are faced with a higher risk regarding floods are those people least prepared for the impacts of floods.

When examining the impacts of climate change on the coastal area of Bangladesh, Islam et al. (2013) and Rabbani et al. (2013) use a similar approach as Brouwer et al (2007). Islam et al. (2013) examine two fishing communities and how climate change interacts with vulnerability for fishery-based livelihoods. Combining their qualitative interviews with quantitative climate data, Islam et al. (2013) show that the approach for reducing vulnerability needs to be multifaceted. This means that the approach for reduction needs to simultaneously consider sensitivity and exposure, as well as the adaptive capacity due to different levels of exposure. Additionally, their results show that households who are the most sensitive to climate change do not need to be the most exposed ones. This implies that climate events impact communities in an unbalanced matter; sensitivity and vulnerability both depend on factors such as socio-economic characteristics of the household and community. Rabbani et al. (2013), explore the impacts of climate change on ponds (small isolated wetlands) focusing on two districts in the south-west Bangladesh. Their results suggest that improved water management is needed to mitigate the effects of climatic events, such as floods and droughts, on the quality and quantity of water sources.  The need for water management is needed on a regular basis and not solely ex-post. Other solutions are discussed as well, such as shifts in crop production from traditional crops to crops more tolerant to salinity and droughts. Brouwer et al. (2007), Islam et al. (2013) and Rabbani et al. (2013) all examine the impacts of climate change on specific study areas of Bangladesh. By building on their work our research is conducted on the whole population, leading to a more generalized approach and result.

Resilience to climate change is an additional aspect to consider, i.e. the capacity to recover from an external shock such as a flood or drought. This aspect is examined by Akter & Mallick (2013). They study the linkage between poverty and vulnerability to climate change using the cyclones which hit Bangladesh in 2009 as a natural experiment. They study the impacts of the cyclones on households in a “before-after” method considering the households located in a low-income community within a cyclone prone area. Their findings support the results by Brouwer et al. (2007) that poorer households are more sensitive and vulnerable to natural disasters. Additionally, their findings indicate that poorer household suffer higher economic, physical and structural damage. This is despite their results which showed that poorer households acquire a better ability to recover from a shock. Sen (2003) examines drivers which descend people into poverty as well as which drivers help people escape poverty. To examine the drivers and what direction they effect households, Sen (2003) uses a panel dataset of 279 rural households which were interviewed in 1987-88 and 2000. The approach is to use before-after comparisons. The main contribution from this research is the insight that people ascending out of poverty use multiple strategies and not solely focus on one approach. People descending into poverty are mainly driven by shocks to income, shocks such as natural disasters, or health issues. Our research builds on the approach by Akter & Mallick (2013) to examine the impacts of natural disasters on households, as well as Sen (2003) when considering the channels which descend households into poverty.

In relation to the research mentioned above regarding Bangladesh, Banerjee (2010) finds evidence that floods can have a positive impact on agricultural performance. That study examines more and less flood-prone areas in Bangladesh and measures the annual average yield for rice and jute over 20 years. As Banerjee (2010) discusses, floods occurring due to monsoons might have a positive impact. These floods could act as inputs to the agricultural sector in the form of irrigation. This further results in the conclusion that flood-prone areas can have a higher annual yield in relation to less flood-prone areas.

Haque & Jahan (2015) studies what sectors in the economy that are affected by climate change and how the effects differ across sectors. By conducting an input-output model they examine national and regional outputs in different regional divisions of Bangladesh. Their results indicated that the Rajshahi division is the most vulnerable division and that the Dhaka division loses output to the largest extent during floods. The results regarding Dhaka are expected due to the population density in the division, containing approximately 30 percent of the total population. Our thesis builds on a theoretical framework which considers the impacts of climatic events on two sectors, the "agricultural" and the "modern" sector. The two studies by Banerjee (2010) and Haque & Jahan (2015) give vital information regarding how floods can interact with the agricultural sector.

Arouri et al. (2015) establish a research similar to our approach when examining the entire population of Vietnam. They research the effects of natural disasters on household welfare. Using storms, floods and droughts as their disaster types they use a fixed-effects regression, eliminating unobserved time-invariant and commune-level variables. They find that all three disaster types have a significant effect on household income and household expenditure. Their findings include that the decrease in per capita income for households living in areas with storms were 1.9%, floods 5.9% and droughts 5.2%. As this paper examines the impacts of floods, droughts and extreme temperature on household income, we establish a similar fixed-effects examination as the one established by Arouri et al. (2015). Using the same dataset as our thesis, Mishra et al. (2015) investigates how households of different income-levels are affected differently by off-farm work. Similar to their approach, we also establish an unconditional quantile regression based on income-levels. They find evidence that off-farm work increases food consumption in Bangladesh, an effect which they conclude differs between quantiles. The 50$^{th}$ quantile and above are more likely to gain from an off-farm income in relation to the quantiles below. Our thesis, in relation to Mishra et al. (2015), makes use of a quantile regression when considering the effects of climate events on household income.

As our focus is on the entire country of Bangladesh and not on a specific study-area or on a specific part of the population, our approach is similar to the approach Arouri et al. (2015) had in Vietnam. We add an additional dimension by establishing an unconditional quantile regression in addition to the fixed-effects model in Arouri et al. (2015). This methodology is introduced by Firpo et al. (2009) and implemented by Mishra et al. (2015), who uses the same household data as is used in our thesis. Benefitting from the previous research when conducting our paper, we further analyze the effects of climate events on economic development in Bangladesh.

## 3. Institutional Context

Bangladesh is a developing country located in South Asia. It has a population over 160 million people, of which approximately 36 percent live in urban areas. In the past two decades, the country's real GDP per capita growth has averaged around 5 percent, making it one of the fastest growing economies in the world (World Bank 2018). A large influx of foreign capital and investments in infrastructure has enabled the economy in Bangladesh to modernize, shifting more of the efforts from the agricultural sector towards manufacturing industry. The textile industry, being one of the main industrial sectors in the country, accounts for more than 80 percent of the exports (CIA 2018). In 2008 the Bangladeshi government declared the so called "Vision 2021", a plan which was designed for the country to reach middle income status by 2021 (Bangladesh Government 2008). However, this vision was adjusted to in 2019 to a "Vision 2041" which has a goal for Bangladesh to be a developed country by 2041 (Bangladesh Government 2019).

The geographical context of the country has in many ways blessed the country historically. Being a lowland country with over 230 freshwater rivers situated close to the equator, the country has been endowed with some of the most fertile lands in the region. Still, the agricultural sector employs half of the country's working population, with rice being the single most important product in the country (CIA 2018). However, the geography of the country also comes with the risk of climate shocks. Floods, for example, are major events that strike the country every year. Since 1989, the Dartmouth Flood Observatory (DFO) has recorded 83 major flooding events in Bangladesh (DFO 2018). Two of the most extreme events occurring in the past decades were floods in 2003 and 2007, which respectively dislocated 9.5 million and 5 million people in the country. As small-scale floods can be necessary to sustain the agricultural sector, floods of larger scale, however, have devastating consequences to Bangladesh. Casualties, dislocation of people, and destruction of property is a threat to the country's wellbeing and economic development. On top of this, future forecasts predict that climate change is expected to increase the severity and frequency of major floods in the region while the rise in sea level is expected to put 27 million people at risk by the year of 2050 (IPCC 2014).

Considering the economic and geographic contexts of the country, Bangladesh makes an interesting case-study for economic impact of climate events and climate shocks. As the country aims for long term economic growth, climate change is expected to stall this process during the modernization of the country's economy (IPCC 2014). Climate events as a consequence of climate change can be a great hurdle in overcoming their goals. Thus, investigating the effects that climate events have on household income can be of great importance for policy makers when implementing adaption and mitigation strategies.

# 4. Theoretical Framework and Hypotheses

## 4.1 Theoretical Framework

To evaluate the effect of climate change and climatic shock on the economy, we put forward a stylized theoretical framework (Cobb & Douglas 1928). In this framework, output is derived from the level of production input via three production factors. The production factors are: labor, represented by *L*; capital, represented by *K;* and land, represented by *T*. *P* represents total factor productivity, capturing factors such as technological level. A climate shock may then adversely affect the stock of capital and land by destroying machinery and lowering land quality.[1] We consider an economy with two sectors. The reason for this is to differentiate and represent different sectors for households of different income levels. The first sector is called the modern sector, subscript *M*, and represents the sector where households of higher income are engaged. The second sector is called the agricultural sector, subscript A, and represents the sector where households of lower income are engaged. The production function for the modern sector is as follows:

$$Y_M = P_M K_M^{\alpha_M} T_M^{\beta_M} L_M^{1-\alpha_M-\beta_M} \quad (1)$$

Where $\alpha_M, \beta_M > 0$ and $\alpha_M + \beta_M < 1$. The parameters $\alpha_M$ and $\beta_M$ represent the output elasticities of capital and land, respectively. They represent the responsiveness of output due

[1] In principle, labor can also be affected due to casualties. However, the main channels for economic output affected are more likely to be capital and land; thus, these are the main focus of our model.

to a unit change in the production factor they represent. The production function for the agricultural sector is as follows:

$$Y_A = P_A K_A^{\alpha_A} T_A^{\beta_A} L_A^{1-\alpha_A-\beta_A} \tag{2}$$

Where again $\alpha_A, \beta_A > 0$ and $\alpha_A + \beta_A < 1$ and the specifications for $\alpha_A$ and $\beta_A$ are the same as for the modern sector.

We assume that land is a more important production factor in the agricultural sector *A* as crop yields highly depend on land quality. Furthermore, we assume that capital is more important in the modern sector *M* as industrial output is highly dependent on e.g. machinery. The main purpose of these assumptions is to differentiate and show that the two sectors mainly rely on different inputs to the economy. Further, the different inputs can be affected differently by climatic events.

To capture the assumptions that land is more important in the agricultural sector and capital is more important in the modern sector, we assume that $\beta_M < \beta_A$ and that $\alpha_A < \alpha_M$. We assume that labor $L_M$ and $L_A$ are fixed and exogenous. Land and capital are given by:

$$T_i = \bar{T}_i e^{-\gamma_T \Omega} \tag{3a}$$

$$K_i = \bar{K}_i e^{-\gamma_K \Omega} \tag{3b}$$

Where $\bar{T}_i$ represents the given land endowments, $\bar{K}_i$ the initial capital endowments. The Ω then captures an exogenous climate event, such as a flood, drought or extreme temperature, while $\gamma_T$ and $\gamma_K$ represents the sensitivity of *T* and *K* to such an event, respectively. Then, if Ω > 0, the event adversely affects land and capital. The larger Ω is, the more adverse is the event.

To consider the effect of climate events on household income, we determine the effect of an event on wages. Therefore, we first need an expression for wages. In each sector the wage is equal to the marginal output of labor:

$$\frac{\delta Y_i}{\delta L_i} = (1 - \alpha_i - \beta_i)\frac{Y_i}{L_i} = w_i \tag{4}$$

Where $i = A, M$. Thus, wages are a negative function of the output elasticity of capital and land, meaning that the more important other production factors are to the economy, the lower wages are payed to workers. Incorporating marginal output per worker and how it is affected by climatic events is represented in Equation 8 below. We start with the marginal effect of a climatic event on land and capital:

$$\frac{\delta T_i}{\delta \Omega} = -\gamma_{\mathrm{T}} T_i \tag{5a}$$

$$\frac{\delta K_i}{\delta \Omega} = -\gamma_{\mathrm{K}} K_i \tag{5b}$$

Deriving wages subject to stock of land leads to:

$$\frac{\delta w_i}{\delta T_i} = (1 - \alpha_i - \beta_i) \frac{1}{L_i} \frac{\delta Y_i}{\delta L_i} = \beta_i \gamma_T w_i \frac{1}{T_i} \tag{6a}$$

And subject to stock of capital leads to:

$$\frac{\delta w_i}{\delta K_i} = (1 - \alpha_i - \beta_i) \frac{1}{L_i} \frac{\delta Y_i}{\delta L_i} = \alpha_i \gamma_K w_i \frac{1}{K_i} \tag{6b}$$

Combining marginal effects on land and capital by climatic events and marginal effects on wages by land and capital leads to:

$$\frac{\delta w_i}{\delta \Omega} = \frac{\delta w_i}{\delta T_i} \frac{\delta T_i}{\delta \Omega} + \frac{\delta w_i}{\delta K_i} \frac{\delta K_i}{\delta \Omega} = -\,(\beta_i \gamma_T w_i + \alpha_i \gamma_K w_i) \tag{7}$$

Or:

$$\Delta w_i = -\,[\beta_i \gamma_T w_i(\Delta\Omega) + \alpha_i \gamma_K w_i(\Delta\Omega)] \tag{8}$$

Thus, a climatic event Ω will have a negative effect on wages and the magnitude of the effect is dependent on the output elasticities for capital and land ($\alpha_i$ and $\beta_i$), as well as the production factor sensitivities to climate events ($\gamma_K$ and $\gamma_T$). From this model we can conclude that the loss of wages due to land destruction is larger in the agricultural sector than it is in the modern sector. Similarly, we can conclude that the loss of wages due to capital destruction is larger in the modern sector than it is in the agricultural sector. We can conclude this due to our assumptions that land is more important in the agricultural sector ($\beta_M < \beta_A$) and that capital is more important in the modern sector ($\alpha_A < \alpha_M$). This conclusion, however, relies on the assumptions that wages and factor-sensitivity to climate events are identical in both sectors. Since we assume that low income households primarily act in the agricultural sector and vice versa, this is not the case for wages. Looking at the percentage effects we can however conclude that the effect is always given by output elasticity and factor sensitivity:

$$\%\Delta w_i \approx \frac{\delta w_i}{w_i} = -\left[\beta_i \gamma_T (\Delta\Omega) + \alpha_i \gamma_K (\Delta\Omega)\right] \tag{9}$$

Subsequently, we have illustrated that the adverse effect will always increase with the magnitude of the shock Ω.

In conclusion, we have a model that represents two sectors: the modern sector and the agricultural sector. Both sectors rely on capital, land and labor as production factors and assume labor as exogenously given. Land and capital are given by functions of endowments and climatic events. Climatic events have a negative effect on the stock of productive land and capital. The agricultural sector relies primarily on land and the modern sector relies primarily on capital, which is represented by their elasticity of output in the different sectors. Thus, given this stylized model, we can draw three main conclusions about how climatic shocks affects household income. First, climatic shocks hit the stock of productive land and capital negatively. Second, the reduction in productive land and capital has an adverse effect on labor wages, reducing the marginal output per worker. Third, since the agricultural sector is more dependent on land inputs, the loss of wages due to land destruction is larger in this sector and vice versa for the modern sector.

## 4.2 Hypotheses

Based on the theoretical framework and previous literature we draw a hypothesis that climate events, such as floods, droughts and extreme temperature, have an adverse effect on household income. Furthermore, we conclude that the effect differs depending on the level of household income, i.e. what sector of the economy the household is engaged in. If land is more sensitive to climate events than capital ($\gamma_T > \gamma_K$), then lower income households would be more affected by climate events, since these households are engaged in a sector that relies more heavily on land as input. However, if capital is more sensitive to climate events ($\gamma_K > \gamma_T$), then higher income households would be more affected by climate events, since these households are engaged in a sector that relies more heavily on capital as input. The previous literature such as Brouwer et al. (2007), Toya & Skidmore (2007) as well as Akter & Mallick (2013) mainly support the former rather than the latter, which leads to our additional hypothesis to be that low-income households are more sensitive to climate events than high income households.

## 5. Data

Data used in this research was obtained from several sources. Household data was obtained from the Bangladesh Bureau of Statistics (2007, 2012) and originates from their household income and expenditure survey. Data on temperature was obtained from the Bangladesh Meteorological Department (2016). Data regarding floods was collected from the Dartmouth Flood Observatory (2019) and for droughts the Standardized Precipitation- Evapotranspiration Index (SPEI) is used and obtained from the SPEI Global Drought Observatory (Santiago et al. 2019).

### 5.1 Household Data

The household income and expenditure surveys were conducted by the Bangladesh Bureau of Statistics. This thesis makes use of the surveys conducted in 2005 and 2010. The survey from 2005 includes 10 080 households while the survey from 2010 includes 12 240 households. All households in the surveys are randomly selected and are all located in 64 zilas (districts). To ensure random selection, a two-stage stratification is used. The first stage is stratifying on a geographical level and within these sampling units 20 households are randomly selected. The survey contains questions regarding the household's economic activities, consumption, health, and education, as well as general information concerning the household.

From this household survey we calculate household net income. This variable is our main dependent variable throughout this paper. Income is determined using the Rural Income Generating Activities (RIGA) approach. This approach is developed by the World Bank, Food and Agriculture Organization of the United Nations (FAO), and the American University in Washington DC. It determines total household income by adding up multiple income bearing components of household income, according to the model below:

$$TOTY_i = Agwage_i + Nonagwage_i + Crop_i + Livestock_i + Selfemp_i + Transfer_i + Other_i \tag{10}$$

Where *i* indicates each household. Agwage and Nonagwage are income received from agricultural and non-agricultural activities for which the household has been compensated for by cash or in-kind wage payments. Crop denotes all income from produced crops which are either sold or consumed by the household. Livestock is defined accordingly; this category includes the sale and barter of livestock, by-products, as well as consumption of own livestock and by-products from livestock. Selfemp includes the part of income earned from non-farm households, such as enterprises, and is calculated from the net revenue of the enterprise and the households share of that enterprise. Transfer incudes all non-labor income through private transfers, such as national and international remittances. Other includes all other non-labor income, such as income from rental of land or assets, insurance money and other non-labor sources not specified. To obtain net income, agricultural expenses are subtracted (Covarrubias et al 2009).

We recoded all observations for which household net income is negative. Such negative values most likely originate from wrongly stated agricultural expenses. This led to 16 recoded values for 2005 and 87 in 2010. No meaningful difference was detected when dropping the values instead of recoding; thus, the observations have been recoded. Household net income is deflated using the GDP-deflator from the World Bank and 2006 is used as a base year.

Table 1 presents some descriptive statistics. Our main variable of interest is the monthly net income for households. From Table 1 we observe that average income does not change substantially between the two surveys.

Urban is a dummy variable which takes the value 1 if the household is located in an urban area. From Table 1 we then observe that approximately 65 percent of the population lives in a rural area. Agricultural dependence indicates what percentage of the household's income originates from agricultural activities (on average 31 percent originates from agricultural related income). Household size presents the number of people living in the household and the head-of-household age is the age of the head of the household in question. The number of people of working age indicates the number of people living in the household between 13 and 59 years old. Head of household education indicates the highest class completed by the head of household ranging from 0 to 13, 13 being post-graduate or equivalent. Average education levels are low, and about 50% of the heads of household in our sample have not completed any classes. The last variable in the table presents information regarding the head of household's gender, a dummy variable which takes the value 1 if the head of household is a female. As the table presents, approximately 10 percent of the households have a female head in 2005, a value which slightly increases between the two years. In Table 11 in the appendix, further descriptive statistics can be found regarding the four quantiles which we examine.

*Table 1 - Descriptive Statistics (Households)*

| | 2005 | | | | | 2010 | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Observations | Mean | Std. Devi | Min | Max | Observations | Mean | Std. Dev | Min | Max |
| **Net income** | 10 080 | 7323 | 16777 | 0 | 1011174 | 12 240 | 7765 | 12960 | 0 | 706750 |
| **Urban** | 10 080 | 0,365 | 0,481 | 0 | 1 | 12 240 | 0,359 | 0,4799 | 0 | 1 |
| **Agricultural dependence** | 10 080 | 31,053 | 36,573 | 0 | 100 | 12 240 | 31,929 | 39,112 | 0 | 100 |
| **Household size** | 10 080 | 4,858 | 2,074 | 1 | 20 | 12 240 | 4,541 | 1,888 | 1 | 17 |
| **No. of people in working age** | 10 080 | 2,989 | 1,509 | 0 | 14 | 12 240 | 2,829 | 1,412 | 0 | 12 |
| **Household head age** | 10 075 | 45,409 | 13,507 | 12 | 99 | 12 240 | 46,007 | 13,883 | 11 | 122 |
| **Household head education** | 10 080 | 3,793 | 4,443 | 0 | 13 | 12 240 | 3,840 | 4,449 | 0 | 13 |
| **Household head gender** | 10 080 | 0,103 | 0,304 | 0 | 1 | 12 240 | 0,143 | 0,349 | 0 | 1 |

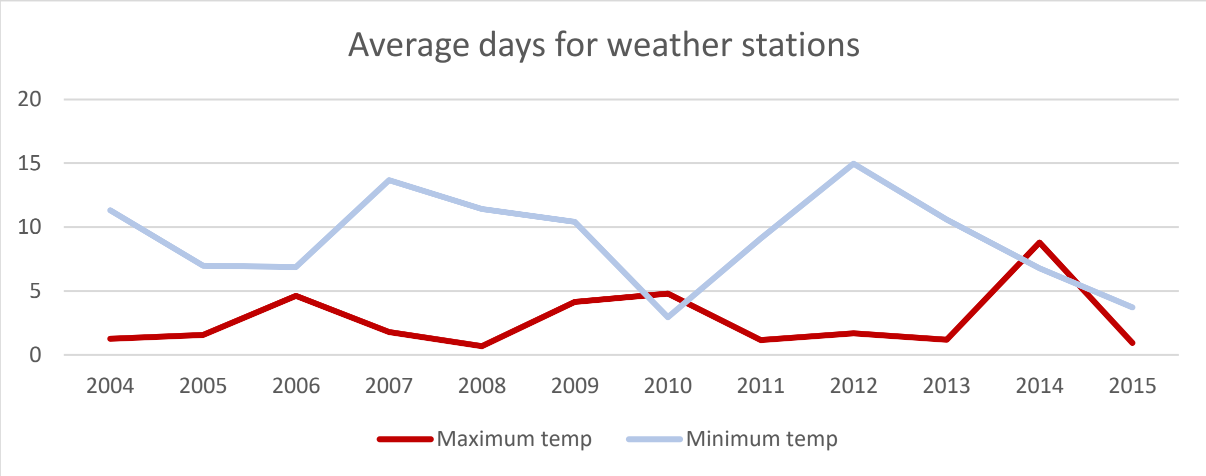
*Source: Household Income and Expenditure Survey (2005 & 2010)*

## 5.2 Temperature Data

Our temperature data is obtained from the Bangladesh Meteorological Department (2016). It is collected by 34 weather stations on a daily basis. Further the weather stations are matched to zila(s), determining the daily average temperature for each zila. This is a vital process to be able to match weather and household data. To incorporate weather shocks in our analysis we construct a measure of the number of days each zila has experienced an extreme temperature. The measurement is as follows: the number of days the maximum (minimum) daily temperature deviates above (below) the mean by two standard deviations. This measurement is calculated for each weather station and month over the time period 2004-2015. This gives us the number of days which the temperature has deviated from normal in that specific weather station, allowing for an analysis of impacts from extreme temperatures.

Figure 1 presents the average number of days which the temperature has deviated more than two standard deviations from the mean for the 34 weather stations over the time-period of 2004-2015. The figure indicates that on average the years of 2007 and 2012 had on average more very cold days.

*Figure 1 - Maximum and Minimum Temperature days*



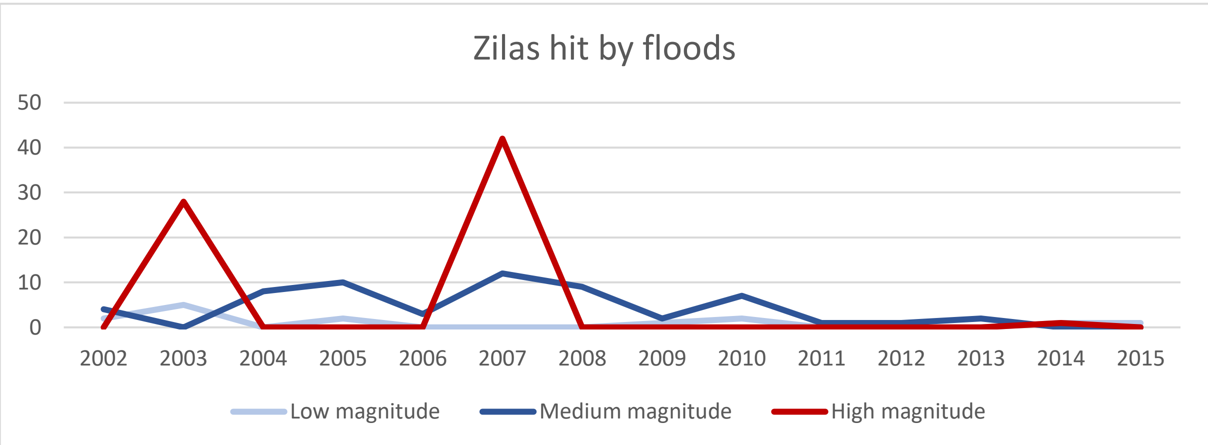

*Source: Bangladesh Meteorological Department (2016)*)

## 5.3 Floods Data

Data regarding floods was collected from the Dartmouth Flood Observatory (2019). The data is collected at the zila-level. Floods are categorized according to three levels of magnitude: low, medium, and high. The categorization is performed taking how large area the flood covered, how many people were dislocated, deaths, and duration of the flood, with more severe floods more likely ranked as medium or high.

Figure 2 presents the frequency of floods by magnitudes for 2002-2015. We can see that the number of zilas hit by floods has decreased substantially from the time periods 2007 and onwards. The two spikes in 2003 and 2007 indicate two extreme floods that affected many zilas those years.

*Figure 2 - Floods*



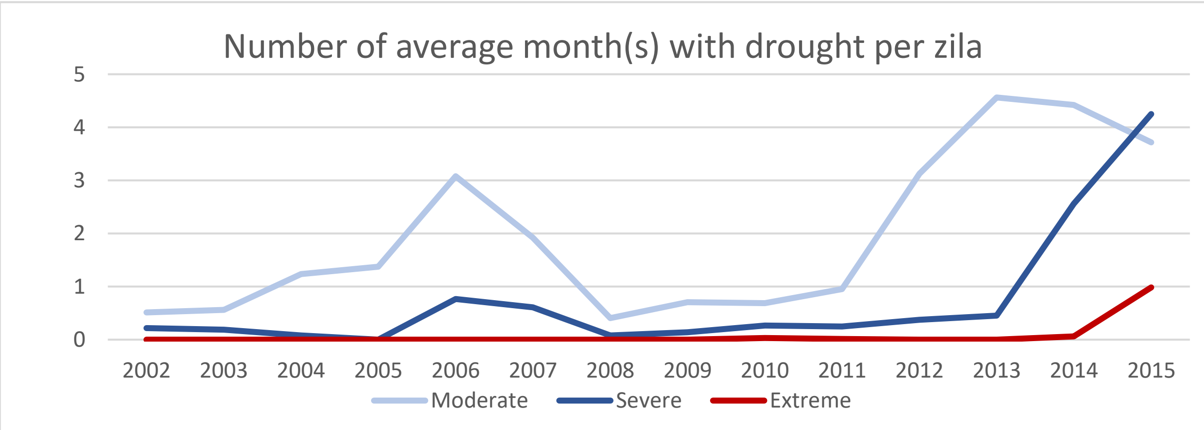

*Source: Bangladesh Meteorological Department (2016)*

## 5.4. Droughts Data

Data on droughts is obtained from the SPEI Global Drought Observatory. The Standardized Precipitation- Evapotranspiration Index (SPEI), incorporates aspects such as precipitation as well as humidity when determining if a drought has occurred. This data has been collected on a zila-level to match with household data. The SPEI-data is on a monthly basis, meaning the index tells us if a specific month is determined as a month with a drought. Similar to floods, droughts are categorized in three levels: moderate, severe and extreme.

Figure 3 presents the average yearly number of dry months experienced by all zilas from 2002 to 2015. As, the figure shows the average number of months with droughts have increased substantially from 2011 onwards. Severe droughts have an increasing pattern from 2013 while moderate droughts are slightly decreasing the most recent years. In our dataset only one extreme drought occurred in 2015, as Figure 3 presents.

*Figure 3 - Droughts*




*Source: SPEI Global Drought Observatory (2019)*

A correlation matrix has been produced to examine if the climate events correlate. Table 2 presents the correlations between the climate variables. Only the temperature variables have a positive correlation above 0.6. Moderate droughts and low magnitude floods have a negative correlation of approximately 0.5. This leads us to believe that multicollinearity is not present in our regressions. It should be noted that the data included in the correlation matrix is solely from the time span three years prior to each household survey, i.e. 2002-2004 and 2007-2009.

*Table 2 - Correlation Matrix over Climate Variables*

| | Floods low magnitude | Floods medium magnitude | Floods high magnitude | Moderate droughts | Severe droughts | Minimum temp. days | Maximum temp. days |
|---|---|---|---|---|---|---|---|
| Floods low magnitude | 1.0000 | | | | | | |
| Floods medium magnitude | 0.1577 | 1.0000 | | | | | |
| Floods high magnitude | -0.3810 | -0.1151 | 1.0000 | | | | |
| Moderate droughts | -0.4697 | 0.2655 | 0.0958 | 1.0000 | | | |
| Severe droughts | 0.1132 | 0.1863 | 0.1071 | 0.1833 | 1.0000 | | |
| Minimum temp. days | -0.3169 | 0.3240 | 0.2856 | 0.3336 | 0.0923 | 1.0000 | |
| Maximum temp. days | -0.1425 | 0.1946 | 0.2345 | 0.1640 | 0.1238 | 0.7699 | 1.0000 |

*The matrix is excluding zila fixed-effects and only incorporates data three years prior to each survey.*

# 6. Methodology

This thesis utilizes data collected from four different sources. To examine the impact that climate events has on household income, three approaches are conducted. Firstly, a fixed-effects regression is conducted to establish the effect on an average household in Bangladesh. Secondly, an unconditional quantile regression is conducted to examine how the effects differ between income-levels. Thirdly, a deeper analysis of the extreme floods in 2003 and 2007 is conducted to enhance the understanding of extreme floods. To connect floods, droughts and temperature to the household data in a precise matter, a three-year period is chosen, meaning only climate events occurring three years prior to the household surveys are incorporated in the analysis. Throughout these approaches, logged household net income is used as the dependent variable.

## 6.1 Fixed-Effects Regression

The fixed effects regression estimates the impact of our climate variables on the entire population, estimating the average impact across the country. Our fixed effects approach is to a large extent based on Arouri et al. (2015) and Dell et al. (2012), who both implement similar approaches. Our specification is depicted by:

$$\ln\left(Household\ Net\ income_{ijt}\right) = \beta_0 + \beta_1 Floods_{jt} + \beta_2 Droughts_{jt} + \beta_3 Temp_{jt} + \beta_4 Head\ charact_{ijt} + \beta_5 Household\ charact_{ijt} + \gamma_t + \delta_j + u_{ijt} \quad (11)$$

Where the subscript I indicates household (i=1,…,N), subscripts j is for zilas (j=1,…64) and subscript t indicate which year (t=2005 & 2010). Our main variables of interest are, $Floods_{jt}$, $Droughts_{jt}$ and $Temp_{jt}$ which are defined and discussed in section five above. $Head\ charact_{ijt}$ and $Household\ charact_{ijt}$ are vectors of control variables regarding household head and household characteristics while $\gamma_t$ and $\delta_j$ indicate time fixed-effects and zila fixed-effects, respectively.

The dependent variable is logged, which implies that the coefficient on the independent variables denotes the percentage effect on household income of a unit change in the independent variables. The main reason for using the log of household income is based on our theoretical model in Equations 8 and 9. The theoretical model considers that the linear effects (when the coefficient on the independent variables denotes a unit effect on household income for unit change in the independent variables) is dependent on the wage variable itself.. I.e. the effect on wages in nominal terms is dependent on the initial level of wages. (Equation 8). This is overcome by examining the effect in percentage, as presented in Equation 9.

To determine the causal effect of our variables of interest on household income, controlling for unobserved effects that correlate with our climate variables is essential. Since the climate variables are measured on zila-level and we are estimating the impacts on household-level, there is a possibility that unobserved zila-level variables might correlate with our climate variables. Unobserved variables might be time-invariant as well as time-variant.

Time-invariant variables which could correlate with the climate variables are entity (zila) fixed and could capture characteristics such as the geographical aspect. If mountains or plains are located in the zila, this could impact effect of our climate variables on household income. Another factor which could affect our estimates is, for instance, that poorer households are more likely to settle in zilas with low-quality land that are more often exposed to climate shocks. This would lead to an overestimation if we do not control for zila fixed effects. Local policies and local socioeconomic and demographic structures could also bias the estimates. If the unobserved variables decrease (increase) the impact of the climate shocks, we would underestimate (overestimate) the effects without zila fixed effects. Controlling for zila fixed effects account for this issue regarding reverse causality across zilas.

We additionally include time fixed-effects to account for any time fixed-effects, common across zila's. Including such effects is important because these variables may bias our estimates leading to an over- or underestimation. Variables which are controlled for with time fixed-effects are within-country migration, if high-income earners move due to climate events between the two surveys. Such migration could lead us to over/underestimate the effects.

Migration of low-income earners due to decreased demand for low-skilled workers because of climate events, might also lead to an over/underestimation of the effects. Other examples of time-variant variables could be economic and/or technological developments between the two survey years, which could impact the effects that the climate events have on households.

It would be optimal to estimate the effects with panel-data, which would allow us to control for entity and time fixed-effects on a household level. This would allow us to control for variables which might bias the estimates on a household level. An example of such variables could be where households move or develop on a household level such as number of income earners and income levels. These unobserved characteristics might bias the estimates in our regression, and controlling for such characteristics is the optimal approach when panel-data is available. Due to the unavailability of household-level panel-data in Bangladesh, we are not able to control for these effects (i.e. the unobserved time-variant variables might cause endogeneity issues). Although we are not able to control for time fixed-effects on household level, the years in which the survey was conducted allows us to control for the average differences in the dependent variable by including the survey year in the regression. This controls for the endogeneity issues on a national level. The final issue regarding internal validity of our regression is the possibility of within zila correlations with the error-term. This issue is solved with clustered standard errors.

### 6.2 Unconditional Quantile Regression

To examine the impacts of climatic events for households with different income-levels, the fixed-effects regression is complemented with an unconditional quantile regression (UQR). Our UQR approach is similar to the approach by Mishra et al. (2015), although examining different variables. The UQR allows for the estimation of the explanatory variables for different quantiles. These quantiles are determined by the dependent variables which in our regression is household net income. Dividing the households by quantiles allows for the examination of the climatic events on different income-levels, i.e. if low-income households are more vulnerable to climatic events in relation to high-income households. This aspect of low-income households being more vulnerable to climate events relates to our theoretical model and hypothesis, which indicate that an agricultural sector with lower wages are more affected by climate events than a modern sector with higher wages. A quantile regression allows us to observe the effect of weather shock by income level, and thus enables us to investigate whether low- and high-income households are affected differentially.

The unconditional quantile regression approach was primarily developed by Firpo et al. (2015) and has increased in popularity due to its easy implementation and interpretation. The approach uses a so-called influence function (IF), more precisely the re-centered influence function (RIF). The re-centered influence function determines what households are located in which quantile; this is exclusively determined regarding the dependent variable household net income. Further, it implies that households solely are included in one quantile, i.e. households do not cross. Furthermore, when established what household are in what quantile, the RIF determines the weight by which an observation influences the estimate based on its position in the distribution of the dependent variable. In the appendix, section A.4 Table 11, descriptive statistics is presented for the different quantiles. The table there presents the average income for the quantiles and how the quantiles differ in characteristics. The purpose of using a RIF and a UQR is that the RIF determines which households are in the preferred quantile prior to running the regression, i.e. it is not conditional on any independent variables.

By determining which quantile each household is situated in prior to the regression, its outcome cannot change in the set of conditioning covariates, which is the case when running a standard conditional quantile regression (CQR). The CQR approach was developed by Koenker & Hallock (2001) and is conditioned on a set of covariates which changes over the distribution while the UQR is marginally measured over the whole distribution. This thesis builds on the UQR approach by Firpo et al. (2009) by including zila fixed effects to mitigate potential endogeneity problems mentioned above. A further explanation and discussion of the unconditional quantile regression approach, as well as a deeper analysis of the RIF, can be found in the appendix, section A.1. Determining the marginal effects of the independent variables for a certain quantile is proven by Firpo et al. (2009). By taking the average of our RIF regression in respect to the change of the distribution of our covariates, this leads to our specification:

$$E[RIF(y;q_\tau)|X,C] = X_{ij}\beta + C_j\alpha + \varepsilon_{0j} + u_{ij} \qquad (12)$$

Just as in (11), the outcome variable is the log households net income (y), which in (12) is measured at quantile $\tau$. $X_{ij}$ is a vector of observed attributes for household i in zila j, with $\beta$

as its coefficient. $C_j$ is a vector of the climate variables mentioned in (11) which affect zila j and $\alpha$ as its coefficient. The results can be interpreted as an ordinary least squared estimator. Similar to the estimation in (11), there may be unobserved variables which correlate with our explanatory variables. Not accounting for these variables may then again bias the coefficient of our variable of interest. To accommodate this, we again control for time and zila fixed effects. A further discussion regarding potential endogeneity and bias can be found in section 6.1.

### 6.3 Extreme Floods

To extend the analysis further, a deeper analysis regarding the impacts of the extreme flood events of 2004 and 2007 is conducted. The approach to examine the extreme floods of 2004 and 2007 is influenced by Banerjee (2010), who examines these events as well. Being a lowland country with a vast river delta, Bangladesh experiences floods almost every year (Dartmouth Floods Observatory 2019). Compared to the other climate shocks we have analyzed, floods are the more occurring one, with higher variation. This indicates that floods are the major climate shock that the households of Bangladesh are subject to. Therefore, it seems most relevant to perform a deeper analysis of this topic. Further, we analyze these two events specifically as it is the two floods with highest magnitude score by Dartmouth Flood Observatory (2019) that match our timeframe. The flood of 2003 is the most severe flood, dislocating approximately 9.5 million people while the flood in 2007 dislocated approximately 5 million people. Both floods affected 27 zilas around the country. By substituting the variable for floods of high magnitude with a dummy variable each for these two flood events, we can look separately and analyze their impacts on household income.

# 7. Results

## 7.1 Baseline Regression

*Table 3 - Baseline Regression*

| | Fixed effects<br>(1) | Floods<br>(2) | Droughts<br>(3) | Temperature<br>(4) | Baseline<br>(5) |
|---|---|---|---|---|---|
| Floods low magnitude | | -0.117 | | | -0.168 |
| | | *(0.073)* | | | *(0.102)* |
| Floods medium magnitude | | 0.053 | | | 0.080* |
| | | *(0.040)* | | | *(0.047)* |
| Floods high magnitude | | -0.038 | | | -0.035 |
| | | *(0.035)* | | | *(0.033)* |
| Moderate droughts | | | 0.004 | | 0.000 |
| | | | *(0.005)* | | *(0.008)* |
| Severe droughts | | | 0.004 | | 0.003 |
| | | | *(0.006)* | | *(0.007)* |
| Maximum temp. days | | | | 0.007 | 0.008 |
| | | | | *(0.007)* | *(0.006)* |
| Minimum temp. days | | | | -0.001 | -0.005** |
| | | | | *(0.003)* | *(0.002)* |
| 2010 | 0.093*** | 0.082** | 0.088*** | 0.086 | 0.142** |
| | *(0.028)* | *(0.031)* | *(0.030)* | *(0.085)* | *(0.061)* |
| Household head female | -0.098*** | -0.098*** | -0.098*** | -0.097*** | -0.098*** |
| | *(0.033)* | *(0.034)* | *(0.033)* | *(0.033)* | *(0.034)* |
| Household head age | 0.015*** | 0.015*** | 0.015*** | 0.015*** | 0.015*** |
| | *(0.003)* | *(0.003)* | *(0.003)* | *(0.003)* | *(0.003)* |
| Age squared | -0.000*** | -0.000*** | -0.000*** | -0.000*** | -0.000*** |
| | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* |
| Household head education | 0.059*** | 0.059*** | 0.059*** | 0.059*** | 0.059*** |
| | *(0.002)* | *(0.002)* | *(0.002)* | *(0.002)* | *(0.002)* |
| Household size | 0.078*** | 0.078*** | 0.078*** | 0.078*** | 0.078*** |
| | *(0.004)* | *(0.004)* | *(0.004)* | *(0.004)* | *(0.004)* |
| Number of people in working age | 0.148*** | 0.148*** | 0.148*** | 0.148*** | 0.148*** |
| | *(0.006)* | *(0.006)* | *(0.006)* | *(0.006)* | *(0.006)* |
| Agricultural dependence | -0.004*** | -0.004*** | -0.004*** | -0.004*** | -0.004*** |
| | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* |
| Urban | 0.097*** | 0.097*** | 0.097*** | 0.097*** | 0.098*** |
| | *(0.021)* | *(0.022)* | *(0.021)* | *(0.021)* | *(0.022)* |
| Constant | 7.111*** | 7.127*** | 7.098*** | 7.123*** | 7.184*** |
| | *(0.069)* | *(0.075)* | *(0.068)* | *(0.074)* | *(0.071)* |
| Observations | 22,196 | 22,196 | 22,196 | 22,196 | 22,196 |
| R-squared | 0.330 | 0.331 | 0.330 | 0.330 | 0.332 |
| Number of zila | 64 | 64 | 64 | 64 | 64 |

*All monetary values are computed into real Tk. Using GDP-deflator and 2006 = 100*
*Numbers in parenthesis are clustered robust standard errors.*
*Significant at the * 10% level, ** 5% level, *** 1% level*

The results from our baseline regression are presented in Table 3. The first column indicates the fixed-effects model without our climate variables; these are added in columns two, three and four. When including each climatic event separately, no significant effect was found. The baseline regression is presented in column five where all climatic events are included.

All the climate shock variables except floods with medium magnitude and the variable indicating extreme low temperatures are insignificant. The coefficient of medium magnitude floods can be interpreted as household experience on average an 8% higher household net income if situated in a zila where a medium flood has occurred within the past three years. Due to the low significance, one needs to be careful drawing to many conclusions from this result. The extreme low temperature variable indicates that for each day the minimum daily temperature is two standard deviations below the mean, households in that zila will experience a 0.5% lower household net income. These results do not completely align with our hypothesis that climate shocks have an adverse effect on households.

As for our control variables on household-level, they are all statistically significant at a one percent level. Coefficient signs are expected. A female as a head of household and a greater share of income originating from agricultural income is associated with 9.8% and 0.4% lower income, respectively. Education levels for the head of household is associated with a positive impact of 5.9% for each additional completed year of education. The age of the head of household has an expected association with household income, increasing in a diminishing sense. Household size and the number of working age persons in the household are both positively associated with household net income: 7.8% for each additional member of the household and an additional 14.8% if the person is of working age. The control variables indicate robust estimates across all columns.

## 7.2 Unconditional Quantile Regression

In Table 4 we present the results for the UQR for the 25th and 90th quantiles; the full estimation including all the quantiles can be found in Table 6 in the appendix. The dependent variable for household income is again logged, and all regressions are run with fixed-effects and clustered standard errors.

For the 25th quantile in Column 7 we see a negative effect for cold days indicating a 0.5% drop in household income for each day cold day experienced by a household, just as the baseline regression presented. However, the significance level is quite low at ten percent. Additionally, no other climate shock variables show significant results.

The results for the 90th quantile in Column 8 show a different story: statistically significant negative effects for floods of low and high magnitude. Floods of low magnitude have a negative effect on household income by 31.2%, a result which is significant at the five percent level. The implication is that households in the 90th quantile situated in a zila that has experienced a flood of low magnitude has a 31.2% lower income than other households. The size of this effect is alarmingly high, which raises doubts regarding what the variable is actually measuring. Further, floods of high magnitude have a negative effect of 17.4% significant at a one percent level. Cold days are insignificant as are all other climate shock variables.

*Table 4 - Unconditional Quantile Regression*

| | Floods 25Q | Floods 90Q | Drought 25Q | Drought 90Q | Temp. 25Q | Temp. 90Q | Full 25Q | Full 90Q |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Floods low magnitude | -0.080 | -0.233** | | | | | -0.128 | -0.312** |
| | *(0.081)* | *(0.106)* | | | | | *(0.119)* | *(0.143)* |
| Floods medium magnitude | 0.049 | 0.078* | | | | | 0.084 | 0.090 |
| | *(0.051)* | *(0.045)* | | | | | *(0.057)* | *(0.055)* |
| Floods high magnitude | 0.001 | -0.171*** | | | | | 0.006 | -0.174*** |
| | *(0.040)* | *(0.053)* | | | | | *(0.040)* | *(0.053)* |
| Moderate droughts | | | 0.001 | 0.005 | | | -0.002 | -0.006 |
| | | | *(0.006)* | *(0.007)* | | | *(0.010)* | *(0.008)* |
| Severe droughts | | | 0.001 | 0.009 | | | 0.001 | 0.006 |
| | | | *(0.006)* | *(0.008)* | | | *(0.006)* | *(0.009)* |
| Maximum temp. days | | | | | -0.002 | 0.007 | -0.001 | 0.010 |
| | | | | | *(0.008)* | *(0.009)* | *(0.008)* | *(0.007)* |
| Minimum temp. days | | | | | -0.002 | 0.002 | -0.005* | -0.001 |
| | | | | | *(0.004)* | *(0.004)* | *(0.003)* | *(0.004)* |
| Control variables | *Yes* | *Yes* | *Yes* | *Yes* | *Yes* | *Yes* | *Yes* | *Yes* |
| Constant | 6.831*** | 8.080*** | 6.830*** | 7.980*** | 6.859*** | 7.964*** | 6.900*** | 8.102*** |
| | *(0.127)* | *(0.160)* | *(0.126)* | *(0.158)* | *(0.130)* | *(0.169)* | *(0.124)* | *(0.172)* |
| Observations | 22,196 | 22,196 | 22,196 | 22,196 | 22,196 | 22,196 | 22,196 | 22,196 |
| R-squared | 0.170 | 0.151 | 0.170 | 0.149 | 0.170 | 0.149 | 0.171 | 0.151 |
| Number of zila | 64 | 64 | 64 | 64 | 64 | 64 | 64 | 64 |

*All monetary values are computed into real Tk. Using GDP-deflator and 2006 = 100*
*Numbers in parenthesis are clustered robust standard errors.*
*Significant at the * 10% level, ** 5% level, *** 1% level*

Looking at Column 2 in Table 4, where climate shocks except for floods are omitted, we see a similar pattern, although the size of the effect for floods of low magnitude is smaller. Additionally, in Column 2, floods of medium magnitude have a positive effect of 7.8%, which is similar to the results in our baseline. These results do not confirm the hypothesis that poorer households are more vulnerable to climatic events in relation to richer households.

The full UQR table is presented in Table 6. There we can observe the effect for the 50$^{th}$ and the 75$^{th}$ quantile as well. For the 75$^{th}$ quantile, floods of low magnitude are associated with a negative effect of 22.9%, significant at the five percent level. Medium magnitude floods have once again a positive association on household income, an effect of 8.6% significant at the five percent level. For the 75$^{th}$ quantile, the effect of extremely low temperatures is similar to the baseline and significant at the five percent level.

## 7.3 Extreme Floods

*Table 5 -UQR and Baseline Regression with Major Floods separate*

| | 25Q | 50Q | 75Q | 90Q | Baseline |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Major Flood in 2003 | -0.009 | -0.024 | -0.039 | -0.108 | -0.032 |
| | *(0.066)* | *(0.068)* | *(0.065)* | *(0.067)* | *(0.054)* |
| Major Flood in 2007 | 0.052 | 0.018 | -0.065 | -0.170** | -0.021 |
| | *(0.068)* | *(0.069)* | *(0.062)* | *(0.069)* | *(0.055)* |
| Floods Low magnitude | -0.123 | -0.099 | -0.206* | -0.228* | -0.150 |
| | *(0.117)* | *(0.115)* | *(0.106)* | *(0.132)* | *(0.097)* |
| Flood medium magnitude | 0.077 | 0.077* | 0.096** | 0.118** | 0.083* |
| | *(0.010)* | *(0.009)* | *(0.008)* | *(0.009)* | *(0.008)* |
| Moderate droughts | -0.002 | 0.005 | -0.001 | -0.004 | 0.001 |
| | *(0.010)* | *(0.009)* | *(0.008)* | *(0.009)* | *(0.008)* |
| Severe droughts | 0.002 | -0.001 | 0.004 | 0.005 | 0.003 |
| | *(0.007)* | *(0.012)* | *(0.009)* | *(0.010)* | *(0.007)* |
| Maximum temp. days | -0.002 | 0.007 | 0.008 | 0.009 | 0.008 |
| | *(0.008)* | *(0.008)* | *(0.007)* | *(0.008)* | *(0.007)* |
| Minimum temp. days | -0.004 | -0.006* | -0.006** | -0.003 | -0.005** |
| | *(0.003)* | *(0.003)* | *(0.003)* | *(0.005)* | *(0.003)* |
| Control variables | *Yes* | *Yes* | *Yes* | *Yes* | *Yes* |
| Constant | 6.897*** | 7.010*** | 7.529*** | 8.085*** | 7.182*** |
| | *(0.125)* | *(0.104)* | *(0.096)* | *(0.174)* | *(0.074)* |
| Observations | 22,196 | 22,196 | 22,196 | 22,196 | 22,196 |
| R-squared | 0.171 | 0.247 | 0.237 | 0.150 | 0.332 |
| Number of zila | 64 | 64 | 64 | 64 | 64 |

*All monetary values are computed into real Tk. Using GDP-deflator and 2006 = 100*
*Numbers in parenthesis are clustered robust standard errors.*
*Significant at the * 10% level, ** 5% level, *** 1% level*

Table 5 presents the results when conducting a deeper analysis for the impacts of extreme floods by breaking down the extreme floods and focusing on the two biggest floods which occurred in our timespan, when considering floods of the highest magnitude. The first four columns indicate the UQR while the fifth indicates the fixed-effects regression. Column one presents the effects for the 25th quantile; no variables of interest are significant for this quantile. As for the second column, which indicate the impacts on the 50th quantile, floods with medium magnitude and extreme cold temperatures are weakly significant. The results indicate a positive effect of 7.7% for medium magnitude floods and a negative effect of 0.6% for cold days in the 50th quantile, Column 2.

Column 3 presents the effect for the 75th quantile, where floods of low magnitude are weakly significant while floods of medium magnitude and cold days are significant on a five percent level. These effects are similar to the estimates using the high magnitude flood variable presented in the appendix, Table 6. Floods of low magnitude have a weakly significant negative effect of 20.6%. Floods of medium magnitude positively affect household income, with each flood increasing expected income by 9.6%. This effect is significant at the five percent level. Finally, an additional day with extreme cold temperature negatively affects income by 0.6%. Looking at Column 4 which presents the impacts for the 90th quantile, the major flood from 2007 indicates a negative effect on household income, an effect associated with a decrease of 17% for households experiencing the extreme flood of 2007 and belonging to the 90$^{th}$ quantile. This effect is significant on the five percent level. Medium magnitude floods indicate a positive effect of 11.8%, significant at the five percent level. Low magnitude floods are associated with a negative effect of 22.8%. An effect weakly significant at the 10 percent level.

Column 5 in Table 5 presents the baseline approach when the extreme floods are included. The only variables of interest which are significant are days with extremely cold temperatures and floods of medium magnitude. Days with extremely cold temperatures are associated with a negative effect of 0.5% at the five percent level. Floods of medium magnitude are weakly significant at the 10 percent level, showing a positive effect of 8.3%.

## 7.4 Robustness Checks

The primary estimation using the logarithm of income in the estimation model is tested for robustness from different aspects. First, we examine a specification which considers dependent variables income as linear, as opposed to the log income used in the baseline estimation. All regression results regarding the linear estimation can be found in the appendix, A.3.1. Second, we examine the sensitivity of our results to outliers. These results can be found in the appendix, A.3.2. Third, we consider gross income as the dependent variable as opposed to the net income. These results regarding gross income can be found in the appendix, A.3.3.

### *7.4.1. Linear Specification*

A linear specification is conducted to examine if the causal effects are robust in consideration to the logarithmic specification. As our theoretical model predicts, a linear specification can give progressive results (effect increasing with wages) since the loss of income is tied to the given wage level. Thus, low wage workers will have a smaller effect because they have less income to lose. The results of our linear specification are presented in the appendix, A.3.1. Table 7 presents the baseline regression. The significance for our variables of interest increase substantially. All floods are now significant on a five percent level. Minimum temperature is insignificant in the linear specification, a variable significant on a five percent level for the logarithmic specification. As presented in Equation 7, an overestimation might occur when examining climate events in absolute terms.

Table 8 presents the UQR with a linear estimation. In relation to the baseline regression no major difference regarding significance is distinguished between the linear and logarithmic specifications. Observing the effects for the linear estimation, a progressive trend is found regarding the impacts of the floods with respect to the income levels, an observation which is in line with the theoretical framework, implying that the magnitude of the impacts is increasing in income when looking at absolute values rather than percentage changes (Equation 8 and Equation 9).

### *7.4.2. Outlier Examination*

To examine if the results in our baseline and UQR approach are sensitive to outliers, an outlier examination is conducted by only including the middle 80%, i.e. dropping the richest and poorest 10% for each zila. These estimates can be found in the appendix, A.3.2, Table 9. The table shows that floods of high magnitude lose significance for the 90$^{th}$ quantile, although medium magnitude floods show similar positive impacts, just as the effect of extreme minimum temperature days. This suggests that floods of medium magnitude are less sensitive to outliers than floods of low and high magnitude.

### *7.4.3. Estimating with Gross Income*

To examine if income and/or expenditures are affected by the climate events presented in our baseline and UQR approach, an estimation regarding gross income is conducted. If expenditures are increased due to climate events, household net income would decrease. This could imply that households increase expenditure/investments due to climate events, performing some spending adjustments. This would further imply that the effect estimated in our baseline regressions are wrongly interpreted. The estimation is presented in the appendix, A.3.3, Table 10. The estimates indicate no significant difference regarding the size and statistical significance of the climate variables. This further implies that the impact of climate events represents a hit on income and not an increase in expenditures.

## 8. Discussion

To summarize the results, the baseline regression shows that only extreme low temperature days has a negative impact on household income that is statistically significant. Furthermore, our estimates in the UQR presents that floods of low and high magnitude have an adverse effect on top income households while medium magnitude floods show positive effects.

The results represented in Tables 3 and 4 do not confirm our main hypothesis regarding the impacts of climatic events, neither where the impacts would be the largest. First of all, in Table 3 there seems to be a positive effect on floods of medium magnitude and no effect on the other flood variables. Our estimates of floods contrast the results presented by Arouri et al. (2015) regarding Vietnam. They find that households in flood prone communes are expected to have a 5.9% lower household per capita income. Other studies such as Padli et al. (2009) confirm that a poorer country such as Bangladesh would be sensitive to climate events considering economic impact. This was expected to be confirmed by our thesis in our baseline approach. One reason this might not be observed in our baseline could be that our study has fewer household surveys over the time span that is analyzed. This reduces the variation we can observe in both climate events and household income. Arouri et al. (2015) has a frequency of four income surveys in the same period that we only have two. This could make their estimates more robust in contrast to ours.

Furthermore, they only examine the effect on rural households while we use this as a control in our analysis. Another reason could be the precision of what households are exposed to floods. While Arouri et al. (2015) uses data where households state whether they have been exposed to floods. However, our study endeavors to match floods and households from different data sources. This process comes with the risk of losing precision by wrongfully matching a household with a flood which it has not actually been exposed to. Moreover, the ambiguity can be explained by the magnitude classifications by the DFO. They equally weigh all factors in the index and normalize them logarithmically, meaning a flood covering a vast area affecting almost no households can have the same or higher classification than a flood covering a small densely populated area, even though the latter is more likely to cause economic damage.

The observation which we observe for the slight positive effect on floods of medium magnitude is quite surprising, especially considering it is a medium magnitude flood and not a low magnitude flood. As Banerjee (2010) presents, small floods can enhance agricultural yield if exploited as an agricultural input in the form of irrigation. As households in Bangladesh are more familiar to floods, medium magnitude floods might be managed and employed as something positive. The magnitude classifications should be considered as an explanation. The classification of what constitutes a low, medium or high magnitude flood might be different between the studies. What Banerjee (2010) constitute as a small flood might very well be what the DFO classifies as a flood of medium magnitude. In that case our estimates regarding medium magnitude would align with Banerjee (2010).

For the other climate variables, only the one indicating extreme low temperatures seems to have a statistically significant effect as well as a negative one, which is in line with our hypothesis. As for the lack of significant effect on the drought variables, this could possibly be explained by the fact that there is little variation in the drought index for the analyzed years. As Figure 3 presents, zilas experiencing extreme droughts during the time span of three years prior to the conducted income surveys is zero, and close to none experienced where severe. Moderate droughts seem to have occurred more frequently throughout the years, especially after 2010. In other words, dry weather does not seem be a frequent problem in Bangladesh during the time period that was analyzed and might therefore not cause significant damage to household income. Furthermore, the index definition of droughts by the SPEI should also be discussed as it is set by a global standard. Thus, what SPEI classifies as a moderate drought globally could be considered normal weather in Bangladesh.

Our estimates regarding temperature does not go in line with Dell et al. (2012), who found support regarding an increase in temperatures causing negative impact on economic growth. Although their research focused on a longer historical aspect, some resemblance was expected. This lack of effect in our variables indicating extreme temperature could be explained in two ways. The first way is similar to the explanation regarding our drought indicators. As Figure 1 presented in section 5.2, the extremely hot days per year and zila seem to range from zero to four days. In such a short time span the extreme heat is not likely to have any significant effect on the overall household income.

As for extremely cold days, the variation is larger, which could explain the fact that we identify a significant negative effect of this variable.  Furthermore, it is more likely that extreme temperature has an effect when these days occur consecutively, something which is not measured in our analysis. Looking deeper into consecutive days of extreme temperature might show a more precise picture of the actual effects of extreme temperature. It is less likely that one or two separate days of extreme temperature would significantly affect the income of a household. The second explanation is that the temperature data could not be collected on a zila level but were obtained from 34 weather stations. Thus, the temperature data for each zila was matched with the closest weather station. Therefore, the temperature data could be rather imprecise in regards to the targeted region. A more precise data source is unfortunately not available for Bangladeshi weather today.

In the unconditional quantile regression in Table 4 we see further results that contradict our second hypothesis, which implied that poorer households would experience a larger negative impact of climatic events. This hypothesis is in line with previous literature which found poorer household being more vulnerable by climatic events (Brouwer 2007 and Akter & Mallick 2013). There seems to be a progressive effect on floods, i.e. the magnitude of the effects for the higher quantiles are larger than the lower ones. The pattern stands for both the negative effects of floods of low and high magnitude as well as the positive effect from medium magnitude floods. This is the opposite of what was primarily expected in regards to our hypothesis. Our theoretical model opens up the possibility, however, that higher income households can be more sensitive to climate shocks than lower income households. This is represented by the factor sensitivity parameters $\gamma_K$ and $\gamma_T$. Where if ($\gamma_K > \gamma_T$) holds, high income households, engaged in the modern sector, would be more adversely affected by a climate event. Our results indicate that this in fact is the case in Bangladesh. This does not completely contradict Akter & Mallick (2013) since they find that poor households have a better ability to recover from shocks. Furthermore, Haque & Jahan (2015) find that different sectors are affected differently by natural disasters. Intuitively, one could thus assume that the inputs required in the modern sector, such as machinery, transportation vehicles and other capital goods, are more sensitive to climate events in Bangladesh. This could thus cause household income to drop for top earners. This could also be a consequence of the modern sector trying to adapt to the Bangladeshi institutional context of frequently occurring climate shocks, something the traditional agricultural sector has had time to adapt to.

Our results could also be explained by the fact that low income households have a lot less to lose during a disaster in monetary terms than high income households, meaning there is little downward variation due to an adverse shock, making it hard to detect a negative effect in the regression. Another explanation could be that higher income households are not as shielded from climatic shocks as we initially expected, something that does not necessarily contradict the findings of Brouwer et al. (2007). They find that poor households are more often situated close to riverbanks where there is a high flood risk; in their study, richer households might not have been exposed to climate shocks in the same extent as in our study. Brouwer et al. (2007) and similar literature lack the examination of high-income households, which might be why our estimates do not align with previous literature. Furthermore, Akter & Mallick (2013) find evidence supporting the aspect that poorer households have a better ability to recover from shocks such as climatic events. These findings of recovery regarding poorer households could confirm the situation which our UQR approach estimates: that richer households are not as quick to recovery from such events. As we can see in the results, richer households exposed to the flood of 2007 are still affected negatively during the survey year of 2010, while the bottom three quantiles show no significant effect. This could indicate that richer households take longer time to recover or that they are not as prepared and adapted to floods as poorer households.

Table 5 presents the specification where the two extreme floods occurring in 2003 and 2007 are examined separately. Once again, the results from the estimation do not confirm the suggestion that poorer households are more vulnerable. The results indicate similarities with Table 4 that the impact on poorer households is insignificant while richer households experience a larger negative effect. Regarding the two extreme flood events, the flood of 2003 is insignificant across all columns while the flood in 2007 indicate negative effects for the 90$^{th}$ quantile. Floods of low magnitude demonstrate, once again, a negative and weakly significant impact on the higher quantiles. The floods of medium magnitude have a positive effect, weakly significant for the 50$^{th}$ quantile and higher significance for the top two quantiles. These effects and directions are not in line with neither the hypothesis nor parts of the previous literature, which find evidence that poorer households are more vulnerable to climate shocks (Brouwer et al. (2007), Akter & Mallick (2013) and Arouri et al. 2015). Further, as Haque & Jahan (2015) discuss, different sectors are affected in different manners. As previously mentioned, our theoretical framework opens up for this possibility depending on the sensitivity for the production factors land and capital. As the modern sector is a relatively new sector in Bangladesh, it might not be as adaptable to the institutional context to the same extent as the agricultural sector. This would imply that higher income households are affected to a larger extent than lower income households.

Further, considering the income data that is gathered in a survey setting, there could be a correlation between income and precise answers. This means that respondents with higher income might have more precise information about their actual income during the time of the survey than respondents of lower income households, thus giving more precise answers that lead to a more precise analysis regarding the richer households. This is something which might be present in our analysis, since we see almost no effect of any climatic shock variable when we analyze the bottom quantiles in Table 6. As with any survey analysis, there is a risk to its validity, and this can especially be the case in poor communities with low educational level. Especially as our data indicates that approximately half the heads of households have not completed a single class in school. Respondents might not have their income information at hand, leading to over or underestimation. Further, respondents might deliberately over or understate some information expecting to get something in return or they might not fully understand the questionnaire. The fact that the results show robust and expected estimates for the household control variables, however, indicates that the household income data is reliable.

Running a similar analysis with more data over a longer time period, both on household income and climate data could confirm or contradict the results found in this thesis. As the explanations for the unexpected results might be confirmed, such as that different sectors are affected differently as Haque & Jahan (2015) imply and Banerjee (2010) who find positive effects for certain floods in Bangladesh. This considered, there is always the possibility that a vital variable has been omitted which we could not identify, such as migration patterns for affected households. For future research, a longer time period would strengthen the results as well as their validity. This could also solve some of the estimation issues that we suspect are present. Another aspect for future researchers is to consider urban and rural differences and how different elements of the society are affected, not only considering income. If panel data becomes available in Bangladesh, it could track household's migration patterns across the country, which would solve the implication that people move due to climate shocks.

## 9. Conclusion

This thesis estimates the effects of climate events on household income in Bangladesh, and further investigates how households of different income-levels are affected differently. Our thesis does not confirm that climate shocks are making poor people poorer. We find that the floods of low and high magnitude have a negative effect on income for the high-income households. These results indicate that high-income households are more sensitive to floods in relation to low-income households, and this is not in line with our hypothesis. Further, the impacts of the different classifications of floods were surprising and not anticipated. A larger negative effect for a low magnitude flood than a high magnitude flood was not expected. The results concerning high-income households were similar when estimating the effects from the extreme floods in 2003 and 2007. As presented in Table 4, the effect from high magnitude floods mainly originates from the extreme flood in 2007.

The lack of significant estimates regarding low-income households might imply that they are better equipped to recover from climate events. Further, the impacts might differ between sectors. The agricultural sector, where a larger share of low-income household's work might benefit from floods if treated as an input as irrigation. The newly established modern sector, where higher-income households work to a larger extent, is mainly built on capital. Capital could be more sensitive to climate events as it might not be as adjusted to the context of Bangladesh, like the traditional agricultural sector. An additional aspect to consider is that low-income households have initially low income, implying a lack of downward possibility when estimating negative effects.

Even though the results of this analysis show higher vulnerability to richer households regarding climatic shocks, the degree of how precise the estimates were should be taken into consideration. The lack of precise data on what households are exposed to what climate events in this report might bias the results.

As this area of research is of great importance, future researchers are advised to expand the time period of the analysis, which might increase the variation of climate shocks and give more precise estimates. As this research exclusively examined household income, additional aspects are vital to consider such as consumption patterns, investment rates and migration patterns, especially as poorer households might be affected in other forms when considering their vulnerability to climate change.

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# Appendix

## A.1 Unconditional Quantile Regression

When examining the impacts of climate events on household net income, the unconditional quantile regression (UQR) approach can be used. An approach developed by Firpo et al. (2009) which is increasing in popularity. The UQR approach allows for an identification of heterogeneous effects of impacts across income levels. Compared to the classical conditional quantile regression (CQR), UQR allows for all independent variables to vary between quantiles. The CQR approach, developed by Koenker & Hallock (2001), changes in the set of conditioning covariates while the UQR is marginally measured over the whole distribution. This allows for the partially interpretation at the different quantiles.

As mentioned, the UQR is based on the re-centered influence function which can be defined as:

$$RIF(y; \mathrm{v}) = \mathrm{v(F)} + IF(y; \mathrm{v})$$

Where v(F) indicate the distributional statistics which in our case is the specific quantile while the $IF(y; \mathrm{v})$ is the influence function. The RIF primarily defined and introduced by Hampel (1974) and represents an individual's influence on the entire distributional statistics. The RIF can furthermore be defined as follows when desiccating the IF.

$$RIF(y; q_\tau) = q_\tau + \frac{\tau - 1\{y \leq q_\tau\}}{f_Y(q_\tau)}$$

Where $q_\tau$ is the value of our outcome variable net income (y), at quantile $\tau$ as for our example the net income at the 25th quantile. The function $1\{y \leq q_\tau\}$, an indicator function which equals 1 if the value is less than or equal to the dependent variable at that specific quantile, otherwise it takes the value 0. This means that the function indicates if a household is identified as a household with a net income equal to or below the value at quantile $\tau$. $f_Y(q_\tau)$ determines the density function of the dependent variable y at quantile $\tau$. The RIF equation above gives two important insights to note: firstly, that the outcome variable is determined prior to the regression leading to the identical definition for each quantile; secondly, the definition is considerably dependent on the density function (Porter 2015).

Firpo et al. (2009) presents this approach by analyzing the effects of being a union member on male wages. The UQR allows for a non-linear examination throughout the sample. This in contrast to CQR which they present to be more linear, as quantiles of an OLS regression. As we are interested in analyzing the difference in sensitivity and exposure to climatic events for different shares of the population, a standard OLS approach is not suitable. More specifically, and as previous literature has shown, we are interested in the different household income brackets. Since the UQR models allows for the possibility of analyzing the difference in income brackets, it will be implemented throughout this paper.

As further discussed by Firpo et al. (2015), the UQR estimates which often is named the unconditional quantile partial effect (UQPE). The UQPE is the average marginal effect and defined as:

$$\alpha_\tau = E[dE[RIF(y; q_\tau)|X]/dx]$$

The estimation of UQPE for quantile $\tau$, which further can be represented as the weighted average of the conditional quantile partial effect (CQPE). These propositions as well as the proofs of theorems can be found in Firpo et al. (2015)'s appendix.

Furthermore, the dataset used in this paper is in the need for fixed-effects due to the zila-level clusters, meaning that the households which are located in zilas might have specific characteristics. Such characteristics could be a certain income-type or income-level which could bias the results if not controlled. This leads to the usage of the UQR, including fixed-effects on zila-level, an approach discussed by Borgen (2016). By using this approach, the UQR allows for the adjustment of fixed effects without in the need for the redefinition of the quantiles which is a major advantageous which cannot be established running a CQR.

## A.2 Full Unconditional Quantile Regression

*Table 6 - Unconditional Quantile Regression - All Quantiles*

| | 25Q | 50Q | 75Q | 90Q |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Floods low magnitude | -0.128 | -0.111 | -0.229** | -0.312** |
| | *(0.119)* | *(0.119)* | *(0.112)* | *(0.143)* |
| Floods medium magnitude | 0.084 | 0.080* | 0.086** | 0.090 |
| | *(0.057)* | *(0.042)* | *(0.040)* | *(0.055)* |
| Floods high magnitude | 0.006 | -0.013 | -0.055 | -0.174*** |
| | *(0.040)* | *(0.037)* | *(0.037)* | *(0.053)* |
| Moderate droughts | -0.002 | 0.005 | -0.002 | -0.006 |
| | *(0.010)* | *(0.009)* | *(0.008)* | *(0.008)* |
| Severe droughts | 0.001 | -0.001 | 0.005 | 0.006 |
| | *(0.006)* | *(0.011)* | *(0.008)* | *(0.009)* |
| Maximum temp. days | -0.001 | 0.007 | 0.008 | 0.010 |
| | *(0.008)* | *(0.008)* | *(0.007)* | *(0.007)* |
| Minimum temp. days | -0.005* | -0.006** | -0.006** | -0.001 |
| | *(0.003)* | *(0.003)* | *(0.003)* | *(0.004)* |
| 2010 | 0.189** | 0.184*** | 0.183*** | 0.123 |
| | *(0.076)* | *(0.068)* | *(0.068)* | *(0.088)* |
| Household head female | -0.235*** | 0.051* | 0.205*** | 0.273*** |
| | *(0.035)* | *(0.027)* | *(0.028)* | *(0.030)* |
| Household head age | 0.018*** | 0.019*** | 0.012*** | -0.003 |
| | *(0.004)* | *(0.003)* | *(0.003)* | *(0.006)* |
| Age squared | -0.000*** | -0.000*** | -0.000 | 0.000** |
| | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* |
| Household head education | 0.037*** | 0.062*** | 0.083*** | 0.092*** |
| | *(0.003)* | *(0.002)* | *(0.002)* | *(0.006)* |
| Household size | 0.065*** | 0.061*** | 0.059*** | 0.099*** |
| | *(0.006)* | *(0.005)* | *(0.006)* | *(0.009)* |
| Number of people in working age | 0.120*** | 0.150*** | 0.171*** | 0.166*** |
| | *(0.010)* | *(0.009)* | *(0.008)* | *(0.015)* |
| Agricultural dependence | -0.005*** | -0.004*** | -0.003*** | -0.002*** |
| | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* |
| Urban | 0.065*** | 0.072*** | 0.104*** | 0.210*** |
| | *(0.023)* | *(0.023)* | *(0.027)* | *(0.037)* |
| Constant | 6.900*** | 7.012*** | 7.531*** | 8.102*** |
| | *(0.124)* | *(0.100)* | *(0.093)* | *(0.172)* |
| Observations | 22,196 | 22,196 | 22,196 | 22,196 |
| R-squared | 0.171 | 0.247 | 0.237 | 0.151 |
| Number of zila | 64 | 64 | 64 | 64 |

*All monetary values are computed into real Tk. Using GDP-deflator and 2006 = 100*
*Numbers in parenthesis are clustered robust standard errors.*
*Significant at the * 10% level, ** 5% level, *** 1% level*

## A.3 Robustness Checks

### *A.3.1 Linear Specification*

*Table 7 - Baseline Regression with Net Income as Dependent Variable*

| | Fixed effects | Floods | Droughts | Temperature | Baseline |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Floods low magnitude | | -1,201.202** | | | -1,734.034** |
| | | (517.132) | | | (781.589) |
| Floods medium magnitude | | 448.473** | | | 632.364** |
| | | (204.631) | | | (279.871) |
| Floods high magnitude | | -588.395** | | | -575.972** |
| | | (251.715) | | | (250.544) |
| Moderate droughts | | | 24.077 | | -30.326 |
| | | | (42.232) | | (64.658) |
| Severe droughts | | | 52.353 | | 44.763 |
| | | | (36.833) | | (48.279) |
| Maximum temp. days | | | | 33.051 | 45.373 |
| | | | | (51.737) | (45.703) |
| Minimum temp. days | | | | -2.478 | -27.339 |
| | | | | (20.730) | (21.984) |
| 2010 | 745.576*** | 695.204*** | 708.235*** | 616.397 | 973.032** |
| | (228.781) | (245.941) | (228.577) | (550.211) | (465.239) |
| Household head female | 1,395.232*** | 1,393.238*** | 1,394.548*** | 1,395.214*** | 1,390.666*** |
| | (287.769) | (288.200) | (287.962) | (287.096) | (288.873) |
| Household head age | -17.197 | -16.094 | -16.961 | -17.573 | -16.765 |
| | (52.343) | (52.400) | (52.322) | (52.523) | (52.846) |
| Age squared | 0.853 | 0.844 | 0.850 | 0.856 | 0.850 |
| | (0.566) | (0.566) | (0.565) | (0.567) | (0.570) |
| Household head education | 574.765*** | 574.431*** | 574.711*** | 574.840*** | 575.216*** |
| | (39.041) | (38.982) | (39.066) | (38.883) | (38.976) |
| Household size | 734.016*** | 736.415*** | 734.474*** | 734.300*** | 735.632*** |
| | (81.622) | (81.713) | (81.709) | (81.667) | (81.637) |
| Number of people in working age | 1,151.910*** | 1,149.038*** | 1,151.835*** | 1,151.972*** | 1,150.121*** |
| | (116.162) | (116.264) | (116.387) | (116.685) | (117.509) |
| Agricultural dependence | -21.170*** | -21.027*** | -21.153*** | -21.139*** | -20.884*** |
| | (3.811) | (3.801) | (3.811) | (3.829) | (3.802) |
| Urban | 1,046.884*** | 1,050.550*** | 1,045.067*** | 1,048.022*** | 1,051.850*** |
| | (299.177) | (299.963) | (299.113) | (299.908) | (299.804) |
| Constant | -2,861.947*** | -2,583.458** | -2,954.151*** | -2,864.639*** | -2,211.032** |
| | (993.645) | (1,005.636) | (955.408) | (1,047.632) | (1,044.795) |
| Observations | 22,315 | 22,315 | 22,315 | 22,315 | 22,315 |
| R-squared | 0.086 | 0.087 | 0.086 | 0.086 | 0.087 |
| Number of zila | 64 | 64 | 64 | 64 | 64 |

*All monetary values are computed into real Tk. Using GDP-deflator and 2006 = 100*
*Numbers in parenthesis are clustered robust standard errors.*
*Significant at the * 10% level, ** 5% level, *** 1% level*

*Table 8 - Unconditional Quantile Regression with Net Income as Dependent Variable*

| | 25Q | 50Q | 75Q | 90Q |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Floods low magnitude | -433.229 | -511.140 | -2,008.578** | -4,731.922** |
| | (350.110) | (553.548) | (969.917) | (2,167.366) |
| Floods medium magnitude | 248.940 | 362.847* | 745.617** | 1,366.878 |
| | (160.398) | (190.328) | (340.597) | (835.943) |
| Floods high magnitude | 20.665 | -67.509 | -465.080 | -2,731.795*** |
| | (121.278) | (176.752) | (315.933) | (817.792) |
| Moderate droughts | -5.164 | 23.682 | -16.658 | -97.078 |
| | (28.501) | (40.975) | (66.508) | (127.383) |
| Severe droughts | 1.810 | -4.289 | 42.122 | 110.447 |
| | (19.314) | (53.004) | (72.905) | (136.361) |
| Maximum temp. days | -0.762 | 36.239 | 72.480 | 168.586 |
| | (24.683) | (38.347) | (60.561) | (114.097) |
| Minimum temp. days | -15.956* | -30.435** | -49.223** | -16.686 |
| | (8.490) | (12.904) | (23.623) | (65.327) |
| 2010 | 512.320** | 858.219** | 1,546.015*** | 1,769.789 |
| | (228.384) | (325.435) | (580.673) | (1,368.444) |
| Household head female | -699.602*** | 225.149* | 1,752.767*** | 4,124.337*** |
| | (100.498) | (128.597) | (243.278) | (449.586) |
| Household head age | 50.354*** | 86.575*** | 99.758*** | -50.822 |
| | (11.698) | (13.381) | (26.932) | (89.135) |
| Age squared | -0.524*** | -0.539*** | -0.177 | 2.280** |
| | (0.112) | (0.127) | (0.270) | (0.923) |
| Household head education | 105.510*** | 286.825*** | 699.809*** | 1,404.490*** |
| | (8.277) | (10.214) | (20.598) | (85.228) |
| Household size | 186.521*** | 288.648*** | 500.113*** | 1,505.661*** |
| | (18.356) | (22.377) | (54.949) | (133.166) |
| Number of people in working age | 352.442*** | 695.153*** | 1,449.566*** | 2,563.106*** |
| | (27.579) | (39.523) | (67.931) | (233.200) |
| Agricultural dependence | -13.376*** | -19.047*** | -24.122*** | -26.876*** |
| | (1.054) | (1.599) | (2.864) | (6.241) |
| Urban | 195.946*** | 336.871*** | 900.191*** | 3,213.423*** |
| | (67.658) | (106.133) | (226.297) | (565.517) |
| Constant | -103.005 | -1,987.876*** | -4,409.028*** | -8,096.448*** |
| | (358.440) | (465.134) | (793.955) | (2,657.801) |
| Observations | 22,315 | 22,315 | 22,315 | 22,315 |
| R-squared | 0.168 | 0.245 | 0.237 | 0.151 |
| Number of zila | 64 | 64 | 64 | 64 |

*All monetary values are computed into real Tk. Using GDP-deflator and 2006 = 100*
*Numbers in parenthesis are clustered robust standard errors.*
*Significant at the * 10% level, ** 5% level, *** 1% level*

### A.3.2 Outlier Examination

*Table 9 - Unconditional Quantile Regression with Dropped Outliers*

| | 25Q | 50Q | 75Q | 90Q | Baseline |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Floods low magnitude | -0.099 | -0.092 | -0.154** | -0.099 | -0.111 |
| | (0.088) | (0.099) | (0.074) | (0.072) | (0.072) |
| Floods medium magnitude | 0.065* | 0.060* | 0.052* | 0.033 | 0.059** |
| | (0.038) | (0.033) | (0.027) | (0.025) | (0.029) |
| Floods high magnitude | 0.014 | 0.000 | -0.016 | -0.039 | -0.006 |
| | (0.026) | (0.032) | (0.029) | (0.027) | (0.025) |
| Moderate droughts | -0.004 | 0.002 | -0.003 | -0.004 | -0.002 |
| | (0.007) | (0.007) | (0.005) | (0.004) | (0.006) |
| Severe droughts | 0.003 | -0.000 | -0.001 | 0.004 | 0.001 |
| | (0.005) | (0.010) | (0.007) | (0.004) | (0.005) |
| Maximum temp. days | 0.002 | 0.007 | 0.008 | 0.006 | 0.004 |
| | (0.007) | (0.007) | (0.005) | (0.004) | (0.005) |
| Minimum temp. days | -0.003 | -0.004* | -0.003 | -0.001 | -0.003* |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| 2010 | 0.109* | 0.119** | 0.090** | 0.056 | 0.099** |
| | (0.061) | (0.057) | (0.044) | (0.043) | (0.040) |
| Household head female | -0.011 | 0.107*** | 0.161*** | 0.141*** | 0.060*** |
| | (0.023) | (0.026) | (0.026) | (0.034) | (0.018) |
| Household head age | 0.012*** | 0.012*** | 0.009*** | 0.004 | 0.010*** |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.002) |
| Age squared | -0.000*** | -0.000** | -0.000 | 0.000 | -0.000*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Household head education | 0.027*** | 0.045*** | 0.048*** | 0.040*** | 0.036*** |
| | (0.002) | (0.002) | (0.002) | (0.004) | (0.001) |
| Household size | 0.035*** | 0.043*** | 0.034*** | 0.032*** | 0.037*** |
| | (0.005) | (0.004) | (0.005) | (0.007) | (0.003) |
| Number of people in working age | 0.087*** | 0.115*** | 0.111*** | 0.090*** | 0.092*** |
| | (0.010) | (0.008) | (0.007) | (0.011) | (0.005) |
| Agricultural dependence | -0.003*** | -0.003*** | -0.002*** | -0.001*** | -0.002*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Urban | 0.050*** | 0.055*** | 0.049*** | 0.075*** | 0.052*** |
| | (0.018) | (0.020) | (0.018) | (0.019) | (0.013) |
| Constant | 7.249*** | 7.387*** | 7.948*** | 8.536*** | 7.625*** |
| | (0.101) | (0.086) | (0.073) | (0.105) | (0.047) |
| Observations | 17,826 | 17,826 | 17,826 | 17,826 | 17,826 |
| R-squared | 0.110 | 0.174 | 0.148 | 0.080 | 0.254 |
| Number of zila | 64 | 64 | 64 | 64 | 64 |

*All monetary values are computed into real Tk. Using GDP-deflator and 2006 = 100*
*Numbers in parenthesis are clustered robust standard errors.*
*Significant at the * 10% level, ** 5% level, *** 1% level*

### *A.3.3 Gross Income*

*Table 10 - Gross Household Income*

| | 25Q | 50Q | 75Q | 90Q | Baseline |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Floods low magnitude | -0.152 | -0.027 | -0.142 | -0.209* | -0.350** |
| | *(0.095)* | *(0.116)* | *(0.109)* | *(0.111)* | *(0.167)* |
| Floods medium magnitude | 0.068 | 0.127** | 0.100** | 0.051 | 0.053 |
| | *(0.045)* | *(0.051)* | *(0.042)* | *(0.048)* | *(0.056)* |
| Floods high magnitude | -0.040 | -0.007 | -0.011 | -0.077* | -0.154*** |
| | *(0.033)* | *(0.048)* | *(0.038)* | *(0.040)* | *(0.053)* |
| Moderate droughts | -0.001 | 0.003 | 0.004 | -0.002 | -0.011 |
| | *(0.007)* | *(0.010)* | *(0.008)* | *(0.007)* | *(0.008)* |
| Severe droughts | 0.001 | -0.001 | -0.002 | 0.002 | 0.017 |
| | *(0.007)* | *(0.008)* | *(0.009)* | *(0.007)* | *(0.011)* |
| Maximum temp. days | 0.007 | -0.002 | 0.006 | 0.009 | 0.006 |
| | *(0.007)* | *(0.009)* | *(0.006)* | *(0.007)* | *(0.009)* |
| Minimum temp. days | -0.005** | -0.009*** | -0.005* | -0.002 | 0.002 |
| | (0.002) | (0.003) | (0.003) | (0.003) | (0.005) |
| 2010 | 0.508*** | 0.669*** | 0.517*** | 0.449*** | 0.351*** |
| | (0.059) | (0.079) | (0.063) | (0.070) | (0.100) |
| Household head female | -0.111*** | -0.221*** | 0.035 | 0.204*** | 0.249*** |
| | (0.034) | (0.036) | (0.026) | (0.027) | (0.031) |
| Household head age | 0.015*** | 0.020*** | 0.019*** | 0.012*** | 0.002 |
| | (0.003) | (0.004) | (0.003) | (0.003) | (0.005) |
| Age squared | -0.000*** | -0.000*** | -0.000*** | -0.000 | 0.000* |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Household head education | 0.062*** | 0.046*** | 0.063*** | 0.079*** | 0.087*** |
| | (0.002) | (0.003) | (0.002) | (0.002) | (0.005) |
| Household size | 0.079*** | 0.069*** | 0.067*** | 0.058*** | 0.097*** |
| | (0.004) | (0.006) | (0.005) | (0.006) | (0.009) |
| Number of people in working age | 0.150*** | 0.133*** | 0.147*** | 0.177*** | 0.156*** |
| | (0.006) | (0.010) | (0.009) | (0.008) | (0.014) |
| Agricultural dependence | -0.002*** | -0.003*** | -0.003*** | -0.002*** | -0.001** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Urban | 0.078*** | 0.047** | 0.059** | 0.080*** | 0.185*** |
| | (0.022) | (0.023) | (0.023) | (0.028) | (0.036) |
| Constant | 9.573*** | 9.147*** | 9.421*** | 9.944*** | 10.529*** |
| | (0.073) | (0.146) | (0.090) | (0.088) | (0.165) |
| Observations | 22,297 | 22,297 | 22,297 | 22,297 | 22,297 |
| R-squared | 0.369 | 0.205 | 0.267 | 0.246 | 0.150 |
| Number of zila | 64 | 64 | 64 | 64 | 64 |

*All monetary values are computed into real Tk. Using GDP-deflator and 2006 = 100*
*Numbers in parenthesis are clustered robust standard errors.*
*Significant at the * 10% level, ** 5% level, *** 1% level*

## A.4 Descriptive Statistics over Quantiles

*Table 11 - Descriptive Statistics per Quantile*

| | 25th quantile | | | 50th quantile | | | 75th quantile | | | 90th quantile | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Observations | Mean | Std. Dev | Observations | Mean | Std. Dev | Observations | Mean | Std. Dev | Observations | Mean | Std. Dev |
| **Net income** | 5 550 | 1802.604 | 697.422 | 11 100 | 5047.494 | 1580.061 | 5 551 | 18525.13 | 26628.87 | 2 221 | 29656.64 | 39512.35 |
| **Urban** | 5 550 | 0.232 | 0.422 | 11 100 | 0.358 | 0.479 | 5 551 | 0.505 | 0.500 | 2 221 | 0.569 | 0.495 |
| **Agricultural dependence** | 5 550 | 45.506 | 42.41 | 11 100 | 31.078 | 37.046 | 5 551 | 17.720 | 28.571 | 2 221 | 15.497 | 27.241 |
| **Household size** | 5 550 | 3.754 | 1.621 | 11 100 | 4.703 | 1.691 | 5 551 | 5.581 | 2.386 | 2 221 | 6.023 | 2.709 |
| **No. of people in working age** | 5 550 | 2.114 | 1.082 | 11 100 | 2.882 | 1.237 | 5 551 | 3.730 | 1.727 | 2 221 | 4.053 | 1.905 |
| **Household head age** | 5 546 | 45.137 | 15.299 | 11 099 | 44.419 | 13.089 | 5 551 | 48.971 | 12.755 | 2 221 | 50.528 | 12.772 |
| **Household head education** | 5 550 | 1.966 | 3.336 | 11 100 | 3.379 | 4.133 | 5 551 | 6.558 | 4.746 | 2 221 | 7.512 | 4.666 |
| **Household head gender** | 5 550 | 0.196 | 0.397 | 11 100 | 0.094 | 0.292 | 5 551 | 0.117 | 0.322 | 2 221 | 0.113 | 0.316 |

*Source: Household Income and Expenditure Survey (2005 & 2010)*