THE EFFECT OF NATURAL DISASTER ON

INDIVIDUAL-LEVEL ASPIRATION:

EVIDENCE FROM RURAL NEPAL

by

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ABSTRACT

In this study, I analyze the effect of the 2015 Nepal earthquake on individual-level aspiration. I use the data from a longitudinal household survey in rural Nepal from 2014 and 2016, and the earthquake intensity data from the United States Geological Survey (USGS). Using a fixed effects model, I find that compared to those who experienced below median earthquake intensity in terms of Modified Mercalli Scale (MMI), those who experienced MMI between the 50th and 75th percentile had their aspiration index drop by 0.14 of a standard deviation. Similarly, the drop was 0.33 of a standard deviation for those experiencing MMI more than 75th percentile. This finding adds to the literature that natural disaster not only damages physical infrastructure but also curtails individual's overall aspiration, which, as the economic literature illustrates, has a negative effect on investment. There was, however, no consistent statistically significant effects on the individual components of aspiration.

CHAPTER ONE

INTRODUCTION

Aspiration is increasingly being used by economists as a mechanism and a framework to study poverty dynamics and economic development. Since the seminal literature by Appadurai (2002) and Ray (2006), many economists have identified aspiration as a factor that dictates an individual's forward-looking, future-oriented behavior, and as a determinant of investments. Empirical work in low-income countries suggests that `aspiration failure'[1] can explain the behavioral pattern of the extremely poor underinvesting in agricultural ventures, even when there are clearly noticeable prospects of higher returns from increased investment (Bernard et al 2011; Duflo et al 2003; Goldstein and Udry 2006; Miguel and Kremer 2006; Munshi and Rosenzweig 2006). In addition, development economics papers illustrate how positive exogenous shocks, especially in the form of development programs targeted to improve aspiration of low-income households, can change this behavior (Beaman et al 2012; Janzen et al 2017).

There is, however, a dearth of literature investigating how a negative exogenous shock affects aspiration. Kosec and Mo (2017) is the only work in economics explaining this effect. They analyze how the 2010 Pakistan floods negatively affected aspiration. Apart from their paper, there is a handful of studies conducted from the stance of other

[1] I will explain this terminology in detail later in the paper. Ray (2006) coined the term denoting the condition in which one's `aspiration gap' (the difference between one's aspired state and their current state) is either too low or too high, leading to the lack of future-oriented effort/investment exerted. Aspiration failure simply is the inability to capitalize on one's aspiration gaps.

disciplines, mostly psychology, assessing post-disaster mental health, specifically exploring individuals' levels of happiness and/or satisfaction level (Naoi et al 2012; Kimball et al 2006; Luechinger and Raschky 2009; Yamamura 2012). However, post-disaster aspiration *per se* has not been studied yet except Kosec and Mo (2017). A look at aspiration is crucial, especially from an economic point of view, as it influences an individual's future-oriented behavior and may have long-lasting impacts.

Apart from the aspiration literature, another source of motivation for this study is the natural disaster component. There has been various studies conducted assessing the economic impacts of natural disaster, for instance, on Gross Domestic Product (GDP), the labor market dynamics, investment and saving behavior of those affected (Noy 2009; Myers 2008; Cochrane 2004). However, natural disaster also affects mental health of those affected, which is often overlooked. These psychological effects are important to analyze due to their impact on the performance of individuals in various fields of life (Yamamura 2012).

In this study, I use unique primary data obtained from a household survey in rural Nepal between 2014 and 2016 to analyze the effect of a negative shock, in the form of the 2015 Nepal earthquake, on individual-level aspiration. My dataset encompasses a wide range of questions pertaining to individual and household characteristics. This allows me to control for a wide range of time-variant characteristics. In addition, the panel nature of the data allows me to control for time-invariant individual and household characteristics using fixed effects, which is vital to my identification strategy.

For the earthquake data, I use the ShakeMap[2] by the United States Geological Survey (USGS) to extract village-level Modified Mercalli Scale (MMI) measure of earthquake intensity. The MMI is a scientifically derived 12-point earthquake intensity scale[3] that is based on the locally observed effects like the depth of the earthquake and the shaking of the ground. My identification strategy relies on the intensity of the earthquake in the household's[4] village as measured by the MMI, or the categorization of households into several percentile bins based on the MMI.

Results show that there is a sizable effect of the earthquake on individual-level aspiration. Using my primary fixed effects model and the first principal component (PC1) as the aspiration index, I find that compared to those who experienced below median earthquake intensity, those who experienced the earthquake intensity between the 50th and 75th percentile MMI had their aspiration index value drop by 0.14 of a standard deviation. Similarly, the drop was 0.33 of a standard deviation for those who experienced the earthquake intensity above the 75th percentile MMI. The former estimate is statistically not different from zero, but the latter estimate is significant at one percent significance level.

I also analyze the effect of the earthquake on individual components comprising the composite aspiration index, which includes aspiration of income, asset, children's education level, and social status. Among these aspiration components, I only find a

[2] https://earthquake.usgs.gov/earthquakes/eventpage/us20002926/shakemap/intensity
[3] For a 10-point Mercalli scale, refer: https://earthquake.usgs.gov/learn/topics/mercalli.php
[4] In this study, I use the terms household and individual respondent interchangeably since all households had the same respondent in both the surveys. I will explain more of this in the data section.

statistically and economically significant effect on aspiration of children's education. Similarly, while exploring heterogeneous effects of the earthquake on aspiration, I find an attenuated effect of the earthquake based on whether a respondent received aid post-disaster. I also find a higher drop in aspiration among those who were living in temporary shelters during the post-earthquake survey conducted one year after the shock.

In general, the findings of this study add to the literature that natural disaster not only damages physical infrastructure but also curtails an individual's overall aspiration, which, as the economic theory illustrates, has a negative effect on the amount invested, or the amount of future-oriented effort exerted. The study contributes to two bodies of literature. The first contribution is to the limited but growing empirical literature on aspiration. And the second is to the limited amount of empirical work on the mental health effects of natural disaster, and specifically, the almost non-existent empirical work on the effect of natural disaster on aspiration.

I start the paper reviewing the related literature. I then describe the background and the context, the data, the outcome variable, and the empirical strategy of the research. Finally, I will illustrate and describe the main findings from my regressions, before providing the concluding remarks.

CHAPTER TWO

REVIEW OF THE LITERATURE

Seminal Contributions

Arjun Appadurai (2002) incited the interest of many social scientists toward research on aspiration, specifically linking it with poverty and development. He juxtaposed the disciplines of anthropology and economics. The former, according to him, is very fixated upon the traditional, the (cultural) things of the past that have been bequeathed to the present generations, and thus not explicitly talking about the future. The latter is fixated upon future and in the process, disregarding the elements of people's experiences and subjectivities that play a role on how they shape their behavior, including how individuals belonging to one people group aspire differently than those belonging to other groups.

Appadurai explains that the poor lack the capacity to aspire due to the socioeconomic and sociopolitical conditions that they are entangled in. These include the structures that constrict the poor and which further aggravates the inequality between the rich and the poor, the lack of opportunities for the poor, and the lack of voice for them that takes away their proper engagement in policy decisions that affect their lives. The paper suggests that bolstering the capacity to aspire among the poor can enable them to get out of poverty. This concept has motivated development economists to use aspiration as a framework to investigate how cultural background, specifically related to socially projected image of one's self, affects poverty.

Ray (2006) was one of the first to contribute to the literature of aspiration from an economist's perspective. Inspired by Appadurai (2002), in his paper, he attempted to answer two questions: first, what determines one's `aspiration window,' and second, how aspirations in turn affect one's behaviors. He coined several terminologies that have become almost colloquial within the broader aspiration literature, and which I will frequently use in this paper as well. These include:

- *Aspiration window* is created from an individual's cognitive window, formed through their set of 'similar' and 'attainable' individuals. This window basically shapes an individual's aspiration, for they try to emulate those in this window, specifically those in a comparatively higher standard of living.
- *Aspiration gap* is the difference between the aspired state and the current state.
- *Aspiration failure* is the inability of an individual to capitalize on their aspiration gap by putting more effort.

Ray (2006) explains that it is an individual's aspirations gap, but not aspiration *per se* or one's current level of living *per se,* that affects their future-oriented behavior. Individual investment efforts are the lowest for both high and low aspiration gaps. The efforts are low for low aspiration gap because an individual would have no incentive to add more effort if their aspired state is very close to their current state. On the other hand, it is also low for high aspiration gap, in which case either the poor would not include the rich in their aspiration window to begin with, or even if they do, the gap is simply too large, and therefore they would mostly end up not putting much effort at all, since no matter how much effort they would put in, they would not be getting very close to their aspired state. Bernard (2011) illustrate this relation graphically as shown in figure 2.1.

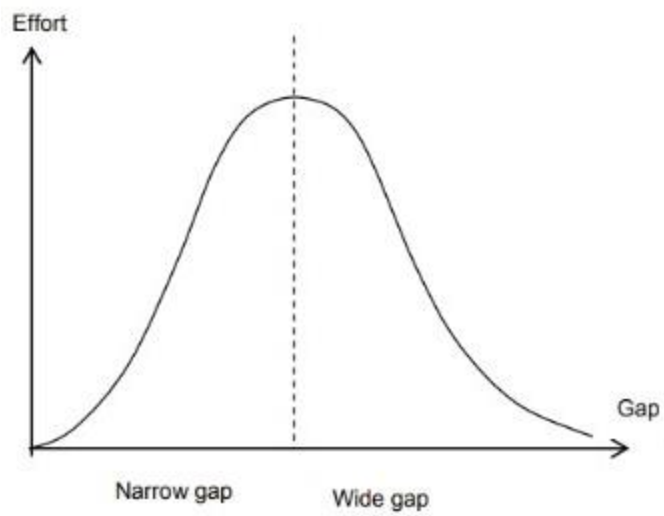

Figure 2.1: Relationship between Aspiration Gap and Effort from Bernard et al (2014)

Aspiration and Future Investments

Papers by Appadurai (2002) and Ray (2006) have been cited by almost all the economics papers on aspiration that were published after them. A lot of these subsequent papers dealt with the effect of aspiration on the future-oriented investment decisions of an individual. Genicot et al (2014) for instance illustrated that aspirations that are moderately higher than an individual's current standard of living motivates them to invest for the future, while much higher aspirations lead to frustration. Janzen et al (2018) empirically tested this theoretical framework and articulated that individuals' future investment increases with aspiration till it reaches a threshold beyond which it tends to decline. They illustrate this phenomenon using the figure 2.2, where investment is a function of aspiration.

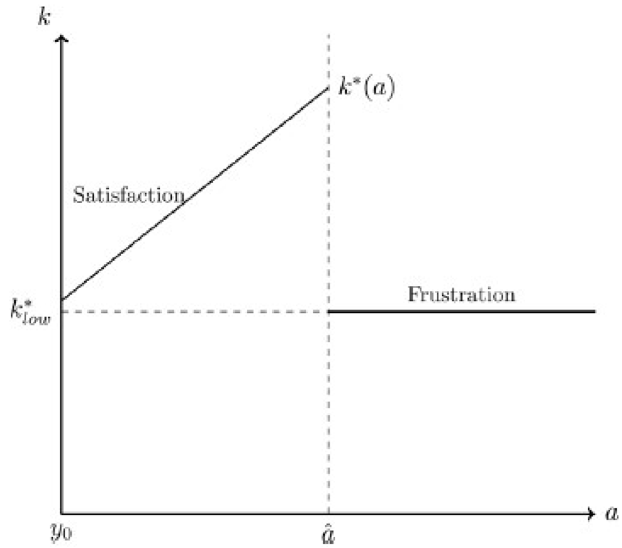

Figure 2.2: Relationship between Aspiration and Investment, Janzen et al (2017)

Here, *a* on the x-axis is the aspiration level, and *k* on the y-axis is the investments for the future. Investment is seen as a linearly increasing function of aspiration level, with the y-intercept at k_{low}, and $\hat{a}$ being the aspiration threshold beyond which the investment level plunges back to the level less than the y-axis intercept and then runs constant horizontal to the x-axis. The upward-sloping part of the function is what Janzen et al (2018) describe as 'satisfaction,' and they call the state beyond the threshold, 'frustration.' Also, the magnitude of investment when aspiration is too high is similar to or even lower than the investment when the individual has no aspiration. Therefore, their model, following Ray (2006) and Genicot et al (2014), illustrates that having a moderate level of aspiration (gap) is necessary to maximize the level of future investment, and either too low and too high gaps lead to lesser investments, with the former leading to lesser satisfaction and the latter leading to frustration.

Aspiration Failure and the Poverty Trap

Aspiration has been a novel framework in studying the various aspects of poverty, particularly regarding what keeps the poor people from investing in sectors that are noticeably more lucrative, which ultimately engulfs them in a 'poverty trap'[5]. Various empirical papers have shown that people in poverty make sensible choices, but those choices may not always be in line with the basic economic principles of profit maximization, as they do not always seek to maximize their profit. This could be due to various reasons including, as Bernard et al (2011) specified, lack of proper information about the actual benefits of making those choices, the feeling or the expectation that those choices would not lead to any remarkable changes from their status quo, and lack of proper opportunities to invest, among others. These tell that it may not be that the poor are acting contrary to the standard economic reasoning, but that it may in fact be rational reasoning on part of the poor, from their vantage.

There are various empirical examples of this behavioral pattern, in which people in poverty fail to invest properly even when there are perceived good prospects of getting higher returns. Goldstein and Udry (2006) in their study in Ghana explain that the pineapple farming normally provided returns of up to 300 percent; however, pineapple

[5] A poverty trap is a process that leads poverty to continue, oftentimes reinforcing poverty as a cycle. The book "The End of Poverty" by Jeffrey Sachs was one of the first to use the terminology

was being cultivated in a meagre 18 percent of the total cultivable land. Similarly, Duflo et al (2003) found that although the use of fertilizers gave returns larger than a hundred percent, only 15 percent of the farmers in Kenya were using fertilizers. Other studies by Munshi and Rozensweig (2006) and Miguel and Kremer (2006) in India and Kenya respectively, also observed similar behavioral pattern, of shying away from higher-return investment. The various constraints come into play to keep the poor from making optimal choices.

Various development economics papers illustrate how an external intervention can bring about positive changes in aspiration of individuals in the developing world leading to more profitable investments. A study conducted in West Bengal, India analyzing the effects of randomized allocation of a certain number of village council seats to women, by Beaman et al (2012) found that the policy positively changed the education and career aspiration of young girls as well as their parents.

Aspiration Following a Negative Shock

Along with aspiration that dictates individuals' forward-looking behavior and the investment through either time, money, or efforts, another factor of interest for economist that alters individuals' psychological state of mind and which can even affect work productivity is the negative shocks, specifically natural disasters. The psychological distress caused by such disasters leads to subpar performance in the labor market and thus decreases their productivity (Yamamura 2012), which has been a concern for economists.

Kimball et al. (2006) found that following the Hurricane Katrina in 2005, there was a decrease in happiness among residents in the South-Central region, closest to the devastation region, and the drop lasted for two to three weeks. Similarly, Leuchinger and Raschky (2009) found that floods have a detrimental effect on individuals' life-satisfaction level. However, owing to possibly the experimental design limitations, and the totally unanticipated nature of the exogenous shock, there is a dearth of papers comparing between these psychological and mental health indicators pre- and post-shock.

Among the papers that do study the effect of natural disaster on aspiration is Kosec and Mo (2017) that explored the aspiration levels of people in rural Pakistan following the 2010 heavy rainfall and the subsequent floods. The study found that the flooding significantly decreased the level of aspiration among the victims. In 2010, there was one standard deviation higher rainfall, which, after one-and-a-half years, led a 0.15 standard deviation decrease in affected individuals' aspiration, compared to those who did not experience the flood. They explained that this reduction is congruent to the negative shock to aspiration following 50 percent reduction in household expenditures. They maintained that this negative effect is starker among the poor and those most vulnerable towards shocks. Moreover, another policy-relevant crucial finding they illustrated was that the government's social protection programs could drastically reduce the negative impact of the flood on the victims' aspiration.

CHAPTER THREE

BACKGROUND AND CONTEXT

The Earthquake

Nepal ranks high in the list of earthquake-prone countries due to its precarious location between the Indian and Eurasian tectonic plates[6]. The first earthquake formally recorded in Nepal dates back to 1255 AD that killed one-third of the population of the present-day country capital, Kathmandu, including its king, Abhaya Malla (Sapkota et al, 2013). Since then, earthquakes have been a regular occurrence in the country, with a big one coming once every few generations (PDNA report, 2015).

On April 25, 2015, 11.56 am, Nepal witnessed its biggest natural shock in the last 80 years. Earthquake of moment magnitude[7] 7.9 hit the country with the epicenter[8] at Barpak village of Gorkha district, 53 miles northwest of Kathmandu. It was the first major earthquake in the country after the 1934 Nepal-Bihar earthquake. The earthquake was then followed by more than 300 aftershocks. The earthquake and the subsequent aftershocks killed more than 8,000 people, injured more than 22,000[9], and affected more than eight million people. It pushed over 700,000 people below the poverty line (Golam

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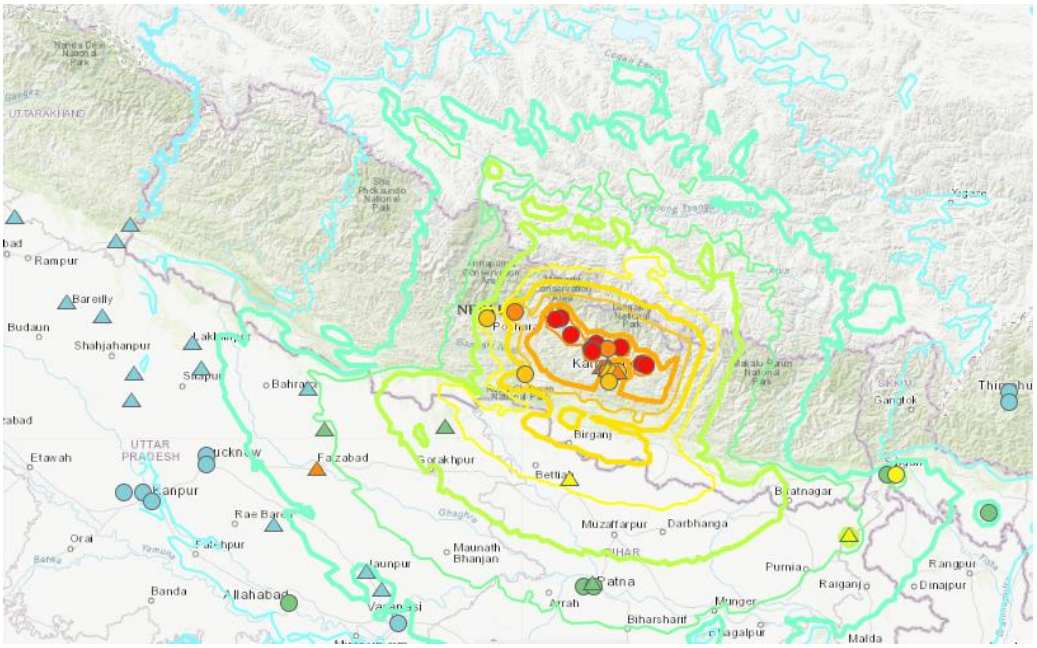
[6] Jonathan Amos, "Why Nepal is so vulnerable to quakes" (BBC; April 25, 2015); http://www.bbc.com/news/science-environment-32462763

[7] Moment magnitude, often denoted as M_w is distinct from the traditional Richter scale measurement of earthquake intensity, which was created after the Richter scale was proved to be valid only in certain frequency and distance ranges.

[8] Coordinates: 28.230°N 84.731°E

[9] http://drrportal.gov.np/

et al, 2015). Thirty-one of the country's 75 districts were affected, out of which 14 were officially declared `crisis-hit' (PDNA report, 2015).



PERCEIVED SHAKING	Not felt	Weak	Light	Moderate	Strong	Very strong	Severe	Violent	Extreme
POTENTIAL DAMAGE	none	none	none	Very light	Light	Moderate	Mod./Heavy	Heavy	Very Heavy
PEAK ACC.(%g)	<0.05	0.3	2.8	6.2	12	22	40	75	>139
PEAK VEL.(cm/s)	*<0.02*	*0.1*	*1.4*	*4.7*	*9.6*	*20*	*41*	*86*	*>178*
INSTRUMENTAL INTENSITY	I	II–III	IV	V	VI	VII	VIII	IX	X+

Scale based upon Worden et al. (2012)

Figure 3.1: Modified Mercalli Scale Intensities in Nepal and the Surrounding Region, as Taken from the United States Geological Survey Shake Maps

In case of the effect on physical infrastructure, more than half a million houses were affected, enormous damage was done to various private and public infrastructure, including buildings and monuments of historical, cultural and religious importance. Rural roads, bridges, water supply systems, agricultural land, trekking routes, hydropower plants and sports facilities all were impacted in various levels (PDNA report, 2015).

Nepal's Post Disaster Needs Assessment (PDNA) marked the total financial loss from the earthquake at USD 7 billion. For a developing country that is still recovering from its decade-long civil war (1996-2006), it was a matter of immense humanitarian crisis. Outside of Nepal, the two earthquakes led to 172 deaths in India, China and Bangladesh combined, and more than a thousand people getting injured.

Recovery and Relief

The one year following the earthquake was loaded with controversies that debilitated the relief and recovery process of the Government of Nepal. This especially included the bureaucratic constraints. A proper description of the relief and recovery events is necessary to understand the situation of survey respondents in 2016, which illustrates that the condition of those affected by the earthquake had not changed much in the one-year duration.

A local-level damage assessment was started a few weeks after the earthquake, which aimed to inform district and the central government officials and agencies about the level of damage while also helping them target and distribute immediate relief. Villages[10] conducted the assessment in an ad-hoc manner with the involvement of local leaders, teachers and residents (The Asia Foundation, 2016). However, the assessment was ignored and eventually, the government issued instructions to the districts to conduct

[10] I use 'village' for Village Development Committee (VDC), which is an administrative unit equivalent to a village

a more formal assessment of the damage to standardize the assessment process. The assessment team for this second round of survey was led by an engineer. This data was to be used to prepare beneficiary lists and distribute victim ID cards that would be used for the provision of earthquake assistance.

It was already late May, and the obstacles in the distribution of victim ID cards had only just started. Dissatisfied households registered complaints against the second assessment, ranging from inclusion and exclusion errors to households listed in the wrong damage category. Moreover, the Ministry of Federal Affairs and Local Development reported that one out of every six villages in the affected districts were without a village secretary, and therefore, in these villages it was unclear who would in practice register the victims and issue the IDs[11].

Starting June 2015, the government began distributing initial cash assistance, which included Rs. 30,000[12] for funeral costs for those households that lost a member during the earthquake, Rs. 15,000 for households with 'red cards' (those whose house was 'fully damaged') to build temporary shelters, and Rs. 3,000 for households with 'yellow cards' (those with 'partially damaged' houses). This process continued throughout the monsoon of 2015. Moreover, in several districts, both national and international non-governmental organizations were involved in cash distribution process, working in coordination with or on behalf of the government.

[11] http://localnepaltoday.com/the-id-card-issue-how-a-relief-program-got-delayed
[12] Approximately, US dollar 1 = Rs. 107 (mid-2016 rate).

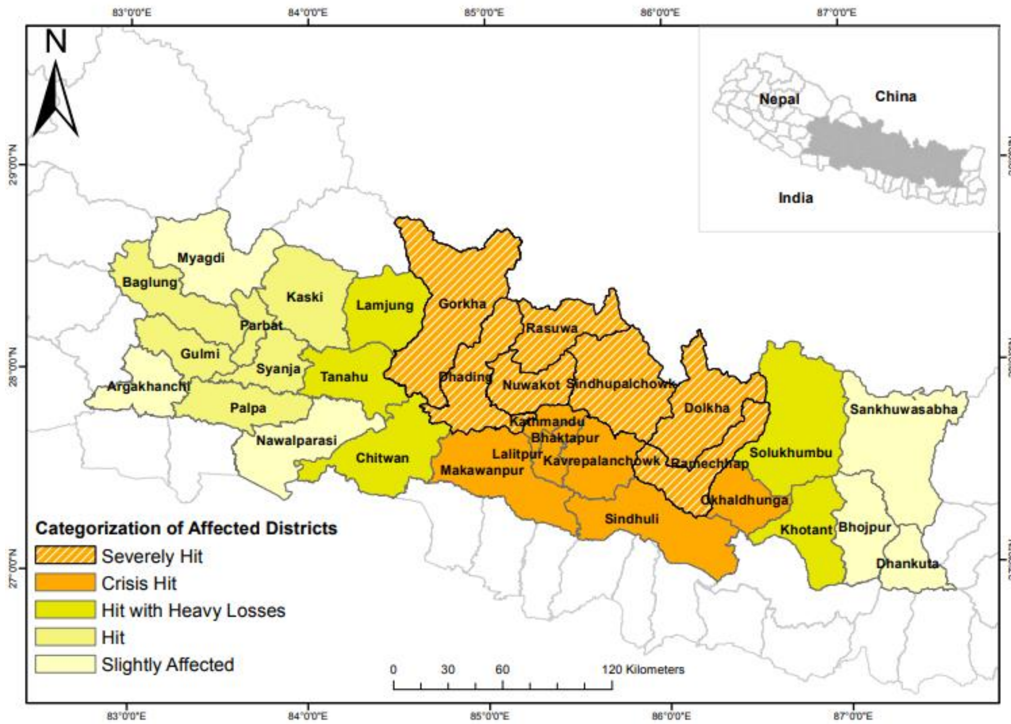


Figure 3.2: Categories of Earthquake-affected Districts, Source: Ministry of Home Affairs, Government of Nepal, 2015

At the outset of winter 2015, after the early cash grants were distributed, the government decided to provide winter relief grants of Rs. 10,000 for those who received 'red card' (full damaged households) intended to assist victims in purchasing clothes to withstand the winter cold. Although it officially started in October, many villages did not receive the grant until winter was over. Citizens and local officials complained that the winter cash assistance 'was too little and arrived too late.' As districts with larger damage were prioritized, those with lesser damaged were ignored, so they received the assistance much later (The Asia Foundation, 2016).

All these complaints led to the government's decision to conduct an entirely new third round of assessment in early 2016. This was conducted by Central Bureau of Statistics (CBS). This third round of damage assessment started in February 2016. The CBS deployed engineers to the 11 most-affected districts, excluding districts categorized as being 'hit with heavy losses' or 'hit.' The exclusion of these less-affected districts meant that cash distribution was postponed indefinitely in these districts causing frustration. Moreover, the CBS assessment led to a reduction in the number of beneficiaries in most districts, and many complained. A survey by The Asia Foundation showed that among those who were declared ineligible for the reconstruction grant, almost one-third believed they should be eligible (The Asia Foundation, 2016).

The size of the housing reconstruction grant was initially set at Rs. 200,000. The original plan was for the grant to be dispersed in three installments of Rs. 50,000, Rs. 80,000, and Rs. 70,000 respectively. Until mid-2016, the government had just started to distribute the first tranche of the amount.

CHAPTER FOUR

DATA

Household Data

The data for this study comes from a randomized controlled trial (RCT) experiment[13] conducted in rural Nepal. The surveys were conducted as a part of an evaluation of the welfare impacts of an international NGO, Heifer International's livestock transfer program. For this study, I am using data from 2014 and 2016 surveys. Although the surveys took place from 2014 through 2018, there was no survey conducted in 2015, the year the earthquake took place. The original sample size was around 3,300 respondents in each of the two surveys, and the survey location spanned 60 randomly chosen villages from seven districts of Nepal. All respondents of the survey were women, who were either potential beneficiaries of one of three treatment groups of the livestock transfer program, or from a control group.

From the original sample, I drop households and observations in a few different ways, and for a few different reasons. First, I dropped households that were only surveyed in 2014. The attrition rate in the 2016 survey was 9.10 percent. The earthquake could be a potential reason for the attrition; however, I will show in latter chapters that this was not the case, by regressing a binary attrition variable on earthquake intensity.

[13] However, the purpose of the RCT experiment was different. It just happened that an earthquake struck in the midst of the RCT that I could use the data for this study.

Second, there were sizable number of households in the 2016 survey with respondents different from the 2014 survey. Acknowledging that different members within a household may have vastly different levels of aspiration, and thus for the sake of analyzing the individual-level changes in aspiration, I dropped households that included two different respondents in the two years. Around 10 percent of the remaining sample was dropped for this reason. In addition, observations with no children in both of the surveys were also dropped[14]. The total sample size after dropping observations was 5,422. Furthermore, depending on the variables used in the regressions, certain observations were further dropped from analysis, that had missing values.

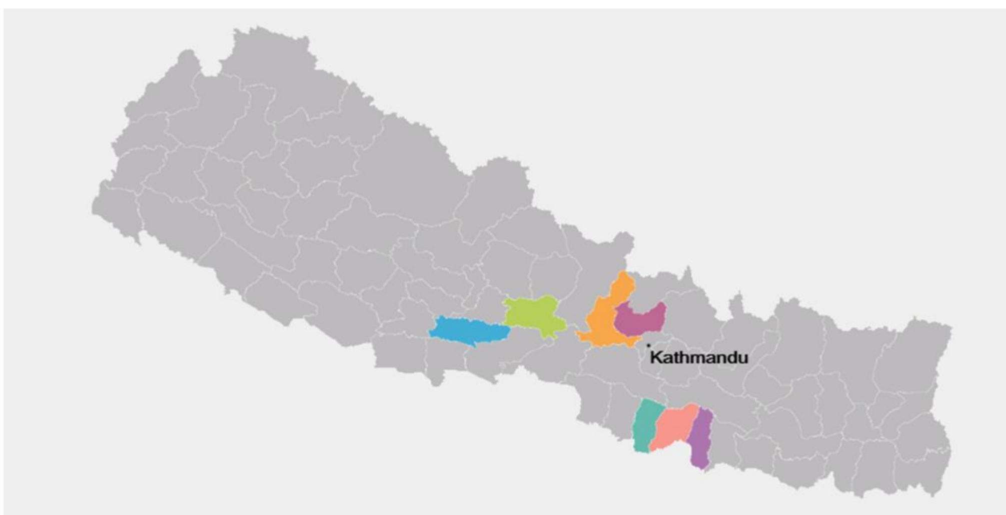


Figure 4.1: Seven Survey Districts in Nepal Map

[14] I could have dropped observations with children's education aspirations of zero in both time periods, instead of dropping respondents without a child in both time periods. This could be done because the way the questions were posed inferred “if you had a child...” in a hypothetical way. However, I deem it would be more accurate and based on realistic expectations if I omit those without children. Having said that, a fair number of respondents with no child in both surveys did report non-zero aspiration for (children’s) education.

The survey content was thorough, with the average time of survey between two to three hours. The survey attempted to capture the household- and individual-specific variables as extensively as possible. It captured variables including incomes and expenditures, assets, time use, division of labor within household, livestock practices, health and nutrition components, savings and credits, empowerment components, aspiration, shock, and coping strategies, among others. Apart from these variables, the 2016 survey also comprised of detailed questions regarding the earthquake, the damages that the households faced following the disaster, as well as the aid received from various governmental and non-governmental sources. This wide range of variables covered in the survey allows me to control for the various aspects of the individual and their household that therefore allows me to minimize the bias.

MMI Data

For the earthquake data, I use the ShakeMap[15] by the United States Geological Survey (USGS) to extract village-level Modified Mercalli Scale (MMI) measure of earthquake intensity. The MMI is an objective 12-point[16] earthquake intensity scale that is based on the locally observed effects like the shaking of the ground and the extent of damage to the physical structures. The 12 points range from imperceptible shaking (Level

[15] https://earthquake.usgs.gov/earthquakes/eventpage/us20002926/shakemap/intensity
[16] For a 10-point Mercalli scale, refer: https://earthquake.usgs.gov/learn/topics/mercalli.php

I) to catastrophic destruction (Level XII). The histogram in Figure X in Appendix X illustrates the MMI density. My identification strategy relies on the intensity of the earthquake in the household's village as measured by the MMI, or the categorization of households into treatment and control groups based on the MMI.

Apart from the objective, USGS-derived MMI data, the 2016 survey data also contains a ward[17]-level MMI data captured from the ward leader recalling the earthquake incident. If these were accurate, then I could have a wider variation of the MMI measures (neighborhood level compared to village level). However, I decide that the ward-level MMI is not accurate because of two reasons, apart from the fact that they are subjective. First, there is not much correlation between the objective, USGS-derived MMI data, and the subjective, ward-leader recalled data (correlation coefficient of -0.0415). And, second, the subjective recalling of the earthquake intensity was done one year after the actual earthquake, and therefore the inclination toward overstating (or understating) would be higher.

Two Other Shocks

Apart from the earthquake shock that I am analyzing, there were two other shocks that I control for: Heifer International's BASIS program, a positive shock, and the 2015-2016 trade embargo/blockade, a negative shock.

[17] A village consists of 9 wards. It entirely depends on the geographical region, but a ward typically has between 100 to 250 households in a rural setting.

BASIS program[18] is a livestock transfer program in rural Nepal, which seeks to improve beneficiary's aspiration as one of its program objectives. The program started in late 2014 and is still continuing during the time I am writing this thesis in early 2019. Not all the respondents of the survey data are BASIS beneficiaries. There were various levels of intervention where some treatment groups received more than other groups[19].

The BASIS program's treatment was totally random, in that the site selection as well as the selection of program beneficiaries were randomly selected as a part of an RCT to evaluate the program's impacts. However, following the earthquake, the treatment status of all beneficiaries of the two most affected districts, Dhading and Nuwakot, irrespective of their level of treatment status pre-earthquake, were changed into the highest treatment level. This was decided by the NGO, Heifer International themselves, in order to support the earthquake victims. The status of the control group in the two districts did not change post-earthquake though. The survey respondent's affiliation with the groups is reflected in the data. The type of Heifer group the respondent was a part of, will be controlled for in order to remove the effect of the program on aspiration, if any.

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[18] For the details of the project, read this website: https://basis.ucdavis.edu/project/evaluation-welfare-impacts-livestock-transfer-program-nepal

[19] The three levels of treatment were: 1. full treatment (FT) package that included a livestock transfer, skills-based technical training and values-based non-technical training; 2. not goats (NG) package that received skills-based technical training and values-based non-technical training, but not goats; and 3. not values-based non-technical training (NVT) package that received a livestock transfer and skills-based technical training, but not values-based non-technical training (NVT). In addition to these three treatment original groups (OGs), since the program encourages to pay forward benefits, there were also pay-it-forward (POG) groups. Through these sets of intervention, the BASIS program tried to increase the beneficiary's overall aspiration, which I control for in my model. The data shows that around 23 percent of the sample belonged to FT, around 15 percent to NG, around 16 percent to NVT, and around 45 percent to the control group.

The second shock, the unofficial embargo/blockade[20] by the Indian government on Nepal due to various political discontentment between the two governments was in effect for around five months between September 2015 and February 2016. The effect of this on the lives of general populace was uneven, depending on the location of the households, particularly whether they were in rural or urban areas[21]. Rural households, that comprise a large portion of my sample, were mostly able to sustain the embargo more than their urban counterparts because they had sustainability of resources through locally generated or available goods and materials that the urban households did not have due to their dependence on goods imported from India. However, to nullify the blockade's effect, if any, I will be controlling with some blockade-related variables that were captured by the 2016 survey.

Defining the Outcome Variable

I am using the principal component analysis (PCA) method of dimension reduction as my primary measure of aspiration. PCA generates one or more index variables using a set of existing variables. For instance, it generates an aspiration index using the aspired values of four aforementioned aspiration dimensions (values for aspired income, aspired asset, aspired education level of children, and aspired social status). Just like the Bernard

[20] http://kathmandupost.ekantipur.com/news/2015-10-05/ioc-refuses-to-provide-fuel-despite-assurances.html

[21] This comes from my anecdotal experience, being present in the country during the blockade. I cannot attest this using the available data because of the lack of data regarding whether a household is located in urban or rural setting.

and Taffesse index, PCA does this through a linear combination of a set of variables. The newly generated index variables are called components. The advantage of this method over Bernard and Taffesse index is that PCA uses the correlation between (the four) variables to assign optimal weights to the four variables, rather than using respondent-assigned weights to those variables.

Doing this, the PCA method maintains the information contained in the four variables by using a smaller number of variables or components. These components can describe a large percentage of the variance by retaining the original variables' correlation matrix (Cahill and Sanchez, 1998). The first PC is generally the one that explains the largest variance, the second PC is the one that explains the second largest variance, and so on. The number of components generated is based on analysis of the percentage of variation explained by that particular number of components. I will only use one PC[22]. More of this is explained and graphically illustrated in the appendices. Furthermore, the components are orthogonal to one another, and have a mean of zero and a standard deviation of 1.

To calculate PC for my research, as stated, I apply the aspired values of four dimensions of aspiration as the four variables. The variables chosen in this study are designed to measure four dimensions of aspiration in order to capture the breadth of aspiration and minimize the errors and differences in measurement in the sample of diverse individuals. Generally, while most indices use only a few variables, PCA allows

[22] The rule of thumb is that only the components with eigenvalue greater than 1 are considered and the rest are omitted. The scatter plot diagram illustrating this relation is in Figure 3 under Appendix B

for a large number of variables be employed to create a PC-based index. I could add more dimensions of aspiration into the PCA-based index, however, since the aspiration section of the RCT experiment surveys were specifically created to measure Bernard and Taffesse aspiration index, I cannot relax the constraint.

Summary Statistics

Tables 4.1, 4.2, and 4.3 describe the data that I am using, using the full sample. Table 4.1 illustrates the summary statistics of earthquake-related variables in the year 2016. These statistics are related exclusively to the post-earthquake survey. The mean village-level MMI generated from USGS ShakeMap is 6.76, with minimum and maximum values at 5.2 and 8.2 respectively. Referring to figure 9.4 in the appendix with the explanation of MMI intensities, 5.2 is a moderate shock, felt by nearly everyone with many awakened, with some dishes, windows broken, and unstabled objects overturned. Likewise, 8.2 MMI is a severe shock, with slight damage in specially designed structure, considerable damage in ordinary substantial buildings with partial collapse, and great damage in poorly built structures, along with fall of chimneys, factory stacks, columns, monuments, walls, and even heavy furniture overturned[23]. The ward-level MMI as subjectively recalled by ward-leaders is at 5.54, but has a greater variation with range MMI_{ward} = [1, 10], which does not correlate much with the USGS-generated village-level MMI (correlation coefficient of -0.0415).

[23] https://earthquake.usgs.gov/learn/topics/mercalli.php

The table also shows that 35 percent of the respondents reported at least some damage to their home[24], 24 percent reported to have received at least some aid, 43 percent reported that they were forced out of home temporarily, and 36 percent reported they were still living in temporary shelter during 2016 survey. Moreover, 17 percent had their house severely damaged[25], and 9 percent had their house partially damaged. The table 4.1 below displays the statistics of a wide range of earthquake-related variables.

Table 4.2 illustrates the summary statistics regarding the respondents' individual and household characteristics. An average respondent of the survey is in late 30s to early 40s. They have gone to school for an average of two-and-a-half years. Around half of them are literate. Around 71 percent of them have a child[26]. The average personal income of the respondents seems to have increased from around Rs.[27] 59,000[28] to around Rs. 101,000[29] per annum. This average also includes those who have zero income. In 2014, 31 percent of the respondents reported having no personal income, whereas only 6 percent of the respondents reported having no personal income.

Likewise, regarding the respondents' household characteristics, an average household size was around six household members. The total household income was around Rs. 170,000 in 2014, and which dropped to Rs. 164,605 in 2016. This makes

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[24] This is subjective, and not verifiable, unlike the variables regarding whether the house was severely damaged or partially damaged, for which the respondent required to have an earthquake relief card given to them.
[25] This stat is verifiable from the fact that they received earthquake relief card of a particular type denoting the level of damage of their house.}, and 9 percent had their house partially damaged.
[26] These stats come from the data set sample before dropping respondents with no child in both the surveys.
[27] Rs. = Nepali Rupees
[28] The 2014 amounts are converted to 2016 value.
[29] Approximately, US dollar 1 = Rs. 107 (based on June 2016 values, on which the values are based).

either this amount or the amount on current personal income noted above very dubious, as the current personal income, in average, increased almost two-fold between two years[30]. The current value of land and home, however, increased from around Rs. 1,305,000 to around Rs. 1,513,000 between the two years. In 2014, 62 percent of the households had migrant[31]. This slightly increases to 69 percent in 2016.

Likewise, table 4.3 shows the summary statistics related to aspired values of aspiration components. Aspired values of all components changed positively between the two years, at least to some extent. The data shows that aspired years of education for boy children and girl children are both around 13-14 years.

Finally, table 4.4 compares a group of pre-shock characteristics between three groups[32]: first group, experiencing below median MMI, second group experiencing MMI between 50th and 75th percentile, and third group experiencing MMI above 75th percentile.

The comparison shows that individuals experiencing below-median MMI were in average in better conditions than those experiencing above-average MMI. This could be observed in variables including education level, literacy, current personal income, percentage of respondents reporting no personal income, and total household income. The only variable that put the latter groups in a better position was the current value of land and home.

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[30] This is not much of a problem for analysis purpose, since I will not be including the current values in the analysis, but only the aspired values

[31] This includes both migrants to some other parts of the country, as well as abroad.

[32] More about these groups will be discussed in the empirical strategy section, where I talk about percentile bins.

Table 4.1: Summary Statistics: Earthquake-induced Variables (Full Sample)

Variables	Mean (St. dev.)
MMI (Village-level; USGS generated)	6.76 (0.94)
MMI (Ward-level; subjective recall of ward officials)	5.54 (2.16)
Earthquake damaged home or property	0.35 (0.48)
Received aid after earthquake	0.24 (0.43)
Received some aid if home or property damaged	0.63 (0.48)
Received earthquake card	0.52 (0.50)
Received earthquake card if home or property damaged	0.58 (0.49)
Type of card: Red (fully damaged house)	0.42 (0.49)
Type of card: Yellow (partially damaged house)	0.09 (0.29)
Forced out of home by earthquake	0.43 (0.50)
Living in temporary shelter during 2016 survey	0.36 (0.48)
Rebuilding home during 2016 survey	0.17 (0.38)
Amount saved for rebuilding (Rs.) during 2016 survey[c]	5,960 (26,140)
Earthquake affected monsoon season crops	0.20 (0.40)
Earthquake affected normal water sources	0.24 (0.43)
Total aid received from various sources until the post-survey	4,660 (10,711)
Total aid received if relief card received (Rs.)[d]	21,856 (11,315)
Total aid received if relief card not received (Rs.)[e]	510 (7,182)
Total amount spent on rebuilding house infrastructure	58,208 (130,377)
Migrant returned home after earthquake (if migrant present)	0.26 (0.44)
N	2,997

Notes:
[a] Standard deviations in parantheses. All these values are strictly of year 2016.
[b] Approximately, US dollar 1 = Rs. 107 (based on June 2016 values, on which the values are based).
[c] Minimum: Rs. 0; Maximum: Rs. 300,000.
[d] Minimum: Rs. 0; Maximum: Rs. 64,000.
[e] Minimum: Rs. 0; Maximum: Rs. 140,000.

Table 4.2: Summary Statistics: Individual and Household Characteristics (Full Sample)

Variables	2014	2016
Panel A: Individual characteristics:		
Respondent's age	38.73 (13.15)	40.83 (13.11)
Respondent's years of education	2.62 (3.88)	2.63 (3.87)
Respondent is literate[e]	0.52 (0.50)	0.48 (0.50)
Respondent has a child	0.92 (0.28)	0.92 (0.27)
Current personal income (Rs.)[d]	58,945 (704,105)	101,663 (148,418)
Respondent reports no personal income	0.31 (0.46)	0.06 (0.23)
Panel B: Household characteristics:		
Household size	5.87 (2.61)	6.86 (2.80)
Total household income[d]	170,085 (278,633)	164,084 (200,053)
Current value of land and home (Rs.) [c,d]	1,305,635 (2,558,850)	1,513,533 (2,940,808)
Household has a migrant	0.62 (0.49)	0.69 (0.46)
N	1,984	1,984

Notes:
[a] Standard deviations in parantheses.
[b] Approximately, US dollar 1 = Rs. 107 (based on June 2016 values, on which the values are based).
[c] Land or home as the household's property.
[d] To remove potential outliers, I top-coded at 99th percentile, the variables current personal income, total household income, and current value of household land and home.
[e] The term literate is vague though. The term in the questionnaire meant those who were able to at least read and write decently.

Table 4.3: Summary Statistics: Aspiration-related Variables (Full Sample)

Variables	2014	2016
First Principal Component (PC1)	-0.25 (0.94)	0.26 (1.30)
Aspired personal income (Rs.)[d,e]	112,252 (254,566)	384,079 (876,726)
Aspired land and home value[c,d,f]	2,465,005 (7,194,572)	3,723,410 (8,267,559)
Aspired years of education for children	13.93 (3.96)	15.09 (3.24)
Aspired years of education for boy children	13.61 (4.79)	14.78 (3.37)
Aspired years of education for girl children	12.67 (544)	14.30 (3.85)
Aspired no. of people seeking advice	15.72 (72.69)	17.17 (19.95)
N	1,984	1,984

Notes:
[a] Standard deviations in parantheses.
[b] Approximately, US dollar 1 = Rs. 107 (based on June 2016 values, on which the values are based).
[c] Land or home as the household's property.
[d] To remove potential outliers, I top-coded at 99th percentile, the variables aspired income and aspired asset.
[e] Current personal income averages at Rs. 58,945 with standard deviation of 112,878 in 2014. The average for 2016 is Rs. 101,663 with the standard deviation of 148,418.
[f] Current land and home value averages at Rs. 1,278,530 with standard deviation of 2,568,082 in 2014. The average for 2016 is Rs. 1,513,533 with the standard deviation of 2,940,808.

Table 4.4: Summary Statistics: 2014 Comparison between Three Groups of Different MMI Percentiles

Variables	1st to 50th[c] percentile	50th to 75th[c] percentile	75th to 99th[c] percentile
Panel A: Individual characteristics:			
Respondent's age	40.25 (13.75)	36.46 (12.12)	37.75 (12.49)
Respondent's years of education	3.26 (3.98)	2.36 (4.06)	1.70 (3.35)
Respondent is literate[d]	0.62 (0.48)	0.42 (0.49)	0.42 (0.49)
Current personal income (Rs.)[e]	75,809 (133,223)	45,829 (84,372)	39,112 (84,576)
Respondent reports no personal income	0.27 (0.44)	0.37 (0.48)	0.35 (0.48)
Panel B: Household characteristics:			
Household size	6.40 (2.70)	6.52 (2.40)	6.25 (2.44)
Total household income[e]	175,762 (246,903)	145,841 (221,989)	147,793 (237,819)
Current value of land and home (Rs.) [e,f]	1,067,802 (2,370,244)	1,421,128 (2,774,897)	1,542,195 (2,710,967)
Household has a migrant	0.71 (0.45)	0.48 (0.50)	0.60 (0.49)
N	995	422	567

Notes:
[a] The values reported are the mean values. Standard deviations are shown inside parantheses.
[b] Approximately, US dollar 1 = Rs. 107 (based on June 2016 values, on which the values are based).
[c] The first group is exclusive of the 50th percentile MMI. Similarly, the second group is inclusive of the 50th percentile but exclusive of the 75th percentile MMI. The third group is inclusive of the 75th percentile MMI.
[d] The term literate is abstract, and was used to mean someone who can at least read and write.
[e] To remove potential outliers, I top-coded at 99th percentile, the variables current personal income, total household income, and current value of household land and home.
[f] Land or home as the household's property.

CHAPTER FIVE

EMPIRICAL STRATEGY

Ideal Empirical Model

To analyze the effect of the earthquake on aspiration, ideally, I would randomly select households that experienced earthquake, and households that did not. A crucial assumption made is that the earthquake is random and exogenous, and therefore, following the law of large number, the two groups would asymptotically be identical in average. I would observe the variables before and after the shock, to detect changes in the differences between mean aspiration values between the two groups. This approach is illustrated in econometric equation (5.1) given below.

$$y_{iv} = \beta_0 + EQ_v + u_{iv} \qquad (5.1)$$

Equation (5.1) is the more straightforward and simplified Ordinary Least Squares (OLS) approach, where y_{ivt} is an outcome variable that is some form of aspiration measure of individual *i*, living in village *v*. *EQ* is a dummy for whether a household experienced the earthquake, denoting the treatment group of the analysis (if *EQ*=1; control otherwise), and *u* is an idiosyncratic error term. This is a one time period cross-sectional analysis based on the variable values after the earthquake. If the two groups are identical in average, a comparison between the groups post-earthquake would suffice.

A crucial pitfall of this ideal approach given by equation (5.1), however, is that in reality almost the entire set of households in my sample experienced the earthquake to some extent, and so the approach would not be able to capture the variation in the explanatory variable. In other words, all observations in 2016 will equal 1. Moreover, it discounts the great variation in earthquake intensities that the different regions were subject to.

To tackle this, I modify my ideal experiment by replacing the earthquake dummy by some variable that preserves the heterogeneity of earthquake intensity. For this I use village-level Modified Mercalli (MMI) scale extracted from ShakeMap by the United States Geological Survey (USGS) as a metric. As already explained in the data section, MMI is an objective 12-point earthquake intensity scale that is based on the locally observed effects like the depth of the earthquake, and shaking of the ground. The 12 points range from imperceptible shaking (Level I) to catastrophic destruction (Level XII). Figure 9.4 in the appendix explains what each level of MMI refers to. In addition, the histogram in Figure 9.5 in the appendix illustrates the MMI density in the sample data.

$$y_{iv} = \beta_0 + \beta_1 MMI_v + u_{iv} \qquad (5.2)$$

This approach of using MMI is given by equation (5.2) where all other indices and variables remaining the same, the continuous variable MMI_{vt} gives the measure of the village-level earthquake intensity (post-earthquake value) captured in MMI. Compared to the first approach, it has the benefit of retaining the variation in the explanatory variable, and it thus allows to analyze how severity of an earthquake in one's village, affects individual aspiration. The coefficient of interest is β_1 that captures the effect of the earthquake intensity in terms of MMI, on aspiration.

Identification Strategy

There are several weaknesses of the model given by equation (5.2). First, although the earthquake is totally random and exogenous to aspiration, from the data as illustrated in summary statistics table 4.4, the intensity of earthquake was concentrated, by chance, mostly on geographical locations with comparatively poorer households. This means I have characteristically different treatment and control groups[33]. To compare the average between the post-earthquake aspiration values between them would therefore result in biased and inconsistent coefficient estimates.

This could be tackled, however, if I control for the trend of individual households, which could be done through the use of household fixed effects. Doing this, it would account for the heterogeneity of the intercept of each household in the dataset. This is a crucial part of my identification strategy.

[33] I do not have a pure control group though, as all households experienced at least some degree of earthquake. By treatment and control in the text, it can mean the three MMI percentile bin groups that I will explain in a bit.

The second concern of the model given by equation (5.2) is that they do not control for the observed and unobserved time-variant and time-invariant factors. If these factors are not included in the model as control variables, the coefficients are going to be biased and inconsistent.

I introduce *X* vector as my set of control variables, controlling for my household/individual characteristics, embargo and BASIS treatment status. For my research, the household controls include respondent's years of education, whether the respondent has a child, and a dummy for whether the household received any aid[34] following the survey by the time the second survey was conducted. I am not controlling for earthquake-induced variables, however. I have data on these variables from the survey, but these are the mechanisms through which the household can very well be affected. Controlling for these factors would mean that I am taking away the effect of these variables[35] that were affected by the earthquake.

Furthermore, my embargo controls include logged values of the price of oil, salt, and sugar. And I use three dummies representing three Heifer BASIS treatments to control for the effect of the project if any, on the beneficiaries' aspiration. Controlling for these time-variant characteristics would remove the bias of the coefficient estimates, and help achieve more precise coefficient estimates.

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[34] I use a dummy to capture this variable rather than the amount of aid received, because the amount of aid received, at least the amount that the respondents reported, has little variance.
[35] I will, however, be interacting some of these with these variables with the MMI.

Fixed Effects Models

I tackle the shortcomings of the OLS approach by adding fixed effects in equation (6.2), which would take the following form, given in equation (5.3).

$$y_{ivt} = \beta_0 + \delta_0 T2016_t + \beta_1 MMI_{vt} + X'_{ivt}\theta + \zeta_i + u_{it} \qquad (5.3)$$

Here, ζ_i is the individual fixed-effects. Since the sample is not homogeneous across time and space, the addition of the individual or household fixed effects in the model removes the effect of the unobserved, time-invariant variables, and adding the time fixed-effects removes the time-specific trend or universal shock common to all observations.

A shortcoming of the model presented in equation (5.3) is that it imposes linear effect MMI_{vt} on aspiration, which may not be the case. Therefore, in addition to the model in equation (5.3), I will use my second econometric model, by making three MMI percentile bins based on four quartiles of MMI measure: the first bin consisting of half of the observations till Q_2 (median), the second bin consisting of observations with MMI from Q_2 to Q_3, and the third bin consisting of MMI beyond Q_3. From the data, Q_1=5.9813, Q_2=6.9505, and Q_3=7.4376. Therefore,

- MMIThreeBin^1 = Observations with MMI<6.9505
- MMIThreeBin^2 = Observations with 6.9505>=MMI<7.4376
- MMIThreeBin^3 = Observations with MMI>=7.4376

This is given by equation (5.4), where $MMIBin^k$ (k=2 and 3, with 1 as base) is a dummy variable corresponding to an observation's association to a particular bin.

$$y_{ivt} = \beta_0 + \beta_1 T2016_t + \sum_{k=2}^{3} \beta_k \{T2016_t \times MMIThreeBin_v^k\} + X_v'\theta + \zeta_i + u_{it} \quad (5.4)$$

In absence of breaks (or gaps) in the MMI values, the demarcation of the bins is ad hoc though, which is based on the MMI values located in quartiles. This is however trivial as the bins approach is comparing between the mean values of each bin, making the exact demarcation unimportant.

Furthermore, the approach in comparison to the approach in equation (5.4) allows to retain the original number of observations, but also if there is any non-linear effect of earthquake intensities, then this model should illustrate that situation. If that is the case, then $\beta_3<\beta_2<0$.

Testing for the Randomness of Attrition

It is a matter of concern if the attrition (of 9.10 percent) in the 2016 survey is concentrated largely in districts highly affected by the earthquake. If that is the case, which could be due to many factors including households relocating somewhere else, then I may have very different groups post-earthquake. To test this, I also run auxiliary regressions with $Attrition_{iv2016}$ as the outcome variable, which is a binary variable that equals to 1 if individual *i* from village *v* was interviewed only in the 2014 survey but not in the 2016 survey.

$$\mathrm{Attrition}_{iv2016} = \beta_0 + \beta_1 \mathrm{IntensityVar}_{v2016} + X'_{iv2014}\theta + u_{iv} \qquad (5.5)$$

Where, *IntensityVar* is one of two variables, MMI_{v2016}, or $MMIBin^2_{v2016} + MMIBin^3_{v2016}$, based on three aforementioned fixed effects models. These are cross-sectional regressions, and therefore are without individual or year fixed-effects, as well as without the *t* index in the variables, denoting that the variables are time-invariant. Furthermore, with the unavailability of 2016 data on the individual and household characteristics, the best estimates for controls would be the pre-shock, 2014 data. I use logged household income, logged household asset, age, years of education, and a dummy for whether the household has migrant as the 2014 controls. If regions with high earthquake intensity have the same follow-up rates, my estimates from other regressions would be more reassuring.

CHAPTER SIX

RESULTS

Main Results

I use PC1 as my outcome variable, which is a composite index measure of aspiration. Table 6.1 illustrates my main results using the primary fixed effects model given in equation 5.4. The five columns in table 6.1, from (1) to (5) illustrate the effect of adding various control variables and then the household fixed effects on the model, on the coefficient estimates, their statistically significance, and the R-squared. For each of the five regressions, I have used the sample size as allowed by each regression, without fixing it to a particular size based on the variables included in my main regression given by column (5). This therefore translates to the difference in the number of observations in each column.

The main results, as illustrated in column (5), show that compared to those who experienced below median earthquake intensity in terms of MMI, those who experienced the earthquake intensity between 50th and 75th percentile had their PC1 aspiration index dropped by 0.159 points. Similarly, the drop is 0.378 points for those experiencing the earthquake intensity of more than 75th percentile. In terms of the percentage of standard deviation, the two drops are 13.7 percent and 32.6 percent of one standard deviation respectively. Only the latter coefficient is statistically significant though, which is highly significant, at one percent significance level. This magnitude of effect on the group experiencing the highest MMI, in terms of the percentage of one standard deviation, is twice the magnitude that Kosec and Mo (2017) found in their study in rural, northern Pakistan[36].

Among other statistically significant coefficient estimates in the control variables, it is seen that one percent increase in the price of oil leads to the aspiration index increase by 0.004 percentage points, and one percent increase in the price of sugar leads to the aspiration index increase by 0.003 percentage points. Although these coefficient estimates are statistically significant, they are not economically significant. Similarly, the effect of BASIS treatment type 3 is positive and statistically significant. Compared to the BASIS control group, those in treatment type 3 had their aspiration index higher by 0.227 points. This however is weakly statistically significant at 10 percent level.

Similarly, the coefficient on the dummy for whether a respondent has a child is 0.147 which is statistically significant at 10 percent level. This means in average, those with at least a child have their aspiration index value higher than those without a child, by 0.147 points. Finally, the effect of receiving aid is positive and statistically significant, as illustrated by the coefficient 0.232, which means that all other things being constant, those who received aid had their aspiration index higher than those who did not, by 0.232 points.

Additionally, I also use the regression from equation 5.3, using the continuous MMI variable as the primary explanatory variable. The results from this regression is illustrated

[36] However, they used the Bernard and Taffesse index. I will compare my results with theirs in the latter pages as well, for a fairer comparison, using the same aspiration index.

in table 9.1 in the appendix. Like my primary results table 6.1, I show coefficient estimates in five columns, from (1) to (5) showing the effect of adding the various controls and the household fixed effects. The results show that one unit increase in MMI leads to 0.144 points drop in PC1. This is however not statistically different from zero and has a p-value of 0.111.

Effects on Individual Aspiration Components

Table 6.2 illustrates the effect of MMI on individual aspiration components. All four columns, (1) through (4), illustrate coefficient estimates from regressions showing the effect of earthquake intensity in terms of MMI on aspired education, aspired social status, logged aspired asset, and logged aspired income respectively. They use all controls and the household fixed effects. The econometric specification used is given by equation (5.4).

Column (1) shows the coefficient estimates of the effect of MMI on education aspiration. The results show that compared to those who experienced below-average MMI, the second bin group had their education aspiration dropped by 0.566 years, whereas the third bin group had their aspiration dropped by 1.993. Only the latter coefficient estimate is statistically significant though, which is significant at one percent level.

Similarly, column (2) displays the coefficient estimates of the effect of MMI on social status aspiration. The result shows that compared to those who experienced below-average MMI, the second bin group had their social status aspiration increased by 2.650 person[37], whereas the third bin group had their aspiration dropped by 1.643. None of these coefficients are statistically significant though.

Similarly, column (3) displays the coefficient estimates of the effect of MMI on asset aspiration. The outcome variable is the logged value of the aspired asset. The primary model under Panel C shows that compared to those who experienced below-average MMI, the second bin group had their social status aspiration increased by 66.6 percent, whereas the third bin group had their aspiration dropped by 8.6 percent. The former coefficient is statistically significant at one percent significance level; however, it is economically not significant.

While running this regression, I dropped observations with zero asset aspiration in 2014. Keeping these would have created a very high percentage change, of infinity, if the aspired asset value in 2016 was non-zero. However, the first coefficient in column (3) is still showing statistically significant and positive value. This can very much be because of this same reason: an infinitesimal value in 2014 that is close to zero, and a higher value in 2016, leading to a very large percentage change between the two years.

While regression level value of asset aspiration on earthquake intensity though, the coefficients for the second and the third bins are -1.3 and -1.2 respectively (in terms of Rs. 1,000,000), with p-values of 0.326 and 0.108 respectively. This confirms the

[37] Just a reminder that social status aspiration was captured by the variable, aspired no. of people who sought advice from them

aforementioned suspicion of large percentage change leading to positive coefficient estimates while using logged values of asset aspiration.

Finally, column (4) illustrates the coefficient estimates of the effect of MMI on aspired income. The results show that using the primary fixed effects model, those who experienced below-average MMI, the second bin group had their aspired income increase by 147 percent, whereas the third bin group had their aspiration increase by 160 percent. Although the latter coefficient is statistically significant at one percent significance level, it is not economically significant.

Contrary to asset aspiration though, while regressing level value of income aspiration on the earthquake intensity, I still get positive coefficients on the two bins: 37 and 84 respectively (in terms of Rs. 1,000). They are again statistically not different from zero though, with p-values of 0.661 and 0.270 respectively.

Therefore, overall, in case of analysis using individual aspiration components instead of a composite aspiration index, there was a statistically and economically significant results in only aspired (children's) education, where there was a negative effect of MMI on the aspiration component.

Testing Heterogeneity in the Effects of MMI

I tested heterogeneity in the effects of MMI on aspiration index based on three attributes: pre-whether the household received any aid, whether they were still living in temporary shelter during the 2016 survey, and earthquake wealth status. I test this heterogeneity using the econometric specification given in equation 5.3 but adding an interaction term between the continuous MMI variable and the variable of interest that may drive the heterogeneity.

Table 6.3 and 6.4 illustrate the first two heterogeneity tests I explained. Table 6.3 shows the heterogeneous effects based on whether the household received any aid after the earthquake. The five columns, column (1) through (5) show the effect on the coefficient estimates after adding various controls and the household fixed effects. The year fixed effects is substituted using the year dummy as in the previous regressions.

My main results, as illustrated in column (5), show that the difference between those who did not received any aid and those who did was 0.031 points, for each unit increase in the index. This is statistically significant at 10 percent level. This means that while one unit increase in MMI would lead to 0.155 points drop in the aspiration index of those who did not receive aid, the drop is only 0.124 points for those who received aid. While those who did not receive aid will have their aspiration index drop by 0.13 of a standard deviation for each unit increase in MMI, the drop is only 0.10 of a standard deviation per a unit increase in MMI for those who received aid. This is not statistically precise though, as the coefficient on those who did not receive aid is statistically not different from zero.

Similarly, I try to show the heterogeneous effects based on whether the respondent was still living in temporary shelter during the 2016 survey. Table 6.4 shows the estimates from this regression. Similar to the above heterogeneity test, the five columns, from (1) to (5), show the effect of adding various controls and the household fixed effects on the estimates.

Table 6.4 shows that the coefficient estimates on MMI are economically not significant, although statistically significant, as they are positive coefficients. For instance, column (5) shows that for every unit increase in MMI, the aspiration index increases by 0.054, which is not sensible. The coefficient estimate on the interaction between MMI and the dummy for whether they are living in temporary shelter, is statistically significant though. Column (5) shows that compared to those not living in shelter, those who are living in temporary shelter, have their aspiration drop by 0.040 points more, for each additional unit of MMI.

Randomness of Attrition

I check whether respondents' attrition is due to earthquake or due to some exogeneous factors using the linear probability model given by equation (5.5).

Using the three-bin fixed effects model, the results show that compared to those who experienced below average earthquake intensity in terms of MMI, those who experienced the next higher earthquake intensity (between 50th and 75th percentile) were 3.7 percent likelier to not appear in the post-earthquake survey. Similarly, the drop was 1.8 percent for those experiencing the highest level of earthquake intensity (more than 75th percentile). These coefficients are statistically significant at five percent significance level.

Although this shows that MMI has a positive, and statistically significant causal effect on attrition, the magnitude of this effect is trivial.

Reduced form Findings

Apart from the regressions I also performed reduced form regressions analysis. For this, I ran a series of linear probability model regressions with a binary outcome variable denoting whether the respondents experienced the earthquake-induced incident.

These include dummies for whether the respondent was still living in temporary shelter during the 2016 survey, whether their house was severely damaged[38], whether they experienced low monsoon yield due to the earthquake, whether they experienced damaged source of water for drinking and irrigation purposes due to the earthquake, whether any of their household members faced serious illness in the last one year, whether they lost their employment, and whether they experienced falling agricultural prices.

For the sake of simplicity, I have used the continuous MMI variable as the primary explanatory variable (akin to the first fixed effects model given in equation 5.3). Individual fixed effects were added, and the year dummy substituted the year fixed effects. However, no control variables were added unlike in the usual regressions above, because the earthquake or its intensity is completely exogeneous to these dependent variables[39]. The coefficient estimates from these linear probability model regressions are shown in table 9.2, column (1) through (7).

[38] For this, I use proxy for whether they received a red colored earthquake relief card, which is not transferable, and which was provided to the household after a careful investigation of the physical structures of the house by a government-sent, official team of engineers and others.
[39] ...possibly except for the variables, serious illness and loss of employment

Column (1) shows that one unit increase in MMI increases the probability of a respondent reporting living in the temporary shelter in the 2016 survey, by 29.8 percent. This estimate is statistically significant at one percent level. Similarly, column (2) shows that one unit increase in MMI increases the probability of a respondent reporting their house being severely damaged by the earthquake, by 19.0 percent, which is also statistically significant at one percent level. Likewise, column (3) shows that one unit increase in MMI increases the probability of a respondent reporting low monsoon yield by 15.6 percent. This is also statistically significant at one percent level. Furthermore, column (4) shows that one unit increase in MMI increases the probability of a respondent reporting damaged water source by 18.7 percent, which is also statistically significant at one percent level.

Column (5) shows that one unit increase in MMI increases the probability of a respondent reporting serious illness of household member in the last one year by 3.1 percent. This is statistically significant at 10 percent level. Similarly, column (6) shows that one unit increase in MMI increases the probability of a respondent reporting loss of employment by 1 percent, which is statistically significant at five percent level. Finally, column (7) shows that one unit increase in MMI leads to a respondent reporting fallen agricultural prices by 8.9 percent. This is statistically significant at one percent level.

These estimates illustrate that the earthquake did affect the probability of the respondent in experiencing these earthquake-induced factors strongly. If these variables are controlled for in the main regressions, would remove the effect of these earthquake-induced factors on individual aspiration, and which would bias my estimates.

Table 6.1: Effect of MMI on PC1

	PC1				
	(1)	(2)	(3)	(4)	(5)
Independent variables:					
Year is 2016	0.661***	0.636***	0.604***	0.542***	0.472***
	(0.043)	(0.046)	(0.055)	(0.054)	(0.103)
Year is 2016 × MMI Threebin 2	−0.279***	−0.300***	−0.271***	−0.182***	−0.159
	(0.063)	(0.066)	(0.067)	(0.067)	(0.189)
Year is 2016 × MMI Threebin 3	−0.269***	−0.262***	−0.256***	−0.277***	−0.378***
	(0.059)	(0.059)	(0.059)	(0.067)	(0.139)
Logged price of salt		−0.065	−0.068	−0.067	−0.039
		(0.097)	(0.097)	(0.094)	(0.180)
Logged price of oil		0.121	0.115	0.060	0.410***
		(0.089)	(0.089)	(0.087)	(0.126)
Logged price of sugar		0.085	0.103	0.076	0.289**
		(0.074)	(0.076)	(0.074)	(0.131)
BASIS treatment type 1			−0.083	−0.106	0.028
			(0.125)	(0.074)	(0.116)
BASIS treatment type 2			0.157**	0.152**	0.150
			(0.068)	(0.067)	(0.181)
BASIS treatment type 3			0.027	0.041	0.227*
			(0.070)	(0.069)	(0.113)
Respondent's years of education				0.065***	0.028
				(0.005)	(0.022)
Respondent has a child				−0.024	0.147*
				(0.063)	(0.079)
Household received aid				0.242***	0.232**
				(0.070)	(0.106)
Embargo controls	No	Yes	Yes	Yes	Yes
BASIS status controls	No	No	Yes	Yes	Yes
Individual controls	No	No	No	Yes	Yes
HH fixed effects	No	No	No	No	Yes
N	4,157	4,001	4,001	3,986	3,968
R^2	0.057	0.055	0.058	0.107	0.129

Notes:
[a] The regressions use robust standard errors clustered at village level. ***p < 0.01 **p < 0.05 *p < 0.1.

Table 6.2: Effect of MMI on Individual Aspiration Components

	(1) Aspired education	(2) Aspired social status	(3) Aspired asset (log)	(4) Aspired income (log)
Independent variables:				
Year is 2016 × Threebin 2	−0.566	2.650	0.666*	1.473
	(0.477)	(6.354)	(0.396)	(0.551)
Year is 2016 × Threebin 3	−1.993***	−1.643	−0.086	1.602***
	(0.520)	(4.076)	(0.352)	(0.403)
Embargo controls	Yes	Yes	Yes	Yes
BASIS status controls	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes
HH fixed effects	Yes	Yes	Yes	Yes
N	3,968	3,968	3,412	2,930
R^2	0.115	0.013	0.030	0.045

Notes:
[a] The regressions use robust standard errors clustered at village level. ***p < 0.01 **p < 0.05 *p < 0.1.

Table 6.3: Effect of MMI on Aspiration Indices: Exploring the Heterogeneity of Effects Based on Aid Received

	(1)	(2)	(3)	(4)	(5)
Independent variables:					
MMI	−0.170***	−0.172***	−0.167***	−0.119***	−0.155
	(0.031)	(0.031)	(0.031)	(0.031)	(0.093)
MMI × Aid received	0.170***	0.037***	0.039***	0.038***	0.031*
	(0.031)	(0.009)	(0.009)	(0.009)	(0.117)
Embargo controls	No	Yes	Yes	Yes	Yes
BASIS status controls	No	No	Yes	Yes	Yes
Individual controls	No	No	No	Yes	Yes
HH fixed effects	No	No	No	No	Yes
N	4,083	3,928	3,928	3,918	3,900
R^2	0.058	0.057	0.059	0.112	0.128

Notes:
[a] The regressions use robust standard errors clustered at village level. ***p < 0.01 **p < 0.05 *p < 0.1.

Table 6.4: Effect of MMI on Aspiration Indices: Exploring the Heterogeneity of Effects Based on Whether Living in Temporary Shelter Post-survey

	(1)	(2)	(3)	(4)	(5)
Independent variables:					
MMI	0.118**	0.126***	0.123***	0.163***	0.054
	(0.046)	(0.046)	(0.047)	(0.049)	(0.064)
MMI × Temporary shelter	−0.039***	−0.044***	−0.043***	−0.037***	−0.040***
	(0.012)	(0.013)	(0.013)	(0.013)	(0.013)
Embargo controls	No	Yes	Yes	Yes	Yes
BASIS status controls	No	No	Yes	Yes	Yes
Individual controls	No	No	No	Yes	Yes
HH fixed effects	No	No	No	No	Yes
N	2,872	2,769	2,769	2,761	1,588
R^2	0.068	0.072	0.073	0.146	0.152

Notes:
[a] The regressions use robust standard errors clustered at village level. ***$p < 0.01$ **$p < 0.05$ *$p < 0.1$.

Table 6.5: Effect of MMI on Aspiration Indices: Exploring the Heterogeneity of Effects Based on Pre-earthquake Wealth Status

	(1) Wealth Bin 1	(2) Wealth Bin 2	(3) Wealth Bin 3	(4) Wealth Bin4
Independent variables:				
Year is 2016 × MMI Threebin 2	−0.166	−0.125	−0.038	−0.101
	(0.172)	(0.269)	(0.189)	(0.320)
Year is 2016 × MMI Threebin 3	−0.431*	−0.285	−0.403*	−0.280
	(0.223)	(0.192)	(0.204)	(0.254)
HH controls	Yes	Yes	Yes	Yes
Embargo controls	Yes	Yes	Yes	Yes
BASIS status controls	Yes	Yes	Yes	Yes
HH fixed effects	Yes	Yes	Yes	Yes
N	834	1,142	922	1,070
R^2	0.262	0.196	0.160	0.048

Notes:
[a] The regressions use robust standard errors clustered at village level. ***p < 0.01 **p < 0.05 *p < 0.1.

CHAPTER SEVEN

CONCLUSION

In this study, I analyzed the effect of natural disaster, in the form of the 2015 Nepal earthquake, on individual-level aspiration. To do this, I used the primary household-level data from rural Nepal from years 2014 and 2016, and the earthquake intensity data in terms of MMI from USGS. I used the composite index called the first principal component as my primary measure of aspiration that has a standard normal distribution. I then used a fixed effects model through which I compared the aspiration index value between three groups of respondents before and after the earthquake: those who experienced below median MMI, those who experienced MMI between 50th and 75th percentile, and those who experienced MMI above 75th percentile. The use of fixed effects model helped me remove the effect of any time-invariant variables correlated to aspiration and earthquake.

I find a negative causal relationship between earthquake intensity in terms of MMI, and the aspiration index value in terms of PC1. Estimates from my primary fixed effects regression model showed that compared to those who experienced below median earthquake intensity, those who experienced the earthquake intensity between the 50th and 75th percentile MMI had their aspiration index value drop by 0.14 of a standard deviation. Similarly, the drop was 0.33 of a standard deviation for those who experienced the earthquake intensity above the 75th percentile MMI. The former estimate is statistically not different from zero, however, while the latter estimate is significant at one percent significance level.

Furthermore, I do not find consistent results regarding the effect of earthquake intensity of the individual aspiration components. I only find statistically and economically significant estimates for aspired education. Compared to those who experienced below median MMI, those who experienced above 75th percentile MMI had their education aspiration drop by 1.993 points. This is statistically significant at one percent significance level.

While testing heterogeneity in the effect of MMI on aspiration index, I find heterogeneity based on whether the respondent received any aid after the earthquake, and whether they were living in temporary shelter during the post-survey. Compared to those who did not receive any aid, those who received aid had their aspiration index drop by 0.031 points lesser, for each unit increase in MMI. Similarly, compared to those who were not living in temporary during the 2016 survey, those who were living in temporary shelter had their aspiration index drop by 0.040 points higher, for each unit increase in MMI. Both of these estimates are statistically significant, the former at 10 percent, and the latter at one percent significance level.

These findings contribute to the existing literature in a few different ways. First, it adds to the limited set of empirical work on aspiration. While there has been several work on the effect of a positive shock on aspiration, the effect of a negative shock has not been analyzed, apart from Kosec and Mo (2017). Second, it contributes to the literature pertaining to the mental health effects of natural disaster. Moreover, it also illustrates policy-significant findings that the provision of aid would help attenuate the negative effects of a disaster on aspiration. This would in turn attenuate the adverse effects on their investment behavior, which the economic literature says, is a function of an individual's aspiration.

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APPENDICES

APPENDIX A

ADDITIONAL REGRESSION TABLES

Table A1: Effect of MMI on PC1 (Using MMI Continuous Variable as the Primary Explanatory Variable)

	PC1				
	(1)	(2)	(3)	(4)	(5)
Independent variables:					
Year is 2016	1.246***	1.220***	1.145***	1.121***	1.308**
	(0.185)	(0.027)	(0.189)	(0.200)	(0.588)
MMI	−0.106***	−0.106***	−0.099***	−0.103***	−0.144
	(0.027)	(0.027)	(0.027)	(0.030)	(0.089)
Logged price of salt		−0.039	−0.047	−0.070	−0.007
		(0.097)	(0.097)	(0.095)	(0.143)
Logged price of oil		0.096	0.095	0.058	0.424***
		(0.088)	(0.088)	(0.086)	(0.150)
Logged price of sugar		0.057	0.077	0.063	0.283**
		(0.074)	(0.076)	(0.074)	(0.119)
BASIS treatment type 1			−0.078	−0.102	0.032
			(0.075)	(0.074)	(0.119)
BASIS treatment type 2			0.176	0.157**	0.136
			(0.068)	(0.066)	(0.184)
BASIS treatment type 3			0.026	0.045	0.228*
			(0.071)	(0.069)	(0.119)
Respondent's years of education				0.066***	0.029
				(0.005)	(0.022)
Respondent has a child				−0.028	0.129
				(0.064)	(0.079)
Household received aid				0.247***	0.210*
				(0.066)	(0.120)
Embargo controls	No	Yes	Yes	Yes	Yes
BASIS status controls	No	No	Yes	Yes	Yes
Individual controls	No	No	No	Yes	Yes
HH fixed effects	No	No	No	No	Yes
N	4,087	3,931	3,931	3,918	3,900
R^2	0.054	0.053	0.055	0.107	0.127

Notes:
[a] The regressions use robust standard errors clustered at village level. ***p < 0.01 **p < 0.05 *p < 0.1.

Table A2: Effect of MMI on Probability of Occurrence of Various Earthquake-induced Factors

	(1) Temporary shelter	(2) Severely damaged	(3) Low yield	(4) Water source damaged	(5) Serious illness	(6) Loss of employment	(7) Falling ag prices
Independent variables							
MMI	0.298***	0.190***	0.156***	0.187***	0.031*	0.010**	0.089***
	(0.025)	(0.035)	(0.006)	(0.029)	(0.003)	(0.004)	(0.020)
N	1,652	860	1,652	1,652	4,076	4,076	4,056
R^2	0.621	0.851	0.562	0.664	0.260	0.031	0.285

Notes:
[a] The regressions use robust standard errors clustered at village level. ***$p < 0.01$ **$p < 0.05$ *$p < 0.1$.
[b] No controls were added in the regressions, as the earthquake is totally exegenous to the occurrence of incidents taken as dependent variables.

APPENDIX B

BERNARD AND TAFFESSE INDEX

Bernard and Taffesse (2014) explain that although various empirical work has tried to capture aspiration, they are ad hoc, and the indices largely different from one another, precluding economists from comparing the indices and the findings between different studies. Macours and Vakis (2009), one of the first empirical papers attempting to empirically gauge aspiration, use Center for Epidemiological Studies Depression (CESD) scale, originally designed by Radloff (1977). Although the scale captures various mental health dimensions of respondents, it does not measure aspiration *per se* as per its theoretical underpinnings.

Similarly, Bernard et al (2011) asked respondents which of the two statements related to locus of control they agreed with the most, and thus analyzed how much they inclined toward fatalistic versus non-fatalistic attitudes as a proxy for aspiration. This approach infers that the more a person inclines toward non-fatalistic attitudes, the higher aspiration they have, and vice-versa, which may not be true. A fatalistic person may very well have high aspiration, and vice-versa.

Furthermore, following Stutzer (2004), Knight and Gunatilaka (2014) ask respondents what income they deem as 'good,' 'sufficient,' and 'absolute minimum to make ends meet without running into debt.' This approach does not consider the attainability of the 'good' amount in relation to their current position, as well as whether the respondents are making any effort toward attaining that amount, which are crucial components of the definition of aspiration I am using, borrowed from Ray (2006). Finally, Beaman et al (2012) employ a rather direct way of capturing aspiration by asking respondents about their aspired levels. In a study conducted in India, they asked respondents the education level they wished their children to attain, the type of occupation that they wished their children had at age 25, the age which they wished their children to marry, and so on. This approach does not make a distinction between a 'wish' and an 'aspiration,' which is vital. Moreover, as I will state below, the approach is direct and so may lead to measurement error.

Apart from this set of attempts, Bernard and Taffesse (2014), also arguing that these hitherto used indices are largely inconsistent from one another, proposed their aspiration index. The Bernard and Taffesse aspiration index is one of the methods I am using to quantify aspiration in this research.

Bernard and Taffesse (2014) index uses the following formula to quantify aspiration:

$$A_i = \sum_k \left[\left(\frac{a_i^k - \mu^k}{\sigma^k} \right) . w_i^k \right] \qquad (5.1)$$

In equation (5.1), A_i is the aggregate aspiration index value of individual *i*, based on *k* dimensions of aspiration. a_i^k is the aspired value of individual *i* on dimension *k*, μ_k is the sample mean of the *current value*[40] of dimension *k*, and σ_k is the standard deviation of the *current value* of dimension *k*. Similarly, w_i is the weight given by the individual *i*, on dimension *k*[41].

[40] Kosec and Mo (2017) borrow this index but they instead of subtracting mean of the current values of dimension *k* (response to question C), subtract mean of the aspired values of dimension k (response to question D) in a particular district. I argue that the former method as employed by Bernard and Taffesse (2014) is more reasonable for the fact that whether the first term inside the summation is positive, i.e. $(a_i^k - \mu_k)/\sigma_k > 0$ is determined by whether a person aspires to be above or below the village mean value in that particular dimension, but not where their village neighbors aspire to achieve, which may be an abstract amount.

[41] This is based on the assumption that an individual has their own priority of aspiration dimensions that they aspire.

By subtracting sample mean and dividing by sample standard deviation, the index standardizes the aspired value, a_{ik}, making it dimension-free. This enables to compare measurements between different *k* dimensions. The four *k* dimensions included in their study and the subsequent studies that use the index (Kosec and Mo 2017; Janzen et al 2017) include income, assets, children's education attainment, and social status.

This approach also maintains that an individual's aspiration A_i is a function of the current values of others in their locality, which acknowledges the real aspiration window effect. The index can take a negative value if their level of aspiration is below the mean of current values of dimension *k* in village *v*.

Therefore, this index retains two essential properties of aspiration as explained by Ray (2006) that other, previous aspiration measurement indices failed to. First, it acknowledges the `aspiration window' property by making the index a function of the current values of others in the sample. And second, it captures the multidimensionality of aspiration that encompasses multiple components.

Regression Results Using Bernard and Taffesse Index

I use the Bernard and Taffesse aspiration index equation instead of the first principle component index to run regressions specified in equation (5.4), which is my main model, and equation (5.3). Table 10.1 and 10.2 exhibit the coefficient estimates from these two regressions respectively.

Column (5) of table 10.1 shows that compared to individuals who experienced below median earthquake intensity in terms of MMI, those who experience MMI between 50th and 75th percentile had their Bernard and Taffesse index drop by 0.041 points. The drop is 0.296 points for those who experienced MMI above the 75th percentile. These coefficients are 0.02 and 0.17 of one standard deviation respectively. The latter effect is almost similar in magnitude compared to Kosec and Mo's (2017) findings in their Pakistan paper. However, these coefficient estimates of mine are not statistically significant at 10 percent significance level.

Table 10.2 shows the coefficient estimates using MMI continuous variable as the primary explanatory variable. I find that, as shown in column (5), one unit increase in MMI leads to 0.086 points drop in the Bernard and Taffesse index of aspiration. This is equal to 0.05 of a standard deviation. However, this coefficient is also statistically not significant at 10 percent significance level.

Therefore, using the Bernard and Taffesse index, I do not generate any statistically significant results, although I get the expected direction of effect. As I stated above, I still prefer the first principal component analysis as my primary index for aspiration due to it having the standard normal distribution. However, these results using the Bernard and Taffesse index are just for illustrative purpose, to experiment how different the effects are, when I use this measure of aspiration. I see no significant results.

Table A.3: Effect of MMI on Bernard and Taffesse Index

	PC1 (1)	(2)	(3)	(4)	(5)
Independent variables:					
Year is 2016	0.900***	0.888***	0.805***	0.749***	0.642***
	(0.064)	(0.069)	(0.082)	(0.083)	(0.149)
Year is 2016 × MMI Threebin 2	−0.210**	−0.240**	−0.174*	−0.091	−0.041
	(0.093)	(0.099)	(0.101)	(0.101)	(0.280)
Year is 2016 × MMI Threebin 3	−0.269***	−0.268***	−0.263***	−0.251**	−0.296
	(0.087)	(0.088)	(0.088)	(0.102)	(0.201)
Logged price of salt		−0.135	−0.128	−0.128	−0.168
		(0.145)	(0.145)	(0.144)	(0.223)
Logged price of oil		0.143	0.135	0.076	0.401*
		(0.133)	(0.133)	(0.131)	(0.228)
Logged price of sugar		0.184*	0.178	0.149	0.390**
		(0.112)	(0.114)	(0.113)	(0.173)
BASIS treatment type 1			−0.001	−0.017	0.160
			(0.112)	(0.112)	(0.214)
BASIS treatment type 2			0.360***	0.347***	0.424
			(0.103)	(0.102)	(0.270)
BASIS treatment type 3			−0.023	−0.008	0.105
			(0.105)	(0.104)	(0.172)
Respondent's years of education				0.072***	−0.012
				(0.007)	(0.035)
Respondent has a child				−0.065	0.069
				(0.096)	(0.110)
Household received aid				0.193**	0.216
				(0.107)	(0.151)
Embargo controls	No	Yes	Yes	Yes	Yes
BASIS status controls	No	No	Yes	Yes	Yes
Individual controls	No	No	No	Yes	Yes
HH fixed effects	No	No	No	No	Yes
N	4,156	4,001	4,001	3,986	3,968
R^2	0.054	0.053	0.057	0.083	0.112

Notes:
[a] The regressions use robust standard errors clustered at village level. ***p < 0.01 **p < 0.05 *p < 0.1.

Table A4: Effect of MMI on Bernard and Taffesse Index (using MMI Continuous Variable as the Primary Explanatory Variable)

	PC1				
	(1)	(2)	(3)	(4)	(5)
Independent variables:					
Year is 2016	1.517***	1.502***	1.371***	1.221***	1.161
	(0.272)	(0.275)	(0.281)	(0.303)	(0.935)
MMI	−108***	−0.108***	−0.099**	−0.081*	−0.086
	(0.039)	(0.040)	(0.040)	(0.045)	(0.141)
Logged price of salt		−0.131	−0.135	−0.156	−0.145
		(0.145)	(0.145)	(0.143)	(0.192)
Logged price of oil		0.128	0.131	0.083	0.395
		(0.132)	(0.132)	(0.131)	(0.241)
Logged price of sugar		0.161	0.164	0.144	0.397**
		(0.111)	(0.114)	(0.112)	(0.159)
BASIS treatment type 1			0.000	−0.014	0.153
			(0.112)	(0.112)	(0.212)
BASIS treatment type 2			0.360***	0.338***	0.391
			(0.102)	(0.101)	(0.274)
BASIS treatment type 3			−0.023	−0.004	0.097
			(0.105)	(0.104)	(0.174)
Respondent's years of education				0.074***	−0.010
				(0.007)	(0.036)
Respondent has a child				−0.072	0.056
				(0.096)	(0.112)
Household received aid				0.166*	0.152
				(0.099)	(0.167)
Embargo controls	No	Yes	Yes	Yes	Yes
BASIS status controls	No	No	Yes	Yes	Yes
Individual controls	No	No	No	Yes	Yes
HH fixed effects	No	No	No	No	Yes
N	4,086	3,931	3,931	3,918	3,900
R^2	0.054	0.054	0.057	0.085	0.114

Notes:
[a] The regressions use robust standard errors clustered at village level. ***p < 0.01 **p < 0.05 *p < 0.1.

APPENDIX C

EARTHQUAKE-RELATED FIGURES

The following is an abbreviated description of the levels of Modified Mercalli intensity.

Intensity	Shaking	Description/Damage
I	Not felt	Not felt except by a very few under especially favorable conditions.
II	Weak	Felto nly by a few persons at rest,especially on upper floors of buildings.
III	Weak	Felt quite noticeably by persons indoors, especially on upper floors of buildings. Many people do not recognize it as an earthquake. Standing motor cars may rock slightly. Vibrations similar to the passing of a truck. Duration estimated.
IV	Light	Felt indoors by many, outdoors by few during the day. At night, some awakened. Dishes, windows, doors disturbed; walls make cracking sound. Sensation like heavy truck striking building. Standing motor cars rocked noticeably.
V	Moderate	Felt by nearly everyone; many awakened. Some dishes, windows broken. Unstable objects overturned. Pendulum clocks may stop.
VI	Strong	Felt by all, many frightened. Some heavy furniture moved; a few instances of fallen plaster. Damage slight.
VII	Very strong	Damage negligible in buildings of good design and construction; slight to moderate in well-built ordinary structures; considerable damage in poorly built or badly designed structures; some chimneys broken.
VIII	Severe	Damage slight in specially designed structures; considerable damage in ordinary substantial buildings with partial collapse. Damage great in poorly built structures. Fall of chimneys, factory stacks, columns, monuments, walls. Heavy furniture overturned.
IX	Violent	Damage considerable in specially designed structures; well-designed frame structures thrown out of plumb. Damage great in substantial buildings, with partial collapse. Buildings shifted off foundations.
X	Extreme	Some well-built wooden structures destroyed; most masonry and frame structures destroyed with foundations. Rails bent.

Figure A.1: Modified Mercalli Intensity

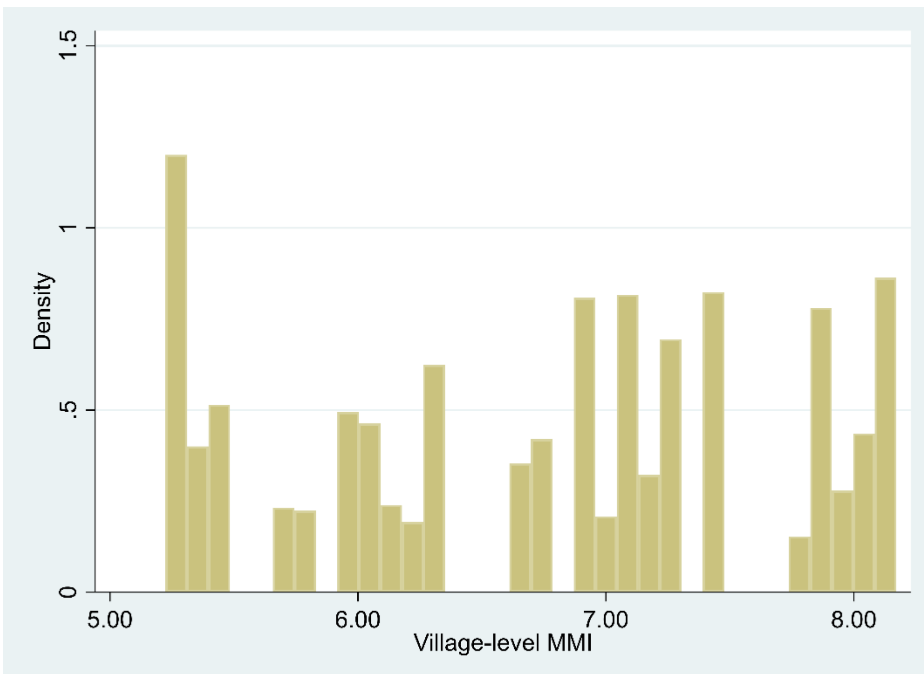

Figure A.2: Village-level MMI Histogram

APPENDIX D

PRINCIPAL COMPONENT ANALYSIS

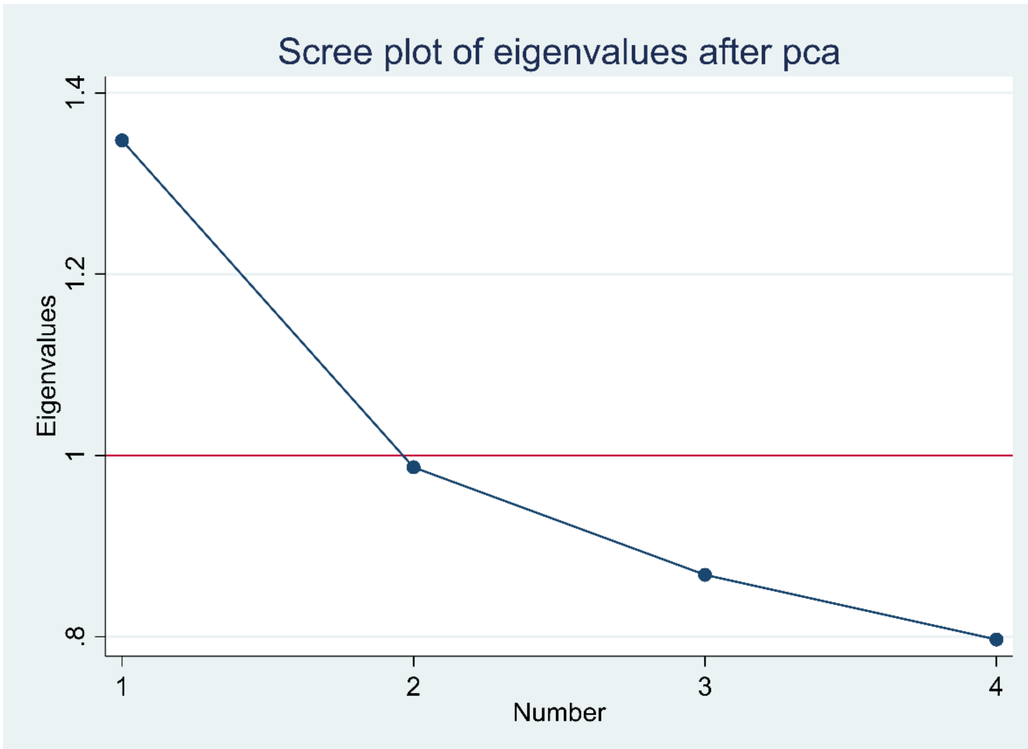

Figure A.3: Scree Plot for Principal Component Analysis

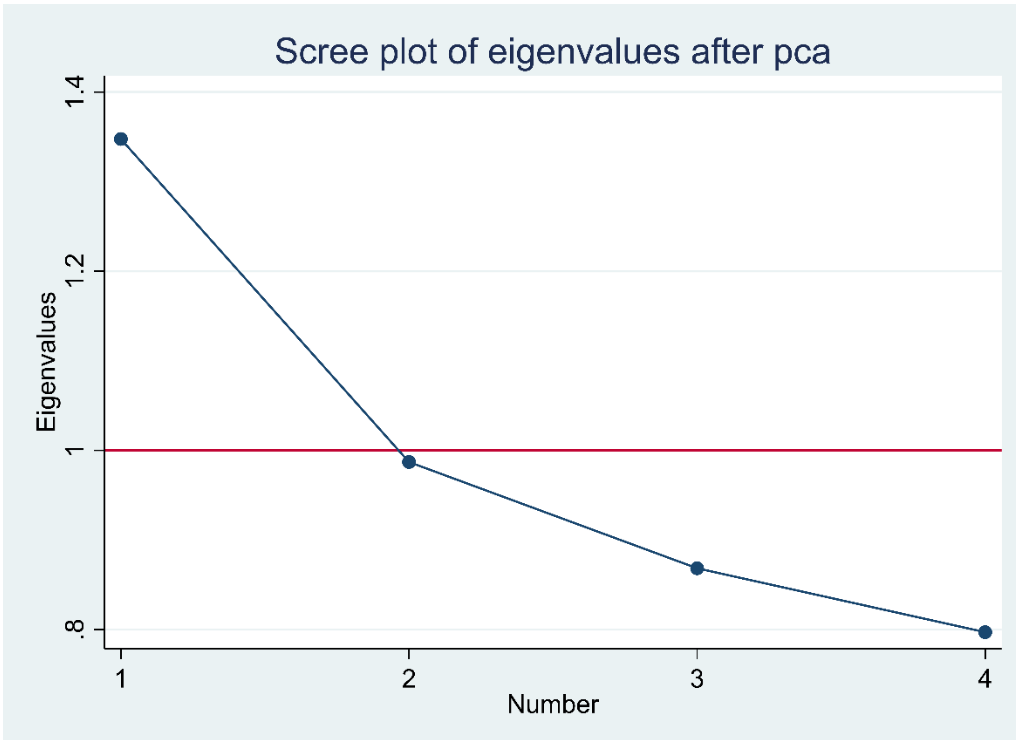

Figure A.4: Loading Plot for Principal Component Analysis

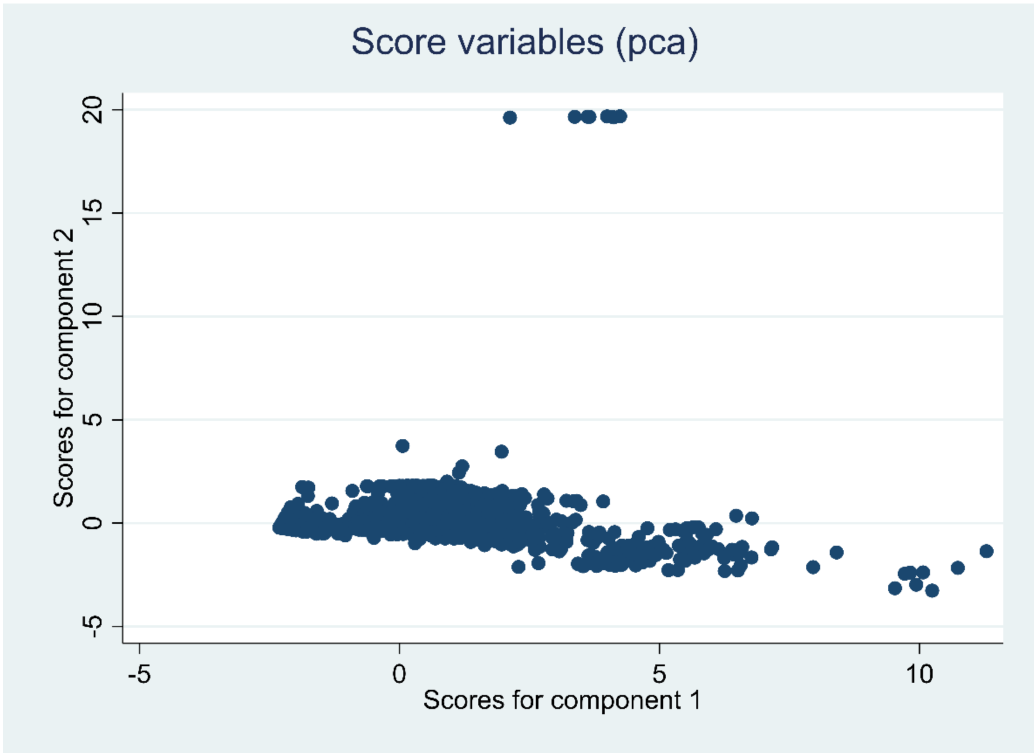

Figure A.5: Score Plot after dimensions reduced through PCA