Natural Disasters in Latin America: The Role of Disaster Type and Productive Sector on the Urban-Rural Income Gap and Rural to Urban Migration

Madeline Alice Messick
University of Southern Mississippi

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NATURAL DISASTERS IN LATIN AMERICA: THE ROLE OF DISASTER TYPE AND PRODUCTIVE SECTOR ON THE URBAN-RURAL INCOME GAP AND RURAL TO URBAN MIGRATION

by

Madeline Alice Messick

A Dissertation
Submitted to the Graduate School and the Department of Political Science, International Development, and International Affairs at The University of Southern Mississippi in Partial Fulfillment of the Requirements for the Degree of Doctor of Philosophy

Approved:

________________________________________________________
Dr. Shahdad Naghshpour, Committee Chair
Professor, Political Science, International Development, and International Affairs

________________________________________________________
Dr. David Butler, Committee Member
Professor, Political Science, International Development, and International Affairs

________________________________________________________
Dr. Robert Pauly, Committee Member
Associate Professor, Political Science, International Development, and International Affairs

________________________________________________________
Dr. Joseph J. St. Marie, Committee Member
Associate Professor, Political Science, International Development, and International Affairs

________________________________________________________
Dr. Karen S. Coats
Dean of the Graduate School

August 2016
ABSTRACT

NATURAL DISASTERS IN LATIN AMERICA: THE ROLE OF DISASTER TYPE AND PRODUCTIVE SECTOR ON THE URBAN-RURAL INCOME GAP AND RURAL TO URBAN MIGRATION

by Madeline Alice Messick

August 2016

This research provides insight into the impact of natural disasters as drivers of rural to urban migration in Latin America and the Caribbean (LAC). Disasters of varying types are predicted to have differing impacts on the productive sectors of agriculture, industry, and services, which due to the concentration of the various productive sectors in either urban or rural areas, subsequently changes the urban-rural wage differential. Changes to the wage differential (as measured by the urban-rural income gap) are predicted to lead to movement between urban and rural areas until a new equilibrium wage is reached.

This dissertation first identifies a cut-off point for “large” disasters, where large is defined as having a substantial negative impact on the growth in GDP. The next question investigates whether the type of disaster economically impacts the sectors of agriculture, industry, and services in varying degrees. The third question examines changes to the urban-rural income gap in LAC countries as a result of the type of disaster. The final question analyzes rural to urban migration post-disaster in LAC countries. These macroeconomic analyses are conducted at the country-level using a fixed effects regression estimator.
Droughts, floods, storms, and wildfires negatively affect the growth in agricultural output in LAC countries, while industry is negatively affected by earthquakes. Floods, landslides, and wildfires are also inversely associated with output in industry. Earthquakes are associated with decreases in output in the service sector, while floods are associated with increases.

Droughts and wildfires are associated with a decline in the relative position of rural incomes when compared to urban. Earthquakes are associated with a decrease in the relative strength of urban incomes when compared to rural. The urban-rural income gap is most likely a moderating factor between disasters and migration.

Migration peaks one to two years after a disaster. This dissertation concludes that there is support for the hypothesis that different types of disasters have differing impacts on the sectors of production, which in turn leads to changes in the urban-rural income gap, which subsequently plays a role in rural to urban migration.
ACKNOWLEDGMENTS

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DEDICATION

This dissertation is dedicated to my husband, Brian Messick, and to all the cats that “helped” me study over the years. It is also dedicated to my parents, Tom and Pat Puckett.
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CHAPTER I - INTRODUCTION

This research provides insight into the impact of natural disasters as drivers of rural to urban migration in Latin America. Disasters of varying types are predicted to differentially impact rural and urban areas, which subsequently leads to changes in the wage differential between rural and urban areas and migration.

It posits that natural disasters of varying types (i.e. droughts, earthquakes, wildfires, etc.) have differing impacts on the productive sectors of agriculture, industry, and services, which due to the concentration of certain productive sectors in urban or rural areas, subsequently results in differing impacts on economic inequality and migration between rural and urban areas. Droughts and wildfires are predicted to affect rural areas more than urban due to the concentration of agriculture in rural areas, while earthquakes are predicted to affect urban areas more than rural due to destruction of capital used in manufacturing.

The first question determines at what magnitude a disaster begins to have an effect on a country’s economic output. The second research question investigates whether the type of disaster economically impacts the sectors of agriculture, industry, and services in varying degrees. This question utilizes a global sample with developing countries as a sub-group. The first and second questions lay the groundwork for questions three and four. The third question examines changes to the urban-rural income gap in Latin American countries as a result of the type of disaster. The final question analyzes rural to urban migration post-disaster in Latin America.
Background

The National Climate Assessment (Melillo, Richmond, and Yohe 2014) predicts that extreme weather events and greater weather volatility will become increasingly common as a result of warming temperatures. Heat waves, droughts, floods, hurricanes (including storm surges that reach farther inland), and winter storms are all expected to increase in frequency (ibid.). Developing countries are highly vulnerable to severe natural disasters due to their limited resources for preparedness and recovery (Mohapatra, Joseph, and Ratha 2012).

Natural disasters are an exogenous shock to the economy of a country. Depending on the severity of the disaster, the shock to the economy may be confined to a local area or have far-reaching impacts across the entire economy. The economic impact of disasters not only includes direct losses – such as damaged or destroyed buildings, crops, or equipment – but also indirect losses resulting from decreased productive capacity due to the displacement or loss of labor or damaged infrastructure (Guha-Sapir, Hargitt, and Hoyois 2004). Secondary losses can result from changes to capital availability, government spending, or interest rates.

The Internal Displacement Monitoring Centre (IDMC) estimates that 26.4 million people annually were displaced by disasters since 2008. IDMC defines displacement as “forced or obliged” movement, evacuation or relocation of individuals or groups of people from their homes or places of habitual residence in order to avoid the threat or impact of a disaster” (IDMC 2015, 13-14). Displacement following disasters is often long-term – IDMC has identified people that have been displaced for over 26 years. IDMC is
currently tracking over 750,000 long-term displaced persons (using a definition of a minimum of one year of displacement) but estimates that there are many more (ibid.).

While estimates of damages from natural disasters has grown since the 1960s, this may be due in part to better reporting of disasters and increasing locating of assets in vulnerable locations (Hallegatte, Hourcade, and Dumas 2007). Climate change may modify costs of extreme weather events either through increasing the frequency of extreme events or through changing trajectories, so that areas unadapted to extreme weather events are impacted (ibid.).

Developing countries are more vulnerable to disasters. For example, Loayza et al. (2012) find that more sectors are affected in developing countries and that the effects of disasters are larger. Richer countries have higher disaster costs, yet poor countries have a higher burden in terms of lives lost. And while damages are higher in industrialized countries, damages form a larger percentage of gross domestic product in developing countries (Guha-Sapir, Hargitt, and Hoyois 2004). The poor, particularly in developing countries, may be more prone to live on marginal land that is exposed to disasters. For example, Chan (1995) finds that impoverished residents of floodplains in Malaysia are confined by structural factors in their choice of residence.

The combination of increasing extreme weather events and the vulnerability of developing countries highlights the need to understand the impact of natural disasters on the economies of developing countries. Repeated natural disasters may permanently affect growth if a country is not able to sufficiently recover between disasters. At the household level, disasters can result in poverty traps for poor households. Increased understanding of the ways that disasters, and type of disaster, affect inequality and rural
to urban migration plays a critical role in addressing the negative externalities associated with disasters.

Rural to urban migration is a concern due to the inability of urban areas to effectively absorb the large numbers of migrants from rural areas. In addition, events, such as natural disasters that influence income in urban and rural areas, will indirectly have an impact on migration (Todaro and Smith 2009). Rural to urban migration results in excess labor and is both a cause of under-development and a sign of it (ibid.).

Introduction to the Research Questions

This research predicts that changes to the urban-rural income gap will result from the differential impact of disasters on the productive sectors of agriculture, industry, and services. In keeping with neoclassical migration theory and the Todaro Model, changes to the urban-rural income gap are predicted to subsequently lead to changes in rural to urban migration as the new wage differential leads to movement between urban and rural areas until a new equilibrium is reached. Figure 1 outlines the predicted impact of disasters.
This dissertation first determines a cut-off point for when a disaster might be considered “large” in that it has an effect on the GDP of a country. Question 2 examines whether disasters of varying types have differing impacts on the three sectors of agriculture, industry, and services. Question 3 uses the urban-rural inequality gap to analyze relative changes to post-disaster rural and urban incomes in Latin America based on the type of disaster. Question 4 examines the impact of disasters on rural to urban migration in Latin America.
Figure 2. Property damage following a microburst storm (photo by author)
CHAPTER II – MIGRATION THEORY AND NATURAL DISASTERS

This section presents common migration theories and connects them to the impact of natural disasters on migration.

Lewis Dual Sector Model

In the Lewis dual sector model, migration is not related to conditions in a migrant’s region of origin but rather the needs and opportunities in the destination region. It focuses on the pull factors of migration. Rural to urban migration takes place in response to wage differentials and ends once there is no longer surplus rural labor. The Lewis dual sector model is criticized, however, because it cannot explain who migrates and who does not. It also cannot explain why migration to urban areas continues despite high urban unemployment. Application of the Lewis dual sector model to explain migration following a disaster is limited due to the model’s lack of focus on push factors.

Neoclassical Theory

Migration is caused by geographic wage differentials in neoclassical theory. Labor migrates to capital-rich areas with high wages while capital flows to capital-poor areas with low wages. This process continues until an equilibrium is reached, at which point the wage differential reflects only the costs of movement between regions (including both financial and psychological costs). Similar to the Lewis dual sector model, neoclassical theory is also not able to explain why some choose to migrate and others do not. In neoclassical theory, loss of capital stock following a natural disaster would result in movement of labor to other more capital-rich regions (and an opposite flow of capital) until a new wage equilibrium is reached.
Todaro Model

According to Todaro and Smith (2009), migration to urban areas occurs because of expected, rather than actual, differences in income between rural and urban areas. In the Todaro Model, the decision to migrate is based on expected future earnings. There are two factors in the calculation of expected future earnings: the wage at a destination and the probability that the individual will find employment there. The Todaro Model augments the neoclassical model in that the migrant takes the likelihood of employment at the destination into account in addition to the wage differential. Persistent wage differences are caused by market imperfections, in particular, the risk that a migrant to urban areas will be unemployed.

Human Capital Theory of Migration

The human capital theory of migration attempts to answer the question of why some people migrate and others do not. It provides a microeconomic foundation for the Lewis and Todaro models. According to human capital theory, migrants tend to be younger, better educated, less risk-averse, and more achievement oriented than non-migrants. Migrants are also more likely to have networks at the destination. Human capital is portable and can migrate to avoid declines in wages associated with some disasters (Yamauchi, Yohannes, and Quisumbing 2009a). Losses in human capital may be due to fatalities or migration that occurs as a result of the disaster. The human cost of a disaster may be less observable than damage to the physical capital stock and may only be apparent in analysis of long-term growth (Noy 2009).
New Economics of Labor Migration (NELM)

The new economics of labor migration emphasizes household decision-making about whether to migrate and which member of the family will migrate. Households are believed to act collectively to maximize income, minimize risks, and loosen constraints created by market failures, including those caused by natural disasters. The collective action of the household is able to explain why migrants remit income, which the previous models could not.

Migrants are believed to migrate in response to market failures such as missing or incomplete capital, insurance, or labor markets. Market imperfections in rural areas are seen as a primary motivation for migration, and consequently income differentials are not a requirement for migration. Families engage in migration in order to minimize risk from natural disasters and economic shocks as the physical distance between family members decreases the likelihood that all sources of a family’s income will be affected by a natural disaster or other shock.

Gravity Model of Migration

Gravity models examine the relationship between 1) migration and distance and 2) migration and origin and destination population sizes. The closer someone is to another person, the more likely they are to be a part of that person’s reference group. Having a relative that migrated due to a disaster increases the likelihood that another person who experiences a disaster will also migrate, even more so than when a relative migrated but not due to a disaster (Saldaña-Zorrilla 2008). Modified gravity models add additional variables, including unemployment rates, the degree of urbanization,
climatological variables, measures of public expenditures and/or taxes, and behavioral measures.

**Theoretical Orientation of this Research**

This research is based on the Todaro Model. Rural migrants are assumed to migrate to urban areas due to perceived wage differentials as well as their expectation that they will be more likely to find employment in urban areas. Migrants take into account not only the likelihood of finding employment, but also the percentage of time that they can expect to be employed, and the amount of income that could be earned during that time period if the person does not migrate.

Through differentially affecting the productive sectors in rural and urban areas, natural disasters change the perceived or actual wage differentials and likelihood of finding employment between rural and urban areas, and thus, affect expectations of finding employment in the area affected by the disaster and the destination as well as the perceived wage differential.
CHAPTER III - REVIEW OF THE LITERATURE

Disaster Definitions

According to the International Disaster Database used in this research, a disaster is a “situation or event, which overwhelms local capacity, necessitating a request to national or international levels for external assistance” (CRED 2015). A natural hazard becomes a disaster only when “lives are lost and livelihoods damaged or destroyed” (ibid., 12). Natural disasters can be exacerbated by human activity, resulting in complex emergencies (Guha-Sapir, Hargitt, and Hoyois 2004). While disasters are often characterized as sudden events, slow onset disasters, such as droughts, also occur. In addition, while many disasters appear to occur without warning, advanced early warning systems are increasingly able to see foresee disasters (Burnham 2008).

Disaster Types

The disaster data is from the International Disaster Database (EM-DAT) from the Center for Research on the Epidemiology of Disasters (CRED). The definitions used by the EM-DAT are covered in this section. The disaster types fall into six categories, only four of which are used here (see Figure 3).

**Figure 3.** Disaster categories as defined by CRED
Droughts

Drought is defined as “An extended period of unusually low precipitation that produces a shortage of water for people, animals, and plants” (Guha-Sapir, Hoyois, and Below 2015, 37). Droughts and famines result in crop and livestock loss, but not damage to infrastructure or buildings. They tend to cover large areas and last over multiple years. In fact, the onset of droughts can be difficult to detect. Famines have more complex causes than droughts and can lead to mass migration. Droughts are often predictable and there are several regional early warning systems in place (Guha-Sapir, Hargitt, and Hoyois 2004).

Earthquakes

Earthquakes are a “sudden movement of a block of the Earth’s crust along a geological fault and associated ground shaking” (Guha-Sapir, Hoyois, and Below 2015, 38). Earthquakes are the least predictable disasters as they strike with minimal or no notice. They also have the highest immediate mortality and structural damage rates, however, they do not affect crops unless landslides are triggered by the earthquake. The risk from earthquakes varies based on the population density, the resistance of buildings and other structures to tremors, the time of the quake (earthquakes that take place when people are sleeping tend to have larger numbers of fatalities), and the intensity of the earthquake (Guha-Sapir, Hargitt, and Hoyois 2004). The earthquake sub-group also includes tsunamis.

Floods

Flood is “a general term for the overflow of water from a stream channel onto normally dry land in the floodplain (riverine flooding), higher-than-normal levels along
the coast and in lakes or reservoirs (coastal flooding) as well as ponding of water at or near the point where the rain fell (flash floods)” (Guha-Sapir, Hoyois, and Below 2015, 38). Floods have the highest ratio of those affected to those killed, meaning while many are affected few are killed. Most of the deaths that do take place are the result of flash floods. The impact on agriculture depends on the timing of the flood. Floods may cover large areas, and can develop slowly or suddenly.

*Landslides*

Landslide is “any kind of moderate to rapid soil movement including lahar, mudslide, [or] debris flow. A landslide is the movement of soil or rock controlled by gravity and the speed of the movement usually ranges between slow and rapid, but not very slow. It can be superficial or deep, but the materials have to make up a mass that is a portion of the slope or the slope itself. The movement has to be downward and outward with a free face” (CRED 2015). While most landslides result from heavy rain or snow or ice melt, dry landslides can happen following earthquakes. Landslides are typically sudden onset disasters.

*Storms*

Storms include convective storms, extra-tropical storms, and tropical cyclones. Convective storms are “generated by the heating of air and the availability of moist and unstable air masses” and include thunderstorms and tornadoes (ibid.). Extra-tropical storms are a “type of low-pressure cyclonic system in the middle and high latitudes (also called mid-latitude cyclone) that primarily gets its energy from the horizontal temperature contrasts (fronts) in the atmosphere” (ibid.). When extra-tropical storms take place during winter, they can be very damaging (i.e. blizzards). Tropical cyclones are
“characterized by a warm-core, non-frontal synoptic-scale cyclone with a low pressure center, spiral rain bands and strong winds” (ibid.). They go by various names depending on the region, including hurricane, typhoon, or cyclone.

Windstorms are among the most destructive disasters. They tend to cover large areas and the loss in terms of deaths, injuries, agriculture, and property can be quite large. Mortality is often caused by collapsed buildings while flooding and flying debris account for many injuries (Guha-Sapir, Hargitt, and Hoyois 2004).

**Volcanoes**

Volcanic activity is a “type of volcanic event near an opening/vent in the Earth’s surface including volcanic eruptions of lava, ash, hot vapor, gas, and pyroclastic material” (Guha-Sapir, Hoyois, and Below 2015, 40). For volcanoes the ratio of people killed to affected is similar to earthquakes. Ash can destroy crops and make it difficult for livestock to find food and water (Guha-Sapir, Hargitt, and Hoyois 2004).

**Wildfires**

Wildfires are defined as “any uncontrolled and non-prescribed combustion or burning of plants in a natural setting such as a forest, grassland, brush land, or tundra which consumes the natural fuels and spreads based on environmental conditions (e.g., wind, topography)” (Guha-Sapir, Hoyois, and Below 2015, 40). Wildfires can have natural causes (such as lightening) or may be human caused.

**Comparison of Disaster Impacts**

Since 2008, floods have been responsible for the majority of persons displaced by disasters, with 55% of displacements resulting from floods. Storms also affected a large percentage of people, with 29% of displacements caused by storms. Displacements from
earthquakes were also a large percentage at 14%. All the other disasters were responsible for only a minimal percentage of displacements (1% or less) (IDMC 2015).

Distinguishing Rural and Urban Areas

Each country develops its own measure for how rural and urban areas are delineated, resulting in a number of ways in which rural and urban areas can be defined. The most commonly used method in Latin America is to define urban areas as cities with a population of more than 1,500 to 2,000 and then define all remaining areas as rural (Ferranti et al. 2005). The Organisation for Economic Cooperation and Development defines urban areas as having population densities greater than 150 persons per square kilometer (ibid.).

A report by the World Bank recommends that countries use a definition based in population density and remoteness from large metropolitan areas (Chomitz, Buys, and Thomas 2005). This definition recognizes that the distinction between urban and rural areas is not a dichotomous one, rather it is a gradient that typically involves a gradual transition from remote rural areas to increasingly urban areas around mega-cities (ibid.).

Almost all of the growth in the world population in coming decades will be in the urban areas of less developed countries (DESA Population Division 2012). Rural area populations are expected to increase to 3.4 billion in 2021 and then begin declining, reaching just over 3 billion in 2050. The growth through 2021 will be in developing countries, as rural areas in developed nations have been declining for some time. Many cities are at risk for natural hazards. Out of 633 cities analyzed, 233 cities are located in or close to areas at high risk for flooding. Drought is the next most common risk to
cities, with 132 out of 633 cities at risk, followed by cyclones (68 cities) and earthquakes (40 cities) (ibid.).

Rural areas are characterized by low population densities, thin markets, a shortage of skilled labor, and a high unit cost of delivering social services and infrastructure (Chomitz, Buys, and Thomas 2005). Rural to urban migration becomes a concern when urbanization exceeds the capacity of urban areas to productively and safely assimilate the number of migrants. In addition, rural to urban migration is often blamed for shortages in housing, excess demand on infrastructure, over-crowding, and congestion (Tacoli, McGranahan, and Satterthwaite 2015).

The Macroeconomic Impact of Natural Disasters

Severe disasters result in a shock to the economy of a country. There is no agreed upon definition of shock as it can be difficult to delineate a shock from economic volatility, especially when the shock, such as droughts, occurs on a recurring basis. In fact, shocks can be considered as a type of extreme volatility. One approach is to define shocks as “a significant change in the value of a variable from its underlying trend, as determined using standard measures of dispersion such as the standard deviation or the coefficient of variation” (Varangis et al. 2014, 3). Alternatively, the International Monetary Fund defines exogenous shocks as “a sudden event beyond the control of authorities that has a significant impact on the economy” (International Monetary Fund 2003, 4).

Macroeconomic shocks in low income countries tend to persist over time as low income countries have few options for adjustments. The lack of financial resources such as foreign exchange reserves also makes it difficult for low income countries to engage in
consumption smoothing. Negative shocks often increase poverty and countries may not be able to recover from repeated shocks (Varangis et al. 2014). Natural disasters disrupt capital accumulation through the destruction of capital, which requires replacement and sets back economic growth as capital is diverted from other productive uses (Cavallo and Noy 2011).

**GDP Output Most Likely Falls Following Disasters**

Albala-Bertrand (1993), in one of the earlier studies of natural disasters and GDP output, finds that capital loss following a disaster is unlikely to affect the growth rate of output and moderate expenditures are most likely sufficient to keep the growth rate from falling. Since Albala-Bertrand’s early study, no clear consensus has developed on the growth effects of natural disasters. Multiple studies of short- and long-run effects on growth have contrasting conclusions, including negative, positive, and insignificant effects.

In a survey of literature on short- and long-run growth effects of disasters, Cavallo and Noy (2011) classify the short-run as several years and long-run as at least five years. The studies reviewed estimate short-run growth effects between -9.7% of GDP in developing countries to a positive 1.33% in OECD countries. For analyses that are not broken out by the type of disaster or the country’s income group, the growth effect ranges from -0.8% to 0.4%.

Long-run growth effects for climatic events (such as droughts and wildfires) varied from -0.6% of GDP to a positive 0.42% (ibid.). Geological events (such as earthquakes and volcanoes) have impacts that are insignificant or -0.32% on long-run growth. For both short- and long-run effects, there are some studies that find the growth
effects to be insignificant. The remaining portion of this section summarizes studies that have been published since Cavallo and Noy’s 2011 review.

Domestic output falls following hurricanes in Central America and the Caribbean (Strobl 2012). Loayza et al. (2012) finds differences in growth effects between earthquakes, droughts, floods, and storms based on the sector of production. Floods are the only type of disaster found to have a positive effect on growth of services; floods have a positive impact on agriculture, yet droughts and storms are negatively associated with growth of agriculture; and none of the disaster types are associated, either positively or negatively, with growth in industry.

Fomby, Ikeda, and Loayza (2013) reach four conclusions about the growth effects of natural disasters, including that the impacts on developing countries are more severe; not all disasters have similar effects and some may be positive; severe disasters have a more strongly negative impact while moderate disasters can have beneficial effects on growth; and the impact varies based on the sector of production. In developing countries, droughts have a negative effect on growth, floods have a positive effect, earthquakes do not have a significant effect but do effect some sectors significantly (the impact on agriculture is negative while the impact on industry is only negative for severe earthquakes while it is positive for moderate earthquakes), and severe storms have a negative impact, while for moderate storms the impact is positive. The effect of a climatological disaster on non-agricultural growth tends to be delayed a year or two after the effect is seen on agricultural growth.

Felbermayr and Gröschl (2014) find that for the years with the worst 5% of disaster damages, there was a negative impact on growth of 0.45%. This was primarily
caused by large earthquakes and meteorological disasters, in poor countries, however, geophysical disasters had a larger role. A further analysis over a five-year time period found negative effects on GDP per capita between 0.098 and 0.071. The reconstruction process is facilitated by institutional quality and financial openness (ibid.). Hochrainer-Stigler (2015) concludes that, on average, whether the growth impact of disasters is positive or negative depends on the socio-economic situation of a country prior to the disaster.

Using a novel method of estimating the impact of a disaster, Klomp (2016) uses the change in night-time light intensity as visible from satellites as a method of measuring the impact. Klomp uses this technique due to a desire to find an alternate measure to GDP per capita because of concerns over the quality of GDP per capita data in low-income countries. Klomp finds that light intensity is reduced by geophysical and meteorological disasters in industrialized countries and climatic and hydrological disasters in developing countries. Klomp also concludes that the use of GDP per capita as a measure underestimates the impact of disasters.

Meta-Analyses. Van Bergeijk and Lazzaroni (2015) conduct a meta-analysis to address the conflicting research on the growth effects of natural disasters. They find that the growth effect of disasters is clearly negative, yet report that the results vary depending on whether direct costs or indirect costs are estimated. Estimates using direct costs show a stronger negative effect. In another meta-analysis, Klomp and Valckx (2014) also find a negative growth effect for disasters, with climatic disasters in developing countries having the strongest negative growth effect. Yet Klomp and Valckx
also conclude that some of the tendency towards results showing a negative impact is due to publication bias.

The Productivity Effect

It is possible that disasters temporarily increase GDP through the rebuilding efforts that take place following a natural disaster. The “productivity effect” refers to the positive economic consequences of accelerated capital replacement following disasters (Hallegatte and Dumas 2009). In the productivity effect, new technology replaces old technology, leading to a posited long-term positive impact on the economy. With an imperfect productivity effect, technology embedded in capital is not upgraded but replaced with technology similar to the old.

Hallegatte and Dumas (ibid.) model post-disaster scenarios using endogenous technical change and perfect or imperfect productivity effects. The first model, with perfect productivity effects, shows a small decline in productivity in the first year following a disaster due to decreases in production. The following years see a rise in productivity associated with increased investment. In this scenario, the productivity effect results in more production, however, the absolute impact on the economy is small. In the second scenario, an imperfect productivity effect amplifies the negative consequences of disasters. The reconstruction investment crowds out investments in updates to production technologies which reduces the rate of productivity growth (ibid.).

Remittances Decrease Output Volatility

Remittances decrease GDP volatility following natural disasters, however, the stabilizing effect is mitigated if remittances exceed 6% of GDP (Combes and Ebeke 2011). This stabilizing impact is the greatest in countries that are less developed.
financially. Previous research finds that remittance inflows tend to increase in response to both climatic and geological disasters (David 2010). An increase in inflows from a variety of sources, including foreign aid, private investment, and other inflows, results over the three years following a hurricane. The increase in inflows is on average equal to about 4/5s of the total damage (Yang 2008).

Other Macro Disaster Impacts

After a disaster, it takes some time for investment to be directed toward reconstruction. Reconstruction may also be delayed due to limitations in the capacity and skills of those involved in the reconstruction process. A bifurcation in GDP losses comes about when the reconstruction process cannot keep pace with repeated disasters (Hallegatte, Hourcade, and Dumas 2007).

In richer countries, hurricanes lead to new multilateral lending but the lending is offset by declines in private investment inflows, resulting in the possibility that none of the estimated damage is replaced by inflows (Yang 2008). Strong institutions, high per capita income, high degree of openness to trade, and high levels of government are associated with increased resilience to the shock of natural disasters at the country level and also help reduce the impact of disasters on the macroeconomy (Noy 2009).

Toya and Skidmore (2007) find that higher levels of per capita income are associated with lower levels of the number killed and lower economic damages from disasters in developing countries. Disasters with slow onsets, such as floods, cause less loss of life than hurricanes (Benson and Clay 2004).
Governments Face Disincentives to Engage in Disaster Preparedness

Government preparedness makes a difference in reducing disaster impact, however, the presence of international aid creates a moral hazard where governments under-invest in preparedness (Cohen and Werker 2008). Neumayer, Plümper, and Barthel (2014) find that while governments have incentives to underinvest in disaster preparedness, differences in preparedness across countries are due to the frequency with which a country experiences disasters. Government actors in countries with a high propensity for disaster face stronger incentives to invest in preparedness and mitigation.

Following a disaster in Bangladesh, both agricultural and non-agricultural wages suffer declines in the short-run (Mueller and Quisumbing 2011). A movement by agricultural workers to non-agricultural employment resulted in less of a reduction in short-term wages for those workers. Salaried agricultural and non-agricultural workers saw a greater decline in wages than day laborers, however, the decline was only short-term.

The Microeconomic Impact of Natural Disasters

Households that are more economically vulnerable face greater threats following a disaster-related shock. Households often engage in adaptive or coping strategies in order to reduce their economic vulnerability (Saldaña-Zorrilla 2008, 584). According to the World Health Organization, there are three types of coping mechanisms: non-erosive coping, erosive coping, and failed coping (World Health Organization 1998). In non-erosive coping, damage resulting from coping strategies is minimal or not permanent. Examples include cutting back on consumption and sales of assets that are not used for production. With erosive coping, permanent harm results, while failed coping can result
in destitution for households. Erosive coping includes predatory lending, child and bonded labor, or sale of productive assets. Failed coping results in prostitution, sale of children, begging, dependence on others, or migration (ibid.).

Households and Communities Utilize Various Strategies to Manage Disaster Risks

Households engage in both ex-ante and ex-post strategies to address the risk associated with natural disasters (Skoufias 2003). Economic recovery strategies used by households include migration (internal or external), changes in the labor supply of the household (including increased child labor), loans, micro-credit, sale of assets (i.e. oxen, land, or equipment), government/public transfers, increased reliance on remittances, insurance, savings, and cutting back on consumption, including food consumption. Insurance and credit markets are likely to be under-developed, and thus under-utilized, in developing countries.

Coping strategies for managing risk include those that smooth consumption across time (such as savings, borrowing, and accumulating and selling assets) and those that smooth consumption through sharing risk across households (such as insurance and informal mechanisms like remittances) (Alderman and Paxson 1994). Risk management includes actions taken to minimize variability in income. These include crop diversification or diversifying risk through migration (ibid.).

Risk-sharing networks are more effective when shocks to the income of the members of the network are uncorrelated, which typically is not the case for natural disasters (Becchetti and Castriota 2011). A shock that affects individuals without affecting other members of a group are referred to as idiosyncratic, while those that affect groups (such as disasters) are covariant (Oviedo and Moroz 2014). Microfinance can
help the poor rebuild assets and serve as a form of emergency assistance following natural disasters. Using a natural experiment, Becchetti and Castriota (2011) find that microfinance leads to increases in real income and hours worked following a tsunami in Sri Lanka.

Communities may be reluctant to engage in prior (ex-ante) disaster preparedness if the perceived costs of preparedness outweigh the anticipated gains. For example, poverty and the expectation of government aid create a disincentive to engage in ex-ante vulnerability reduction (Saldaña-Zorrilla 2008). This applies as well to community leaders and local and state authorities in Mexico, who appear to rely on anticipated federal government aid following a disaster rather than take on the expense of disaster preparedness (ibid.).

To overcome shocks to income and assets stemming from a disaster, households in Mexico are most likely to turn to relatives in the community followed by government aid and neighbors (ibid.). They are less likely to sell assets, while insurance is the last choice for post-disaster financing (ibid.). The lack of affordable crop insurance has led farmers in Mexico to first give up cultivating coffee and ultimately to forgo farming (ibid.).

Disasters Result in Both Income and Asset Shocks

Disasters can result in both income and asset shocks for households. Households engage in post-disaster consumption smoothing which may result in the sale of assets such as livestock. In this case, assets serve as a buffer against income shocks. Households may alternatively engage in asset smoothing where they cut back on
consumption in order to avoid selling an asset, especially if that asset is essential to future income (Kurosaki 2013).

Household assets are “the stock of wealth used to generate well-being” (Siegel and Alwang 1999, 10). Household assets can fall into many categories, including natural, physical, financial, human, and social assets. Natural assets include, for example, land and fisheries. Physical assets include productive assets such as equipment and stock such as livestock. Financial assets include cash and access to credit and insurance markets. Human assets include education, skills, and health, while social assets include links to a community or other network (ibid.).

The sale of assets is complicated during covariant shocks (when shocks affect a group rather than an individual or household) as prices are lowered when many households attempt to divest assets simultaneously (Oviedo and Moroz 2014). In addition, the “lumpiness” of assets means that households cannot sell part of some types of assets, such as livestock, without selling all of it, which limits the options available to households (ibid.).

*Natural Disasters Can Result in Poverty Traps for Households*

Disasters may result in poverty traps if households are required to sell productive assets to cope. Poverty traps also result when households are not able to recover from one disaster before experiencing a subsequent event (ibid.). Households with low expected returns to assets and high variability of returns are vulnerable to poverty traps (Siegel and Alwang 1999). For some households, an attempt to avoid risk results in the households engaging in low-risk low-return activities that inadvertently increase the risk
of poverty traps as lower returns slow down the rate of recovery between shocks (de la Fuente 2007).

Low levels of human capital may also result in poverty traps that exacerbate inequalities (Yamauchi, Yohannes, and Quisumbing 2009a). In addition, shocks may reduce levels of human capital through reducing school enrollment rates and negatively affecting health (Oviedo and Moroz 2014). Systems intended to target households in need following a disaster may struggle to do so, as most are intended to identify the structurally poor and are unable to identify those made temporarily poor by the crisis (Skoufias 2003, 1097).

The adoption of new technologies can help households escape poverty through increasing returns on assets, however, technological improvements for poor households often require access to credit markets (Carter and Barrett 2006). When credit rationing is present, households who wish to adopt new technologies must engage in an “autarchic accumulation strategy” that involves considerable sacrifice of short- and medium-term consumption. This is a practical step for certain households that are close to an asset level where returns are increasing, however, for other families, in particular poorer families, and autarchic accumulation strategy with reduced consumption may not be feasible. The asset threshold where an autarchic accumulation strategy is feasible is called the Micawber threshold. Households below the threshold are unable to accumulate assets and become stuck in a poverty trap (ibid.).

Remittances Reduce Vulnerability through Both Ex-Ante and Ex-Post Strategies

Remittances reduce vulnerability to natural disasters through multiple mechanisms, including diversifying income and risk, increasing \textit{ex-ante} preparedness,
and assisting with ex-post recovery. Ex-ante effects of remittances include building residences that can better withstand a disaster or moving to a less disaster-prone area (i.e. out of a flood zone). Ex-post, remittances serve as a form of private insurance and aid in faster recovery for the household (Combes and Ebeke 2011).

While risk can come from a number of sources, for households in developing countries, natural disasters are a primary source of risk (Savage and Harvey 2007). Remittances serve as a form of private insurance for migrant-sending households. Remittances sent following a disaster-related income shock in the Philippines help smooth household consumption (Yang and Choi 2007). In Pakistan, remittances decrease vulnerability to natural disasters through increasing resiliency (Suleri and Savage 2006).

Wu (2006) documents the experiences of migrants who sent remittances home following natural disasters in Indonesia. While some migrants shared wanting to send remittances immediately after the disaster, they were unable to do so due to not being able to locate family members, delays in the banking system reopening, or not having a valid address for their family as required by certain types of money transfers. Due to delays in the receipt of remittances, remittance-receiving families had similar needs immediately following the disaster as non-remittance receiving families. Wu also documents changes in migration patterns, with some migrants choosing to return to assist in reconstruction efforts.

Remittance flows may be easier to restore post-disaster than other types of income. Yet barriers to transmission of remittances following a natural disaster exist, for example, identification documents may be lost in the disaster (Savage and Harvey 2007) or infrastructure (including telecommunications, banking, and transportation
infrastructure) may be damaged (Suleri and Savage 2006). In addition, remittance senders may not be able to re-emigrate and restore remittances if they return home to assist with the recovery (ibid.).

*High Levels of Human Capital Can Mitigate the Impact of a Disaster Shock*

Accumulated human capital can mitigate the negative impact of a disaster both in the long and short run (Yamauchi, Yohannes, and Quisumbing 2009a). Higher rates of human capital pre-disaster help maintain the investment in human capital following the disaster (Yamauchi, Yohannes, and Quisumbing 2009b). Human capital is portable, and can migrate to avoid the decline in wages associated with some disasters.

Human capital and resilience to disasters has also been connected at the country level. For example, countries with higher levels of literacy are better able to withstand shocks from disasters (Noy 2009). Educational attainment outcomes are negatively impacted by a shock due to natural disasters, however, this effect is only seen if credit rationing is also present (Gitter and Barham 2007).

Any positive increases in productivity (for example, due to rebuilding or to increased agricultural productivity) may be negatively offset by losses in human capital. Losses in human capital may be due to fatalities or migration that occurs as a result of the disaster. Toya and Skidmore (2007) find that in addition to income, educational attainment, openness, a strong financial sector, and smaller government are all inversely associated with greater losses from disasters.

Disasters have the greatest negative impact on women, the elderly, and minorities (Ibarrarán et al. 2009). Households headed by a female with damaged dwellings and without an adult male member resort to the production of handicrafts and other
traditionally female, low-paying income earning activities in exchange for help from male laborers (Takasaki 2012). Women’s lower socio-economic status makes them more vulnerable to disasters, as they experience both higher mortality rates and a greater gender gap in life expectancy as a result of disasters. The life expectancy gap decreases as women’s socio-economic status increases (Neumayer and Plümper 2007).
CHAPTER IV – THE DATA

The dependent variable of this research, used in the analysis in Chapter VIII, is the change in the percentage of people living in rural areas. Preliminary analyses are conducted in Chapter VI and 7. The dependent variables in the analysis in Chapter VI include the annual percentage growth in agriculture, the annual percentage growth in services as a percentage of GDP, and the annual percentage growth in industry. The dependent variable in Chapter VII is the urban-rural income gap.

The explanatory variables include a dummy for each type of disaster and either a “large” disaster dummy (the analysis determining the cut-off point for the large disaster dummy can be found in Chapter V) or interaction terms between the type of disaster and a measure of severity. While damages as a percentage of GDP is the primary measure of severity for the disasters, analyses are also conducted for the percentage of the population affected and the percentage of the population killed. Because of the low correlation between these measures (see section below titled “Choice of a Severity Measure” for more information), the results vary quite a bit depending on which severity measure is used.

Control variables include remittances, foreign direct investment (FDI), aid, and government consumption. The control variables are chosen because of their potential to impact internal migration, either through creating jobs, changing the wage differential, or providing a transfer of income. A measure of government capability to respond to disasters was considered, however, fixed effects analyses omit time invariant variables and there were not sufficient data points to allow for variation.
The Disaster Data

The data on disasters is from the Emergency Events Database (EM-DAT) from the Centre for Research on the Epidemiology of Disasters (CRED). This is the most comprehensive database of natural disasters and is also the one used by the majority of researchers of natural disasters (Cavallo and Noy 2011). The database includes information on geophysical, meteorological, hydrological, biological, climatological, and extraterrestrial disasters\(^1\). In order for a disaster to be included in the database, one or more of the following criteria must be true: ten or more people reported killed, a hundred or more people reported affected, a declaration of a state of emergency, or a call for international assistance (Guha-Sapir, Hoyois, and Below 2015).

Table 1

*Number of Disasters in Latin America from 1980 to 2013*

<table>
<thead>
<tr>
<th>Disaster Type</th>
<th>Number</th>
</tr>
</thead>
<tbody>
<tr>
<td>Droughts</td>
<td>96</td>
</tr>
<tr>
<td>Earthquakes</td>
<td>112</td>
</tr>
<tr>
<td>Floods</td>
<td>404</td>
</tr>
<tr>
<td>Landslides</td>
<td>89</td>
</tr>
<tr>
<td>Storms</td>
<td>292</td>
</tr>
<tr>
<td>Volcanic Events</td>
<td>49</td>
</tr>
<tr>
<td>Wildfires</td>
<td>43</td>
</tr>
</tbody>
</table>

For the countries included in the analysis, there were 96 droughts, 112 earthquakes, 404 floods, 89 landslides, 292 storms, 49 volcanic events, and 43 wildfires for the time period from 1980 to 2013 (see Table 1). Not all of the disasters were included in each analysis due to missing data for some variables. The most common disasters are hydro-meteorological ones, which primarily impact the agricultural sector, either through washing away crops and destroying plants or leaving land too saline to

\(^1\) Extraterrestrial disasters are events such as meteor impacts and space weather.
farm (Guha-Sapir, Hargitt, and Hoyois 2004). Due to missing data and lagged variables, the number of disasters included in each model is smaller than the full dataset.

Choice of Severity Measure

The severity measures used in this research, and most commonly used by researchers, are the number of deaths, the number of people affected, and the total damages in dollars. There is low correlation among the severity measures in the EM-DAT (see Table 2). It follows that the outcome of the analysis will also vary based on the measure chosen. For example, Noy (2009) finds that only damages are associated with negative GDP growth and there is no connection between the number affected or the number of deaths and GDP growth.

Table 2

Correlations Among the Severity Measures

<table>
<thead>
<tr>
<th></th>
<th>Total deaths</th>
<th>Total affected</th>
<th>Total damages ($)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total deaths</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total affected</td>
<td>0.1481</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Total damages ($)</td>
<td>0.2476</td>
<td>0.2246</td>
<td>1</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Deaths as a % of total pop</th>
<th>Affected as a % of total pop</th>
<th>Damages as a % of GDP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Deaths as a % of total pop</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Affected as a % of total pop</td>
<td>0.2052</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Damages as a % of GDP</td>
<td>0.4233</td>
<td>0.3936</td>
<td>1</td>
</tr>
</tbody>
</table>

The choice of which measure to use for analysis varies among researchers. Ebeke and Combes (2013), for example, use the number of persons affected by a disaster as the variable of interest, as they believe that estimates of the number affected are more
accurate than estimates of damage. Loayza et al. (2012) take a similar approach. Other researchers, however, state that the amount of damages and total deaths are preferred measures over the number affected (Cavallo et al. 2013).

The EM-DAT documentation, in addition, points out the limitations of each measure. Deaths, for example, are often under-reported in the case of drought due to being assigned to other causes such as malnutrition and measles caused by micronutrient deficiency (Guha-Sapir, Hargitt, and Hoyois 2004). In addition, deaths are more common with certain types of disasters than others. For example, earthquakes often have a high death toll while the impact of volcanoes is often indirect and not fatal. The number of deaths is more commonly reported than the number of persons affected or the amount of damages, with information being provided on the number of deaths in nearly 90% of disasters.

In two-thirds of disaster reports, the number affected is reported, yet according to documentation supplied by the preparers of the EM-DAT, reports of the number affected tends to be inexact:

**The definition of “affected” is open to interpretation**, political or otherwise. Certain countries may wish to maximize sympathy or humanitarian aid and hence exaggerate the numbers of people reported to be affected. Even in the absence of political manipulation, data is often extrapolated from old census information with assumptions being made about percentages of an area’s population being affected (ibid., 17). [emphasis in the original]

The number of persons affected also varies by the disaster type, as landslides tend to have a more limited impact than floods or windstorms (ibid.).

Data on economic losses, however, are not necessarily more reliable, as losses were reported for only 25% of disasters between 2000 and 2003 and rarely exceed more
than a third of disasters historically (ibid.). Economic costs are least likely to be reported for small recurring disasters such as minor droughts, and most likely to be reported for large disasters, in particular when international aid is requested or needed for insurance valuation. Damages are most likely to be reported for windstorms, followed by earthquakes and floods. In the middle are wildfires, droughts, volcanic eruptions, wave surges, and extreme temperatures, while fewer than 10% of landslides report damages.

Exchange rate shifts can also complicate assessment of economic losses and losses vary greatly between rich and poor countries. Guha-Sapir, Hargitt, and Hoyois (ibid.) recommend using damages relative to prior year’s GDP to standardize losses between rich and poor countries. They also point out that GDP may increase in a disaster year due to investment in reconstruction.

Because this research is primarily focused on the economic impact of disasters, the amount of damages is used as the primary measure of the severity of a disaster. However, as damages are missing for many of the disasters, many of the analyses are conducted using the other two measures as well.

*Other Limitations of the Disaster Data*

Not all disasters are reported and developing countries in particular may have poorly developed mechanisms for reporting disaster data. More frequent reporting of smaller disasters in recent decades may have created a time bias in the data. Pinpointing disaster dates can also be challenging, as certain types of disasters (droughts for example) may span several months or years. In this case, CRED uses the date recorded by the reporting government.
Other Data

The data for other variables in this research are primarily drawn from two other sources (see Table 3). Data from the Socio-Economic Database for Latin America and the Caribbean (CEDLAS and the World Bank) is used to calculate the urban-rural income gap by dividing urban per capita income by rural per capita income. The second source of data is the World Development Indicators (WDI). The percent rural population, remittances, foreign direct investment (FDI), official development assistance (foreign aid), government consumption, the primary school enrollment rate, gross domestic product (GDP), the real exchange rate, the real interest rate, the inflation rate, and value added by services, agriculture, and industry are all from the WDI. For summary statistics for the variables, see Appendix A, Table A1.

Agriculture, as defined by the World Development Indicators, includes crop and livestock production, forestry, hunting, and fisheries (World Bank 2016a). Industry includes manufacturing, mining, construction, electricity, water, and gas (World Bank 2016b). Services include wholesale and retail trade (including hotels and restaurants), transport, and professional and personal services such as government, financial services, education, and health care. Also included in services are statistical discrepancies that arise when the data is compiled (World Bank 2016c). Agriculture, industry, and services are measured as the annual percentage growth.

Remittances, FDI, foreign aid, and government consumption are included in the model as the growth from the previous year as a percentage of GDP. These variables are calculated by subtracting the previous year’s value from the current year’s and dividing
by GDP (all in current dollars). This provides the growth in the variable that is scaled by the size of the economy.

Table 3

*Data Description and Sources*

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percent rural population</td>
<td>Rural population (% of total population)</td>
<td>WDI¹</td>
</tr>
<tr>
<td>All disaster dummies</td>
<td>Incidence of disaster type</td>
<td>EM-DAT CRED²</td>
</tr>
<tr>
<td>Urban-rural income gap</td>
<td>Ratio of urban per capita income to rural per capita income</td>
<td>CEDLAS³</td>
</tr>
<tr>
<td>Remittances</td>
<td>Personal remittances, received</td>
<td>WDI</td>
</tr>
<tr>
<td>Foreign aid</td>
<td>Net official development assistance and official aid received</td>
<td>WDI</td>
</tr>
<tr>
<td>Government consumption</td>
<td>General government final consumption expenditure</td>
<td>WDI</td>
</tr>
<tr>
<td>FDI</td>
<td>Foreign direct investment, net inflows</td>
<td>WDI</td>
</tr>
</tbody>
</table>

¹Note: This is an unbalanced panel dataset that covers the time period from 1980-2013 and is comprised of 41 countries.

²Emergency Events Database from the Center for Research on the Epidemiology of Disasters

³Socio-Economic Database for Latin America and Caribbean (CEDLAS and the World Bank)

*The Urban-Rural Income Gap*

The urban-rural income gap is a measure of inequality of income in rural and urban areas. Inequality is both a push and a pull factor for migration regardless of occurrence of a disaster, however, disasters can strengthen the effect of inequality on migration. The urban-rural income gap (the ratio of urban income to rural income) is used to measure whether differentials in expected wages increase the likelihood of migration. An increase in the ratio means that the gap between rural and urban income
has become larger. The income gap is the dependent variable in Chapter VII, while Chapter VIII also includes the urban-rural income gap as an explanatory variable.

In the dataset, rural per capita income is always smaller than urban. Jamaica in 1990 had urban and rural incomes that were close to being equal, resulting in the smallest income gap in the dataset at 1.009. The largest gap, with a ratio of 3.865 (indicating that urban per capita income was almost 4 times that of rural), was seen in Bolivia in 1999.
CHAPTER V – DEFINING “LARGE” DISASTERS

Research Question 1: Defining “Large” Disasters

This question determines at what magnitude a disaster begins to have an effect on a country’s economic output. It identifies a cut-off point for damages as a percentage of GDP where the group of disasters below the cut-off point (i.e. smaller disasters) are significantly different from the group of disasters above the cut-off point (i.e. larger disasters).

There is no consensus among disaster researchers regarding what constitutes a “large” disaster (see Table 4 for a sample of definitions of large natural disasters). Hallegatte, Hourcade, and Dumas (2007, 333) define Large-Scale Extreme Weather Events (LEWE) as “causing important capital destruction over time period[s] ranging from one-day (cyclones) to several weeks (floods).” Their definition excludes events or changes that develop more slowly, such as droughts, although these events may result in larger damages.

Alternatively, Cavallo and Noy (2011) consider a disaster as “large” if the number of people killed as a percentage of the population exceeds the world pooled mean for the sample period. Because the number of deaths and the amount of damages are not strongly correlated, Cavallo and Noy’s method could result in some disasters being classified as “large” that are not large in terms of dollar damages, including those that have zero damages.

The International Monetary Fund categorizes “large” disasters as those affecting over 0.5% of a country’s population, 0.5% of the national GDP, or having more than one fatality per 10,000 persons (International Monetary Fund 2003). This same definition is
used in other IMF documents, including David (2010). The U.S. Agency for International Development’s Office of Foreign Disaster Assistance (OFDA) classifies a natural disaster as “major” if it causes more than 50 deaths and affects more than 100,000 people.  

Table 4

A Sampling of Definitions of Large Natural Disasters

<table>
<thead>
<tr>
<th>Source</th>
<th>Number affected</th>
<th>Number deaths</th>
<th>Damages</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cavallo and Noy (2011)</td>
<td>-</td>
<td>% of population killed &gt; the world pooled mean for the sample period</td>
<td>-</td>
</tr>
<tr>
<td>CRED - Guha-Sapir, Hargitt, and Hoyois (2004)</td>
<td>≥ 150,000 affected</td>
<td>≥ 50 deaths</td>
<td>≥ US$200 million (2003 dollars)</td>
</tr>
<tr>
<td>CRED - Guha-Sapir, Hargitt, and Hoyois (2012)</td>
<td>≥ 150,000 affected</td>
<td>≥ 75 deaths</td>
<td>≥ US$589 million (in 2011 values)</td>
</tr>
<tr>
<td>Hallegatte, Hourcade, and Dumas (2007, 333)</td>
<td></td>
<td></td>
<td>Large-scale Extreme Weather Events (LEWEs) cause “important capital destruction over time period[s] ranging from one-day (cyclones) to several weeks (floods)” that are “characterized by their media impact and their capacity to generate sudden and large social concerns.”</td>
</tr>
<tr>
<td>Hochrainer (2009)</td>
<td>-</td>
<td>-</td>
<td>&gt; 1% of GDP</td>
</tr>
<tr>
<td>International Monetary Fund (2003, 35)</td>
<td>&gt;0.5% of a country’s population</td>
<td>≥ one fatality per 10,000 population</td>
<td>&gt;0.5% of the national GDP</td>
</tr>
<tr>
<td>Loayza et al. (2012)</td>
<td>Top 10% of events</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>NOAA NCEI SED</td>
<td>Presence of injuries</td>
<td>Loss of life</td>
<td>Significant property damage or disruption to commerce</td>
</tr>
<tr>
<td>USAID's OFDA</td>
<td>&gt; 100,000 affected</td>
<td>&gt; 50 deaths</td>
<td>-</td>
</tr>
</tbody>
</table>

1 Pre-2012 definition
2 2012 definition
3 National Oceanic and Atmospheric Administration’s (NOAA) National Centers for Environmental Information’s (NCEI)
4 U.S. Agency for International Development’s Office of Foreign Disaster Assistance

2 As reported in Guha-Sapir, Hargitt, and Hoyois (2004), a USAID/OFDA contractor.
Prior to 2012, CRED (the publishers of the EM-DAT database used in this study) considered a natural disaster “large” when “the number of deaths was greater than or equal to 50, the number of people affected was greater than or equal to 150,000, or the amount of reported economic damages was greater than or equal to US$200 million, adjusted to 2003 dollars” (Guha-Sapir, Hargitt, and Hoyois 2004, 22). The authors state that “the thresholds were fixed according to the distribution of frequencies and percentiles in the number of deaths, people affected, and economic damages, taking into account the different types of disasters, regions of occurrence and the evolution of the impact,” but do not give specifics on how the thresholds were determined (ibid., 21). The pre-2012 CRED definition is frequently used by researchers; for example, Ibarrarán et al. (2009).

In 2012, CRED revised its definition of large disasters, which resulted in fewer disasters being included. Based on the quintiles of the disaster data, the new definition includes “reported deaths equal to or greater than 75; a number of people reported affected equal to or greater than 150,000 and an amount of economic losses equal to or greater than US$ 589 million (in 2011 values)” (Guha-Sapir and Hoyois 2012, 14).

CRED’s definition of large disasters is not the only organizational definition used by researchers. For example, Boero, Bianchini, and Pasqualini (2015), in their study of severe storms in the southwest United States, use events included in the National Oceanic and Atmospheric Administration’s (NOAA) National Centers for Environmental Information’s (NCEI) Storm Events Database (SED). To be included in the database, a storm or other weather event must have “sufficient intensity to cause loss of life, injuries, significant property damage, and/or disruption to commerce” (NOAA NCEI 2016).
Other disaster researchers choose an arbitrary number as a cut-off point. For example, Hochrainer (2009, 14) states, “the threshold for a large event [is] defined arbitrarily to [be] a loss exceeding 1 percent of GDP.” In most cases, no explanation is offered by the researchers for their choice of a cut-off point for large disasters. The intent of this research is to find a cut-off point that is not arbitrarily determined.

Research Question – Defining “Large” Disasters

This research identifies a cut-off point for large disasters that is supported by underlying evidence. The goal is to determine at what magnitude a disaster begins to have an effect on a country’s economic output. This analysis uses measures based on a percentage of GDP per capita and thus controls for country size effects. It also determines if the cut-off point at which the impact of disasters on the economy is statistically significant.

<table>
<thead>
<tr>
<th>Research Question 1:</th>
<th>Is there a threshold point, measured as a percentage of the population affected/killed or damages as a percentage of GDP, at which natural disasters have a noticeable impact on a country’s GDP?</th>
</tr>
</thead>
<tbody>
<tr>
<td>H₀:</td>
<td>There are identifiable differences between “large” disasters that affect GDP output and smaller disasters that do not.</td>
</tr>
</tbody>
</table>

Figure 4. Research question and hypothesis for question one

Methodology – Defining “Large” Disasters

A threshold analysis is conducted to determine a cut-off point at which disasters can be considered as “large,” where large is defined as having a significant impact on annual GDP growth at the national level. This analysis is conducted with multiple geographies (all countries, Latin America and Caribbean only, developing only, and high income only) using total damages as a percentage of GDP (economic damages) as the
severity indicator. Economic damages are measured as a percentage of pre-disaster GDP to avoid confounding effects due to changes to GDP caused by the disaster. The time period of the analysis is from 1980 to 2013. The analysis includes all years in which a country had a disaster, while years without disasters are omitted.

*Data Preparation*

1. If a country had multiple disasters in one year, the amounts for all disasters for that year are added together.

2. The variable used for analysis is the *growth difference in GDP*, which compares GDP growth for the most recent year to a 5-year weighted average in annual GDP growth.

3. The steps in conducting the analysis of the *growth difference in GDP* are:
   
   o A weighted average in the annual growth in GDP for each country for the prior 5 years is determined. The most recent year is given 30% of the weight, with the second-most recent year receiving 25%, the third receiving 20%, the fourth receiving 15%, and the fifth receiving 10%.

   o The 5-year average growth in GDP is subtracted from the current annual GDP growth to provide an indication of how much the disaster year varied from a country’s recent history of growth (this is the *growth difference in GDP* variable).

4. The observations are ordered by the values of the severity indicator (i.e. *economic damages*) from smallest to largest.
5. The observations are divided into deciles with equal numbers of observations based on the ordered values of the severity indicator. For example, if there are 500 observations in the dataset, each decile has 500/10=50 observations in it.

6. The bottom deciles now have those disasters with smaller values of economic damages. The top deciles have those disasters which can be considered more severe, in that they have larger values of economic damages.

Analysis

7. The two equal-sized groups containing the top five deciles and the bottom five are compared.

8. The average of the growth difference in GDP is determined for both the group containing the bottom five deciles ($g_1$) and the top group containing the top five deciles ($g_2$).

9. A t-test is used to compare the means of the growth difference in GDP of $g_1$ and $g_2$. If significant, the data is examined to ensure that the mean of $g_2$ is larger than the mean of $g_1$ as expected (as $g_2$ contains the larger disasters).

10. If the t-test is insignificant, i.e. the mean of the smaller disasters group is not different from the larger disasters, then the next step is to compare the bottom 6 deciles ($g_{12}$) to the top 4 deciles ($g_{22}$). $g_{22}$ now contains disasters that are on average more severe than those in $g_{21}$. If the t-test is significant, the analysis continues with step 12.

   - This process is repeated until the t-test shows that the lower decile group ($g_{ix}$) is significantly different from the larger decile group ($g_{2x}$), indicating
that the *growth difference in GDP* for the larger disaster group is significantly different from that of the smaller disaster group.

11. If the t-test between the bottom five and top five deciles is significant, then the sixth decile is moved from $g_{21}$ to $g_{11}$ and the t-test is repeated.

   - The process of moving deciles from the top decile grouping to the bottom decile grouping continues until the difference in the means of the two groups is insignificant as determined by the t-test. Then the last significant decile is used as the cut-off point.

12. If no significant difference is found between the means of any of the decile groupings, then a cut-off point may be unable to be determined for a particular geography (i.e. high income countries).

**Benjamini and Hochberg Correction**

Conducting multiple comparisons using t-tests increases the chance of Type 1 error, thus requiring a correction to the significance level. This research uses the Benjamini and Hochberg correction (1995) to address this problem. The Benjamini and Hochberg correction is similar to the Bonferroni Correction, but is believed to address the overly conservative nature of the Bonferroni Correction.

Using the Benjamini and Hochberg correction calculator developed by Manuel Weinkauf (2012), the adjusted significance level is determined. Because the top five and bottom five deciles are used as the starting point, the maximum number of t-tests that can be calculated is five. A target significance level, before the correction, of $\alpha=0.1$ is chosen. To achieve this target level, the calculator returns a cut-off $p$ value of 0.06.
Results – Defining “Large” Disasters

Significant cut-off points between the decile groupings are found for each of the geographies except for the high income only countries. The proposed cut-off points resulting from the analysis are reported in Table 5 below. For the grouping with all the countries, the cut-off point is damages that exceed 0.37351% of GDP. When only developing countries are included (developing countries are those that are classified by the World Bank as low income, lower middle income, and upper middle income), the cut-off point is lower at damages that exceed 0.22951% of GDP. This suggests that economies of developing countries are more strongly affected by disasters, as compared to the global sample smaller disasters have a statistically significant impact.

Table 5

*Proposed Cut-Off Points for Large Natural Disasters*

<table>
<thead>
<tr>
<th>Region</th>
<th>Damages</th>
</tr>
</thead>
<tbody>
<tr>
<td>World</td>
<td>≥ 0.37351% of GDP</td>
</tr>
<tr>
<td>Developing</td>
<td>≥ 0.22951% of GDP</td>
</tr>
<tr>
<td>High income</td>
<td>--¹</td>
</tr>
<tr>
<td>Latin America</td>
<td>≥ 0.83098% of GDP</td>
</tr>
</tbody>
</table>

¹There is no cut-off point that is significant for high income countries.

In contrast, when only high income countries are included, there is no significant cut-off point, suggesting that disasters are rarely large enough to noticeably affect the economies of high income countries. When only Latin American countries are included, the cut-off point for damages as a percentage of GDP is raised to 0.83098%. This may be because Latin America includes some countries that are considered to be high income.
countries, so on average a disaster must be larger in order to impact the economies of Latin American countries.

Testing the Statistical Significance of the Cut-Off Points

In order to determine if the cut-off points are statistically significant in indicating disasters that are large enough to affect the GDP output of a country, indicator variables are created using the cut-off points. These are used in robust fixed effects regressions using the dataset with all disasters with the annual growth in GDP as the dependent variable. In all cases, the coefficients on the variables are significantly and negatively associated with the growth in GDP, suggesting that disasters exceeding the cut-off point for damages as a percentage of GDP are associated with decreases in annual GDP growth.

Evaluating Other Definitions of “Large” Natural Disasters

After testing the cut-off points determined in this chapter, the definitions used by other researchers are revisited to see if their cut-off points are statistically significant (see Table 4 earlier in this chapter for a summary of definitions used by other researchers). Some researchers use a static cut-off point that does not depend on the size of a country’s economy (i.e. over $1 million in property damage). For the purposes of determining whether a disaster is likely to affect a country’s economy, a static cut-off is not likely to be useful (for example, a $1 million disaster may have a large impact in Ghana but no impact in the U.S.).

Others use vague constructs such as “significant property damage or disruption to commerce” (National Oceanic and Atmospheric Administration’s (NOAA) National Centers for Environmental Information’s (NCEI) 2016) or “important capital destruction”
Due to the vagueness of these definitions, it is impossible to test them for significance.

Only two definitions in Table 4 specifically define a cut-off point for economic damages as an indicator of large disasters that is scaled to the size of a country’s economy. The first is the definition used by the International Monetary Fund (IMF). The IMF’s cut-off point for large disasters is 0.5% of GDP. This is less than the cut-off point for Latin American countries and is significant when regressed on the growth in GDP. However, based on the research conducted here, it may be too high a cut-off point for developing countries, and excludes some disasters that might have impacted the economies of low, lower middle, and upper middle income countries. The second definition that uses a cut-off point that is scaled to the size of a country’s economy is Hochrainer (2009). Hochrainer uses damages that exceed 1% of GDP as a cut-off point. The coefficient for this cut-off point, twice as large as that of the IMF, is also significantly associated with the annual growth in GDP.

In conclusion, country groups with higher income, such as Latin America, have higher cut-off points where disasters need to cause a greater amount of economic damage in order to have a statistically significant impact on the growth in GDP. For the grouping of only high income countries, there is no cut-off point where the impact of disasters significantly affects the economy of the country on a macro-level. Using fixed effects regression to confirm the results of the t-tests shows that the coefficients for all of the cut-off points are statistically significant when the annual growth in GDP is the dependent variable.
CHAPTER VI – IMPACT OF DISASTERS ON THE SECTORS OF PRODUCTION

Research Question 2: Productive Sector Impact by Type of Disaster

This analysis focuses on the major sectors of the economy (also referred to here as the sectors of production or productive sectors). The sectors of the economy can be grouped into the “mega-sectors” of agriculture, industry, and services which are respectively referred to as the primary, secondary, and tertiary sectors. Kenessey (1987) includes a fourth (quaternary) sector with activities that were traditionally included in the service sector. For the purposes of this research, Kenessey’s quaternary sector is grouped with the tertiary service sector. The activities pertaining to each sector are listed in Figure 5.

Figure 5. Kenessey's (1987) sectors of production

The CIA Factbook (2015) provides information on the percentage of the workforce employed in each sector for each country. Employment in most of the 223
countries listed is grouped into the three categories of agriculture, industry, and services. The World Factbook (ibid.) defines agriculture as farming, fishing, and forestry. Industry includes mining, manufacturing, energy production, and construction, while services includes government activities, communications, transportation, finance, and any other productive activity that does not result in a material good.

According to the World Factbook (ibid.), Dominica, at 40%, has the most workers employed in agriculture, while the Bahamas has the least at 3% (no data are available for Guyana or St. Kitts and Nevis). Interestingly, Dominica also has the greatest percentage employed in industry, at 32%. Not surprisingly, given that it was the highest in the other two categories, Dominica also has the least number employed in services at 28%. For most countries, the percentage employed in industry is around 20% of the workforce. At 14%, Uruguay has the lowest percentage working in industry. Antigua and Barbuda have the highest percentage employed in services at 82%.

Impact of Disasters on the Sectors of Production

Little prior research has been done on the differential impact of disasters by type of disaster on the sectors of production. Loayza et al. (2012) find that some moderate disasters, in particular moderate floods, can have positive effects on growth. On the other hand, severe disasters are never associated with growth in output. Loayza et al. (ibid.) also study a reduced sample of developing countries. They find that droughts are associated with negative growth in agriculture. For services, floods are the only type of disaster found to have a positive effect on growth (ibid.).

Outside of Loayza et al., it is difficult to find research on the impact of disasters on the growth of output in industry or services. The research that does exist tends to be
on agriculture. Agriculture may be the most researched due to concerns over the effect of climate change on crop production and livestock.

Balgah and Buchenrieder (2014) in their research on the long-term impact of a disaster in rural Cameroon, find negative impacts on livestock and human capital and that some households had not recovered to pre-disaster levels 25 years after the disaster. Characteristics of small farms, such as the interwoven nature of the household and farm as well as labor being the primary asset, make small farms vulnerable to disasters (ibid.).

A study by the Food and Agriculture Organization of the United Nations (FAO) (2015) finds that damage to agriculture accounts for 22% of the economic losses from medium and large disasters in developing countries. Yet in contrast to the size of the economic losses, agriculture only receives 3.4% of humanitarian aid (ibid.).

Most of the agricultural damage from disasters, at 42.4%, is to crops. Over half the damage to crops is caused by floods, yet storms and droughts also cause substantial damage to crops. Damage to livestock is 35.8% of total agricultural damage. Damage to livestock is almost exclusively from droughts (85.8%), however, storms, floods, and earthquakes also make up small percentages of the losses. Fisheries are primarily harmed by tsunamis, while forestry is harmed by storms (ibid.).

Markets for agricultural insurance are poorly developed and insurance is unlikely to be held by small farmers in developing countries. Factors that limit insurance utilization include information asymmetries, high transaction costs for the insurers, a lack of an insurance culture in developing countries, low awareness of the risk on the part of farmers, and high costs of the policies (Romero and Molina 2015). Crop insurance policies in Latin America cover 17% of the total crop area, yet only a small portion of
agricultural GDP is covered, ranging from less than 0.1% in many countries to 1.05% in Uruguay (The World Bank 2010).

Following a 1999 earthquake in Turkey, older, heavy industrial buildings sustained more damage from earthquakes than newer buildings (Erdik and Durukal 2003). Concrete cast structures were particularly vulnerable. Anchoring of equipment affected the amount of losses from the earthquake though very sensitive equipment was still at risk. Tall structures were vulnerable to collapse, as were external holding facilities such as storage tanks. Pipelines and transmission lines were susceptible to the earthquake as well.

Interruption of production can occur as a result of labor or capital loss. Because the value of manufacturing is in production rather than in the assets, any interruption in production negatively affects the business (ibid.). Earthquake damage to infrastructure, such as roads and utilities, can cause indirect losses for manufacturing even if the assets of the manufacturing plant are undamaged.

Research Question – Productive Sector Impact by Type of Disaster

Question 2 uses the global population of countries to determine the impact of natural disasters by type of disaster on the agricultural, industrial, and service sectors of the economy. Analyses are conducted on worldwide sample, a sample of developing countries, and a sample of all countries in Latin America.

A drawback of the research on disasters and the productive sectors by Loayza et al. is that they aggregate the data into five-year non-overlapping time periods. According to Loayza et al., this focuses the analysis on the medium-term impact of disasters, however, it appears to over-aggregate the data, as the effects of a disaster that occurs near
the beginning of the 5-year period will be different from that at the end of the period. Aggregation can result in inflated coefficient estimates and loss of information when compared to disaggregated data (Clark and Avery 1976). This research seeks to verify the results of Loayza et al. and improve on the methodology by using annual data.

<table>
<thead>
<tr>
<th>Research Question 2: Are the productive sectors of agriculture, industry, and services impacted differently by disaster type?</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>H(_{A1}):</strong> Growth in the productive sector of agriculture is inversely impacted by droughts and wildfires.</td>
</tr>
<tr>
<td><strong>H(_{A2}):</strong> Growth in the productive sector of industry is inversely impacted by earthquakes.</td>
</tr>
<tr>
<td><strong>H(_{A3}):</strong> Growth in the productive sector of services is inversely impacted by earthquakes.</td>
</tr>
</tbody>
</table>

**Figure 6.** Research question and hypotheses for question two

**Methodology – Productive Sector Impact by Type of Disaster**

This analysis uses a fixed effects regression to test the hypothesis that the sectors of agriculture, industry, and services are affected differently by the type of disaster. This analysis uses panel data, which is a dataset that combines cross-section and time series data.

This question is answered using a model of the form

\[
Y^{M}_{it} = \alpha_i + \delta\text{DIS}_{it} + \vartheta V_{it} + \gamma\text{DIS}_{it} V_{it} + \beta X_{it} + u_{it}
\]

where \(Y^{M}_{it}\) is the annual growth in sector \(M\) of the economy \(i\) at time \(t\) where \(M\) indicates either agriculture, industry, or services; \(\alpha_i\) is an intercept specific to each country; \(\delta\text{DIS}_{it}\) is a set of dummy variables indicating the type of disaster; \(\vartheta V_{it}\) is a term indicating the magnitude of the impact of the disaster using damages as a percentage of GDP; \(\gamma\text{DIS}_{it} V_{it}\) is the interaction between the type of disaster and the indicator of magnitude; \(\beta X_{it}\) is a set
of control variables; and $u_{it}$ includes the unobserved country-specific effects, $v_i$, and the observation-specific error term, $e_{it}$.

**Fixed Effects Estimator**

The analysis is conducted using a fixed effects estimator. A fixed effects analysis is chosen over a random effects analysis because of its focus on “the relationship between predictor and outcome variables within an entity” (Torres-Reyna 2010), as opposed to the random effects model where the unobserved effect is believed to be random across the explanatory variables. Because this research is interested in what happens within a country as a result of a natural disaster, the fixed effects estimator with its focus on the relationship within an entity is preferred. The choice of a fixed effects model is confirmed through the use of the Hausman test. A post-estimation test of joint restrictions on the parameters suggests that time fixed effects should be used in addition to country fixed effects. Use of time fixed effects also controls for trends in the data over time.

The regressions are implemented using Driscoll-Kraay standard errors (Driscoll and Kraay 1998). Driscoll-Kraay standard errors are robust to spatial correlation, serial correlation, and heteroskedasticity and perform well with finite samples. When other estimators are used in the presence of cross-sectional dependence (spatial correlation), the standard error estimates are severely downward-biased. Driscoll–Kraay standard errors, on the other hand, “are well calibrated when the regression residuals are cross-sectionally dependent” (Hoechle 2007, 310).

The Driscoll–Kraay standard errors are implemented using the *xtscc* Stata command developed by Daniel Hoechle (ibid.). The *xtscc* estimator is able to handle
unbalanced panels with missing data. All the regressions reported here use the default number of lags provided by the software. The \textit{xtsc} command does not allow lagged explanatory variables, presumably because lags are already built into the analysis.

A multivariate regression was also considered. A multivariate regression analysis performs tests of multiple dependent variables simultaneously. In multivariate regression, the individual coefficients and standard errors are the same as when estimating each equation separately. The joint estimate, however, provides estimates of the between-equation covariances, allowing for coefficients to be tested across equations (StataCorp 2013b).

A drawback of multivariate regression is that it is not able to use a fixed effects estimator, so it does not automatically take into account the within-country variation. In addition, the multivariate estimator in Stata is unable to calculate heteroskedasticity robust standard errors. Therefore, it is concluded that the \textit{xtsc} fixed effects estimator, with its ability to address spatial and temporal correlation, as well as heteroskedasticity, is the preferred option.

\textit{The Data}

The dependent variable is the percent annual growth in value added from agriculture, industry, and services. The explanatory variables are from the EM-DAT CRED disaster database and include separate analyses for the percentage of the population affected, the percentage of the population killed, and damages as a percentage of GDP. The explanatory variables include an indicator variable for each type of disaster, where a value of “1” indicates that a disaster took place.

\footnote{The default lag length, \(m(T)\), from Hoechle (2007), is \(m(T) = \text{floor}[4(T/100)^{2/9}]\).}
Interaction terms between the type of disaster indicator and damages as a percentage of GDP (also referred to as percent damages or economic damages) are included. The percentage of the population killed or affected is calculated by dividing the total killed or affected by the total population. Damages as a percentage of GDP is calculated by dividing the damages for each disaster by GDP. For more information on the disaster data see Chapter IV.

Control variables include the inflation rate, the real interest rate, and the real exchange rate, as well as the growth in foreign aid, FDI, and government consumption as a percentage of GDP. The growth rates in aid, FDI, and government consumption are calculated as the present value in current dollars minus the previous year’s value, which is then divided by GDP. Dividing by GDP scales the growth in the variables by the size of the economy.

The analysis is conducted for the time period from 1980 to 2013. The population consists of all countries globally, with the sample consisting of the set of countries for which a complete set of data is available. Separate analyses are conducted for the global sample and for sub-samples of developing countries and Latin American countries. Developing countries are those that are classified by the World Bank as low income, lower middle income, and upper middle income.

Diagnostics

Cross-sectional dependence. Tests of cross-sectional dependence (spatial correlation), including the Breusch-Pagan statistic for cross-sectional independence and Pesaran’s statistic, fail to run due to insufficient common observations across the panels. However, the assumption that the error terms are independent across cross-sections is
likely violated as events such as world recessions may cause group-level shocks resulting in correlation in the individual-level fixed effects errors or $u_t$. The advantage of using estimators with Driscoll-Kraay standard errors is that cross-sectional dependence is automatically controlled for.

*Serial correlation.* Wooldridge’s test (2002) for serial correlation in the idiosyncratic errors suggests that serial (temporal) correlation is present in the data. Driscoll-Kraay standard errors are also robust to temporal dependence.

*Heteroskedasticity.* The modified Wald statistic for groupwise heteroskedasticity indicates that a robust regression is appropriate. Groupwise heteroskedasticity refers to errors that, while possibly homoskedastic within cross-sections, vary across units (Baum 2001). Driscoll-Kraay standard errors, in addition to being robust to cross-sectional and temporal dependence, are also heteroskedasticity consistent.

*Unit root tests.* The stationarity of the panel data is checked using the Phillips-Perron Fisher-type unit-root test. The Fisher-type tests, such as the Phillips-Perron test, “conduct unit-root tests for each panel individually, and then combine the p-values from these tests to produce an overall test” (StataCorp 2013c). The Phillips-Perron unit root tests finds that all variables are stationary.

**Results – Productive Sector Impact by Type of Disaster**

Four models are tested. The first uses damages as a percentage of GDP as the severity indicator, the second uses the number of people affected as a percentage of the total population, and the third uses deaths as a percentage of the total population. Each of these models includes a disaster dummy, and interaction term between each disaster dummy and the severity indicator, and the control variables. The fourth model uses the
cut-off point for severe disasters developed in Chapter V to create a set of dummy variables for severe disasters. The severe disaster dummies are included in the model with the control variables.

*Countries and Number of Disasters*

Due to differences in the specifications of the models, the set of countries included in each model varies. Appendix B, Table A1 provides a list of countries for each model. The models that utilize the global sample with the annual growth in agriculture and industry (Models 6.1 and 6.3) have 63 countries, while the same models with only developing countries (Models 6.4 and 6.6) have 49 countries. The models for annual growth in services – Models 6.2 and 6.5 – have one less country in each case. The models for Latin America (Models 6.7, 6.8, and 6.9) all have 21 countries.

Table 6

*Number of Disasters Included in Each Model*

<table>
<thead>
<tr>
<th>Sample</th>
<th>All¹</th>
<th>Developing²</th>
<th>LAC³</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>#</td>
<td>%</td>
<td>#</td>
</tr>
<tr>
<td>Drought</td>
<td>113</td>
<td>9%</td>
<td>106</td>
</tr>
<tr>
<td>Earthquake</td>
<td>123</td>
<td>10%</td>
<td>113</td>
</tr>
<tr>
<td>Flood</td>
<td>464</td>
<td>39%</td>
<td>423</td>
</tr>
<tr>
<td>Landslide</td>
<td>106</td>
<td>9%</td>
<td>101</td>
</tr>
<tr>
<td>Storm</td>
<td>290</td>
<td>24%</td>
<td>249</td>
</tr>
<tr>
<td>Volcano</td>
<td>42</td>
<td>4%</td>
<td>40</td>
</tr>
<tr>
<td>Wildfire</td>
<td>60</td>
<td>5%</td>
<td>43</td>
</tr>
</tbody>
</table>

¹Models with all countries ([6.1], [6.2], [6.3])

²Models with developing countries ([6.4], [6.5], [6.6])

³Models with Latin America and the Caribbean countries ([6.7], [6.8], [6.9])

In addition, the number of disasters varies between the models (see Table 6). The total numbers of disasters included ranges from 424 in the analysis of the Latin American
countries to 1,198 in the analysis of all countries. Floods are the most common disaster type in the samples. Together, floods and storms make up over half of the disasters in the samples. Volcanoes are the least common disaster type with the exception of Latin America, where wildfires are the rarest.

Tests of Joint Significance

Tests of joint significance between the disaster indicator variables and the interaction terms with the severity measure are conducted for each model that has interaction terms. The test of joint significance calculates “point estimates, standard errors, testing, and inference for linear combinations of coefficients” (StataCorp 2013a). Using droughts as an example, the effect of droughts (drought) cannot be estimated from the coefficient for droughts alone, because droughts are also included in the interaction term with damages as a percentage of GDP (percent damages). Thus, the effect of disaster type is the combination of the coefficients for drought and the interaction term (drought * percent damages).

The test of joint significance informs whether the variables are jointly significant, as either drought or (drought * percent damages) may be insignificant in the model, but together they may be jointly significant. Furthermore, because (drought * percent damages) can take on a number of values depending on the value of damages as a percent of GDP, the effect of drought (drought + (drought * percent damages)) can also take on multiple values depending on the amount of damages, or may be insignificant at some values of the severity indicator but not others (for example, the effect may be insignificant for disasters with low levels of damages, but significant for disasters with large damages). The test of joint significance also provides the coefficient for the
combination of drought and (drought X percent damages) as well as the standard error for the coefficient.

**All Countries Results**

The detailed results for the analysis of all countries are available in Appendix B, Table A2. The tests of joint significance at one standard deviation above the mean for disaster damages as a percentage of GDP are shown in Table 7.

**Table 7**

*Tests of Joint Significance at One Standard Deviation above the Mean of Damages as a Percentage Of GDP with the Percentage Annual Growth of Agriculture/Services/Industry as the Dependent Variable - All Countries*

<table>
<thead>
<tr>
<th>Sector of Production</th>
<th>[Model number]</th>
<th>[6.1]</th>
<th>[6.2]</th>
<th>[6.3]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>[Model number]</td>
<td>[6.1]</td>
<td>[6.2]</td>
<td>[6.3]</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Agriculture</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Drought</td>
<td>-15.317</td>
<td>***</td>
<td>1.055</td>
<td>2.529</td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td>(6.036)</td>
<td>[0.016]</td>
<td>(3.104)</td>
<td>[0.368]</td>
</tr>
<tr>
<td>Earthquake</td>
<td>3.171</td>
<td></td>
<td>-0.372</td>
<td>0.813</td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td>(2.891)</td>
<td>[0.281]</td>
<td>(1.022)</td>
<td>[0.359]</td>
</tr>
<tr>
<td>Flood</td>
<td>-1.244</td>
<td></td>
<td>1.666 **</td>
<td>-2.128 **</td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td>(0.751)</td>
<td>[0.108]</td>
<td>(0.811)</td>
<td>[0.048]</td>
</tr>
<tr>
<td>Landslide</td>
<td>-0.638</td>
<td></td>
<td>0.135</td>
<td>-2.121</td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td>(3.572)</td>
<td>[0.859]</td>
<td>(1.103)</td>
<td>[0.903]</td>
</tr>
<tr>
<td>Storm</td>
<td>-1.563</td>
<td></td>
<td>-0.442</td>
<td>0.323</td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td>(1.105)</td>
<td>[0.167]</td>
<td>(0.267)</td>
<td>[0.107]</td>
</tr>
<tr>
<td>Volcano</td>
<td>11.619</td>
<td></td>
<td>47.570 **</td>
<td>-20.092</td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td>(11.318)</td>
<td>[0.312]</td>
<td>(19.368)</td>
<td>[0.020]</td>
</tr>
<tr>
<td>Wildfire</td>
<td>-19.551 **</td>
<td></td>
<td>-6.815</td>
<td>13.677</td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td>(11.527)</td>
<td>[0.100]</td>
<td>(8.052)</td>
<td>[0.202]</td>
</tr>
</tbody>
</table>

* p<0.10, ** p<0.05, *** p<0.01

Note: Standard errors are in parentheses and p values are in brackets.

1Mean value (standard deviation) of damages as a percent of GDP: 1.377% (9.454)
Model 6.1: Agriculture. At one standard deviation above the mean for percent damages, the coefficients for drought (p value=0.016) and wildfires (p value=0.100) both significantly and inversely impact agriculture as predicted. The impact of both droughts and wildfires is large, as a drought lowers the expected annual growth in output from the agricultural sector by approximately 15% and wildfires by over 19%. The effects of the other disasters are statistically insignificant (see Table 7).

Model 6.2: Services. The coefficient for earthquakes is not significant (p value=0.368) at the mean plus one standard deviation for damages as a percent of GDP, however, the sign is consistent with the expectation that earthquakes are associated with a decrease in output in services. The coefficients for floods (p value=0.048) and volcanoes (p value=0.020) are both positive and significant.

Model 6.3: Industry. The coefficient for floods (p value=0.016) is statistically significant and inversely associated with growth in output in industry at the mean plus one standard deviation. The coefficient for earthquakes (p value=0.381) is insignificant and the direction of the impact is counter to expectations, as earthquakes are expected to cause a decline in industry output. It is possible that in wealthy countries, the impact of earthquakes (and other disasters) may not be sufficiently large to noticeably affect output from industry at the country level. To test this idea, the analysis is conducted again using just developing countries.

Developing Countries Results

The detailed results for the analysis of the developing countries are available in Appendix B, Table A3. The tests of joint significance at one standard deviation above the mean for disaster damages as a percentage of GDP are shown in Table 8. While the
previous paragraph suggested that excluding wealthier countries might increase the statistical significance of the coefficients of the disasters on output, with the exception of services, the results for the developing countries do not support this possibility as the number of coefficients of disaster types that are statistically significant remain the same.

Table 8

Tests of Joint Significance at One Standard Deviation above the Mean of Damages as a Percentage of GDP$^1$ with the Percentage Annual Growth of Agriculture/Services/Industry as the Dependent Variable - Developing Countries

<table>
<thead>
<tr>
<th>[Model number]</th>
<th>[6.4] Sector of Production</th>
<th>[6.5]</th>
<th>[6.6]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Agriculture</td>
<td>Services</td>
<td>Industry</td>
</tr>
<tr>
<td>Drought</td>
<td>-14.614 **</td>
<td>1.337</td>
<td>3.943</td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td>(6.039) [0.011]</td>
<td>(3.168) [0.338]</td>
<td>(3.169) [0.111]</td>
</tr>
<tr>
<td>Earthquake</td>
<td>6.246 **</td>
<td>-1.430 **</td>
<td>2.889</td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td>(3.222) [0.031]</td>
<td>(0.835) [0.048]</td>
<td>(3.874) [0.231]</td>
</tr>
<tr>
<td>Flood</td>
<td>-1.240 **</td>
<td>1.802 **</td>
<td>-1.912 **</td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td>(0.814) [0.138]</td>
<td>(0.859) [0.044]</td>
<td>(0.924) [0.047]</td>
</tr>
<tr>
<td>Landslide</td>
<td>-2.589</td>
<td>0.828</td>
<td>-4.373</td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td>(3.044) [0.401]</td>
<td>(1.213) [0.500]</td>
<td>(3.391) [0.206]</td>
</tr>
<tr>
<td>Storm</td>
<td>-0.416</td>
<td>-0.570 **</td>
<td>0.823</td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td>(1.103) [0.709]</td>
<td>(0.270) [0.043]</td>
<td>(0.652) [0.216]</td>
</tr>
<tr>
<td>Volcano</td>
<td>15.653</td>
<td>47.123 **</td>
<td>-19.991</td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td>(12.150) [0.207]</td>
<td>(21.487) [0.036]</td>
<td>(21.776) [0.365]</td>
</tr>
<tr>
<td>Wildfire</td>
<td>-8.880</td>
<td>-10.736</td>
<td>14.166</td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td>(11.689) [0.226]</td>
<td>(11.556) [0.180]</td>
<td>(14.310) [0.165]</td>
</tr>
</tbody>
</table>

* p<0.10, ** p<0.05, *** p<0.01

Note: Standard errors are in parentheses and p values are in brackets.

$^1$Mean value (standard deviation) of damages as a percent of GDP: 1.377% (9.454)

*Model 6.4: Agriculture.* The coefficients on droughts ($p$ value=0.011) and earthquakes ($p$ value=0.031) are statistically significant at one standard deviation above the mean of damages as a percentage of GDP (see Table 8). As predicted, the coefficient
for droughts is inversely associated with output in the agricultural sector. The magnitude of the impact of droughts is slightly higher yet similar to Model 6.1. At \( p = 0.226 \), the coefficient for wildfires is no longer statistically significant.

*Model 6.5: Services.* The coefficients on floods (\( p \) value=0.044) and volcanoes (\( p \) value=0.036) continue to be significantly and positively associated with output in the service sector. In the sample of developing countries, the coefficients on storms (\( p \) value=0.043) and earthquakes (\( p \) value=0.048) are now significantly and inversely associated with service sector output. The sign on the coefficient for earthquakes is consistent with expectations.

*Model 6.6: Industry.* The coefficient for floods (\( p \) value=0.047) continues to be statistically significant and inversely associated with output from industry at one standard deviation above the mean value of damages as a percent of GDP.

*Latin America and the Caribbean Results*

The above analyses are repeated with a sample of countries in Latin America and the Caribbean. This final analysis lays the groundwork for the following two chapters which focus exclusively on Latin America. The detailed results for the analysis of the Latin American and Caribbean countries are available in Appendix B, Table A4. The tests of joint significance at one standard deviation above the mean for disaster damages as a percentage of GDP are shown in Table 9.

Possibly due to the homogeneity of the Latin American sample, the coefficients from more disasters are statistically significant in the agriculture and industry models than for the global or developing country samples. It may be that regional similarities lead disasters to have similar (and significant) impacts on the sectors of production.
Table 9

Tests of Joint Significance at One Standard Deviation above the Mean of Damages as a Percentage of GDP\textsuperscript{1} with the Percentage Annual Growth of Agriculture/Services/Industry as the Dependent Variable - Latin America

<table>
<thead>
<tr>
<th>[Model number]</th>
<th>Sector of Production</th>
<th>[6.7]</th>
<th>[6.8]</th>
<th>[6.9]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>[Agriculture]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Drought</td>
<td>-6.356 **</td>
<td>-2.840 *</td>
<td>4.661 *</td>
<td></td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td>(3.600) [0.044]</td>
<td>(2.095) [0.092]</td>
<td>(3.049) [0.068]</td>
<td></td>
</tr>
<tr>
<td>Earthquake</td>
<td>2.522</td>
<td>-0.870</td>
<td>-5.254 **</td>
<td></td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td>(4.894) [0.305]</td>
<td>(1.236) [0.243]</td>
<td>(2.497) [0.022]</td>
<td></td>
</tr>
<tr>
<td>Flood</td>
<td>-2.404 *</td>
<td>2.068 **</td>
<td>-1.531 **</td>
<td></td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td>(1.194) [0.053]</td>
<td>(0.948) [0.037]</td>
<td>(0.666) [0.028]</td>
<td></td>
</tr>
<tr>
<td>Landslide</td>
<td>-4.043</td>
<td>-1.896</td>
<td>-4.736 **</td>
<td></td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td>(4.589) [0.385]</td>
<td>(1.386) [0.181]</td>
<td>(2.090) [0.030]</td>
<td></td>
</tr>
<tr>
<td>Storm</td>
<td>-4.688 ***</td>
<td>0.280</td>
<td>-0.517</td>
<td></td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td>(1.616) [0.007]</td>
<td>(0.420) [0.510]</td>
<td>(0.897) [0.569]</td>
<td></td>
</tr>
<tr>
<td>Volcano</td>
<td>54.665 *</td>
<td>17.790</td>
<td>33.154 *</td>
<td></td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td>(32.088) [0.098]</td>
<td>(16.989) [0.303]</td>
<td>(17.252) [0.064]</td>
<td></td>
</tr>
<tr>
<td>Wildfire</td>
<td>-53.917 *</td>
<td>6.440</td>
<td>32.984 **</td>
<td></td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td>(40.598) [0.097]</td>
<td>(8.768) [0.234]</td>
<td>(16.530) [0.027]</td>
<td></td>
</tr>
</tbody>
</table>

\* p<0.10, ** p<0.05, *** p<0.01

Note: Standard errors are in parentheses and \( p \) values are in brackets.

\textsuperscript{1}Mean value (standard deviation) of damages as a percent of GDP: 1.377\% (9.454)

\textit{Model 6.7: Agriculture}. At one standard deviation above the mean value for damages as a percentage of GDP, the coefficient for wildfires (\( p \) value=0.097) is significantly and inversely associated with the growth in output from agriculture. The magnitude of the estimated impact of wildfires on agricultural output, which was at -19.6\% for the global sample and -8.9\% for the sample with developing countries, has now increased in absolute magnitude to -53.9\%. This suggests that a wildfire which
causes damage equal to 10.83\% of GDP\(^4\) would be associated with an almost 54\% reduction in the annual growth in agriculture.

No unusually influential observations are identified using the method outlined in Welsch (1980) that might explain this unexpectedly large outcome. Yet a closer examination of the data gives some insight into the large size of the estimate for wildfires. While the mean for damages as a percentage of GDP for all disasters in Latin America from 1980 to 2013 is 1.377\%, the mean for wildfires is 0.300\%. Only one wildfire has economic damages that exceed the mean damages in Latin America. Thus the model is extrapolating from much smaller wildfires to estimate the impact of wildfires at the mean plus one standard deviation. Consequently, the results should be interpreted with caution.

Consistent with expectations, the coefficient for droughts (\(p\) value=0.044) continues to be significantly and inversely associated with decreases in agricultural output. A drought in Latin America with damages as a percentage of GDP at one standard deviation above the mean is associated with a reduction in agricultural output of approximately 6.4\%. Also significant and inversely associated with agriculture output are floods (\(p\) value=0.053) and storms (\(p\) value=0.007).

The coefficient for volcanoes (\(p\) value=0.098) is significant and positive, however, for the same reason as wildfires, these results should be interpreted with caution. The mean for damages as a percentage of GDP for volcanoes, at 0.395\%, is only slightly higher than the mean for wildfires (although there are five volcanoes that exceed the mean for all disasters in Latin America, as compared to just one for wildfires).

\(^4\) 10.83\% is the mean value plus one standard deviation for damages as a percentage of GDP for Latin American and Caribbean countries from 1980 to 2013.
Model 6.8: Services. For Latin America, the coefficient for drought ($p$ value=0.092) is inversely and significantly associated with output from services at one standard deviation above the mean for damages as a percentage of GDP. The coefficient for floods ($p$ value=0.037) is consistent with the results from the global and developing countries samples in that it is positive and significant. Contrary to expectations, however, the coefficient for earthquakes ($p$ value=0.243) is not statistically significantly associated with output from services.

Model 6.9: Industry. For industry, the coefficients for six of the disaster types are significant, including earthquakes ($p$ value=0.022). The sign of the coefficient for earthquakes is negative and consistent with expectations, suggesting that earthquakes are associated with a decrease in output from industry when damages are at one standard deviation above the mean. The coefficients for floods ($p$ value=0.028) and landslides ($p$ value=0.030) are also significant and negative.

Similar to agriculture, the estimated coefficients on volcanoes ($p$ value=0.064) and wildfires ($p$ value=0.027) are again large and statistically significant. The estimate on wildfires differs from the analysis of agricultural output, however, in that wildfires positively impact output from industry while the impact on agriculture was negative. Once again, these results should be interpreted with caution.

Conclusion

For Latin America, these results support the expectation that droughts and wildfires inversely impact agriculture, while earthquakes inversely impact industry. The prediction that earthquakes would be associated with a decline in output from services, however, was not supported for Latin America.
Floods are inversely associated with output in agriculture and industry, however, the association is positive for services. While storms are inversely associated with output in agriculture, landslides are inversely associated with output in industry. The results for volcanoes and wildfires, although significant for agriculture and industry, should be interpreted with caution.
CHAPTER VII – THE URBAN-RURAL INCOME GAP

Research Question 3: The Urban-Rural Income Gap

This chapter examines the impact of natural disasters on the gap between rural and urban incomes in Latin America. It is based on the findings of Chapter VI that natural disasters of varying types (in particular droughts, earthquakes, and wildfires) have differing impacts on the productive sectors of agriculture and industry in Latin America. These differing impacts on the productive sectors are expected to result in changes to the wage differential between rural and urban areas following natural disasters due to the concentration of certain productive sectors in urban or rural areas.

This chapter uses the urban-rural income gap to examine changes to inequality between rural and urban areas in Latin American countries as a result of the type of disaster. Droughts and wildfires are predicted to affect rural areas more than urban due to the concentration of agriculture in rural areas while earthquakes are predicted to affect urban areas more due to the concentration of industry in urban areas.

Income Inequality

Income inequality is associated with rent-seeking, inefficiency of land utilization, lower savings rates, and an overemphasis on higher education (Todaro and Smith 2009). Todaro and Smith (ibid.) also speculate that income inequality may lead to self-defeating populist policies as high levels of inequality spur a focus on redistribution of wealth rather than overall economic growth. In addition, high levels of income inequality are linked over the medium-term to lower growth of output (Dabla-Norris et al. 2015).
Income Inequality Defined

Income inequality is a measure of the extent to which income is equally distributed. Inequality of outcomes is what has traditionally been thought of income inequality and has historically been the primary focus of researchers. Inequality of outcomes refers to indicators, such as level of education, that are important in determining levels of income inequality. Inequality of opportunities, on the other hand, refers to lack of access to opportunities such as the availability of education. Inequality of outcomes is interdependent of inequality of opportunities as both influence the other (UNDP Bureau for Development Policy 2013).

Net inequality is inequality that remains after taxes and transfers (Ostry, Berg and Tsangarides 2014). It is typically measured using the Gini coefficient (see next section for more on the Gini) and is also referred to as net Gini. Market inequality, in contrast, is inequality before taxes and transfers. Market inequality is also referred to as gross inequality.

Methods of Measuring Income Inequality

The two primary measures of income inequality are the Gini coefficient (Gini 1921) and income share ratios, such as the Kuznets’ ratio (Kuznets 1955), that compute the ratio of income pertaining to the upper and lower income percentiles of the population. Gini coefficients indicate the degree of inequality by measuring the amount of space between the Lorenz curve and a line representing perfect equality (ibid.). The Gini coefficient varies from 0 to 1, with 1 representing perfect inequality in income distribution, and 0 representing perfect equality. More unequal countries have higher
coefficients. The Kuznets’ ratio is based on the ratio of the portion of income pertaining to the top two, or wealthiest, deciles to the bottom four, or poorest, deciles.

This research uses a less commonly used measure of inequality, the urban-rural income gap, which focuses specifically on the income gap between rural and urban areas. The income gap is calculated by dividing per capita urban income by per capita rural income. This measure is appropriate for the purposes of this research as it quantifies relative rural and urban incomes which the Gini coefficient and Kuznets’ ratio are unable to do.

One concern with the urban-rural income gap, however, is that the estimates of may be biased. Sicular et al. (2007) mention concerns that the imputed rental value of owner-occupied housing is not included as well as the value of public services (such as infrastructure, education, and health care). While including the value of owner-occupied housing and public services increases the gap, the gap decreases when spatial differences in the cost of living are accounted for.

Young (2013) finds that countries with high levels of overall inequality also have unusually large urban-rural gaps in living standards. Young also finds that urban to rural migration is underestimated. Rural to urban migrants tend to be higher skilled, while urban to rural migrants have fewer skills.

Consumption levels are determined by both income and asset wealth. Wealth can be divided into financial wealth and housing wealth. Sousa (2009) finds that financial wealth has a relatively large impact on consumption when compared to housing wealth, while the impact of housing wealth is statistically insignificant.
Inequality in Latin America

Kuznets (1955) hypothesized that over time, income inequality in developing countries would follow an inverted U-curve, with inequality increasing in the initial stages of growth and then decreasing in the later stages of development. The conclusion that emerged from Kuznets’ research is that higher economic growth involved a trade-off with higher levels of inequality (UNDP Bureau for Development Policy 2013). While Barro (2000) finds evidence for the Kuznets curve, he also finds its ability to explain differences in inequality across countries over time to be weak.

Despite some initial evidence for the inverted U curve, later research suggested that the curve is due to the “Latin American Effect.” When the Latin American countries are removed, the curve essentially disappears (Fields 2001). While higher income countries tend to have lower inequality (ibid.), scholars have not been able to conclusively prove that increased income for a country leads to reduced inequality within that country. According to the United Nations Development Programme (2013, 6), “recent empirical research has refuted the notion that higher inequality is the price to be paid by developing countries in order to achieve sustained growth.”

Inequality in Latin America has been falling since the mid-1990s, yet remains high. Most of the decline can be explained by increases in higher education spending, greater foreign direct investment (FDI), and an increase in revenues from taxes (Tsounta and Osueke 2014). Strong GDP growth also appears to have played a role. According to Gasparini et al. (2009), a “surge in the international prices of commodities” decreased overall income inequality in Latin America in the 2000s.
Cornia (2010) investigates whether increased export volumes and improved terms of trade are responsible for declining inequality in Latin America. He points out various mechanisms through which the terms of trade can impact inequality (both positively and negatively), including rents accruing to owners from land and mining rents more than workers, redistribution of tax income by states, and increased availability of foreign exchange. He concludes that the impact of improved terms of trade on reducing inequality in Latin America is moderate.

Cornia (ibid.) also finds that declining income inequality is related to having a populist or social democratic government, declining educational inequality, a devaluation of the real exchange rate, higher minimum wages, and higher public expenditures. The contribution of remittances by migrants is not significant, while an increase in FDI increases inequality. Educational disparity has the strongest impact on income inequality.

Other factors leading to regional inequalities in Latin America include the level of female participation in the labor force, family size, differences in income level by gender, the large informal market, educational discrepancies, occupational status of the head of household, access to public services, and land concentration (Fazio 2005).

There is a general movement of labor in Latin America from high-productivity jobs in manufacturing to lower-productivity jobs in the informal sector or producing commodities (McMillan and Rodrik 2011). A comparison of fiscal redistribution in Western Europe and Latin America finds that the redistributive impact of the fiscal system is comparatively smaller in Latin America when compared with the redistributive impact of Western Europe. In addition, when Latin American countries do engage in
significant redistribution, they tend to do so through transfers rather than taxes (Goni, Humberto-Lopez, and Serven 2011).

Determinants of Income Inequality

The primary drivers of household income distribution are trade globalization, financial globalization, technical change, macroeconomic policies, labor market policies, wealth inequality, and redistributive fiscal policies such as taxation and transfers (UNDP Bureau for Development Policy 2013). Financial openness and technological progress are associated with higher income inequality when measured using the Gini coefficient, while the ratio measures (such as the Kuznets ratio) show that easing of labor market regulations and technological progress are associated with higher inequality and education, improved health outcomes, and redistributive policies are associated with lower levels of inequality. In developing countries, increasing access to education contributes to increasing income shares for the poor and middle class (Dabla-Norris et al. 2015).

The impact of foreign direct investment (FDI) on inequality is contested among researchers. Proponents of economic liberalization view FDI as an important tool for growth of GDP and subsequent poverty reduction (te Velde 2003) while others see FDI as a means by which industrialized countries extract resources from developing countries and in doing so increase inequality between rich and poor countries. Te Velde (ibid.) finds that FDI brings in new techniques and skills yet also that FDI increases wage differentials in Latin America as a result of increased labor income disparity. Growth in FDI leads to an increase in the relative demand for skilled labor in Latin America (Feenstra and Hanson 1997), suggesting that FDI may increase income inequality.
Also contested is the impact of foreign aid on inequality. While some researchers find that foreign aid increases inequality (Herzer and Nunnenkamp 2012), others find no relationship between aid and inequality (Chong, Gradstein, and Calderon 2009), or that aid increases inequality in some countries and not others. For example, aid may increase inequality more in democratic countries than autocratic ones (Bjørnskov 2010).

Remittances have been suggested to both increase and decrease inequality, with some suggesting a curvilinear relationship where remittances first increase income inequality in earlier stages when the costs of migration are high and those who migrate are likely to be financially better off (Acosta et al. 2008). Migration costs tend to decrease over time as migration channels are established, allowing those who are less well-off to be able to migrate as well and potentially decreasing income inequality (Koechlin and Leon 2007).

*Rural and Urban Inequality*

While many studies have focused on the determinants of income inequality, few have examined rural or urban areas separately. Some studies that do not have an overt rural or urban focus, however, might have implications for rural areas more than urban or vice versa. Agricultural growth, for example, can reduce poverty and income inequality under certain circumstances. De Janvry and Sadoulet (2010) conclude that growth in the share of agriculture in GDP leads to income growth in the poorest two quintiles.

Research on inequality between rural and urban areas focuses almost exclusively on China due to concerns over rising inequality there since 1990. Lynch (2005) notes that much of the research up until 2005 focused on a single city and its surrounding area.
While the body of research has somewhat broadened in the intervening years, macroeconomic cross-country studies of rural or urban inequality continue to be limited.

Research Question – The Urban-Rural Income Gap

This research uses the urban-rural income gap to analyze relative changes to rural and urban income in Latin America following natural disasters, i.e. if there is a large disaster that affects industry, does urban income decrease relative to rural income? Or alternatively, if there is an ongoing drought, does rural income decrease relative to urban income? Relative rural and urban incomes are measured using the urban-rural income gap.

Droughts and wildfires are expected to affect rural incomes adversely more than urban incomes and thus increase the income gap, while earthquakes are predicted to affect urban incomes adversely more than rural incomes and thus decrease the income gap. Storms, floods, and landslides may destroy crops, however, they also have the potential to renew depleted soil, and therefore the expected effect on the income gap is unclear. In addition, the impact from volcanic activity is likely to be on whichever community is the closest, regardless of urban or rural.

<table>
<thead>
<tr>
<th>Research Question:</th>
<th>Does the urban-rural income gap change depending on the type of disaster?</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hₐ₁:</td>
<td>The urban-rural income gap increases following droughts and wildfires.</td>
</tr>
<tr>
<td>Hₐ₂:</td>
<td>The urban-rural income gap decreases following earthquakes.</td>
</tr>
<tr>
<td>Hₐ₃:</td>
<td>The urban-rural income gap changes following storms, floods, landslides, and volcanic activity (non-directional hypothesis).</td>
</tr>
</tbody>
</table>

Figure 7. Research question and hypotheses for question three
Methodology – The Urban-Rural Income Gap

This analysis uses a fixed effects regression analysis with panel data on 18 Latin America countries to test the hypothesis that the urban-rural income gap is affected differently depending on the type of disaster. An equation of the form

\[ Y_{it} = \alpha_i + \delta \text{DIS}_{it} + \vartheta V^K_{it} + \gamma \text{DIS}_{it} V^K_{it} + \beta X_{it} + u_{it} \]

is modeled, where \( Y_{it} \) is the urban-rural income gap for country \( i \) at time \( t \); \( \alpha_i \) is an intercept specific to each country; \( \delta \text{DIS}_{it} \) is a set of dummy variables indicating the type of disaster; \( \vartheta V^K_{it} \) is a term indicating the magnitude of the impact of the disaster where \( K \) indicates either the number affected, number killed, damages as a percentage of GDP, or a threshold dummy; \( \gamma \text{DIS}_{it} V^K_{it} \) is the interaction between the type of disaster and the magnitude indicator; \( \beta X_{it} \) is a set of control variables; and \( u_{it} \) includes the unobserved country-specific effects, \( \nu_i \), and the observation-specific error term, \( e_{it} \). The analysis is conducted for the time period from 1980 to 2013. The population consists of all countries in Latin America.

Fixed Effects Estimator

This analysis uses the same fixed effects estimator with Driscoll-Kraay standard errors that is used in Chapter VI. As in Chapter VI, the Driscoll-Kraay standard errors are used because they are robust to spatial correlation, serial correlation, and heteroskedasticity as well as perform well with finite samples (Driscoll and Kraay 1998). For more details see Chapter VI.
The Data

The dependent variable is the urban-rural income gap. The urban-rural income gap is the ratio of urban per capita income to rural per capita income. An increase in the ratio means that the gap between rural and urban income has become larger. In the dataset, the income gap value is always above 1, meaning that urban per capita income is always larger than rural per capita income in the sample. The largest gap, with a ratio of 3.865 indicating that urban per capita income is almost 4 times that of rural, was seen in Bolivia in 1999. The smallest gap, 1.009, was seen in Jamaica in 1990. A gap of 1.009 means that rural per capita income was almost equal to urban per capita income.

The urban-rural income for the sample data has declined since 1980, although the decline has not been steady. The gap was at its smallest in 1990 and 1991. After increasing in the early 2000s, the income gap has seen an overall decline since then, indicating rural per capita income is getting closer to urban per capita income. For a graph of the cross-sectional yearly means of the income gap see Figure 8.

![Urban-Rural Income Gap](image)

**Figure 8.** The urban-rural income gap over time

Note: the means are cross-sectional means across all countries in Latin America for each year. The urban-rural income gap is the ratio of urban per capita income to rural per capita income. A positive gap means that urban per capita income is higher than rural.
The explanatory variables include indicator variables for each type of disaster (where the occurrence of the disaster is marked with a “1” and non-occurrences are marked with a “0”) and interaction terms between the type of disaster and the percent damage (Model 7.1), percent affected (Model 7.2), or percent deaths (Model 7.3). While damages as a percentage of GDP is the primary measure of severity for the disasters, analyses are also conducted for the percentage of the population affected, the percentage of the population killed, and the “large” disaster dummy severity measure. Because of the low correlation between these measures (see Chapter IV for more information), the results vary extensively depending on which severity measure is used.

In Model 7.4, a “large” disaster severity measure (based on the analysis from Chapter V) uses a cut-off point, or threshold, over which a disaster is considered severe. The cut-off point of damages exceeding 0.456% of GDP for severe disasters is determined in Chapter V. The “large” disaster severity measure is an indicator variable that takes on a value of “1” if damages from the disaster exceed 0.456% of the previous year’s GDP.

Control variables used in all models include the first difference in the primary school enrollment rate as well as the growth rates in remittances, FDI, foreign aid, and government expenditures. The growth rates are the change from the previous year divided by lagged GDP (all in current dollars). This provides the growth rate in a variable that is scaled by the size of the economy. The control variables are chosen because of their potential to impact internal migration, either through increasing skills levels, creating jobs, changing the wage differential, or providing a transfer of income.
Diagnostics

The same diagnostics tests for cross-sectional dependence, serial correlation, groupwise heteroskedasticity, and unit roots are conducted as in Chapter VI (for the results of the tests please see Chapter VI). In addition to the tests conducted in Chapter VI, the Phillips-Perron unit root test shows that the primary school enrollment rate is not stationary. After taking the first difference the variable is stationary.

Results – The Urban-Rural Income Gap

The relationship between disasters and the urban-rural income gap is investigated using four different models. The urban-rural income gap is the dependent variable in all the models. Explanatory variables in Model 7.1 include disaster indicator dummies for drought, earthquakes, floods, landslides, storms, volcanoes, and wildfires as well as interaction terms between the disaster dummies and damages as a percentage of GDP. It also includes the growth in remittances, FDI, foreign aid, and government expenditures as a percentage of GDP as well as the first difference of the primary school enrollment rate.

Model 7.2 includes the same variables as the first, except that the severity indicator used in the interaction term is the number of persons affected as a percentage of the total population. In Model 7.3, the severity indicator in the interaction term is the number of deaths as a percentage of the total population. Model 7.4 examines the impact of severe disasters on the income gap by including only severe disasters which are identified using the cut-off for large disasters that was determined in Chapter V. Model 7.4 includes the same control variables as the previous models, the difference is in the inclusion of severe disaster dummies without the interaction terms.
Countries and Number of Disasters

The sample is the set of countries in Latin America for which a complete set of data is available. The 18 countries included in the analysis are listed in Table 10. The income gap variable is missing for many countries which limits the number of the countries available for analysis.

Table 10

Countries Included

<table>
<thead>
<tr>
<th>Country</th>
</tr>
</thead>
<tbody>
<tr>
<td>Belize</td>
</tr>
<tr>
<td>Bolivia</td>
</tr>
<tr>
<td>Chile</td>
</tr>
<tr>
<td>Colombia</td>
</tr>
<tr>
<td>Costa Rica</td>
</tr>
<tr>
<td>Dominican Republic</td>
</tr>
<tr>
<td>Ecuador</td>
</tr>
<tr>
<td>Guatemala</td>
</tr>
<tr>
<td>Guyana</td>
</tr>
<tr>
<td>Honduras</td>
</tr>
<tr>
<td>Jamaica</td>
</tr>
<tr>
<td>Mexico</td>
</tr>
<tr>
<td>Nicaragua</td>
</tr>
<tr>
<td>Peru</td>
</tr>
<tr>
<td>Paraguay</td>
</tr>
<tr>
<td>El Salvador</td>
</tr>
<tr>
<td>Uruguay</td>
</tr>
<tr>
<td>Venezuela</td>
</tr>
</tbody>
</table>

The number of disasters varies between the models (see Table 11). The total numbers of disasters included in Models 7.1, 7.2, and 7.3 is 243. There are 47 severe disasters in the sample used in Model 7.4. Floods are the most common disaster type in both samples. Together, floods and storms make up almost half of the disasters in Models 7.1, 7.2, and 7.3 and over half of severe disasters (Model 7.4). Wildfires are the
least common disaster type, however, volcanoes are a close second. For severe disasters, landslides and droughts are also rare.

Table 11

*Number of Disasters Included in Each Model*

<table>
<thead>
<tr>
<th></th>
<th>[Model number]</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>[7.1], [7.2], [7.3]</td>
<td>[7.4]</td>
<td></td>
</tr>
<tr>
<td>Drought</td>
<td>18</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>Earthquake</td>
<td>27</td>
<td>8</td>
<td></td>
</tr>
<tr>
<td>Flood</td>
<td>93</td>
<td>17</td>
<td></td>
</tr>
<tr>
<td>Landslide</td>
<td>24</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>Storm</td>
<td>54</td>
<td>13</td>
<td></td>
</tr>
<tr>
<td>Volcano</td>
<td>15</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>Wildfire</td>
<td>12</td>
<td>1</td>
<td></td>
</tr>
</tbody>
</table>

When interaction terms include a continuous variable, the significance of the term as well as the coefficient varies depending on the value of the continuous variable. Tests of joint significance are used to determine the significance of the variables and the coefficients at different levels of the continuous variable. For more details on tests of joint significance, see chapter VI.

Because this analysis is primarily interested in the effect of larger disasters, a test of joint significance is conducted using the value of the severity indicator (i.e. disaster damages as a percentage of GDP, number of persons affected as a percentage of the total population, or number of deaths as a percentage of the total population) equal to the mean plus one standard deviation. Using the mean for the tests of joint significance instead of the mean plus one standard deviation would have examined only the impact of the “average” disaster. This research, however, is interested in the impact of more extreme events, thus resulting in the choice of the mean plus one standard deviation to account for
larger disasters. The results for the tests of joint significance at one standard deviation above the mean for each severity indicator are shown in Table 12.

Table 12

*Tests of Joint Significance at One Standard Deviation above the Mean for Models 7.1, 7.2, and 7.3; with the Results from the Analysis of the Severe Disasters in Model 7.4*

<table>
<thead>
<tr>
<th>[Model number]</th>
<th>Magnitude indicator</th>
<th>[7.1]</th>
<th>[7.2]</th>
<th>[7.3]</th>
<th>[7.4]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>prct damage&lt;sup&gt;1&lt;/sup&gt;</td>
<td>prct affected&lt;sup&gt;2&lt;/sup&gt;</td>
<td>prct deaths&lt;sup&gt;3&lt;/sup&gt;</td>
<td>severe only&lt;sup&gt;4&lt;/sup&gt;</td>
<td></td>
</tr>
<tr>
<td>Drought</td>
<td>0.451 **</td>
<td>-0.468 **</td>
<td>0.637</td>
<td>0.154</td>
<td></td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td>(0.256) [0.046]</td>
<td>(0.264) [0.045]</td>
<td>(2.469) [0.399]</td>
<td>(0.140) [0.140]</td>
<td></td>
</tr>
<tr>
<td>Earthquake</td>
<td>-0.471 ***</td>
<td>-0.346 **</td>
<td>-1.095 ***</td>
<td>0.141 *</td>
<td></td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td>(0.124) [0.000]</td>
<td>(0.167) [0.025]</td>
<td>(0.242) [0.000]</td>
<td>(0.100) [0.085]</td>
<td></td>
</tr>
<tr>
<td>Flood</td>
<td>-0.065</td>
<td>0.026</td>
<td>1.647</td>
<td>0.024</td>
<td></td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td>(0.422) [0.879]</td>
<td>(0.051) [0.619]</td>
<td>(1.707) [0.344]</td>
<td>(0.188) [0.899]</td>
<td></td>
</tr>
<tr>
<td>Landslide</td>
<td>-2.066</td>
<td>0.282</td>
<td>-23.799 ***</td>
<td>-0.362 ***</td>
<td></td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td>(2.298) [0.378]</td>
<td>(0.277) [0.319]</td>
<td>(7.812) [0.006]</td>
<td>(0.109) [0.003]</td>
<td></td>
</tr>
<tr>
<td>Storm</td>
<td>0.032</td>
<td>0.029</td>
<td>0.037</td>
<td>-0.004</td>
<td></td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td>(0.050) [0.531]</td>
<td>(0.051) [0.574]</td>
<td>(0.042) [0.380]</td>
<td>(0.117) [0.971]</td>
<td></td>
</tr>
<tr>
<td>Volcano</td>
<td>-0.857</td>
<td>0.042</td>
<td>-4.916</td>
<td>-0.208</td>
<td></td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td>(0.518) [0.111]</td>
<td>(0.260) [0.873]</td>
<td>(4.982) [0.334]</td>
<td>(0.134) [0.134]</td>
<td></td>
</tr>
<tr>
<td>Wildfire</td>
<td>4.549</td>
<td>-0.290</td>
<td>31.801 ***</td>
<td>0.805 **</td>
<td></td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td>(3.497) [0.103]</td>
<td>(0.296) [0.169]</td>
<td>(4.743) [0.000]</td>
<td>(0.376) [0.022]</td>
<td></td>
</tr>
</tbody>
</table>

<sup>*</sup> p<0.10, ** p<0.05, *** p<0.01

Note: Standard errors are in parentheses and p values are in brackets.

1 Mean value (standard deviation) of damages as a percentage of GDP: 1.377% (9.454)

2 Mean value (standard deviation) of persons affected as a percentage of the total population: 1.423% (6.725)

3 Mean value (standard deviation) of deaths as a percentage of the total population: 0.003% (0.061)

4 This model includes the severe disaster indicator variables without an interaction term.

*Model 7.1*

Model 7.1 includes each disaster type as an explanatory variable along with the control variables and interaction terms between the type of disaster and damages as a
percentage of GDP. The dependent variable is the urban-rural income gap. The detailed results for Model 7.1 are available in Appendix C, Table A1.

According to the tests of joint significance shown in Table 13, the coefficient for drought is significant at one standard deviation above the mean ($p$ value = 0.046) as well as earthquakes ($p$ value = 0.000). The sign is as expected on droughts, as droughts are associated with a greater urban-rural income gap, meaning that urban incomes have increased relative to rural. Earthquakes are associated with a decrease in the urban-rural income gap. This is also consistent with expectations as earthquakes are predicted to decrease the gap between rural and urban incomes due to their greater impact on industry. The coefficient for wildfires ($p$ value=0.103) is not statistically significant.

Model 7.2

This model is similar to Model 7.1 except that it uses the percentage of the population affected as the measure of disaster severity. The detailed results for Model 7.2 are available in Appendix C, Table A1 and the tests of joint significance are shown in Table 12 above. The percent affected seems to be the most weakly associated of the three severity measures with the urban-rural income gap. At one standard deviation above the mean number for percent affected, the coefficients for droughts ($p$ value = 0.045) and earthquakes ($p$ value = 0.025) are significant; however, the sign for droughts is the reverse of what it is for the other two disaster severity measures and counter to expectations.

Noy (2009), upon finding similarly counter-intuitive results when using the percent affected to predict GDP growth, speculates that the impact of the human cost of a disaster on GDP growth may only be visible in long-term growth patterns, while the
impact of disaster damages are more immediately visible. This may be the case with income gap as well. Another possibility is that the percent affected data may not be sufficiently accurate. As mentioned earlier, Guha-Sapir, Hargitt, and Hoyois (2004) caution that the data on the number of persons affected may be biased for political reasons or may be based on outdated census information.

Model 7.3

This model is also similar to Model 7.1 except that it uses the number of deaths as a percentage of the population as the measure of disaster severity. The detailed results are available in Appendix C, Table A2, while the tests of joint significance are shown in Table 12. At one standard deviation above the mean level of deaths as a percentage of the population, the coefficients for earthquakes ($p$ value = 0.000), landslides ($p$ value = 0.006), and wildfires ($p$ value = 0.000) are significantly associated with the urban-rural income gap. The signs of the coefficients for earthquakes and wildfires are as expected, with earthquakes decreasing the urban-rural income gap, indicating that rural incomes are relatively better off when compared to urban, and wildfires conversely increasing the income gap. The results for earthquakes and wildfires are consistent with Model 7.1.

Model 7.4

Only severe disasters are included in this model (along with the control variables), with each disaster type represented with an indicator (dummy) variable that takes a value of “1” if a severe disaster took place. This model uses the cut-off point of 0.456% of damages as a percentage of GDP for severe disasters that was determined in Chapter V. While the cut-off point for severe disasters was found to be significant in Chapter V in identifying a threshold, the results from Model 7.4 show that when the disasters are
examined separately for their impact on the income gap, the coefficients for only three out of the seven disaster types are statistically significant. The detailed results are available in Appendix C, Table A2, while the results for the disaster types are shown in Table 12.

The sign on the coefficient for droughts is consistent with expectations, however, the coefficient is not significant ($p$ value = 0.140). The coefficients for floods ($p$ value = 0.899), storms ($p$ value = 0.971), and volcanoes ($p$ value = 0.134) are also not statistically significant. While the coefficient for earthquakes is significant ($p$ value = 0.085), the sign on the coefficient is counter to expectations and also the opposite of Models 7.1, 7.2, and 7.3. The coefficient for landslides is significant ($p$ value = 0.003) and the sign is consistent with Models 7.1 and 7.3. The coefficient for wildfires is also significant ($p$ value = 0.022) and consistent with expectations and Models 7.1 and 7.3.

**Control Variables**

The coefficient for the growth in remittances variable is statistically significant across all the models except Model 7.4. Remittances, perhaps counter to conventional wisdom, are associated with increases to the urban-rural income gap. A year to year increase in remittances of 1% of GDP increases the income gap by 0.043 to 0.056 points (depending on the model). As remittances tend to flow from urban areas to rural areas, it is surprising that they would widen the gap, however, the result is consistent across the models.

The coefficient for aid is significant in all of the models except Models 7.2. For Models 7.1, 7.2, and 7.3, foreign aid increases the income gap at one standard deviation above the mean of the severity indicator, though the magnitude of the coefficient is less
than that of remittances. The reversed sign in the model with the severe disasters (Model 7.4) indicates that foreign aid has a different effect following severe disasters, which may be related to the increased likelihood for a country to receive foreign aid after a large disaster.

The coefficients for primary school education rates are positive as well as significant in all the models except for the model with the severe disasters (Model 7.4). The role of education in inequality between urban and rural areas may not be the same in the context of severe disasters. The coefficient for FDI is only significant in Model 7.2. The sign on the coefficient for FDI is negative in all models, meaning that an increase in FDI decreases the urban-rural income gap. The positive sign on education and the negative sign on FDI are puzzling, as previous studies have found that education decreases inequality and that FDI increases it.

The sign on the coefficient for government expenditures in Models 7.1, 7.2, and 7.3 suggests that government expenditures are associated with lower inequality, however, the coefficient is insignificant in these models. In the model with severe disasters (Model 7.4), the coefficient for government expenditures is significant and the reverse sign from the other models. This implies that following a severe disaster, rural and urban areas are not benefitting equally from the expenditures of the government. For details of the results of each model see Appendix C, Tables A1 and A2.

Conclusion

Models 7.1 and 7.3 are the most consistent in terms of the signs and significance of the coefficients of the variables. Only one variable, floods, changes sign between the two models and each model has only one variable whose coefficient is not significant in
the other model. The difference between the two models shows up primarily in the magnitude of the effect, with all of the disaster types except storms having a stronger effect in the model with the number of deaths as a percentage of the population as the severity indicator. This is primarily due to the nature of the severity indicators. The number of deaths from a disaster is typically a smaller percentage of the population than the amount of damages is a percentage of GDP. An increase of deaths by 1% is associated with much more extreme disasters than an increase of damages by 1%, thus the impact on the income gap is larger.

The results of Model 7.2 are counter to the results of the other models. Earthquakes are the only disaster type to have a significant coefficient with the same sign between Models 7.1, 7.2, and 7.3. The coefficient on wildfires reverses sign in Model 7.2. The sign on the coefficient for storms is consistent between the three models but the coefficient is not significant. The lack of correspondence between Models 7.1/7.3 and Model 7.2 is not surprising given that the correlation between the number of persons affected as a percentage of the population is lower than between the other two measures.

The results from Model 7.4, which uses the severity indicator using the cut-off point from Chapter V, show that the coefficient for earthquakes is again significant, however, the sign of the coefficient reverses with this model. In addition, the sign changes on a number of other variables. It appears that the impact of severe disasters is different from that of all disasters. Severe earthquakes may have large impacts on rural areas as well as urban due to overall disruptions to the economy and damages to dwellings and roads. Rural areas may be less resilient than urban areas and may benefit less from employment resulting from reconstruction thus leading the urban-rural income
gap to increase rather than decrease. There also may be more rural to urban migration following severe earthquakes, which is an idea which will be explored in the following chapter.

There appears to be sufficient evidence to conclude that earthquakes lead to a decrease in the relative strength of urban incomes when compared to rural. There also appears to be some evidence that droughts and wildfires increase the gap between rural and urban incomes, leading to a decline in the relative position of rural incomes when compared to urban.
CHAPTER VIII – RURAL TO URBAN MIGRATION

Research Question 4 – Rural to Urban Migration

This research provides insight into the role of natural disasters as drivers of rural to urban migration in Latin America. Disasters of varying types are predicted to impact rural and urban areas differentially, which subsequently results in differing impacts on rural to urban migration. Droughts and wildfires are predicted to affect rural areas more than urban due to the concentration of agriculture in rural areas. In addition, changes to the gap in incomes between rural and urban areas post-disaster are explored as the mechanism through which disasters spur migration.

The results indicate that migration one year post-disaster is more common with some disaster types (i.e. droughts and volcanoes) than others. In addition, the time period over which migration takes places varies with the disaster type. Droughts, earthquakes, and storms have their largest impact on rural populations the year after the disaster, while for floods, the largest impact is two years after the disaster.

Some results, in particular the signs of the coefficients for droughts and earthquakes, are counter-intuitive and contrary to expectations. In contrast to expectations, droughts are not associated with more rural to urban migration, and earthquakes do not increase urban to rural migration. This result is consistent with a group of research studies that find that migration does not necessarily increase following a disaster, most likely as a result of income constraints.

The results indicate that changes to rural populations are primarily due to changes in the urban-rural income gap. Disasters appear to indirectly cause migration through affecting the income gap (which reflects the wage differential between urban and rural
areas). Changes to the wage differential between rural and urban areas that result from disasters promote migration until a new equilibrium wage-gap differential is reached. The income gap, however, is less important for severe disasters, as migration increases following severe storms and earthquakes regardless of the income gap.

Migration and Natural Disasters

This section summarizes the current research on whether disasters cause migration directly or indirectly, the time frames associated with post-disaster migration, migration and poverty, migration between rural and urban areas, and internal versus international migration. The literature reviewed here includes studies of environmental degradation or stress resulting from climate change, because many of these studies focus on natural disasters including drought and extreme temperatures.

While there are many examples of persons migrating following extreme weather events (Fritz 2010), research on the underlying dynamics of this phenomenon is still limited. Part of the challenge in researching disaster-induced migration is separating the effect of the disaster from other factors, such as high levels of pre-disaster poverty, inefficient or non-existent government services, and lack of job opportunities, that may also be influencing migration (ibid.). In addition, persons who migrate for environmental reasons (including disasters) tend to be difficult to identify (Véron and Golaz 2015). The decision-making process for whether to migrate is complex and involves multiple factors. Environmental degradation, such as that associated with droughts, takes place over the long-term, meaning that identifying the drought as the reason for the decision to migrate is challenging.
The existing research on migration and disasters tends to focus on a specific event within one country (Koubi et al. 2016). While rigorous studies using multivariate approaches that control for confounders have become more common in recent years (Gray and Wise 2016), these continue to be focused on a single country or a small group of countries. In some cases, researchers examining the same setting, at times using the same data, have come to different conclusions regarding whether environmental stress increases migration (Obokata, Veronis, and McLeman 2014).

Piguet (2010), in an analysis of six methods for studying environmental migration, notes that ecological inference studies (such as this study) have the advantage of controlling for confounding variables and being comparable across studies. Yet these studies also have limitations, including that aggregated measures may not hold true for individuals, it is difficult to study sub-groups such as those based on gender or socio-economic status, and these types of studies are restrictive because they are typically limited to administrative boundaries (such as countries or states) yet disasters often cross administrative lines.

An advantage of using a panel dataset is that it allows for longitudinal cross-country research, which most current disaster studies do not do (Obokata, Veronis, and McLeman 2014). Another advantage of this research is that it allows for comparison across different types of disasters, which many of the existing analyses of specific disasters and migration are not able to do.

Migration between Rural and Urban Areas

While much of migration is rural to urban migration, rural to rural migration is common in agricultural-based societies and urban to urban migration is common in
highly urbanized countries (Tacoli 2009). Rural to urban migration is highest in areas with high levels of economic growth and where industry and services are expanding. Yet even in countries with high levels of growth, rural to rural migration can form a large percentage of migrants. Rural to rural migrants are often poor and do not have the skills and resources to move to urban areas (ibid.).

In Costa Rica, both severe and less severe hydrological emergencies increase migration towards metropolitan areas (Robalino, Jimenez, and Chacón 2015). Less severe hydrological emergencies also increase migration between metropolitan areas. When analyzed individually, both floods and landslides increased migration between metropolitan areas (ibid.).

A study of rural farmholders in Zambia finds that households facing droughts and floods choose to migrate only if they had networks at the destination and perceived that better opportunities existed there (Simatele and Simatele 2015). All of the participants had resumed farming and raising livestock at the destination, which highlights that when rural persons are displaced they do not necessarily move to urban areas.

Migration Timelines – Sudden Onset vs. Slow Onset Disasters

Using evidence from Vietnam, Koubi et al. (2016) find that slow onset disasters, such as droughts, reduce the likelihood of migration, while sudden onset disasters increase the likelihood. Adaptation is the primary coping mechanism over migration for disasters with long time horizons.

Of the disaster types included in this dataset, only droughts can always be considered a slow onset disaster. Many floods are slow onset, however, flashfloods are sudden onset disasters. Some storms may be considered slow onset, especially when
weather forecasting provides advance notice of the storm. The remaining disaster types (earthquakes, landslides, wildfires), with the possible exception of volcanoes, are typically sudden onset disasters.

Households members may be less likely to migrate immediately following a disaster when they are more income constrained (Williams 2015). Disasters temporarily reduce income, and therefore reduce the ability of families to afford the costs of migration over the short-term. While migration initially declines following a disaster, the recovery eventually progresses to the point that migration picks up, with the largest increase in migration taking place four years after the disaster (ibid.).

The displacements seen following natural disasters tend to vary greatly depending on the type of disaster and the warning systems in place (Véron and Golaz 2015). For example, residents often migrate (if only temporarily in many cases) in advance of hurricanes. Sudden onset disasters may trigger mass movements, whereas with slow onset disasters migration may take place over extended periods of time (ibid.).

**Internal vs. International Migration Post-Disaster**

Most of the environmental migration that takes place is internal migration (Obokata, Veronis, and McLeman 2014). Some types of disasters seem to be associated with a particular type of migration, for example, droughts in Africa result in internal, temporary migration over short distances to other rural areas (Henry, Schoumaker, and Beauchemin 2004). Migration abroad and to urban areas tends to be during times of increased rainfall as households are more likely to be able to afford migration costs (ibid.). Residents of villages at risk for losing access to markets (from weather shocks, for example) are more likely to migrate internationally (Mora and Taylor 2005). Circular
migration is a form of temporary migration that may supplement and diversify agricultural income through non-farm labor or labor on other farms (Tacoli 2009).

**Migration and Poverty**

In a study of communities in Mexico, Saldaña-Zorrilla (2008) found that the poorest community studied was the most likely to diversify crops, yet the least likely to migrate, while the most well-off community was the least likely to diversify crops yet the most likely to migrate. This tendency of (relatively) wealthier communities to migrate before the poorest is supported by studies that find that for the initial migrants, the costs of migration are higher, thus reducing migration by poorer households (Koechlin and Leon 2007). Over time, as networks of migrants develop, the cost of migration declines, and poorer individuals are able to migrate as well.

**Do Natural Disasters Cause Migration Indirectly?**

The idea that post-disaster migration is caused by stress on livelihoods and income and indirectly by the disaster is given support from research by Paul (2005). Paul finds that disaster aid enabled residents who were affected by a tornado to remain in their communities. In addition, while many researchers have found evidence of disaster or climate-related migration, there are a number of studies that find the opposite or find conflicting results. For example, Gray and Wise (2016) find that changes in precipitation and temperature levels in four African countries yield differing results, with migration increasing in one country, decreasing in another, and remaining unchanged in two.
Research Question – Rural to Urban Migration

This research question uses the percentage of the population of a country living in rural areas to estimate whether natural disasters result in changes to rural to urban migration rates. Disasters that primarily affect urban industries, such as earthquakes, are predicted to decrease the urban-rural wage differential and deter migration from the countryside to the city. Conversely, disasters that primarily affect agriculture, such as droughts and wildfires, are predicted to increase the urban-rural wage differential and spur migration to the city. This research hypothesizes that the income gap, in reflecting the wage differential, is the mechanism through which natural disasters spur internal (within country) migration.

<table>
<thead>
<tr>
<th>Research Question</th>
<th>Does rural to urban migration change following natural disasters?</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>H_{A1}:</strong></td>
<td>The rate of rural to urban migration increases following disasters that primarily affect agriculture.</td>
</tr>
<tr>
<td><strong>H_{A2}:</strong></td>
<td>The rate of rural to urban migration decreases following disasters that primarily affect industry and services.</td>
</tr>
</tbody>
</table>

*Figure 9.* Research question and hypotheses for question four

Methodology – Rural to Urban Migration

This analysis uses a fixed effects estimator. An equation of the form

\[ Y_{it} = \alpha_i + \delta\text{DIS}_{it} + \vartheta V_{it}^K + \gamma V_{it}^K + \beta X_{it} + u_{it} \]

is modeled, where \( Y_{it} \) is the percentage of people living in rural areas for country \( i \) at time \( t \); \( \alpha_i \) is an intercept specific to each country; \( \delta\text{DIS}_{it} \) is a set of dummy variables indicating the type of disaster; \( \vartheta V_{it}^K \) is a term indicating the magnitude of the impact of the disaster
where $K$ indicates either the number affected as a percentage of the total population, the number killed as a percentage of the total population, damages as a percentage of GDP, or a threshold dummy; $\delta \text{DIS}_{it} V^K_{it}$ is the interaction between the type of disaster and the indicator of magnitude; $\beta X_{it}$ is a set of control variables; and $u_{it}$ includes the unobserved country-specific effects, $v_i$, and the observation-specific error term, $e_{it}$.

The analysis is conducted for the time period from 1980 to 2013. The population consists of all countries in Latin America. This study focuses specifically on internal migration. The focus on internal migration is appropriate since the literature on migration finds that most post-disaster migration is internal rather than international.

*Arellano-Bond Fixed Effects Estimator*

The analysis is conducted using an Arellano-Bond fixed effects estimator. The Arellano-Bond estimator is designed for dynamic panel data with few time periods and many individuals. Dynamic panel data models include lags of the dependent variable as an explanatory variable. Difference General Method of Moments (GMM) estimators, such as the Arellano-Bond, address dynamic panel bias (also called Nickell bias). With Nickell bias, the effect of the explanatory variables is underestimated due to the inclusion of dynamic variables (i.e. a lagged dependent variable) in regressions using Ordinary Least Squares or fixed effects.

An additional advantage of the Arellano-Bond estimator is its ability to handle “independent variables that are not strictly exogenous, meaning they are correlated with past and possibly current realizations of the error” (Roodman 2009, 86). The remittances variable, in particular, cannot be assumed to be exogenous. This means that while migration is expected to lead to more remittances, remittances may also lead to more
migration if the receipt of remittances allows families to be able to afford migration. Difference GMM estimators assume that the only good instruments available for a regression are lags of the variables included in the model (ibid.). The Arellano-Bond estimator can work with panels that are unbalanced and have time gaps.

The Arellano-Bond fixed effects estimator is preferred for this analysis over the fixed effects estimator used in the previous two chapters for its ability to handle variables that are not strictly exogenous and because the *xtscc* estimator is not able to explicitly include lagged values of the variables. Because some researchers find that migration peaks four years following a disaster (Williams 2015), this analysis includes four lags of all the disaster variables.

*The Data*

The dependent variable is the percentage of people living in rural areas. Due to lack of comprehensive information across countries and years on rural to urban migration rates in Latin America, the percentage of the population that is rural is used to represent the migration rate. The connection between the percentage of the population that is rural and migration between rural and urban areas is not exact, however, as the percentage of the population that is rural can be affected by differences in net birth rates. The Arellano-Bond estimator is a difference-in-difference estimator, meaning that as long as net birth rates remain relatively stable or change very slowly, they should not have a strong impact on the estimate.

Overall, the percentage of people living in rural areas has declined between 1980 and 2013 (see Figure 10). The average percentage of the rural population was 45.7\%, with a standard deviation of 21.3\%, in 1980. By 2013, the average rural population
percentage had declined to 35.5%, with a standard deviation of 24.2%. The change in the percentage living in rural areas from the prior year shows that for only 19.3% of the observations across all years, the percentage of people living in rural areas increased over the previous year. Countries that have seen years with increases in the percent rural population are primarily located in the Caribbean. For the remaining four-fifths of the observations, the percent living in rural areas decreased from the prior year. In Latin America in 2013, the country with the lowest rural population percent, at 5.0%, was Uruguay. The highest percent, at 91.3%, was in Trinidad and Tobago.

\[ Figure 10. \] The average rural population percentage in Latin America and the Caribbean 1980-2013

In the first set of models, the explanatory variables include a dummy for each type of disaster, where a value of “1” indicates that a disaster took place, as well as an interaction term between the type of disaster and the damages as a percentage of GDP.
(economic damages), the percentage of population affected (percent affected), or deaths as a percentage of the population (percent deaths). While damages as a percentage of GDP is the primary measure of severity for the disasters, analyses are also conducted for the percentage of the population affected and the percentage of the population killed. Another set of models uses a “large” disaster indicator (based on the analysis from Chapter V) where only severe disasters are included. Some models also include the urban-rural income gap as an explanatory variable.

Control variables include the growth in remittances, foreign direct investment (FDI), aid, and government consumption. The control variables are chosen because of their potential to impact internal migration, either through creating jobs, changing the wage differential, or providing a transfer of income.

Diagnostic Tests

The same diagnostics tests for cross-sectional dependence, serial correlation, groupwise heteroskedasticity, and unit roots are conducted as in Chapters VI. For the results of the tests please see Chapter VI.

Results – Rural to Urban Migration

The relationship between disasters and migration is investigated using eight different models. Model 8.1 uses damages as a percentage of GDP as the measure of severity. The explanatory variables are the disaster dummies, the interaction terms between the severity measure and the disaster dummies, and the controls variables (FDI, aid, remittances, and government expenditures). Model 8.2 adds the measure of inequality (the urban-rural income gap). Models 8.3 and 8.5 use the same variables as Model 8.1, however, Model 8.3 uses the percentage of persons affected as the measure of
severity, while Model 8.5 uses the percentage of deaths. Models 8.4 and 8.6 are the same as 8.2 with the exception of the severity measure. Model 8.4 uses the percentage of affected while Model 8.6 uses the percentage of deaths. The last set of models, 8.7 and 8.8, examines only disasters determined to be severe using the cut-off point determined in Chapter V. Model 8.8 adds the urban-rural income gap to the variables included in Model 8.7. See Appendix D for the complete results of each of the models.

*Countries and Number of Disasters*

The sample is the set of countries for which a complete set of data is available. For Models 8.1, 8.3, 8.5, and 8.7, the sample includes 32 countries. For Model 8.2, 8.4, 8.6, and 8.8, 15 countries are included. The sample is smaller in the second group due to missing values of the income gap variable which is added as an explanatory variable in these models. The countries included in each model are listed in Table 13.

Table 13

*Countries Included in Each Model*

<table>
<thead>
<tr>
<th>[Model number]</th>
<th>[8.1], [8.3], [8.5], [8.7]</th>
<th>[8.2], [8.4], [8.6], [8.8]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Argentina</td>
<td>Belize</td>
<td></td>
</tr>
<tr>
<td>Antigua and Barbuda</td>
<td>Belize</td>
<td>Bolivia</td>
</tr>
<tr>
<td>Aruba</td>
<td></td>
<td>Brazil</td>
</tr>
<tr>
<td>Barbados</td>
<td></td>
<td>Colombia</td>
</tr>
<tr>
<td>Belize</td>
<td></td>
<td>Costa Rica</td>
</tr>
<tr>
<td>Bolivia</td>
<td></td>
<td>Dominican Republic</td>
</tr>
<tr>
<td>Brazil</td>
<td></td>
<td>Ecuador</td>
</tr>
<tr>
<td>Chile</td>
<td></td>
<td>El Salvador</td>
</tr>
<tr>
<td>Colombia</td>
<td></td>
<td>Guatemala</td>
</tr>
<tr>
<td>Costa Rica</td>
<td></td>
<td>Honduras</td>
</tr>
<tr>
<td>Dominica</td>
<td></td>
<td>Mexico</td>
</tr>
<tr>
<td>Dominican Republic</td>
<td>Paraguay</td>
<td></td>
</tr>
<tr>
<td>Ecuador</td>
<td></td>
<td>Peru</td>
</tr>
<tr>
<td>El Salvador</td>
<td></td>
<td>Uruguay</td>
</tr>
</tbody>
</table>
Table 13 (continued).

<table>
<thead>
<tr>
<th>Grenada</th>
<th>Venezuela</th>
</tr>
</thead>
<tbody>
<tr>
<td>Guatemala</td>
<td></td>
</tr>
<tr>
<td>Guyana</td>
<td></td>
</tr>
<tr>
<td>Haiti</td>
<td></td>
</tr>
<tr>
<td>Honduras</td>
<td></td>
</tr>
<tr>
<td>Jamaica</td>
<td></td>
</tr>
<tr>
<td>Mexico</td>
<td></td>
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<tr>
<td>Nicaragua</td>
<td></td>
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<tr>
<td>Panama</td>
<td></td>
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<tr>
<td>Paraguay</td>
<td></td>
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<tr>
<td>Peru</td>
<td></td>
</tr>
<tr>
<td>St. Kitts and Nevis</td>
<td></td>
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<tr>
<td>St. Lucia</td>
<td></td>
</tr>
<tr>
<td>St. Vincent and the Grenadines</td>
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</tr>
<tr>
<td>Suriname</td>
<td></td>
</tr>
<tr>
<td>Trinidad and Tobago</td>
<td></td>
</tr>
<tr>
<td>Uruguay</td>
<td></td>
</tr>
<tr>
<td>Venezuela</td>
<td></td>
</tr>
</tbody>
</table>

Table 14

*Number of Disasters Included in Each Model*

<table>
<thead>
<tr>
<th>[Model number]</th>
<th>[8.1, 8.3, 8.5]</th>
<th>[8.2, 8.4, 8.6]</th>
<th>[8.7]¹</th>
</tr>
</thead>
<tbody>
<tr>
<td>Drought</td>
<td>73</td>
<td>25</td>
<td>15</td>
</tr>
<tr>
<td>Earthquake</td>
<td>76</td>
<td>20</td>
<td>16</td>
</tr>
<tr>
<td>Flood</td>
<td>295</td>
<td>99</td>
<td>48</td>
</tr>
<tr>
<td>Landslide</td>
<td>70</td>
<td>24</td>
<td>11</td>
</tr>
<tr>
<td>Storm</td>
<td>201</td>
<td>44</td>
<td>57</td>
</tr>
<tr>
<td>Volcano</td>
<td>41</td>
<td>7</td>
<td>6</td>
</tr>
<tr>
<td>Wildfire</td>
<td>30</td>
<td>9</td>
<td>2</td>
</tr>
</tbody>
</table>

¹Includes only disasters with damages that exceed 0.456% of GDP.

The number of disasters included varies among the models (see Table 14). The total numbers of disasters included in Models 8.1, 8.3, and 8.5 is 786. There are 228 disasters in Models 8.2, 8.4, and 8.6, and 155 severe disasters in the sample used in
Model 8.7 (where severe disasters are defined at disasters with damages as a percentage of GDP exceeding 0.456%). Floods are the most common disaster type, except among the severe disasters where storms are the most common type. Together, floods and storms make up well over half of the disasters in each of the models. Wildfires are the least common disaster type.

Tests of Joint Significance

When interaction terms include a continuous variable, the significance of the term as well as the coefficient varies depending on the value of the continuous variable. Tests of joint significance are used to determine the significance of the variables and the coefficients at different levels of the continuous variable. For more details on tests of joint significance, see chapter VI.

The tests of joint significance are conducted at one standard deviation above the mean value of the severity indicator (either disaster damages as a percentage of GDP, the number of persons affected as a percentage of the total population, or the number of deaths as a percentage of the total population). The results for the tests of joint significance for Models 8.1 and 8.2 are shown in Table 15.

Model 8.1 Results

The first model uses indicator variables for each type of disaster as well as an interaction term between the disaster type and damages as a percentage of GDP. The detailed results for Model 8.1 are available in Appendix D, Table A1. At the mean of damages as a percentage of GDP, the coefficients for the lagged values of droughts, earthquakes, floods, storms, and volcanoes are statistically significantly associated with the percentage of the population living in rural areas (see Table 15).
The sign of the coefficient for droughts is contrary to expectations and suggests that droughts are associated with a greater percentage of persons living in rural areas.

The sign on earthquakes, while the opposite of droughts, is also contrary to expectations as earthquakes are expected to impact urban areas more than rural and as a result increase the percentage living in rural areas. The sign on wildfires is also contrary to expectations.

Table 15

Tests of Joint Significance for Lagged Disasters at One Standard Deviation above the Mean of Damages as a Percentage of GDP

<table>
<thead>
<tr>
<th></th>
<th>Model 8.1</th>
<th>Model 8.2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>coefficient (std. err.)</td>
<td>coefficient (std. err.)</td>
</tr>
<tr>
<td>Drought(t-1)</td>
<td>0.383 *** [0.000]</td>
<td>-0.164 [0.654]</td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td>(0.066)</td>
<td>(0.367)</td>
</tr>
<tr>
<td>Earthquake(t-1)</td>
<td>-0.082 *** [0.001]</td>
<td>0.230 [0.796]</td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td>(0.025)</td>
<td>(0.886)</td>
</tr>
<tr>
<td>Flood(t-1)</td>
<td>-0.039 ** [0.018]</td>
<td>-0.021 [0.894]</td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td>(0.016)</td>
<td>(0.159)</td>
</tr>
<tr>
<td>Landslide(t-1)</td>
<td>0.019 [0.780]</td>
<td>0.169 [0.923]</td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td>(0.068)</td>
<td>(1.745)</td>
</tr>
<tr>
<td>Storm(t-1)</td>
<td>-0.039 *** [0.000]</td>
<td>0.013 [0.530]</td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td>(0.009)</td>
<td>(0.021)</td>
</tr>
<tr>
<td>Volcano(t-1)</td>
<td>0.771 *** [0.000]</td>
<td>-0.567 [0.547]</td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td>(0.181)</td>
<td>(0.942)</td>
</tr>
<tr>
<td>Wildfire(t-1)</td>
<td>0.912 [0.214]</td>
<td>0.098 [0.973]</td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td>(0.735)</td>
<td>(2.899)</td>
</tr>
</tbody>
</table>

* p<0.10, ** p<0.05, *** p<0.01

Note: Standard errors are in parentheses and p values are in brackets.

1 Mean value (standard deviation) of damages as a percentage of GDP: 1.377% (9.454)

2 Model 8.2 includes the same variables as Model 8.1 with the addition of the urban-rural income gap variable.
With a statistically significant coefficient of 0.771, volcanoes (p value=0.000) have the largest impact on the percent rural population at one standard deviation above the mean value for damages as a percentage of GDP (see Table 15). This number, as well as the coefficient for droughts of 0.383 (p value=0.000), indicates that the percent rural population on average increases in the year following a volcano or drought. Of the disasters that are significantly associated with decreases to the rural population percentage, earthquakes (p value=0.001) have the greatest impact at -0.082, followed by storms (p value=0.000) and floods (p value=0.018), both with a coefficient of -0.039.

**Figure 11.** Interaction plot for drought and earthquakes lagged one year for Model 8.1

Note: The shaded area in green is the 95% confidence interval for droughts. The shaded area in blue is the 95% confidence interval for earthquakes. Disaster size increases from left to right.

Figure 11 shows the effects of lagged droughts and earthquakes over various values of damages as a percentage of GDP. The values of damages displayed in the
graph range from 0 (the minimum plausible level, as economic damages cannot be negative) up to one standard deviation above the mean (10.8%). The blue line shows the predicted value for earthquakes and the green line shows droughts, while the colored plots show 95% confidence intervals for the values. The right side of the graph shows disasters with larger economic damages. The graph visually represents how the expected impact of droughts increases the rural population as economic damages increase, while the direction of earthquakes is the opposite.

Changes over Time

There is some consensus among disaster researchers that different types of disasters are associated with varying migration patterns, however, there is less agreement about how that pattern differs among the disaster types. Four of the disaster types with significant coefficients in the previous section are visually portrayed here with all lags displayed. Each of the four disasters follows a different pattern, however, there are some similarities between storms and floods.

The strongest impact of droughts (at one standard deviation above the mean level of damages as a percentage of GDP) on the percentage of the population living in rural areas is at the first lag (in Figure 12 the line represents the estimate for droughts at one standard deviation above the mean for the time period shown on the horizontal axis and the shaded area represents the 90% confidence interval). After the first lag, the coefficients for further lags are smaller (see Table 16).

At all lags, droughts are associated with an increase to the percentage of the population living in rural areas, however, the coefficient for the fourth lag is not
statistically significant. The sign on the coefficient for droughts is contrary to expectations at all lags.

Figure 12. Effect of droughts over time

Note: Confidence intervals (90%) are shaded in green. The values are for one standard deviation above the mean of damages as a percentage of GDP.

Table 16

| Effect of Droughts Over Time\(^1\) |
|-----------------|-----------------|-----------------|-----------------|-----------------|
|                 | coefficient     | p value         | lower CI\(^2\)  | upper CI\(^2\)  |
| Drought         | 0.169           | ***             | 0.006           | 0.083           | 0.255           |
| Drought\(_{(t-1)}\) | 0.383           | ***             | 0.000           | 0.298           | 0.469           |
| Drought\(_{(t-2)}\) | 0.147           | ***             | 0.002           | 0.081           | 0.212           |
| Drought\(_{(t-3)}\) | 0.088           | **              | 0.033           | 0.027           | 0.149           |
| Drought\(_{(t-4)}\) | 0.001           |                 | 0.496           | -0.065          | 0.066           |

\(^*\) p<0.10, \(^{**}\) p<0.05, \(^{***}\) p<0.01

\(^1\) Measured at one standard deviation above the mean value of damages as a percentage of GDP.

\(^2\) CI refers to a 90% confidence interval.

The strongest effect of earthquakes (at the mean value of damages as a percentage of GDP) is at the first lag (see Figure 13. The coefficient for the year in which the disaster takes place and the remaining lags are all similar in impact on the percentage
living in rural areas (see Table 17). While the coefficients for all the lags are statistically significant, the sign is contrary to expectations.

Figure 13. Effect of earthquakes over time

Note: Confidence intervals (90%) are shaded in blue. The values are for one standard deviation above the mean of damages as a percentage of GDP.

Table 17

<table>
<thead>
<tr>
<th></th>
<th>coefficient</th>
<th>p value</th>
<th>lower CI^2</th>
<th>upper CI^2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Earthquake</td>
<td>-0.031</td>
<td>0.117</td>
<td>-0.064</td>
<td>0.002</td>
</tr>
<tr>
<td>Earthquake_{t-1}</td>
<td>-0.082</td>
<td>***</td>
<td>0.001</td>
<td>-0.115</td>
</tr>
<tr>
<td>Earthquake_{t-2}</td>
<td>-0.036</td>
<td>*</td>
<td>0.070</td>
<td>-0.068</td>
</tr>
<tr>
<td>Earthquake_{t-3}</td>
<td>-0.042</td>
<td>**</td>
<td>0.048</td>
<td>-0.074</td>
</tr>
<tr>
<td>Earthquake_{t-4}</td>
<td>-0.043</td>
<td>**</td>
<td>0.046</td>
<td>-0.075</td>
</tr>
</tbody>
</table>

1 Measured at one standard deviation above the mean value of damages as a percentage of GDP.

2 CI refers to a 90% confidence interval.

Floods follow a U-shaped curve where the effect of the disaster on the percentage of the population living in rural areas (at one standard deviation above the mean level of damages as a percentage of GDP) grows through the second lag and then begins to
diminish (see Figure 14). The coefficient for floods is statistically significant at the first through third lags. At all lags, floods are associated with a decrease in the percentage of the population living in rural areas (see Table 18).

**Figure 14.** Effect of floods over time

Note: Confidence intervals (90%) are shaded in red. The values are for one standard deviation above the mean of damages as a percentage of GDP.

**Table 18**

**Effects of Floods Over Time**

<table>
<thead>
<tr>
<th></th>
<th>coefficient</th>
<th>p value</th>
<th>lower CI</th>
<th>upper CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Flood</td>
<td>-0.010</td>
<td>0.579</td>
<td>-0.039</td>
<td>0.019</td>
</tr>
<tr>
<td>Flood(t-1)</td>
<td>-0.039</td>
<td><strong>0.018</strong></td>
<td>-0.066</td>
<td>-0.012</td>
</tr>
<tr>
<td>Flood(t-2)</td>
<td>-0.049</td>
<td>*<strong>0.003</strong></td>
<td>-0.077</td>
<td>-0.022</td>
</tr>
<tr>
<td>Flood(t-3)</td>
<td>-0.038</td>
<td><strong>0.026</strong></td>
<td>-0.065</td>
<td>-0.010</td>
</tr>
<tr>
<td>Flood(t-4)</td>
<td>-0.028</td>
<td>0.132</td>
<td>-0.058</td>
<td>0.003</td>
</tr>
</tbody>
</table>

* p<0.10, ** p<0.05, *** p<0.01

1 Measured at one standard deviation above the mean value of damages as a percentage of GDP.

2 CI refers to a 90% confidence interval.

Storms follow a similar U-shaped curve as floods (at one standard deviation above the mean level of damages as a percentage of GPD), however, the maximum
impact is at the first lag (see Figure 15). Storms are significantly associated with a decline in the percentage of the population that is rural at all lags (see Table 19).

![Effect of storms over time](chart.png)

**Figure 15. Effect of storms over time**

Note: Confidence intervals (90%) are shaded in orange.

**Table 19**

*Effects of Storms Over Time*

<table>
<thead>
<tr>
<th>Storm</th>
<th>coefficient</th>
<th>p value</th>
<th>lower CI²</th>
<th>upper CI²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Storm</td>
<td>-0.030</td>
<td>***</td>
<td>-0.046</td>
<td>-0.014</td>
</tr>
<tr>
<td>Storm(t-1)</td>
<td>-0.039</td>
<td>***</td>
<td>-0.054</td>
<td>-0.024</td>
</tr>
<tr>
<td>Storm(t-2)</td>
<td>-0.038</td>
<td>***</td>
<td>-0.054</td>
<td>-0.023</td>
</tr>
<tr>
<td>Storm(t-3)</td>
<td>-0.033</td>
<td>***</td>
<td>-0.048</td>
<td>-0.017</td>
</tr>
<tr>
<td>Storm(t-4)</td>
<td>-0.033</td>
<td>***</td>
<td>-0.049</td>
<td>-0.017</td>
</tr>
</tbody>
</table>

* p<0.10, ** p<0.05, *** p<0.01

¹ Measured at one standard deviation above the mean value of damages as a percentage of GDP.

² CI refers to a 90% confidence interval.

The effect of droughts and earthquakes, while contrary to expectations, is consistent with previous research that finds that households in developing countries may be too income-constrained following disasters to engage in migration. In addition, this
research disconfirms the findings of Williams (2015) that migration picks up four years post-disaster. For droughts, earthquakes, and storms, disasters have the strongest effect on the percent rural population the year after the disaster. For floods, the strongest effect on the percent rural population is in the second year after the disaster.

Comparing droughts and earthquakes is interesting as drought is a slow onset disaster while earthquakes are sudden onset disasters. Some migration researchers suggest that migration patterns for slow and sudden onset disasters are different. While this research finds that the signs and magnitudes of the coefficients differ between droughts and earthquakes, the pattern of migration does not differ, with both seeing the largest impact in the first year following the disaster.

Model 8.2 Results

Model 8.2 adds urban-rural income gap to the explanatory variables of Model 8.1 to account for wage differentials. The detailed results can be seen in Appendix D, Table A1. The results of the tests of joint significance are above in Table 15. An increase in the income gap (meaning that urban incomes have increased relative to rural) is, as expected, associated with a decrease in the percentage of the population that is rural. While the coefficient for the urban-rural income gap is statistically significant, none of the disaster coefficients are statistically significant (see Table 15). This lack of significance can also be seen in Figure 16 as the confidence intervals for both droughts and earthquakes cross zero at all levels of damages shown.
Figure 16. Interaction plot for drought and earthquakes lagged one year for Model 8.1

Note: The shaded area in green is the 95% confidence interval for droughts. The shaded area in blue is the 95% confidence interval for earthquakes. Disaster size increases from left to right. Both droughts and earthquakes are insignificant when the income gap is included.

The coefficients for all the variables are in general smaller and fewer are significant than when the urban-rural income gap is not included in Model 8.1.

Volcanoes, which had the largest impact (at one standard deviation above the mean value for damages as a percentage of GDP) in Model 8.1, continues to have the largest impact at -0.567, however, the sign on the coefficient is now reversed.

The purpose of including the income gap variable is to determine if disasters spur migration despite changes to the wage differential between urban and rural areas, or if changes to the wage differential (which may be as a result of a disaster) is the moderating factor that drives post-disaster migration. The change in the results, where the coefficient
for five of the disaster types are significant in Model 8.1 to none in Model 8.2, suggests that while disasters may be an indirect cause of migration, fluctuations in the income gap are the primary catalyst of rural to urban migration.

Many of the control variables, including remittances, aid, and government expenditures, also have coefficients that change sign when the income gap is added. The coefficients on lagged remittances and foreign aid are inversely and statistically significantly associated with the percent rural population in Model 8.1, yet with the inclusion of the urban-rural income gap, they are no longer significant and the coefficients are close to zero.

The remittances variable, in particular, may be endogenous. The receipt of remittances may allow persons to remain in rural areas, yet the sending of remittances implies migration, which in many cases is from rural areas to urban areas. The Arellano-Bond estimator used in these models addresses this problem through use of the explanatory variables as instruments in order to control for endogeneity.

*Cumulative Effect for Models 8.1 and 8.2*

An additional analysis is conducted to determine whether the cumulative impact of the disasters over time is significant. It is possible that while a disaster may not have enough of an effect to be detectable in a single year, the cumulative effect of multiple disasters over a number of years (in this case five, as the current year is also included) may be significant. The tests of joint significance (at one standard deviation above the mean value of damages as a percentage of GDP) for the current year plus four lags are shown in Table 20.
Table 20

*Cumulative Significance Four Years After the Disaster at One Standard Deviation above the Mean of Damages as a Percentage of GDP*

<table>
<thead>
<tr>
<th></th>
<th>Model 8.1 coefficient (std. err.)</th>
<th>Model 8.2 coefficient (std. err.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Drought $(t-1)$</td>
<td>0.787*** (0.157)</td>
<td>-1.897* (1.309)</td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Earthquake $(t-1)$</td>
<td>-0.234*** (0.078)</td>
<td>0.399 (1.909)</td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Flood $(t-1)$</td>
<td>-0.163*** (0.046)</td>
<td>0.52 (0.607)</td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Landslide $(t-1)$</td>
<td>0.105 (0.205)</td>
<td>0.472 (3.223)</td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Storm $(t-1)$</td>
<td>-0.172*** (0.028)</td>
<td>0.161 (0.114)</td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Volcano $(t-1)$</td>
<td>2.679*** (0.503)</td>
<td>0.645 (2.319)</td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wildfire $(t-1)$</td>
<td>1.961* (1.434)</td>
<td>6.994 (5.95)</td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* p<0.10, ** p<0.05, *** p<0.01

1 Mean value (standard deviation) of damages as a percentage of GDP: 1.377% (9.454)

2 Model 8.2 includes the same variables as Model 8.1 with the addition of the urban-rural income gap variable.

More disaster coefficients are significant when the cumulative impact is the focus of analysis. For Model 8.1, the coefficients on all disaster types, with the exception of landslides, are statistically significant. In the prior section, when the urban-rural income gap is added to Model 8.2, all disaster types become statistically insignificant. When the cumulative impact is considered, however, the coefficient for droughts remains significant. In addition, the coefficient for droughts now has the expected direction of impact on the percent rural population.
Models 8.3 and 8.4 Results

Models 8.3 and 8.4 are similar to Models 8.1 and 8.2 except that they use the percentage of the population affected as the measure of disaster severity. Model 8.4 differs from Model 8.3 in that it includes the urban-rural income gap. The results for the tests of joint significance for Models 8.3 and 8.4 are shown in Table 2. The detailed results of both models are available in Appendix D, Table A2.

Table 21
Tests of Joint Significance for Lagged Disasters at One Standard Deviation above the Mean Number of Persons Affected as a Percentage of the Total Population

<table>
<thead>
<tr>
<th></th>
<th>Model 8.3 Coefficient (std. err.)</th>
<th>Model 8.4 Coefficient (std. err.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Drought(t-1)</td>
<td>-0.014 [0.379]</td>
<td>0.094 [0.306]</td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td>0.015</td>
<td>0.092</td>
</tr>
<tr>
<td>Earthquake(t-1)</td>
<td>0.021 [0.300]</td>
<td>-0.079 [0.536]</td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td>0.020</td>
<td>0.128</td>
</tr>
<tr>
<td>Flood(t-1)</td>
<td>-0.037 *** [0.003]</td>
<td>0.033 [0.357]</td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td>0.012</td>
<td>0.036</td>
</tr>
<tr>
<td>Landslide(t-1)</td>
<td>-0.107 ** [0.016]</td>
<td>-0.207 ** [0.047]</td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td>0.045</td>
<td>0.104</td>
</tr>
<tr>
<td>Storm(t-1)</td>
<td>-0.051 *** [0.000]</td>
<td>-0.004 [0.857]</td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td>0.010</td>
<td>0.021</td>
</tr>
<tr>
<td>Volcano(t-1)</td>
<td>0.040 [0.520]</td>
<td>0.230 [0.138]</td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td>0.062</td>
<td>0.155</td>
</tr>
<tr>
<td>Wildfire(t-1)</td>
<td>-0.226 *** [0.007]</td>
<td>0.022 [0.852]</td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td>0.084</td>
<td>0.119</td>
</tr>
</tbody>
</table>

* p<0.10, ** p<0.05, *** p<0.01

Note: Standard errors are in parentheses and p values are in brackets.

1 Mean value (standard deviation) of persons affected as a percentage of the total population: 1.423% (6.725)
2 Model 8.4 includes the same variables as Model 8.3 with the addition of the urban-rural income gap variable.

The signs on the coefficients for droughts and earthquakes are consistent with expectations in Model 8.3, however, when the income gap is added in Model 8.4 the...
signs on the coefficients are again contrary to expectations. The coefficient for droughts ($p$ value=0.379), earthquakes ($p$ value=0.300), and volcanoes ($p$ value=0.520) are not statistically significant in either Model 8.3 or 8.4.

Landslides ($p$ value=0.016) are the only disaster type to have a statistically significant coefficient in both models. Landslides are inversely related to the rural population percentage. The coefficients on floods ($p$ value=0.003) and storms ($p$ value=0.000) continue to be statistically significantly associated with declines in the percentage of the population living in rural areas in Model 8.3 but not Model 8.4.

In contrast to the models using the percentage of persons affected in prior chapters, the coefficients for more than half of the disaster types are statistically significant in Model 8.3. The suggestion made in Chapter VII was that the low levels of significance might be either due to the human impact of disasters being less immediately visible or that the quality of the data on the number of persons affected was too low for accurate analysis. The joint tests of the cumulative impact over five years (the current year plus four lags) show that the coefficients on five disaster types are significant (see Table 22). Only landslides and wildfires do not have statistically significant coefficients. The statistically significant results when a five year cumulative time period is examined provide support to the suggestion that the human impact of disasters may be delayed.

However, the results of the analysis with the income gap (Model 8.4) suggest an alternative explanation. The answer may be found in the behavior of the models when the income gap is added to the analysis. As a reminder, in Models 8.1 and 8.2 (with damages as a percentage of GDP), when the income gap is added to the model, none of the coefficients on disasters are statistically significant after one year, and the cumulative
results over five years show only two statistically significant coefficients. For Models 8.3 and 8.4, with the percentage of persons affected, the number of disasters that have significant coefficients once the income gap variable is added are more than double than that in the economic damages model.

It is possible that when the number of persons affected is high, migration takes place regardless of the urban-rural income gap. In contrast, when the amount of economic damages is high, migration may only take place when there are disparities in the wage differential as reflected in the urban-rural income gap.

Table 22

*Cumulative Significance Four Years After the Disaster at One Standard Deviation above the Mean Number of Persons Affected as a Percentage of the Total Population*

<table>
<thead>
<tr>
<th>Disaster</th>
<th>Model 8.3 coefficient (std. err.)</th>
<th>Model 8.4 coefficient (std. err.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Drought(_{t-1})</td>
<td>(-0.076^{**}) (0.045)</td>
<td>(-0.016) (0.248)</td>
</tr>
<tr>
<td>Earthquake(_{t-1})</td>
<td>(0.100^{**}) (0.055)</td>
<td>(0.062) (0.298)</td>
</tr>
<tr>
<td>Flood(_{t-1})</td>
<td>(-0.129^{***}) (0.034)</td>
<td>(-0.074) (0.109)</td>
</tr>
<tr>
<td>Landslide(_{t-1})</td>
<td>(-0.137) (0.143)</td>
<td>(-0.470) (0.299)</td>
</tr>
<tr>
<td>Storm(_{t-1})</td>
<td>(-0.259^{***}) (0.031)</td>
<td>(0.195^{**}) (0.092)</td>
</tr>
<tr>
<td>Volcano(_{t-1})</td>
<td>(1.129^{***}) (0.153)</td>
<td>(1.582^{***}) (0.472)</td>
</tr>
<tr>
<td>Wildfire(_{t-1})</td>
<td>(-0.210) (0.251)</td>
<td>(0.869^{**}) (0.400)</td>
</tr>
</tbody>
</table>

* \(p<0.10, ** p<0.05, *** p<0.01\)

1 Mean value (standard deviation) of persons affected as a percentage of the total population: 1.423% (6.725)

2 Model 8.4 includes the same variables as Model 8.3 with the addition of the urban-rural income gap variable.
Models 8.5 and 8.6 Results

Model 8.5 is similar to Models 8.1 and 8.3 with the exception that it uses deaths as a percentage of the population as the measure of disaster severity. At one standard deviation above the mean level of deaths as a percentage of the total population, the coefficients in Model 8.5 for droughts ($p$ value=0.060) and earthquakes ($p$ value=0.008) are positively and statistically significantly associated with increases in the percentage of the population living in rural areas while the coefficients for floods ($p$ value=0.001), landslides ($p$ value=0.000), volcanoes ($p$ value=0.054), and wildfires ($p$ value=0.000) are inversely and significantly associated with decreases in the percentage of the population living in rural areas. The only disaster type whose coefficient is not statistically significant is storms ($p$ value=0.158). The tests of joint significance are shown in Table 23. The detailed results of Models 8.5 and 8.6 can be found in Appendix D, Table A3.

The sign on droughts is contrary to expectations and yet similar to Models 8.1 and 8.3 in indicating that the percentage of the population that is rural increases with lagged droughts. The sign on earthquakes is consistent with expectations and also consistent with Model 8.3, and suggests that for earthquakes lagged one year the percentage living in rural areas increases. The sign on lagged wildfires is consistent with expectations that wildfires are associated with a decrease of the percentage living in rural areas. The expectation for floods and landslides is non-directional, so it is interesting to note that after one year both appear to be associated with rural to urban migration.

Model 8.6 is similar to Models 8.2 and 8.4 with the exception that it uses deaths as a percentage of the population as the measure of disaster severity. This model is also the same as Model 8.5 with the inclusion of the urban-rural income gap. Storms and
volcanoes are the only disaster types to undergo a switch in the sign of the coefficient when the urban-rural income gap is included. The most noticeable difference, however, is the number of disaster types with coefficients that are statistically significant. While all the disaster types except storms had significant coefficients in Model 8.5, only wildfires ($p$ value=0.032) has a significant coefficient in Model 8.6 (see Table 23). Similar to Models 8.1 and 8.2, adding in the urban-rural income gap variable greatly reduces the number of disaster types with significant coefficients.

Table 23

Tests of Joint Significance for Lagged Disasters at One Standard Deviation above the Mean Number of Deaths as a Percentage of the Total Population

<table>
<thead>
<tr>
<th></th>
<th>Model 8.5 coefficient (std. err.)</th>
<th>Model 8.6 coefficient (std. err.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Drought $(t-1)$</td>
<td>0.521 ** [0.060]</td>
<td>0.103 [0.936]</td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td>(0.277)</td>
<td>(1.284)</td>
</tr>
<tr>
<td>Earthquake $(t-1)$</td>
<td>0.221 *** [0.008]</td>
<td>0.038 [0.987]</td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td>(0.083)</td>
<td>(2.268)</td>
</tr>
<tr>
<td>Flood $(t-1)$</td>
<td>-0.157 *** [0.001]</td>
<td>-0.065 [0.210]</td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td>(0.046)</td>
<td>(0.052)</td>
</tr>
<tr>
<td>Landslide $(t-1)$</td>
<td>-0.797 *** [0.000]</td>
<td>-0.291 [0.912]</td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td>(0.153)</td>
<td>(2.641)</td>
</tr>
<tr>
<td>Storm $(t-1)$</td>
<td>-0.034 [0.158]</td>
<td>0.016 [0.512]</td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td>(0.024)</td>
<td>(0.025)</td>
</tr>
<tr>
<td>Volcano $(t-1)$</td>
<td>-0.172 * [0.054]</td>
<td>3.039 [0.465]</td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td>(0.089)</td>
<td>(4.164)</td>
</tr>
<tr>
<td>Wildfire $(t-1)$</td>
<td>-6.662 *** [0.000]</td>
<td>-6.176 ** [0.032]</td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td>(1.754)</td>
<td>(2.880)</td>
</tr>
</tbody>
</table>

* $p$<0.10, ** $p$<0.05, *** $p$<0.01

Note: Standard errors are in parentheses and $p$ values are in brackets.

1 Mean value (standard deviation) of deaths as a percentage of the total population: 0.003% (0.061)

2 Model 8.6 includes the same variables as Model 8.5 with the addition of the urban-rural income gap variable.
The results for the cumulative impact over the current year of the disaster plus the four prior years are similar to those for disasters at one lag. The joint tests of significance are shown in Table 24. For Model 8.5, the coefficients on all the disaster types are now statistically significant, and for Model 8.6, the coefficient for volcanoes has become significant. The coefficient for droughts has switched signs, and while it is now consistent with expectations, it is no longer statistically significant. The coefficients on earthquakes and wildfires are consistent with expectations in both models, however, the coefficient for earthquakes is not significant in Model 8.6.

Table 24

*Cumulative Significance Four Years After the Disaster at the Mean Number of Deaths as a Percentage of the Total Population*

<table>
<thead>
<tr>
<th></th>
<th>Model 8.5</th>
<th>Model 8.6</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>coefficient (std. err.)</td>
<td>coefficient (std. err.)</td>
</tr>
<tr>
<td>Drought_{t-1}</td>
<td>2.851 ***</td>
<td>-1.119 (4.15)</td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td>(0.69)</td>
<td>(0.272)</td>
</tr>
<tr>
<td>Earthquake_{t-1}</td>
<td>0.77 ***</td>
<td>0.795 (5.546)</td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td>(0.272)</td>
<td>(0.178)</td>
</tr>
<tr>
<td>Flood_{t-1}</td>
<td>-0.739 ***</td>
<td>-0.193 (0.178)</td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td>(0.137)</td>
<td>(0.178)</td>
</tr>
<tr>
<td>Landslide_{t-1}</td>
<td>-2.012 ***</td>
<td>2.486 (5.731)</td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td>(0.666)</td>
<td>(0.178)</td>
</tr>
<tr>
<td>Storm_{t-1}</td>
<td>-0.248 ***</td>
<td>-0.07 (0.614)</td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td>(0.062)</td>
<td>(0.614)</td>
</tr>
<tr>
<td>Volcano_{t-1}</td>
<td>-0.859 ***</td>
<td>28.429 **</td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td>(0.237)</td>
<td>(11.34)</td>
</tr>
<tr>
<td>Wildfire_{t-1}</td>
<td>-30.886 ***</td>
<td>-23.036 ***</td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td>(5.215)</td>
<td>(7.015)</td>
</tr>
</tbody>
</table>

* p<0.10, ** p<0.05, *** p<0.01

1 Mean value (standard deviation) of deaths as a percentage of the total population: 0.003% (0.061)

2 Model 8.6 includes the same variables as Model 8.5 with the addition of the urban-rural income gap variable.
**Table 25**

*Tests of Joint Significance for the Cumulative Effect of Lagged Severe Disasters*¹

<table>
<thead>
<tr>
<th></th>
<th>Model 8.7</th>
<th>Model 8.8²</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>coefficient (std. err.)</td>
<td>coefficient (std. err.)</td>
</tr>
<tr>
<td>Drought((t-1))</td>
<td>-0.008 (0.071)</td>
<td>-0.064 (0.135)</td>
</tr>
<tr>
<td>Earthquake((t-1))</td>
<td>-0.153 *** (0.065)</td>
<td>0.260 *** (0.106)</td>
</tr>
<tr>
<td>Flood((t-1))</td>
<td>0.069 (0.048)</td>
<td>-0.224 *** (0.081)</td>
</tr>
<tr>
<td>Landslide((t-1))</td>
<td>-0.007 (0.098)</td>
<td>-0.029 (0.138)</td>
</tr>
<tr>
<td>Storm((t-1))</td>
<td>-0.128 *** (0.040)</td>
<td>0.190 *** (0.073)</td>
</tr>
<tr>
<td>Volcano((t-1))</td>
<td>0.524 *** (0.102)</td>
<td>-0.109 (0.140)</td>
</tr>
<tr>
<td>Wildfire((t-1))</td>
<td>-0.062 (0.186)</td>
<td>-0.129 (0.181)</td>
</tr>
</tbody>
</table>

* p<0.10, ** p<0.05, *** p<0.01

¹ Model only includes disasters with damages as a percentage of GDP that exceed the severity threshold of 0.45588% of GDP.

² Model 8.8 includes the same variables as Model 8.7 with the addition of the urban-rural income gap variable.

**Models 8.7 and 8.8 Results**

Only severe disasters are included in Models 8.7 and 8.8 (along with the control variables), with each disaster type represented with a dummy indicator variable (a type of variable that takes on a value of “1” to indicate the occurrence of a disaster). This model uses the cut-off point for severe disasters that was determined in Chapter V. Model 8.8 includes the urban-rural income gap variable. The detailed results of the analysis are available in Appendix D, Table A4. The tests of joint significance shown in Table 25 are for the cumulative impact of each disaster type over five years (including the current year of the disaster and four lags) on the percentage of the population living in rural areas.
Chapter V identified a threshold for when aggregated disasters begin to have a negative impact on GDP that is statistically significant. Yet, when severe disasters are analyzed separately by disaster type for their impact on the percentage of population living in rural areas, the results are mixed, with the coefficients for only three disaster types statistically significantly associated with changes to the percent rural population. For Model 8.7, the coefficients on earthquakes ($p$ value=0.020), storms ($p$ value=0.001), and volcanoes ($p$ value=0.000) are statistically significant. The sign on earthquakes is contrary to expectations as in the other models.

After the urban-rural income gap is included in Model 8.8, the coefficients on earthquakes ($p$ value=0.014) and storms ($p$ value=0.009) are still significant, while the coefficient for volcanoes ($p$ value=0.437) is no longer significant and the coefficient for floods ($p$ value=0.006) has become statistically significant. With the income gap included, the sign on earthquakes is now as expected. The sign is as expected on droughts, however, the coefficient is not statistically significant ($p$ value=0.636). The income gap appears to play less of a role in influencing post-disaster migration with severe disasters as the same number of disasters significantly affects the percent population living in rural areas in the model with the income gap variable as the one without it.

**Conclusion – Rural to Urban Migration**

**The Role of the Urban-Rural Income Gap**

The results are consistent across the models without the urban-rural income gap and display robustness to a variety of specifications, including the use of different severity measures. The robustness across the severity measures is surprising, given that
there is little correlation among the measures. When the urban-rural income gap is included, the coefficients for the disaster variables become insignificant in most of the models, suggesting that the income gap is a moderating factor.

Damages from disasters do not appear to directly cause migration, but rather, do so through affecting the income gap (the wage differential), which in turn affects rural to urban migration in response to changes in the wage differential until a new equilibrium wage is reached. The impact of the urban-rural income gap on the significance of the disaster coefficients is less, however, when the severity indicator is the number of persons affected rather than when economic damages is the severity indicator.

The sign on the urban-rural income gap is negative after the variable is included in the model and, with the exception of Model 8.6 where deaths as a percentage of population is the severity measure, is statistically significant. The negative coefficient indicates that an increase in the urban-rural income gap (i.e. urban incomes are relatively higher compared to rural incomes) is associated with a decreased rural population percentage. This is as expected as a larger wage differential would encourage migration to urban areas and an associated decrease in the rural population.

The results on the urban-rural income gap are consistent with the findings of other migration researchers who have indicated that in addition to “push” factors for migration, “pull” factors are also important. Migration involves significant costs, in addition to monetary costs there are also psychological costs of leaving home and the uncertainty of moving to a new area. Many researchers have noted that there are often multiple factors that influence the decision to migrate, and that disasters alone are unlikely to be a reason
to migrate without other push or pull factors. In this case, an increasing gap between urban and rural incomes is an important factor that adds to the decision to migrate.

There are two exceptions when the income gap is included in the model and does not render the coefficients on the disasters insignificant. The first is when the severity measure is the number of persons affected (Model 8.4). In this model the coefficients on fewer disasters are significant when the income gap variable is included, but the difference is less than in the models with economic damages (Model 8.2) or deaths (Model 8.6) as the severity indicator. When the number of persons affected is high, migration may take place regardless of the urban-rural income gap. In contrast, when the amount of economic damages is high, migration may only take place when there are disparities in the wage differential as reflected in the urban-rural income gap.

The other exception is when only severe disasters are included in the model. In this case, including the income gap variable changes the results but does not reduce the number of disaster types with significant coefficients. The role of the urban-rural income gap appears to be less in this model in that the coefficients for the disaster indicator variables do not vary as much with the inclusion of the urban-rural income gap.

*Do Some Disaster Types Affect Migration More Than Others?*

Volcanoes and droughts have the largest impact on the percent rural population after one year in the model with economic damages as the severity indicator. The coefficients for volcanoes is close to 0.77, suggesting that volcanoes with economic damages at one standard deviation above the mean increase the percent rural population by 0.77 points after one year.
When measured at one standard deviation above the mean damages as a percentage of GDP, no disaster types are significantly associated with changes to the percentage of rural population in all of the models. Droughts, volcanoes, storms, floods, and earthquakes have coefficients that are statistically significant in three out of the four models without the income gap variable. The coefficients for landslides and wildfires are only statistically significantly associated with changes in the percent rural population in two of the models without the income gap.

No obvious explanation can be provided for the counterintuitive results on the sign for droughts and earthquakes. While the coefficients on both are statistically significantly associated with changes in the percentage of the population living in rural areas in the economic damages model (Model 8.1), the signs on both are consistently contrary to expectations. Only when the urban-rural income gap is included does the sign on droughts and earthquakes become negative as expected.

The most likely explanation is one that has been suggested by other researchers – disasters cause income constraints that make migration difficult. An increase in the urban-rural income gap may help potential migrants from rural to urban areas overcome income constraints.

*Migration Timelines*

Williams (2015) finds that after an initial decline post-disaster, migration then peaks four years post-disaster. Williams suggests that constraints on income immediately after the disaster may inhibit migration. The results presented here, while finding some evidence for income constraints, do not find evidence that migration peaks four years after the disaster. Droughts, earthquakes, and storms have the strongest effect on the
rural population percentage the year after the disaster, while for floods, the strongest effect is in the second year after the disaster.
CHAPTER IX – CONCLUSION

“Large” Natural Disasters

This dissertation first identifies a cut-off point for “large” disasters, where large is defined as having a negative impact on the growth in GDP. The cut-off point is based on the level of economic damages as a percentage of the prior year’s GDP. A statistically significant cut-off point is identifiable for the geographies with all countries, developing countries only, and the Latin America and the Caribbean countries only. The only geography that does not have a statistically significant cut-off point is the high-income countries.

Country groupings with higher income, such as the Latin America and Caribbean group, have higher cut-off points where disasters need to cause a greater amount of economic damage in order to have a statistically significant impact on the growth in GDP. For the grouping of only high-income countries, there is not any cut-off point for which the growth in GDP for disasters with larger damages is significantly different from disasters with fewer damages.

Although the difference of between the means of the group above the cut-off point is significant when compared to the group below the cut-off point when the Latin American and Caribbean disasters are aggregated, the analysis in Chapters VII and VIII with the disaster types analyzed separately shows that the effect is not equal for all disaster types, and many disaster types have insignificant impacts.
Sectors of Production

*Droughts and Wildfires Affect Agriculture in Latin America and the Caribbean (LAC)*

Droughts and wildfires inversely impact the growth in agricultural output in Latin America and the Caribbean as expected. Floods and storms also inversely affect agricultural output while volcanoes are associated with increases to agricultural output.

*Industry in LAC is Primarily Affected by Earthquakes*

Earthquakes inversely impact the growth in output from industry as expected. Floods, landslides, and wildfires are also inversely associated with output in industry. The results for volcanoes and wildfires, although statistically significant for agriculture and industry, should be interpreted with caution due to the limited number of available cases.

*Earthquakes Do Not Affect the Service Sector in LAC as Expected*

The results for earthquakes in Latin America and the Caribbean, while significant, are contrary to the expectation that earthquakes would be associated with a decline in output from services. The only other disaster type that is significantly associated with the growth in output from services is flood. While floods are inversely associated with output in industry, for services the association is positive.

The Urban-Rural Income Gap

*The Results from Earthquakes, Droughts, and Wildfires Are Overall as Expected*

As expected, droughts and wildfires are associated with a decline in the relative position of rural incomes when compared to urban. Also as expected, earthquakes are associated with a decrease in the relative strength of urban incomes when compared to
that of rural. Earthquakes are the only disaster type to have a significant coefficient with the same sign in Models 7.1, 7.2, and 7.3.

*The Percentage of Persons Affected as the Severity Indicator Decreases the Significance of the Coefficients of the Disaster Types*

Fewer disaster types in the model with the percentage of persons affected as the severity indicator (Model 7.2) have significant coefficients when compared to the other models. These results are consistent with previous research which finds that the number affected as a percentage of the population is less effective as a predictor of changes to GDP output.

*The Impact of Severe Disasters is Different from that of All Disasters*

In Model 7.4, which uses the severe disaster indicator based on the cut-off point from Chapter V, the coefficient for earthquakes is significant, however, the sign of the coefficient reverses with this model. In addition, the sign changes on a number of other variables. Severe earthquakes may have large impacts on rural as well as urban areas due to overall disruptions to the economy and damages to dwellings and roads. Rural areas may be less resilient than urban areas and may benefit less from increases in employment resulting from reconstruction, thus resulting in an increase in the urban-rural income gap rather than a decrease. There also may be more rural to urban migration following severe earthquakes to assist with reconstruction efforts.

**Rural to Urban Migration**

*Migration Peaks One to Two Years after a Disaster*

In contrast to prior research which suggests that migration peaks around four years after a disaster, this research finds that for droughts, earthquakes, and storms
migration peaks one year after the disaster. For floods, the peak in migration is two years after the disaster. This research is in agreement with prior research, however, that migration does not take place immediately following a disaster. Delays in migration are most likely the result of income constraints after a disaster-induced shock to the income or assets of a household.

*Some Disaster Types Have a Greater Impact on Migration than Others*

In the model with economic damages, volcanoes and droughts have the largest impact on the percentage of the population that is rural after one year. The coefficient for volcanoes is close to 0.77, suggesting that volcanoes with economic damages at one standard deviation above the mean increase the rural population percentage by approximately 0.77 points.

While there is some variation among the models, the impact of disasters on migration is counter-intuitive for both droughts and earthquakes in most of the models. Droughts appear to decrease rural to urban migration, while earthquakes increase it. Earthquakes may increase rural to urban migration if reconstruction efforts lead to increased employment in urban areas. Droughts may decrease rural to urban migration if, as a result of the drought, households are too income-constrained to migrate.

*The Urban-Rural Income Gap is a Moderating Factor between Disasters and Migration*

When the urban-rural income gap is included, the coefficients for the disaster variables become statistically insignificant in most of the models, suggesting that the income gap is a moderating factor. The results indicate that changes to rural populations are primarily due to changes in the urban-rural income gap. Disasters appear to indirectly cause migration through affecting the income gap (which reflects the wage differential
between urban and rural areas). Changes to the wage differential between rural and urban areas that result from disasters promote migration. The results on the urban-rural income gap are consistent with the findings of other migration researchers who have indicated that in addition to “push” factors for migration, “pull” factors are also important.

The income gap, however, is less important for severe disasters, as migration increases following severe storms and earthquakes regardless of the income gap. In addition, the impact of the urban-rural income gap on the significance of the disaster coefficients is less when the severity indicator is the number of persons affected than when economic damages is the severity indicator.

Hypothesized Mechanism of Effect

This research hypothesizes that changes to the urban-rural income gap result from the differential impact of disasters on the productive sectors of agriculture, industry, and services. In keeping with neoclassical migration theory and the Todaro Model, changes to the urban-rural income gap are predicted to subsequently lead to changes in rural-to-urban migration as the new wage differential leads to movement between urban and rural areas until a new equilibrium is reached. The illustration of the hypothesized mechanism of effect from Chapter I is repeated in Figure 17. This dissertation concludes that there is support for the hypothesis that different types of disasters have distinct impacts on the sectors of production, which in turn leads to changes in the urban-rural income gap, which subsequently plays a role in rural to urban migration.
Figure 17. Hypothesized mechanism of effect of natural disasters on the urban-rural income gap and rural to urban migration
APPENDIX A – Summary Statistics

Table A1.

**Summary Statistics**

<table>
<thead>
<tr>
<th>Dependent Variables</th>
<th>Obs.</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min.</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rural population percent</td>
<td>1,326</td>
<td>39.863</td>
<td>22.577</td>
<td>0</td>
<td>91.466</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Explanatory Variables</th>
<th>Obs.</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min.</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Urban-rural income gap</td>
<td>218</td>
<td>2.036</td>
<td>0.538</td>
<td>1.01</td>
<td>3.865</td>
</tr>
<tr>
<td>Total deaths</td>
<td>1,360</td>
<td>274.451</td>
<td>6.146</td>
<td>0</td>
<td>222.641</td>
</tr>
<tr>
<td>Total affected</td>
<td>1,360</td>
<td>135.563</td>
<td>826.057</td>
<td>0</td>
<td>23,338,340</td>
</tr>
<tr>
<td>Total damages ($)</td>
<td>1,360</td>
<td>128,178.748</td>
<td>966,315.604</td>
<td>0</td>
<td>30,000,001,024</td>
</tr>
<tr>
<td>Deaths as a % of total pop</td>
<td>1,342</td>
<td>0.003</td>
<td>0.061</td>
<td>0</td>
<td>2.227</td>
</tr>
<tr>
<td>Affected as a % of total pop</td>
<td>1,342</td>
<td>1.423</td>
<td>6.725</td>
<td>0</td>
<td>110.362</td>
</tr>
<tr>
<td>Damages as a % of GDP</td>
<td>1,112</td>
<td>1.377</td>
<td>9.454</td>
<td>0</td>
<td>150.418</td>
</tr>
<tr>
<td>Drought X prct damage</td>
<td>688</td>
<td>11.839</td>
<td>106.824</td>
<td>0</td>
<td>1,650,000</td>
</tr>
<tr>
<td>Earthquake X prct damage</td>
<td>688</td>
<td>79.570</td>
<td>1,201.922</td>
<td>0</td>
<td>30,000,000</td>
</tr>
<tr>
<td>Flood X prct damage</td>
<td>688</td>
<td>54.108</td>
<td>264.620</td>
<td>0</td>
<td>3,160,000</td>
</tr>
<tr>
<td>Landslide X prct damage</td>
<td>688</td>
<td>3.844</td>
<td>49.076</td>
<td>0</td>
<td>988,800</td>
</tr>
<tr>
<td>Storm X prct damage</td>
<td>688</td>
<td>97.039</td>
<td>540.357</td>
<td>0</td>
<td>7,910,000</td>
</tr>
<tr>
<td>Volcano X prct damage</td>
<td>688</td>
<td>2.032</td>
<td>38.992</td>
<td>0</td>
<td>1,000,000</td>
</tr>
<tr>
<td>Wildfire X prct damage</td>
<td>688</td>
<td>1.769</td>
<td>17.174</td>
<td>0</td>
<td>280,000</td>
</tr>
<tr>
<td>Drought X prct deaths</td>
<td>688</td>
<td>0.11</td>
<td>1.8</td>
<td>0</td>
<td>41</td>
</tr>
<tr>
<td>Earthquakes X prct deaths</td>
<td>688</td>
<td>355</td>
<td>8.494</td>
<td>0</td>
<td>222,570</td>
</tr>
<tr>
<td>Flood X prct deaths</td>
<td>688</td>
<td>73</td>
<td>1.150</td>
<td>0</td>
<td>30,005</td>
</tr>
<tr>
<td>Landslide X prct deaths</td>
<td>688</td>
<td>9.3</td>
<td>46</td>
<td>0</td>
<td>653</td>
</tr>
<tr>
<td>Storms X prct deaths</td>
<td>688</td>
<td>46</td>
<td>586</td>
<td>0</td>
<td>14,600</td>
</tr>
<tr>
<td>Volcano X prct deaths</td>
<td>688</td>
<td>32</td>
<td>831</td>
<td>0</td>
<td>21,800</td>
</tr>
<tr>
<td>Wildfires X prct deaths</td>
<td>688</td>
<td>0.22</td>
<td>2.5</td>
<td>0</td>
<td>50</td>
</tr>
<tr>
<td>Drought X prct affected</td>
<td>688</td>
<td>81.185</td>
<td>892.170</td>
<td>0</td>
<td>20,000,000</td>
</tr>
<tr>
<td>Earthquake X prct affected</td>
<td>688</td>
<td>25.465</td>
<td>222.898</td>
<td>0</td>
<td>3,700,000</td>
</tr>
<tr>
<td>Flood X prct affected</td>
<td>688</td>
<td>92.522</td>
<td>410.585</td>
<td>0</td>
<td>6,080,000</td>
</tr>
<tr>
<td>Landslide X prct affected</td>
<td>688</td>
<td>2.174</td>
<td>28.518</td>
<td>0</td>
<td>700,000</td>
</tr>
<tr>
<td>Storms X prct affected</td>
<td>688</td>
<td>51.080</td>
<td>308.148</td>
<td>0</td>
<td>5,900,012</td>
</tr>
<tr>
<td>Volcano X prct affected</td>
<td>688</td>
<td>1.895</td>
<td>18.069</td>
<td>0</td>
<td>300,263</td>
</tr>
<tr>
<td>Wildfire X prct affected</td>
<td>688</td>
<td>472</td>
<td>7.560</td>
<td>0</td>
<td>152,752</td>
</tr>
<tr>
<td>Primary school enrollment (ratio of total enrolled to corresponding age group)</td>
<td>925</td>
<td>107.04</td>
<td>10.81</td>
<td>67.75</td>
<td>165.19</td>
</tr>
<tr>
<td>Real exchange rate</td>
<td>714</td>
<td>7,429.31</td>
<td>15,696.1</td>
<td>18.71</td>
<td>4,161,494</td>
</tr>
</tbody>
</table>

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Table A1 (continued).

<table>
<thead>
<tr>
<th>Category</th>
<th>Year</th>
<th>Value</th>
<th>Value 2</th>
<th>Value 3</th>
<th>Value 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inflation Rate</td>
<td>967</td>
<td>50.73</td>
<td>484.33</td>
<td>-11.45</td>
<td>11,749.64</td>
</tr>
<tr>
<td>Real interest rate</td>
<td>939</td>
<td>9.02</td>
<td>30.16</td>
<td>-97.81</td>
<td>789.80</td>
</tr>
<tr>
<td>FDI growth (% of GDP)</td>
<td>1,058</td>
<td>0.868</td>
<td>10.807</td>
<td>-34.31</td>
<td>257.423</td>
</tr>
<tr>
<td>Remittances growth (% of GDP)</td>
<td>913</td>
<td>0.392</td>
<td>1.301</td>
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Table A1.

*Countries Included in Each Model*

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**Table A2.**

*Fixed Effects Regression Results with the Percentage Annual Growth of Agriculture/Services/Industry as the Dependent Variable - All Countries*

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<tr>
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<td>(0.548)</td>
<td>(0.455)</td>
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<td>1.762 ***</td>
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<td>Flood X prct damage</td>
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<td>0.131 *</td>
<td>-0.172 **</td>
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<td>(0.051)</td>
<td>(0.076)</td>
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<td>Landslide X prct damage</td>
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<td>4.386 **</td>
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<td>(1.075)</td>
<td>(1.812)</td>
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<td>(1.098)</td>
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Table A2 (continued).

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<td>Annual inflation (%)</td>
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<td>[0.651]</td>
<td>0.000</td>
<td>[0.787]</td>
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<td>(0.000)</td>
<td>(0.001)</td>
<td>(0.001)</td>
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<td>AID growth (% of GDP)</td>
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<td>Govt expenditure growth</td>
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<td>* [0.057]</td>
<td>0.353</td>
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<td>(% of GDP)</td>
<td>(0.130)</td>
<td>(0.089)</td>
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<td>constant</td>
<td>3.844</td>
<td>*** [0.002]</td>
<td>4.795</td>
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<td>(1.119)</td>
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* p<0.10, ** p<0.05, *** p<0.01

Note: Standard errors are in parentheses and p values are in brackets.

^1The default lag length - m(T), from Hoechle (2007), is m(T) = floor[4(T/100)^0.5].
Table A3.

*Fixed Effects Regression Results with the Percentage Annual Growth of Agriculture/Services/Industry as the Dependent Variable - Developing Countries*

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<td><strong>(0.809)</strong></td>
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<td><strong>Earthquake</strong></td>
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<td><strong>(0.634)</strong></td>
<td><strong>(0.556)</strong></td>
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<td><strong>Flood</strong></td>
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<td><strong>(2.007)</strong></td>
<td><strong>(2.081)</strong></td>
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Table A3 (continued).

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<th>AID growth (% of GDP&lt;sub&gt;(t-1)&lt;/sub&gt;)</th>
<th>Govt expenditure growth (% of GDP&lt;sub&gt;(t-1)&lt;/sub&gt;)</th>
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<td>***</td>
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* p<0.10, ** p<0.05, *** p<0.01

Note: Standard errors are in parentheses and p values are in brackets.

<sup>1</sup>The default lag length - m(T), from Hoechle (2007), is m(T) = floor[4(T/100)^0.5].
Table A4.

*Fixed Effects Regression Results with the Percentage Annual Growth of Agriculture/Services/Industry as the Dependent Variable - Latin America*

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<td>(0.686)</td>
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<td>(0.700)</td>
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<td>(0.352)</td>
<td>(0.501)</td>
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<td>1.847 **</td>
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<td>(0.819)</td>
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<td>(1.251)</td>
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<td>-0.404</td>
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<td>(0.447)</td>
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<td>0.374 *</td>
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<td>(0.273)</td>
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<td>-0.188 ***</td>
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<td>-0.608 **</td>
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<td>-0.023 ***</td>
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<td>(0.008)</td>
<td>(0.033)</td>
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<td>1.673</td>
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Table A4 (continued).

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<th>Real interest rate (%)</th>
<th>FDI growth (% of GDP$_{(t-1)}$)</th>
<th>AID growth (% of GDP$_{(t-1)}$)</th>
<th>Govt expenditure growth (% of GDP$_{(t-1)}$)</th>
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<td>(0.195)</td>
<td>(0.280)</td>
<td>(0.339)</td>
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<td>0.080</td>
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<td>(0.169)</td>
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<td>0.230 *</td>
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<td>(0.037)</td>
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<td>(.)</td>
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* p<0.10, ** p<0.05, *** p<0.01

Note: Standard errors are in parentheses and $p$ values are in brackets.

$^1$The default lag length - $m(T)$, from Hoechle (2007), is $m(T) = \text{floor}[4(T/100)^{0.5}]$. 

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Table A1.

*Fixed Effects Regression with the Urban-Rural Income Gap (the Ratio of Urban Per Capita Income to Rural Per Capita Income) as the Dependent Variable; Models 7.1 & 7.2*

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<td>(0.05)</td>
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<td>(0.079)</td>
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<td>(0.063)</td>
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<td>(0.175)</td>
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<td>0.001</td>
<td>0.044</td>
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</tr>
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<td>Govt expenditure growth (% of GDP(_{t-1}))</td>
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<td>-1.00</td>
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<td>0.031</td>
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<tr>
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<td>-0.069</td>
<td>0.013</td>
<td>-6.47</td>
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\(^1\)The default lag length - \(m(T)\), from Hoechle (2007), is \(m(T) = \text{floor}[4(T/100)^{0.29}]\)

\(^* \text{p}<0.10, \ ^{**} \text{p}<0.05, \ ^{***} \text{p}<0.01\)

Note: Standard errors are in parentheses and \(p\) values are in brackets.
Table A2.

*Fixed Effects Regression with the Urban-Rural Income Gap (the Ratio of Urban Per Capita Income to Rural Per Capita Income) as the Dependent Variable; Models 7.3 & 7.4*

<table>
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<th>[7.4] severe only</th>
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<tr>
<td>Remittances growth (% of GDP$_{(t-1)}$)</td>
<td>0.056</td>
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<td>AID growth (% of GDP$_{(t-1)}$)</td>
<td>0.028</td>
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<td><strong>Storms X prct deaths</strong></td>
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**Obs.** 156  **Countries** 18  **#Lags** 2  **R-Squared** 0.228 0.377

* p<0.10, ** p<0.05, *** p<0.01

Note: Standard errors are in parentheses and p values are in brackets.

\(^1\)The default lag length - \(m(T)\), from Hoechle (2007), is \(m(T) = \text{floor}(4(T/100)^{0.20})\)
Table A1.

Arellano-Bond Fixed Effects Regression with the Percentage Rural Population as the Dependent Variable and Damages as a Percentage of GDP as the Severity Indicator

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1 Model 8.2 includes the same variables as Model 8.1 with the addition of the income gap variable.
Table A2.

*Arellano-Bond Fixed Effects Regression with the Percentage Rural Population as the Dependent Variable and the Number of Persons Affected as a Percentage of the Total Population as the Severity Indicator*

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| Remittances growth (% of
GDP(t-1))                | -0.010*** | 0.001     | 0.003     | 0.739     |           |
|                          | (0.003)   | (0.009)   |           |           |           |
| FDI growth (% of GDP(t-1))| 0.001     | 0.278     | -0.002    | 0.707     |           |
|                          | (0.001)   | (0.004)   |           |           |           |
| AID growth (% of GDP(t-1))| 0.000     | 0.969     | 0.004     | 0.554     |           |
|                          | (0.002)   | (0.007)   |           |           |           |
Table A2 (continued).

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* p<0.10, ** p<0.05, *** p<0.01

¹ Model 8.4 includes the same variables as Model 8.3 with the addition of the income gap variable.
Table A3.

*Arellano-Bond Fixed Effects Regression with the Percentage Rural Population as the Dependent Variable and the Number of Deaths as a Percentage of the Total Population as the Severity Indicator*

|                  | Model 8.5 |  | Model 8.6\(^1\) |  |
|------------------|-----------|------------------|---------|
|                  | coefficient (std. err.) | p value | coefficient (std. err.) | p value |
| % rural population\((t-1)\) | 0.990 ** 0.000 | 1.007 *** 0.000 |
|                  | (0.001) | (0.003) |
| Drought | 0.030 ** 0.036 | 0.043 ** 0.064 |
|                  | (0.014) | (0.023) |
| Lag 1 | 0.011 0.459 | 0.045 ** 0.071 |
|                  | (0.015) | (0.025) |
| Lag 2 | 0.002 0.912 | 0.014 0.568 |
|                  | (0.015) | (0.024) |
| Lag 3 | -0.003 0.860 | -0.011 0.633 |
|                  | (0.015) | (0.023) |
| Lag 4 | -0.007 0.627 | -0.007 0.764 |
|                  | (0.015) | (0.023) |
| Earthquake | -0.029 ** 0.032 | -0.058 ** 0.045 |
|                  | (0.014) | (0.029) |
| Lag 1 | -0.048 *** 0.000 | -0.041 * 0.153 |
|                  | (0.013) | (0.028) |
| Lag 2 | -0.034 *** 0.007 | 0.013 0.674 |
|                  | (0.013) | (0.030) |
| Lag 3 | -0.041 *** 0.001 | 0.013 0.644 |
|                  | (0.013) | (0.029) |
| Lag 4 | -0.030 ** 0.021 | 0.024 0.422 |
|                  | (0.013) | (0.030) |
| Flood | -0.040 *** 0.000 | -0.082 *** 0.000 |
|                  | (0.010) | (0.019) |
| Lag 1 | -0.059 *** 0.000 | -0.074 *** 0.000 |
|                  | (0.009) | (0.021) |
| Lag 2 | -0.074 *** 0.000 | -0.081 *** 0.000 |
|                  | (0.010) | (0.021) |
| Lag 3 | -0.057 *** 0.000 | -0.077 *** 0.000 |
|                  | (0.009) | (0.020) |
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<td>AID growth (% of GDP_{t-1})</td>
<td>-0.000</td>
<td>0.974</td>
<td>0.006</td>
<td>0.345</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.007)</td>
<td></td>
<td></td>
<td></td>
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</tbody>
</table>

161
Table A3 (continued).

<table>
<thead>
<tr>
<th>Govt expenditure growth (% of GDP$_{(t-1)}$)</th>
<th>0.001</th>
<th>0.554</th>
<th>0.007</th>
<th>**</th>
<th>0.036</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lag 1</td>
<td>(0.001)</td>
<td>(0.004)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Urban-rural income gap</td>
<td>-0.042</td>
<td>0.259</td>
<td>(0.037)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Obs.</th>
<th>775</th>
<th>146</th>
</tr>
</thead>
<tbody>
<tr>
<td>Countries</td>
<td>32</td>
<td>15</td>
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</tbody>
</table>

* p<0.10, ** p<0.05, *** p<0.01

1 Model 8.6 includes the same variables as Model 8.5 with the addition of the income gap variable.
Table A4.

*Arellano-Bond Fixed Effects Regression with the Percentage Rural Population as the Dependent Variable and Severe Disasters Only as the Severity Indicator*

<table>
<thead>
<tr>
<th></th>
<th>Model 8.7</th>
<th></th>
<th></th>
<th>Model 8.8</th>
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<tbody>
<tr>
<td></td>
<td>coefficient</td>
<td>p value</td>
<td>(std. err.)</td>
<td>coefficient</td>
<td>p value</td>
</tr>
<tr>
<td>% rural population(t-1)</td>
<td>0.997 ***</td>
<td>0.000</td>
<td>(0.001)</td>
<td>1.020 ***</td>
<td>0.000</td>
</tr>
<tr>
<td>Severe drought</td>
<td>-0.012</td>
<td>0.630</td>
<td>(0.024)</td>
<td>-0.010</td>
<td>0.833</td>
</tr>
<tr>
<td>Lag 1</td>
<td>0.064 ***</td>
<td>0.011</td>
<td>(0.025)</td>
<td>0.072 **</td>
<td>0.074</td>
</tr>
<tr>
<td>Lag 2</td>
<td>0.022</td>
<td>0.370</td>
<td>(0.025)</td>
<td>0.053 *</td>
<td>0.157</td>
</tr>
<tr>
<td>Lag 3</td>
<td>-0.017</td>
<td>0.463</td>
<td>(0.024)</td>
<td>-0.040</td>
<td>0.243</td>
</tr>
<tr>
<td>Lag 4</td>
<td>-0.065 ***</td>
<td>0.009</td>
<td>(0.025)</td>
<td>-0.139 ***</td>
<td>0.005</td>
</tr>
<tr>
<td>Severe earthquake</td>
<td>0.018</td>
<td>0.461</td>
<td>(0.024)</td>
<td>0.030</td>
<td>0.353</td>
</tr>
<tr>
<td>Lag 1</td>
<td>-0.048 **</td>
<td>0.049</td>
<td>(0.024)</td>
<td>0.060 **</td>
<td>0.096</td>
</tr>
<tr>
<td>Lag 2</td>
<td>-0.040 **</td>
<td>0.077</td>
<td>(0.023)</td>
<td>0.048</td>
<td>0.260</td>
</tr>
<tr>
<td>Lag 3</td>
<td>-0.024</td>
<td>0.282</td>
<td>(0.022)</td>
<td>0.113 ***</td>
<td>0.019</td>
</tr>
<tr>
<td>Lag 4</td>
<td>-0.059 ***</td>
<td>0.009</td>
<td>(0.022)</td>
<td>0.010</td>
<td>0.815</td>
</tr>
<tr>
<td>Severe flood</td>
<td>0.054 ***</td>
<td>0.001</td>
<td>(0.017)</td>
<td>-0.074 ***</td>
<td>0.002</td>
</tr>
<tr>
<td>Lag 1</td>
<td>0.025 *</td>
<td>0.139</td>
<td>(0.017)</td>
<td>-0.063 ***</td>
<td>0.007</td>
</tr>
<tr>
<td>Lag 2</td>
<td>-0.003</td>
<td>0.850</td>
<td>(0.017)</td>
<td>-0.074 ***</td>
<td>0.003</td>
</tr>
<tr>
<td>Lag 3</td>
<td>-0.012</td>
<td>0.488</td>
<td>(0.017)</td>
<td>-0.033</td>
<td>0.212</td>
</tr>
<tr>
<td>Lag 4</td>
<td>0.006</td>
<td>0.739</td>
<td>(0.017)</td>
<td>0.020</td>
<td>0.427</td>
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</table>
Table A4 (continued).

<table>
<thead>
<tr>
<th></th>
<th>Coefficient</th>
<th>Standard Error</th>
<th>Coefficient</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Severe landslide</td>
<td>-0.046</td>
<td>0.150</td>
<td>0.034</td>
<td>0.497</td>
</tr>
<tr>
<td>Lag 1</td>
<td>0.009</td>
<td>0.780</td>
<td>0.056</td>
<td>0.274</td>
</tr>
<tr>
<td>Lag 2</td>
<td>0.010</td>
<td>0.747</td>
<td>0.018</td>
<td>0.762</td>
</tr>
<tr>
<td>Lag 3</td>
<td>-0.002</td>
<td>0.959</td>
<td>-0.119</td>
<td>** 0.044</td>
</tr>
<tr>
<td>Lag 4</td>
<td>0.022</td>
<td>0.539</td>
<td>-0.017</td>
<td>0.717</td>
</tr>
<tr>
<td>Severe storm</td>
<td>-0.030</td>
<td>** 0.039</td>
<td>0.041</td>
<td>* 0.135</td>
</tr>
<tr>
<td>Lag 1</td>
<td>-0.034</td>
<td>*** 0.014</td>
<td>0.019</td>
<td>0.439</td>
</tr>
<tr>
<td>Lag 2</td>
<td>-0.005</td>
<td>0.692</td>
<td>0.047</td>
<td>** 0.070</td>
</tr>
<tr>
<td>Lag 3</td>
<td>-0.016</td>
<td>0.250</td>
<td>0.050</td>
<td>** 0.049</td>
</tr>
<tr>
<td>Lag 4</td>
<td>-0.043</td>
<td>*** 0.002</td>
<td>0.032</td>
<td>0.305</td>
</tr>
<tr>
<td>Severe volcano</td>
<td>0.161</td>
<td>*** 0.000</td>
<td>0.064</td>
<td>0.232</td>
</tr>
<tr>
<td>Lag 1</td>
<td>0.152</td>
<td>*** 0.000</td>
<td>-0.018</td>
<td>0.728</td>
</tr>
<tr>
<td>Lag 2</td>
<td>0.136</td>
<td>*** 0.000</td>
<td>0.008</td>
<td>0.872</td>
</tr>
<tr>
<td>Lag 3</td>
<td>0.040</td>
<td>0.269</td>
<td>-0.136</td>
<td>*** 0.003</td>
</tr>
<tr>
<td>Lag 4</td>
<td>0.035</td>
<td>0.348</td>
<td>-0.028</td>
<td>0.517</td>
</tr>
<tr>
<td>Severe wildfire</td>
<td>-0.062</td>
<td>0.352</td>
<td>0.024</td>
<td>0.757</td>
</tr>
<tr>
<td>Lag 1</td>
<td>-0.050</td>
<td>0.446</td>
<td>-0.049</td>
<td>0.604</td>
</tr>
<tr>
<td>Lag 2</td>
<td>0.015</td>
<td>0.817</td>
<td>0.000</td>
<td>.</td>
</tr>
<tr>
<td>Lag 3</td>
<td>-0.001</td>
<td>0.986</td>
<td>-0.036</td>
<td>0.677</td>
</tr>
<tr>
<td>Lag 4</td>
<td>0.036</td>
<td>0.606</td>
<td>-0.069</td>
<td>0.382</td>
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</tbody>
</table>

164
Table A4 (continued).

<table>
<thead>
<tr>
<th>Remittances growth (% of GDP(_{(t-1)}))</th>
<th>-0.005 **</th>
<th>0.052</th>
<th>0.013 *</th>
<th>0.103</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lag 1</td>
<td>(0.003)</td>
<td>(0.008)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>FDI growth (% of GDP(_{(t-1)}))</td>
<td>0.000</td>
<td>0.592</td>
<td>-0.002</td>
<td>0.529</td>
</tr>
<tr>
<td>Lag 1</td>
<td>(0.001)</td>
<td>(0.003)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AID growth (% of GDP(_{(t-1)}))</td>
<td>-0.004 ***</td>
<td>0.003</td>
<td>0.006</td>
<td>0.277</td>
</tr>
<tr>
<td>Lag 1</td>
<td>(0.001)</td>
<td>(0.005)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Govt expenditure growth (% of GDP(_{(t-1)}))</td>
<td>0.001</td>
<td>0.390</td>
<td>0.005 **</td>
<td>0.044</td>
</tr>
<tr>
<td>Lag 1</td>
<td>(0.001)</td>
<td>(0.002)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Urban-rural income gap</td>
<td>-0.092 ***</td>
<td>0.001</td>
<td>(0.029)</td>
<td></td>
</tr>
</tbody>
</table>

| Obs. | 755 | 145 |
| Countries | 32 | 15 |

* p<0.10, ** p<0.05, *** p<0.01

1 Model only includes disasters with damages as a percentage of GDP that exceed the severity threshold of 0.45588% of GDP.

2 Model 8.8 includes the same variables as Model 8.7 with the addition of the urban-rural income gap variable.
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—. 2016b. *Industry, value added (annual % growth).*


—. 2016c. *Services, etc., value added (annual % growth).*


World Bank, Sustainable Development Network, Global Facility for Disaster Reduction and Recovery Unit.


