Master's Thesis - International Economics

The Effect of Climate Change on Migration - Predictions for the Twenty-First Century

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Abstract

In this thesis, the effect of climate change on migration is analyzed with the use of a pseudo-gravity model. First, the relationship between migration and precipitation anomalies, temperature anomalies, natural disasters, and sea level rise is discussed. Then, a simulation is used to predict the average bilateral migration rate for the period 2046 to 2065 and the period 2081 to 2100. In this thesis, it is found that climate change has a heterogeneous effect on migration. On the one hand, precipitation anomalies have a positive effect on migration while on the other hand temperature anomalies and natural disasters have a negative effect on migration. However, this relationship is different for certain groups of countries depending on their temperature and groundwater level. With the use of the simulation, it is predicted that the average bilateral migration rate will decrease in the remainder of the twenty-first century if no mitigation and adaption take place. When there is climate change mitigation and adaption, the average bilateral migration rate is expected to increase.

Contents

1 Introduction

In The Global Risks Report 2018, from the World Economic Forum 1000 experts and decision-makers have listed the ten risks that will have the biggest impact on the world in the next 10 years. Eight of the ten listed risks are fueled by climate change. Extreme weather events, natural disasters and large-scale involuntary migration are on the list (World Economic Forum, 2018). We live in a world that is on the verge of a large climate change that will affect life as we know today. In December 2018 world leaders have gathered in Marrakesh to adopt the UN Global Compact for migration. In this compact climate change is mentioned as one of the underlying factors that causes migration. However, some developed countries have blocked the compact. They fear that migration will further increase as a result (United Nations, 2018b). In 2018 the European Parliament has held a briefing in which they acknowledge that climate change can cause migration (European Parliament, 2018). Moreover, this summer ministers from over twenty countries, including Sweden, Kazakhstan, the United Kingdom, and Peru, have addressed the UN Security Council upon the consequences of climate change. Hassan al-Janabi, Minister of Water Resources of Iraq, stated during this meeting that water is becoming scarcer and food insecurity is increasing in the region. In combination with the destruction brought about by the Islamic State, this ‘drives displaced persons and migrants to desperately seek better lives around the world´ (United Nations, 2018a).

In an age where it is necessary to multilaterally combat climate change and regulate migration, sometimes the causal relationship between climate change and migration seems to be overleaped by governments and organizations. In this thesis, I shed light on the connection between climate change and international migration with the use of a pseudo-gravity model. Further, I make predictions about the future bilateral migration rate with the use of a simulation.

As proxies for climate change, I use variables for precipitation anomalies, temperature anomalies, natural disasters, and sea level rise. To my knowledge, no comparable economic analysis has included the effect of the sea level rise yet. Further, a quadratic term for precipitation anomalies and temperature anomalies is used in contrast to existing literature. Overall, I find that climate change has an effect on migration. However, this effect is not homogeneous among the different climate change variables. I find a positive relationship between precipitation anomalies and the bilateral migration rate, but a negative relationship between the variables for temperature anomalies and natural disasters and the bilateral migration rate. The found effect is different for Least Developed Countries (LDCs) and Middle Income Countries (MICs). Further, climate change has a different effect on migration for countries with low groundwater, agricultural countries and countries with a warm climate.

The estimated coefficients from the pseudo-gravity model are used in combination with the climate change forecasts from the IPCC Fifth Assessment Report to simulate the bilateral migration rate for the period 2046 to 2065 and the period 2081 to 2100. Depending on the level of mitigation and adaption, I conclude that the bilateral migration rate is likely to decrease or increase in the remainder of the twenty-first century. In a situation in which there is no climate change mitigation and adaption, the average bilateral migration rate is expected to decrease. In a situation in which there is mitigation and adaption the average migration rate is expected to increase for the period 2081 to 2100. However, what the effect will be on migration itself depends on population growth.

The remainder of this thesis is structured as follows. First, climate change and its effects are described in section 2. In section 3 literature on the topic of climate change and migration is discussed. In section 4 the neoclassical utility maximization approach is set out in relation to the model used in this thesis. Then, in section 5 the data and its limitations are described. In section 6 and section 8 the methodology of the pseudo-gravity model and the simulation are discussed respectively. In section 7 and section 9 the results are given. In section 10 I elaborate on the limitations of the model and assumptions used for this thesis. Lastly, I conclude in section 11.

2 Climate Change

This section focuses on climate change. In the first subsection, climate change is defined. Then I touch briefly upon the IPCC Fifth Assessment Report in subsection 2.2. In the following subsections, the largest consequences of climate change are discussed. The effect of climate change on temperature, precipitation, natural disasters and sea level are described in subsection 2.4, 2.3, 2.5 and 2.6 respectively. Further, I elaborate on the largest risks for humans that are caused by climate change in subsection 2.7. The consequences of climate change discussed in this section are used as indicators for climate change in the pseudo-gravity model in section 6 and the climate change predictions are used for the simulation in section 8.

2.1 Definition Climate Change

In the last century, we have seen that the average global temperature is rising. Since the industrial revolution, the global temperature has increased by one degree Celsius. In the last years, this rise has been even steadier. Arctic ice is melting and oceans are warming up. Droughts become more severe and natural disasters seem to happen more often; the climate is changing (Keller & DeVecchio, 2012; IPCC, 2013). As a consequence climate change is literally and figuratively a 'hot topic'.

Climate change is not something new, the climate on earth has always been prone to change. The earth has encountered temperatures that are much higher than we face today, but there have also been periods that were much colder during which planet was completely covered in ice. However, this is the first time in history that the change in climate has been brought about by us, humans (Berlemann & Steinhardt, 2017).

Since the industrial revolution humankind has been emitting greenhouse gasses in the atmosphere. At the moment we have the highest level of carbon dioxide (CO_2) in 400,000 years. The planet has experienced ice ages and warmer periods, but the level of CO_2 in the atmosphere has always varied between 180 ppm and 280 ppm. In 2013 the level of carbon dioxide reached 400 ppm, which can have enormous impacts on life on this planet as we know today (NASA, 2013).

The Intergovernmental Panel on Climate Change (IPCC), that was set up by the World Meteorological Organization and the United Nations Environment Program, has published the Fifth Assessment Report in 2013 (IPCC, 2013). In this report, the effects of climate change are described with the help of important scientists from the 195 member states that are part of the Panel. This report is aimed to provide information for climate negotiations and climate policies. In this thesis, I use the information from the IPCC Fifth Assessment Report.

2.2 Structure Fifth Assessment Report

In the Fifth Assessment Report, four different greenhouse gas emission scenarios are calculated: the Representative Concentration Pathways (RCPs). The RCP 2.6 scenario is the scenario in which least CO2 is omitted the upcoming century. This scenario is only possible when the worldwide greenhouse gas emission is drastically reduced. The RCP 8.5 is the most severe scenario, which can become reality if countries do not succeed in decreasing CO2 emissions. In all calculated scenarios, climate will change. The magnitude in which the climate changes, however, differs. In this thesis, I use RCP 2.6 and RCP 8.5 to show the effect of climate change in the mildest and most severe scenario.

2.3 Temperature

One of the most obvious effects of climate change is the rise in the global mean temperature. For that reason, climate change is often referred to as 'global warming'. Due to an increase in greenhouse gasses, warmth cannot escape the atmosphere as easily as before. This causes the temperature on our planet to increase.

Like most consequences of climate change, temperature does not increase evenly across regions. In the period 1983 to 2012, which was likely the warmest period in 1400 years, especially the surface temperature of South America, the North Pole and Russia increased (IPCC, 2013). In the twenty-first century, the temperature in the arctic regions will proportionally increase more than the rest of the world. In Appendix A.2 the expected temperature change for the remainder of the twenty-first century is shown for RCP 2.6 and in Appendix A.3 it is shown for RCP 8.5 per country.

2.4 Precipitation

Climate change will also have an effect on precipitation. The increase in temperature has an effect on the amount of moisture that is present in the atmosphere. The Clausius-Clapeyron relationship indicates that a one-degree temperature increase will increase the amount of moisture present in the atmosphere by 7 percent (Rummukainen, 2012). Hence, an increase in temperature will cause global precipitation to increase.

However, this increase will not be uniformly distributed across the planet. Some regions, such as the mid-latitude and subtropical dry regions will experience lower levels of precipitation while other regions such as mid-latitude wet regions, high-latitude regions, and the equatorial Pacific will face larger levels of precipitation (IPCC, 2013). In Appendix A.4 and Appendix A.5 the effect on precipitation can be seen for the two different models as predicted in the Fifth Assessment Report.

The precipitation that will fall, will be more often of extreme proportions. These heavy precipitation events can cause floods and landslides. Furthermore, since the water will be running very fast, it gets a smaller chance to moisture the soil than rain that has gradually fallen. So even larger amounts of water can lead to lower groundwater levels (Rummukainen, 2012; IPCC, 2013). Erosion of the soil is a likely consequence.

2.5 Natural Disasters

Especially weather extremes and natural disasters can be very disruptive for countries and the nature within these countries. Almost all types of weather extremes will experience an increase in magnitude and frequency. Also, natural disasters are more likely to happen. This increase is already happening at the moment, between 1951 and 2003 an increase in heavy precipitation events was observed (Zhang, Zwiers, & Hegerl, 2011). In the Mediterranean region drought has increased (Hoerling, Eischeid, Perlwitz, Zhang, & Perion, 2011) and more heatwaves were observed in Europe, Asia, and Australia (IPCC, 2013).

As previously mentioned, climate change increases the chance of heatwaves. The heatwaves that will occur will also be more intense and last longer. In areas with lower groundwater levels and less precipitation, there will be more droughts. Africa, the Mediterranean region, parts of America, Australia and Southeastern Asia will experience more droughts. As a result, the risk of wildfires will increase in multiple regions in the world (Rummukainen, 2012; Liu, Stanturf, & Goodrick, 2009).

Climate change can also have an effect on volcanic activity, earthquakes, and tsunamis. Kutterolf *et al.* (2013) found that during the last ice age less volcanic activity took place. Now, as arctic ice is melting, the Antarctic Plate and the North American Plate will become lighter. Consequently, the tectonic plates are more likely to move. This will increase the chance of earthquakes and volcanic activity. Tsunamis are caused by earthquakes on the bottom of the ocean, which makes them more likely to happen as well (Kutterolf et al., 2013).

As there will be more precipitation extremes, there is a higher risk of floods. Sudden extreme high sea levels will occur more often (IPCC, 2013). The only type of natural disasters of which the effect of global warming is unknown is hurricanes and typhoons. There is no proof that climate change will increase the amount of tropical and extratropical storms yet. However, these storms are likely to be more intense (Rummukainen, 2012).

2.6 Sea Level

One of the most important effects of climate change is the increase in sea level. Due to increasing temperatures, there will be more water in the oceans as a result of melting glaciers and land ice sheets. While, the water in the oceans will also expand because of the higher temperatures (IPCC, 2013). Both will cause the sea level to be higher in future.

The global mean ocean level has been rising 2 millimeter per year between 1971 and 2010. Between 1993 and 2010 the rise has even been 3.2 millimeter per year. The sea level increase in 2081 to 2100 for the RCP 2.6 scenario is likely to be between 0.26 and 0.55 meter and for the RCP 8.5 scenario, the increase is between 0.52 and 0.98 meter (IPCC, 2013). In Appendix A.1 the predicted sea level rise between 2000 and 2100 is visualized.

2.7 Largest Risks for Humans

The IPCC Fifth Assessment Report reports eight key risks that follow from the consequences of climate change as explained above (IPCC, 2014b). All identified risks have an influence on the quality of life in the affected regions. Therefore, they might all influence migration. The first risk is associated with the rising sea level. As the global average sea level will be rising, coastal areas that are low-lying will be at great risk. Roughly 2 percent of the total land is less than 10 meters above sea level, what makes these areas vulnerable to sea-related consequences of climate change. It is common that such areas are densely populated, as many cities have emerged near the sea. This has resulted in over 10 percent of the world population living in these areas. In LDCs even more people are living in vulnerable areas: 14 percent of the population is living in areas which are less than 10 meters above sea level (McGranahan, Balk, & Anderson, 2007). Not only storm surges and floods can destroy houses and injure people living in these areas, but also the gradual rising of sea level can force people to migrate if there are not enough measures taken. Especially small developing countries and islands are at risk since they have a lower ability to protect themselves against the growing forces of the sea (IPCC, 2014b).

Not only people living close to the sea will experience increased risks, but urban populations will face an increased risk of flooding as well. Inland flooding is the second key risk listed by the IPCC. Inland flooding is more likely to happen as a result of more extreme precipitation events. Rivers might not have enough capacity to deal with sudden amounts of water. This will result in floods. As some rivers are dirty and might contain waterborne illnesses, and vector-borne diseases are also prone to spread as insects lay eggs in stagnant water, affected people face health risks (McMichael, Barnett, & McMichael, 2012). Moreover, houses, infrastructure, and other fatal services can be seriously damaged as a result (IPCC, 2014b).

The third risk that the IPCC (2014b) has addressed is the systematic risk to infrastructure and critical services that is caused by natural disasters and extreme weather events. Floods, earthquakes and more intense hurricanes can damage vital services such as access to food and water, hospitals and electricity. Also, when infrastructure is damaged, it is harder to rebuild vital services and to deal with new weather extremes.

The fourth risk identified by the IPCC (2014b) is the effect of temperature anomalies on human health. Especially long periods of high temperature can be dangerous. For example, there was an exceptionally long heatwave in Europe in 2003 that resulted in 20,000 to 70,000 deaths (Russo, Sillmann, & Fischer, 2015). In countries with even higher temperatures, the effect might be more extreme. People that are vulnerable or working outdoors might face serious health risks. Some outdoor activities will already become impossible during the hot season in certain areas in the world this century (IPCC, 2013).

One of the most important consequences of global warming is the effect on food security. As fifth, sixth, seventh and eighth risk the IPCC (2014b) has listed the four different aspects of food security that come under pressure as a result of climate change. Climate change has a large impact on agriculture because crop yields decrease when temperatures increase. Droughts can be very destructive for crops. Poor areas and countries are at the largest risk because they depend more on agriculture (Marchiori, Maystadt, & Schumacher, 2012). Furthermore, life in the sea will be harmed as a result of ocean acidification and higher temperatures. Also, inland water ecosystems are at risk. Populations that rely on these ecosystems because they live from fishing or other water-related activities are likely to be harmed.

Furthermore, it is possible that climate change can cause conflicts. For example, Raleigh and Urdal (2007) find that water scarcity can increase the number of conflicts in a region, but the effect is small compared to the effect of political and economic factors on conflicts. Barnett and Adger (2007) argue that regions that are greatly dependent on agriculture will become poorer, which makes people living in the areas more tempted to join rebel movements. This, in turn, can increase conflicts. However, as Nordås and Gleditsch (2007) point out, the evidence on the link between climate change and conflict is scarce, mixed and often based on articles that are not peer-reviewed. Although the evidence is mixed on whether climate change causes conflicts at the country of origin, Cattaneo and Bosetti (2017) find that climate-induced migration does not cause conflicts and wars in the country of destination.

3 Literature Review

3.1 Research on Climate Change and Migration

Ever since more articles about climate change were published, the literature about its effect on migration has been gradually growing (Piguet, 2010). Although there exists extensive literature about the relationship between the different aspects of climate change on migration, due to the wide variety of approaches, no consensus about the relationship has been found yet.

In literature there exist two main types of approaches. Authors either write a descriptive and prospective paper in which they address the most vulnerable regions to climate change and thereby predict future migration flows. The other type of approach analyzes past migration flows in relation to one or more factors linked to climate change (Piguet, 2010). In this thesis, I combine the two.

The two approaches can be divided into six different types of research; ecological inference based on area characteristics, individual sample surveys, time series, multilevel analysis, agent-based modeling and qualitative methods. For many years, the main focus has been on qualitative methods. For these studies, the effect of climate change on migration in a particular area is investigated. Mainly interviews and questionnaires are used to determine the relationship (Piguet, 2010). Although extensive research has been done, the results of these qualitative methods are mixed. For example, Feng *et al.* (2010) find that reduced crop yields caused migration from Mexico to the United States, but Mortreux and Barnett (2009) find that the decision to migrate in Tuvalu is not influenced by climate change.

3.2 Aggregate Economic Analysis: Agriculture Intermediate Factor

In the last 10 years, authors have come up with a more aggregate economic analysis on the connection between migration and climate change. The article written by Reuveny and Moore (2009) was one of the first that approached this relationship extensively. The authors analyze migration to 15 OECD countries. As variable for climate change, they not only use the number of natural disasters but also the amount of land farmed with crops and the amount of arable land as proxies for the environmental circumstances. Reuveny and Moore find that natural disasters and a decreasing environment have a positive impact on migration towards the OECD countries.

Marchiori, Maystadt and Schumacher (2012) stress the importance of using agriculture as an intermediate factor between climate change and migration. They explain the effect of climate change with the use of two channels: the amenity channel and the economic geography channel. Climate change in the form of natural disasters and more extreme weather events can cause an increase in diseases or even cause a higher mortality in the affected areas. Consequently, the utility of staying in the country of origin decreases when this happens. Marchiori *et al.* (2012) find evidence that people in sub-Saharan Africa are more likely to migrate as a result of this so-called amenity channel.

Moreover, Marchiori *et al.* (2012) distinguish the economic geography channel. Global warming decreases agricultural productivity. Due to more irregular weather, higher temperatures and more disasters it is harder to grow crops and to do outside work (IPCC, 2014b). Agricultural countries experience a relatively large effect of climate change because their economy depends to a large extent on it. When agricultural productivity falls as a consequence of climate change, people are likely to move from rural areas to urban areas in order to have a higher income. The increased flow of internal migrants to cities has a downward pressure on wages in the cities. The wage gap between countries that are more dependent on agriculture and countries that are less dependent on agriculture widened and people in agricultural countries are more likely to migrate as a result.

Cai *et al.* (2016) elaborate on the effect of climate change on agriculture. They compare the effect of climate change on migration for countries that are largely dependent on agriculture and countries that are not. Indeed, they find that high temperatures only have an effect on out-migration in agricultural countries. The results suggest that the geography economy channel described by Marchiori *et al.* (2012) exists.

3.3 Aggregate Economic Analysis: Gravity Model

One of the most extensive economic analyses on climate change induced migration has been done by Beine and Parsons (2015). In their paper, they use the neo-classical utility maximization framework in which the individual maximizes its utility when it can choose between different options. The (possible) migrant can either stay in its home country or move to all possible other countries in the world. The individual's utility differs per country and is dependent on climate factors. A country that encounters the harsh consequences of climate change gives the individual a lower utility. However, when the individual decides to move, migration costs have to be made. It is possible that individuals endure climate change effects and do not migrate because of the high migration costs.

To investigate empirical data, Beine and Parsons use a pseudo-gravity model. For this model, they use data on migration for 166 destination countries and 137 origin countries between 1960 and 2000. Beine and Parsons split the effect of climate change into short-run factors and long-run factors. The independent variable that captures short-run climate factor is the number of natural disasters that have taken place in a given decennial. For the long-run climate factors, the independent variables temperature anomalies and precipitation anomalies are used. Furthermore, to capture the factors that influence migration as thorough as possible, an extensive set of control variables is used. For example, distance, linguistic proximity, and contiguity are used as proxies for migration costs. To capture the push and pull effects that partly determine the migrant's utility, variables for the wage differential, the demographic conditions and political stability are used.

Beine and Parsons (2015) do not find that the climate factors have a significant impact on migration directly. However, they explain that climate change can have an indirect impact on migration. Natural disasters, temperature anomalies, and precipitation anomalies can increase the wage differential between two countries. The country that undergoes more extreme consequences of climate change, has a higher pressure on wages compared to countries that are mildly affected by climate change. This widens the wage gap between the two countries, which in turn makes migration to the mildly affected country more favorable. The indirect effect is captured by the wage differential variable instead of the climate variables.

Backhaus *et al.* (2015) also use a gravity model based on neo-classical utility maximization theory. Like Beine and Parsons (2015), Backhaus *et al.* control for economic and demographic factors. Further, they have included different cultural controls and the trade-to-GDP share. Also, they use precipitation and temperature data instead of anomalies. The data used by Backhaus *et al.* further differs, since now 142 countries are identified as countries of origin and 19 OECD countries are identified as destination countries. Data on migration between 1995 and 2006 is used.

The results found are considerably different. Backhaus *et al.* (2015) find that an increase in temperature has a positive effect on migration to OECD countries. An increase in precipitation has a positive, but smaller effect on migration as well. The authors explain that this can be caused by the agricultural channel. When they split the countries of origin into agricultural and non-agricultural countries, they find that migration in agricultural countries is positively related to higher temperatures. For non-agricultural countries, no significant relationship is found.

In their article Cattaneo and Peri (2016) criticize the methods used by Beine and Parsons (2015) and Backhaus (2015). Cattaneo and Peri explain that the inclusion of control variables for productivity and income wipe out the direct effect of climate change since the part of the effect is captured by the control variables. Instead, Cattaneo and Peri do control for factors that can also be influenced by climate change. Furthermore, Cattaneo and Peri (2016) make an important distinction between LDCs and MICs as they argue that the effect might be different for the two types of countries. As the income in LDCs countries is very low, some people living there might face liquidity constraints. The constraints prevent the inhabitants of poor countries from migrating. Climate change can intensify the liquidity constraints in poor countries, which makes people less likely to migrate. A different climate change effect is expected in MICs because overall people have a higher income. Firstly, people in MICs are more likely to move to urban areas when climate change effects increase. As explained in Marchiori *et al.* (2012) this will result in an increase in out-migration as well.

As a reaction, Beine and Parsons (2017) have extended their previous model by also making a distinction between low and medium income countries. Additionally, they have removed the control variables to find the net partial effect of climate factors. This is possible since fixed effects are included. As expected, they also find that climate change has a different effect on LDCs than on MICs. For the LDCs, no significant relationship between the climate factors and migration is found. Surprisingly, for the MICs, a negative relationship is found.

To further explore the patterns of migration, Beine and Parsons (2017) include dummies for different characteristics concerning the origin-destination country pairs. A dummy for contiguity and a dummy for colonial links are included. When this is done, the authors find that natural disasters have a negative effect on migration. However, natural disasters do spur migration to countries that share a border for both poor and MICs. Likewise, they also find that natural disasters increase migration to former colonial powers.

Gröschl and Steinwachs (2017) elaborate on Beine and Parsons (2015) and Beine and Parsons (2017) by making a distinction between different types of natural disasters. The authors find that the effect of natural disasters on migration is heterogeneous between the different types of natural disasters and between the different types of countries. The most important result they find is that for MICs natural hazards have a positive push and a negative pull effect.

Coniglio and Pesce (2015) also look at the effect of different types of climatic shocks on migration. By differentiating between different types, sizes, signs and seasonal occurrence of the shock, they extensively sketch the heterogeneous effects. Precipitation, for example, has very different effects depending on the situation. Precipitation variability can increase migration towards OECD countries, but the effect of a rain shortage has a smaller magnitude than the effect of excess rainfall. The authors also find that lower temperatures cause people to migrate, but this effect is larger during the rainy season.

The described literature shows that the effect of climate change depends largely on the circumstances and type of analysis. The effect of climate change is different for a country depending on its dependency on agriculture, its income level, the timing and on the type or even subtype of climate change factor. Therefore, it is difficult to determine what the effect of climate change will be. With this thesis, I shed some more light on this difficult topic. The literature described usually only takes into account certain aspects of climate change, namely temperature, precipitation, and natural disasters, or a combination of the different aspects.

4 Theoretical Framework

In this thesis I conduct both the analysis as in Beine and Parsons (2015) and in Beine and Parsons (2017). In the first model, the migration decision is illustrated in detail with the use of many explanatory variables. I have added two variations of the model compared to Beine and Parsons (2015): a model with a factor for mitigation and a two-period model. As Cattaneo and Peri (2016) pointed out, some of the climate change effects are absorbed by the variable for the wage differential. Therefore, I conduct the parsimonious analysis as in Beine and Parsons (2017). The theory behind the first model is described in the first part of this paragraph. The theory behind the second model is described in the second part of this paragraph.

4.1 Neoclassical Utility Maximization Approach

4.1.1 Original Model

The main theory used to explain the relationship between migration and climate change on the aggregate level is the neoclassical utility maximization theory (Beine & Parsons, 2015; Backhaus et al., 2015; Reuveny & Moore, 2009; Coniglio & Pesce, 2015).

A homogeneous individual living in country i maximizes it utility at time t. Hereby, the individual can choose to stay in its country of origin, country i, or the individual can choose to migrate to every other country in the world. When the individual chooses to migrate, it has to encounter migration costs C.

Utility depends on the income that is received by the individual. As is shown by Grogger and Hanson (2011) and Beine *et al.* (2011), the difference in wages can determine what type of individual will migrate. Thus, the difference in income between countries is an important determinant of the migration choice. Furthermore, utility depends on the characteristics of the country where the individual is living in. Some characteristics can be seen as push factors, such as political instability and environmental degradation (Reuveny & Moore, 2009). Other factors can be seen as pull factors such as a high wages and a comfortable climate.

As in Parsons and Beine (2015) the utility derived from the income in country i is log-linear. Hence, the utility function of an individual that does not migrate can be written as:

$$U_{ii,t} = ln(w_{i,t}) + A_{i,t} + \epsilon_{i,t} \tag{1}$$

Here w are the wages in country i at time t. A captures the country specific characteristics of the country of origin at time t. ϵ is the extreme value term which is independent and identically distributed.

When the individual decides to migrate from its country of origin to another country, the utility function can be written as:

$$U_{ij,t} = ln(w_{j,t}) + A_{j,t} - C_{i,t}(.) + \epsilon_{i,t} \tag{2}$$

Here w are the wages in country j at time t. A captures the country specific characteristics of the destination country at time t. Again, ϵ is the extreme value term which is independent and identically distributed. The individual now also has to move, so $C_{i,t}(.)$ is the function of the migration costs that the individual faces at time t when it moves from country of origin i to country of destination j (Beine & Parsons, 2015).

The number of people that decides to stay in country i is expressed by $N_{i,t}$. $N_{i,t}$ is found by subtracting by all migrants from other countries from the population size of country i. $N_{ij,t}$ is the number of people that decides to migrate to country j (Beine & Parsons, 2015).

Now the bilateral migration rate can be expressed as the following (McFadden, 1984):

$$\frac{N_{ij,t}}{N_{ii,t}} = \frac{exp[w_{j,t} + A_{j,t} - C_{ij,t}]}{exp[w_{i,t} + A_{i,t}]} \tag{3}$$

When this is expressed in logs:

$$ln(\frac{N_{ij,t}}{N_{ii,t}}) = ln(\frac{w_{j,t}}{w_{i,t}}) + (A_j - A_i) - C_{ij,t}(.) \tag{4}$$

Expression 4 shows that the bilateral migration rate depends on the wage differential $\frac{w_{i,t}}{w_{j,t}}$, the country specific characteristics of the country of origin $A_{i,t}$ and the destination country $A_{j,t}$. Also the migration costs $C_{ij}(.)$ determine the bilateral migration rate (Beine & Parsons, 2015).

Migration costs express how easy it is to migrate from country i to country j at time t. The migration costs are different for every country pair and depend on different independent components that vary over time. The formula of the migration costs can be given by:

$$C_{ij,t} = c(M_{ij,t}, d_{ij}, b_{ij}, l_{ij}, x_i, x_j, x_t, x_{j,t}) \tag{5}$$

As can be seen from expression 5, the migration costs are influenced by a large amount of factors. The first factor that plays a role in migration costs is $M_{ij,t}$, which is the migration network. The variable captures the amount of people from country i that are already living in country j. If there is already a large diaspora in country j, the costs to migrate are lower (Beine et al., 2011).

The second and third factor that have an influence on the migration costs are the distance between country i and j and whether they share a common border, indicated by d_{ij} and b_{ij} respectively. The fourth variable to determine migration costs is l_{ij}, the linguistic proximity between the two countries. The dummy indicates whether more than 9 percent of the inhabitants of country j speak the same language as the inhabitants of country i.

Moreover, there are costs related to the countries inquired. Country specific costs for the country of origin, country i, are denoted by x_i and for the country of destination, country j, are denoted by x_j. There are also costs associated with moving to country j that change over time. These costs are expressed by $x_{j,t}$. Not only the costs from moving to country j vary over time, on the world level migration costs are varying over time as well due to technological change and political preferences. Therefore, time fixed effects are also included in the formula, denoted by x_t.

The bilateral migration rate is also determined by the characteristics of country i, $A_{i,t}$ and the characteristics of country j, $A_{j,t}$. The formulas are given by:

$$A_{i,t} = A(P_{i,t}, Dp_{i,t}, E_{i,t}, H_{i,t}) \tag{6}$$

As can be seen in expression 6, the country specific characteristics also depend on a subset of variables. The factors that determine $A_{i,t}$ and $A_{i,t}$ can be considered as push and pull factors that influence the pleasantness of living in country i.

$P_{i,t}$, denoting political stability, is the first variable to be a push or pull factor. Countries that are politically unstable are likely dealing with a lot of out-migration. The second factor that influences the pleasantness of living in a country is, $Dp_{i,t}$, which is the dependency rate of country i. The dependency rate stands for the population living in country i aged under 15 or above 64 divided by the size of the working age population. If the dependency rate is high, it means that there are a lot of young (or old) people living in a country compared to those of working age. The people that are working, therefore, have to bear a higher burden compared to people living in a country with a lower dependency rate. Also, the dependency rate is a proxy for the number of young people in a country. A country with a lot of young inhabitants might see more out-migration because young people are more likely to relocate. Thus, a high dependency rate can be seen as a factor to deter migration or to spur migration.

Most important for this thesis, the bilateral migration rate is depending on environmental factors as well. Beine and Parsons (2015) make a distinction between long-run climatic factors and short-run climatic factors. The climate change factors that are long-lived by the inhabitants of country i are denoted by $E_{i,t}$. These are factors that can be foreseen and will structurally incur, such as changes in temperature, precipitation, and sea-level. There are also climate change factors that have an impact for a shorter time, these are denoted by $H_{i,t}$. Natural disasters belong to this category, as they occur less often and are often unforeseen.

$A_{j,t}$ is influenced by the same factors as $A_{i,t}$ because the individual takes the difference in living conditions into consideration when he decides to move. Only when the individual is better off after migration, the individual is likely to move to another country.

4.1.2 Two-Period Model

To determine whether people adjust their behaviour to climate change predictions, a two-period model that builds on the previous model is used. Now the individual derives its utility from wage and country specific characteristics in two periods. The two-period model has the following underlying assumptions:

- The individual looks ahead one period.
- The individual has no time preference.
- The individual can only migrate in the first period.
- All variables except $E_{i,t}$ and $H_{i,t}$ stay constant over the two periods.
- The individual expects all variables except $E_{i,t}$ and $H_{i,t}$ to stay constant over the two periods.
- Migration costs only occur in the first period.

When an individual decides not to migrate, the utility function now is:

$$U_{ii,t} = ln(w_{i,t}) + ln(E[w_{i,t+1}]) + A_{i,t} + E[A_{i,t+1}]\epsilon_{i,t} \tag{7}$$

Here $E[w_{i,t+1}]$ is the individual's expected wage at time $t+1$ in country i. $E[A_{i,t+1}]$ stands for the expected country specific characteristics in country i at time $t+1$. Climate change is captured by this variable.
When the individual decides to migrate, the utility function becomes:

$$U_{ij,t} = ln(w_{j,t}) + ln(E[w_{j,t+1}]) + A_{j,t} + E[A_{j,t+1}] - C_{i,t}(.) + \epsilon_{i,t} \tag{8}$$

Here $ln(E[w_{j,t+1}])$ stand for individual's expected wage at time $t+1$ in country j. $E[A_{j,t+1}]$ is equal to the expected country specific characteristics in country j at time $t+1$.

Now the bilateral rate can be expressed as the following:

$$\frac{N_{ij,t}}{N_{ii,t}} = \frac{exp[w_{j,t} + E[w_{j,t+1}]) + A_{j,t} - E[A_{j,t+1}] - C_{ij,t}]}{exp[w_{i,t} + E[w_{i,t+1}] + A_{i,t} + E[A_{i,t+1}]]} \tag{9}$$

When this is expressed in logs:

$$ln(\frac{N_{ij,t}}{N_{ii,t}}) = ln(\frac{w_{j,t}}{w_{i,t}}) + ln(\frac{E[w_{j,t+1}]}{E[w_{i,t+1}]}) + (A_{j,t} - A_{i,t}) + (E[A_{j,t+1}] - E[A_{i,t+1}]) - C_{ij,t}(.) \tag{10}$$

In the second period the function becomes:

$$ln(\frac{N_{ij,t+1}}{N_{ii,t+1}}) = ln(\frac{w_{j,t+1}}{w_{i,t+1}}) + ln(\frac{E[w_{j,t+2}]}{E[w_{i,t+2}]}) + (A_{j,t+1} - A_{i,t+1}) + (E[A_{j,t+2}] - E[A_{i,t+2}]) - C_{ij,t+1}(.) \tag{11}$$

Since it is assumed that the wage differential, the costs associated with migration and non-climate factors captured in $A_{i,t}$ and $A_{j,t}$ stay constant, the difference between the bilateral migration rate in period t and $t+1$ becomes $(A_{j,t} - A_{i,t}) - (E[A_{j,t+2}] - E[A_{i,t+2}])$. As a result of climate change, country specific characteristics associated with climate are always better in the previous period. Thus, $A_{j,t+1} < A_{j,t}$ and $A_{i,t+1} < A_{i,t}$. When the climate is better at country j, $A_{i,t} < A_{j,t}$ holds. If both country i and j experience the same percentage of climate change compared to the previous situation, the bilateral migration rate is expected to be lower in the second period. This means that more people in countries with less favorable country specific characteristics will decide to migrate in the first period instead of in the second. If the country specific characteristics are better in country i, the bilateral migration rate is expected to be higher in the second period. From this model, it can also be seen that when country i already has worse country specific characteristics than country j, and climate change is expected to have a larger influence on country i this results in a lower bilateral migration rate in the first period.

4.1.3 Mitigation

If countries mitigate climate change, this might have an effect on the bilateral migration rate. The bilateral migration rate now becomes:

$$ln(\frac{N_{ij,t}}{N_{ii,t}}) = ln(\frac{w_{j,t}}{w_{i,t}}) + (A_j^m - A_i^m) - C_{ij,t}(.) \tag{12}$$

The formula of the country specific characteristics with mitigation is as follows:

$$A_{i,t}^m = A(P_{i,t}, Dp_{i,t}, \delta_i E_{i,t}, \omega_i H_{i,t}) \tag{13}$$

$$A_{j,t}^m = A(P_{j,t}, Dp_{j,t}, \delta_j E_{j,t}, \omega_j H_{j,t}) \tag{14}$$

Both δ and ω stand for the level of mitigation and adaption, and thus $0 < \delta < 1$ and $0 < \omega < 1$. Since it is expected that a negative relationship between the country specific characteristics and the long-run and short-run climatic factors exist, mitigation causes A^m to be higher than A. As a result, the bilateral migration rate is expected to be higher (lower) compared to a situation with no mitigation if country i has worse (better) country specific characteristics and both countries mitigate the same percentage of climate change. Poor countries are expected to have a lower A and less capability to mitigate climate change. Consequently, migration from poor countries is expected to increase compared to a situation with no mitigation.

4.2 Parsimonious Approach

A model with many explanatory variables was criticized by Cattaneo and Peri (2016), because many control variables possibly absorb the effect of climate change. Therefore, for the second analysis, many of the control variables are left out to find the net effect of climate change.

This means that the second analysis does not rest on the utility maximization approach, because this analysis is mainly focused at revealing the effect of climate change on migration and not on the mechanisms that have caused the relationship per se (Beine & Parsons, 2017). How the analysis is conducted can be found in section 6.

5 Data

5.1 Migration

The dependent variable will be migration. Migration data will be retrieved from the Global Bilateral Migration Database (GBMD). The database includes migration information from 226 countries. Since the migration data is matched with the climate data, 53 countries of origin and 129 countries of destination are used for the analysis. The list of countries can be found in Appendix B.1.

The GBMD consists of stock data on how many migrants are currently located in each country and it gives information about their country of origin. It uses the census years 1960, 1970, 1980, 1990 and 2000. Also, similar data is now available for the year 2010 from the World Bank Bilateral Migration Matrix. In Beine and Parsons (2017) modified data from Özden *et al.* (2011) is used because some data is missing from the migration database. However, there does not exist modified data for 2010, therefore the raw data from the database is used.

The International Migration Database of the OECD is another extensive migration database that is often used in analyses on the same topic (Coniglio & Pesce, 2015; Backhaus et al., 2015). In contrast to the GBMD, this database contains information about yearly migration flows between OECD countries. While it is valuable to have yearly data instead of decennial data, I consider the GBMD to be better suited for my thesis because it contains data about all types of countries. Especially MICs and the LDCs are hit hardest by climate change. Also, these countries have the least resources to protect themselves against climate change. Therefore, it is more likely that migration is caused by climate change in these countries.

In Appendix B.2 the descriptive statistics can be found. On average the migration stock is 6929, which means that on average 6929 migrants from each country of origin are located in a destination country. The migration stock seems very high, but the standard deviation is large as well: 86951. Thus, the migration stock differs a lot depending on the country of origin and country of destination. For example the maximum migration stock is 5,211,922 for the country-pair Ukraine and Russia, meaning that in total 5,211,922 Russian migrants were located in Ukraine in 1990. Between many country-pairs, such as Argentina and Haiti in 1960, no migration has taken place.

Migration is calculated by subtracting the migration stock in a certain census year by the migration stock of the census year before that. Hence, only long-term migration is taken into account. As this number is a proxy for the real migration between two countries, and based on migration stocks, this number sometimes turns into a negative number due to nationalization, mortality, and migration back to the country of origin or to a further country (Berlemann & Steinhardt, 2017).

The dependent variable used in my regression is the bilateral migration rate. The rate is calculated by dividing the migration from country i to country j ($N_{ij,t}$) by the people from country i that decided not to migrate ($N_{ii,t}$). $N_{ii,t}$ is calculated by subtracting the total population of country i by the total amount of migrants from other countries present in that country. As can be seen in Appendix B.2, the bilateral migration rate is on average 0.0002961 when the zeros are deleted from the sample. So, on average only about 0.03 percent of all people from the sample decides to migrate. This number is not surprising, because in the data set a lot of extremely low levels of the bilateral migration rate are present, meaning that there hardly exists any migration between many country pairs. Like for the migration stock, the standard deviation is very high, around 0.0024. The bilateral migration rate differs a lot between countries. For example, the highest bilateral migration rate is 0.1046, which is observed between Eritrea and Sudan. The lowest bilateral migration rate is 3.78e-10, and is observed between Indonesia and the Czech Republic.

When Table 3 and Table 2 in Appendix B.2 are compared, it can be seen that on average a little more migration takes place from LDCs than from the MICs. When the standard deviations are compared, it is found that migration is a little more volatile for the LDCs as well.

For the pseudo-Poisson maximum likelihood estimation, it is not possible to have a negative bilateral migration rate. Therefore I changed, like in Cattaneo and Peri (2016) and Gröschl and Steinwachs (2017), all negative values of the bilateral migration to zero as their main cause is likely to be mortality.

5.2 Climate Change Variables

The four independent variables are chosen to capture the largest direct climate change effects; more natural disasters, temperature change and precipitation change and the increase in sea level. As a measure for natural disasters in a country, I use the total number of natural disasters in ten years prior to the census year (Beine & Parsons, 2015, 2017). The data on natural disasters is retrieved from the International Disaster Database from the Centre of Research on the Epidemiology of Disasters. In Appendix B.2 it can be seen that the countries experience on average around 1.84 natural disasters scaled by their area in ten years. Some countries are more affected by natural disasters than other countries, as can be seen by the standard deviation of 2.52. The highest amount of natural disasters scaled by area was observed in China, where between 2000 and 2010 287 natural disasters took place. Since large countries experience more natural disasters than small countries, this variable is scaled with the surface of the country.

It is hard to compare the effect of absolute temperatures and precipitation on migration, as people living in a country are adjusted to the climate. Deviations from normal values have a much larger impact because this can affect crop yields and daily life.

To incorporate the change in temperature, temperature anomalies are calculated from the NASA GISTEMP Land-Ocean Temperature Index. Since this database contains temperature data based on a 2 degree by 2 degree grid, there did not exist country data yet. Luckily, the calculations have been done by Dr. Lipponen from the Finnish Meteorological Institute who provided the temperature data for each country. For the base period 1951 to 1980 the average temperature per country is calculated. The average temperature per year is compared to the average of this base period. Every deviation is seen as a temperature anomaly.

In Appendix B.2 it can be seen that the average temperature anomaly is 4.7 °Celsius over the ten year period. The standard deviation is around 2.5 °C. The largest negative temperature anomaly of -1.7 °C is observed in Egypt between 1980 and 1990 and the largest positive temperature anomaly of 13.6 °C is observed in Russia between 2000 and 2010.

In contrast to previous literature (Beine & Parsons, 2015, 2017; Cattaneo & Peri, 2016), I also use a quadratic component for this variable since I expect larger deviations from normal values to have a larger impact on migration. Using a quadratic component for this variable attaches more weight to larger deviations. The squared deviations per year are added for all ten years prior to the census year to compute the total measure of temperature anomalies for the census year. The anomalies are squared before adding because years with particularly high deviations from normal averages weigh more in this way.

For the same reasoning, a quadratic component is used for rainfall. Larger shortages and anomalies are expected to have a larger impact on migration. Therefore, more weight is attached to greater departures from the normal value. A linear measure for temperature and precipitation anomalies is used in another model as well. I use precipitation anomalies data from the ERA-20C re-analysis data from European Centre for Medium Range Weather Forecast. Here I use a likewise method to calculate the anomalies. Again, 1951-1980 is used as base period. The deviations per year from the base period average are squared and then added.

On average the (negative) precipitation anomaly is 3.7 cm per ten years, as can be found in Appendix B.2. This might not seem like a large deviation from normal values on average, but for some countries, the precipitation anomalies are much more severe as can be seen by the standard deviation of 7.1 cm. The largest precipitation shortage over a ten-period interval was observed in Jamaica which experienced between 1980 and 1990 46.7 cm less precipitation compared to the base period.

Further, I incorporate sea level rise to my model. The rise in sea level is not the same for all countries, but a sea level rise is expected for 95 percent of the ocean area. 70 percent of all coastlines are very likely to encounter an increase in sea level that is within 20 percent of the global mean sea level change (IPCC, 2013). Therefore, I use the global mean sea level data from Church and White (2011). With the use of this data, the change in sea level compared to the situation ten years before is calculated. Especially inhabitants of a country that are living below sea level are at risk. The World Bank Development Indicators database contains data about the percentage of the total population that is living 5 meters below sea level. The global mean sea level change is interacted with the percentage of people that is living 5 meters below sea level in that country.

In Appendix B.2 it can be seen that the sea level rise has been significant since 1960. On average the sea level rose by 23.3 mm per decade. Between 1960 and 1970 the sea level rose the least; 4.4 mm. Between 2000 and 2010 the sea level rose the most; 45.2 mm. The sea level has not been declining over the time period of interest. On average 4.6 percent of the population within the sample lives 5 meters below sea level, but in Suriname over 24.7 percent of the total population lives 5 meters below sea level.

5.3 Control Variables

Furthermore, an extensive set of other control variables will be included in the model. The first control variable that can have an effect on migration is the wage differential. As a proxy of the wage differential, I will use the log of the ratio of per capita GDP in the destination and origin country (Beine & Parsons, 2015). The data is retrieved from the Development Indicators Database from the World Bank.

The second control variable is the migrant network. Piguet (2010) describes that migration can cause further migration. The migrant stock from the country of origin in the destination country is used as a proxy for the migrant network. Again, data from the Global Bilateral Migration Database is used.

Four other control variables that proxy for the migration costs between the countries are included in the first model. The distance between the two countries is described by the control variables geodesic distance and contiguity. Both variables are from the GeoDist Database and are used as in Head *et al.* (2010). Also, migrants are more likely to move to countries that have the same or a similar language, so a language dummy that takes value 1 if the origin country and the destination country share an official language. The language data from Melitz and Toubal (2014) will be used. Lastly, former colonial ties can determine migration flows, so a dummy that takes value one when the country of origin was a former or present colony of the destination country is included. Again, the data from the GeoDist Database is used (Head et al., 2010).

Since demographic conditions can function as a push factor, another control variable that describes the demographic conditions is used; dependency. The variable gives an indication of the total population that has an age under 15 years old or over 64 years old divided by the total population that has a working age (Beine & Parsons, 2015). The data from the World Bank Development Indicators database is used.

Another important push factor is the political situation in the country of origin. An unstable government or violence can cause people to migrate. Therefore the total magnitude of all episodes of international violence within a time span of 10 years at the country of origin is used as control variable (Beine & Parsons, 2015). The data from the Major Episodes of Political Violence database of the Centre of Systemic Peace is used.

5.4 Additional Climate Interactions

Since the effect of climate change is not expected to be homogeneous among all countries, the sample is divided into different groups of countries. Four models are estimated in which a distinction is made based on latitude, groundwater levels, temperature and agriculture. Climate change is expected to have a larger impact on countries with high temperatures (Beine and Parsons, 2015). Further, for countries with significant areas with low groundwater levels, the impact of droughts and high temperatures is likely to be larger. The data is obtained from the Global Groundwater Network. The same holds for countries that are close to the equator. To determine the latitude of each country, the latitude of the largest city is used.

Lastly, Beine and Parsons (2015) expect the impact of climate change to be larger for countries that have a large agricultural sector. This is in line with Cai *et al.* (2016) and Marchiori *et al.* (2012). Therefore countries are divided based on the share of agricultural production in the total GDP. The source of the data is the World Bank Development Indicators database.

6 Methodology Pseudo-Gravity Model

6.1 Pseudo-Gravity Model with Control Variables

At the moment, the analysis conducted by Beine and Parsons (2015) is one of the most extensive models to estimate the effect of climate change on migration. The authors estimate the effect of climate change by a neoclassical utility maximization approach that incorporates climate change effects and an extensive set of control variables that can also explain migration flows. I largely follow their model.

However, I make several adjustments to their model. First, Beine and Parsons (2015) use migration data from 1960 until 2000. I also use data from 2010 to incorporate the most recent migration data. Second, I also estimate a model with a quadratic component for the variables temperature anomalies and rainfall anomalies, since I expect larger deviations from normal values to have a relatively larger effect than smaller deviations. Further, I estimate a model in which climate change predictions play a role.

In this thesis, a pseudo-gravity model is estimated. When this model is log-linearized, the regression looks as follows:

$$ln(\frac{N_{ij,t}}{N_{ii,t}}) = \beta_1 ln(\frac{w_{j,t}}{w_{j,t}}) + \beta_2 ln(P_{i,t}) + \beta_3 ln(Dp_{i,t}) + \beta_4 ln(Pa_{i,t}) + \beta_5 ln(Ta_{i,t}) + \beta_6 ln(H_{i,t}) \quad (15)$$
$$+\beta_7 ln(S_t * R_{i,t}) + \beta_8 ln(Nw_{ij,t}) + \beta_9 ln(D_{ij}) + \beta_{10} C_{ij} + \beta_{11} Cl_{ij} + \beta_{12} Ct_{ij} + \alpha_{j,t} + \mu_i + \epsilon_{ij,t}$$

Here $ln(\frac{N_{ij,t}}{N_{ii,t}})$ is natural log of the bilateral migration rate. $ln(\frac{w_{j,t}}{w_{j,t}})$ is the natural log of the wage differential between the origin country i and the destination country j. $P_{i,t}$ is the political stability in the origin country. $Dp_{i,t}$ is the dependency rate in country i. $Pa_{i,t}$ and $Ta_{i,t}$ are the natural logs of precipitation anomalies and temperature anomalies respectively. $H_{i,t}$ is natural log of the number of natural disasters in country i. $ln(S_t * R_{i,t})$ is the natural log of sea level change S_t interacted with the percentage of the population that is living 5 meters below sea level $R_{i,t}$. The migration costs are captured by the variables $Nw_{ij,t}$, D_{ij}, C_{ij}, Cl_{ij} and Ct_{ij} which stand for the migration network, distance, contiguity, common language and colonial ties. Moreover, $\alpha_{j,t}$ and μ_i are included to capture the destination-time and origin fixed effects. The country specific characteristics $(A_{j,t})$ described in section 4 are also captured by $\alpha_{j,t}$.

To determine whether migration is influenced by climate change predictions, I estimate the following pseudo-gravity model:

$$ln(\frac{N_{ij,t}}{N_{ii,t}}) = \beta_1 ln(\frac{w_{j,t}}{w_{j,t}}) + \beta_2 ln(P_{i,t}) + \beta_3 ln(Dp_{i,t}) + \beta_4 ln(Pa_{i,t}) + \beta_5 ln(E[Pa_{i,t+1}]) + \beta_6 ln(Ta_{i,t}) \quad (16)$$
$$+\beta_7 ln(E[Ta_{i,t+1}]) + \beta_8 ln(H_{i,t}) + \beta_9 ln(E[H_{i,t+1}]) + \beta_{10} ln(S_t * R_{i,t}) + \beta_{11} ln(E[S_{t+1}] * R_{i,t})$$
$$+\beta_{12} ln(Nw_{ij,t}) + \beta_{13} ln(D_{ij}) + \beta_{14} C_{ij} + \beta_{15} Cl_{ij} + \beta_{16} Ct_{ij} + \alpha_{j,t} + \mu_i + \epsilon_{ij,t}$$

Here $E[Pa_{i,t+1}]$, $E[Ta_{i,t+1}]$, $E[H_{i,t+1}]$ and $E[S_{t+1}]$ stand for the expected values of precipitation anomalies, temperature anomalies, natural disasters and sea level rise respectively.

In line with Beine and Parsons (2015, 2017) OECD countries are excluded from the sample as countries of origin. Climate-induced migration is less likely to happen from OECD countries since those countries have more resources to mitigate the effects of climate change. If OECD countries would be included as countries of origin, this would likely cause an underestimation of the effect of climate change on migration. OECD countries kept in the sample as destination countries.

In Cattaneo and Peri (2016) and Beine and Parsons (2017), a different effect was found for poor countries and MICs. It is possible that no result will be found when no distinction is made because Cattaneo and Peri (2016) find that the relationship works in different directions for the two groups of countries. Hence, a distinction is made between LDCs and MICs. In a similar manner, a distinction is made between countries based on their latitude, groundwater level, temperature and amount of agriculture.

The regression is the same as the previous regression, only now the estimation is done for the two groups separately. As a measure for poor countries, the list of LDCs from the United Nations is used. All remaining countries are categorized as MICs.

6.2 Pseudo-Gravity Model without Control Variables

The second type of analysis is done with the exclusion of the control variables. Now only the climate variables are used as independent variables. To capture the push factors in the country of origin, country of origin fixed effects are used. To capture the pull factors associated with the country of destination, country of destination time fixed effects are used (Beine & Parsons, 2017). Again, a distinction between LDCs and MICs is made.

The regression is as follows:

$$ln(\frac{N_{ij,t}}{N_{ii,t}}) = \beta_1 lnPa_{i,t} + \beta_2 lnTa_{i,t} + \beta_3 lnH_{i,t} + \beta_4 ln(S_t * R_{i,t}) + \alpha_{j,t} + \mu_i + \epsilon_{ij,t} \tag{17}$$

Here $ln(\frac{N_{ij,t}}{N_{ii,t}})$ is the natural log of the bilateral migration rate. $lnPa_{i,t}$ is equal to natural log of the precipitation anomalies at country of origin i. $lnTa_{i,t}$ stands for the natural log of the temperature anomalies at country i. $lnH_{i,t}$ stands for the natural log of the natural disasters in country i during the prior decade. $ln(S_t * R_{i,t})$ is the natural log of sea level change S_t interacted with the percentage of the population that is living 5 meters below sea level $R_{i,t}$. The fixed effects are captured by $\alpha_{j,t}$ and μ_i which stand for destination-time fixed effects and country of origin fixed effects respectively.

6.3 Econometric Issues

There are several econometric issues associated with this type of analysis. The first problem is that a large part of the data consists out of zeros. Roughly 58 percent of all the observed values for the bilateral migration rate is zero. There can be two reasons for the observed amount of zero's; there is data missing and therefore the migration is reported as zero, or there is simply no migration. If an ordinary least squares regression is used to calculate the effect of climate change, the result is likely to be biased. In an OLS regression, the observations equal to zero are dropped from the sample, because of the double log model. The estimated coefficients suffer from a selection bias if the countries that are excluded are fundamentally different from the countries that are not. It is feasible that this is the case because mainly small or less developed countries have data with zeros. Large and developed countries have non-zero data.

Another bias can arise if the variance of the error term is dependent on the covariates of the bilateral migration rate and there are zeros in the sample. This results in a biased expected value because it will now depend on some of the regressors (Santos Silva & Tenreyro, 2006).

To solve for this problem, a pseudo-Poisson maximum likelihood (PPML) estimator is used (Beine & Parsons, 2015, 2017). A PPML estimator is better suited for this type of gravity estimation because the zeros are not dropped from the sample. Also, the PPML estimation is better in dealing with heteroskedasticity (Santos Silva & Tenreyro, 2006).

One of the key assumptions of a Poisson regression is that the mean and the variance of the dependent variable are the same. In Appendix B.2 it can be seen that the variance (squared standard error) is larger than the mean. In Figure D.1 it can be seen that the mean and the variance of the natural log of the bilateral migration rate are linearly related, which pleads for the use of a PPML estimation. In literature it is also common to use a PPML estimation to estimate the coefficients, however, there is a chance that overdispersion occurs (Beine & Parsons, 2015, 2017). To solve for this problem, a zero-inflated Poisson model is estimated as a robustness check.

Using this type of data there are negative migration flows because the migration flows are calculated by looking at the migration stock data of a country. When people move back to their country of origin or move to another country, the stock decreases. Also, it is possible that the migrants die, which causes the migration stock to decrease as well. When the decrease in migrants larger than the inflow of migrants, this shows in the data as a negative migration flow.

7 Results Pseudo-Gravity model

In this section the results yielding from the pseudo-gravity model are discussed. The results of the model with control variables, and the model without control variables are described in section 7.1 ad in section 7.2 respectively. For each model a RESET test is conducted. From estimated p-value of the RESET tests it can be concluded that none pseudo-gravity models suffer from misspecification (Silva & Tenreyro, 2006).

7.1 Results Pseudo-Gravity Model with Control Variables

7.1.1 Basic Model

Table C contains the results of the PPML estimation when only negative precipitation anomalies are included in the model. In this table, it can be seen that the coefficients are very different from the model with both negative and positive precipitation anomalies found in Table 6. Further, Table 7 contains the estimated coefficients of a model in which a distinction is made between climate change affected natural disasters and non-climate change affected natural disasters. As can be seen in Table 7 the results are very similar to the results found in Table C. For that reason, I focus on the results with only negative precipitation anomalies and all natural disasters in this section.

For the full sample, climate change has an effect on migration, as can be seen in column 1. Precipitation anomalies have a positive effect on the bilateral migration rate. If there is one percent less rainfall during the ten year period, this results in a 12.5 percent increase in migration over that period.

However, precipitation is the only climate change variable for which a positive relationship with the bilateral migration rate is found. For temperature anomalies and natural disasters, the relationship is significant and negative. If temperature anomalies increase by one percent, then the coefficient of -0.615 indicates that this results in a 46 percent decrease of the bilateral migration rate. Natural disasters have a substantial decreasing effect on migration as well. A one percent increase in natural disasters can decrease the bilateral migration rate by 38 percent. In Table C it can be seen that, contrary to the type of model in Table 6, sea level rise does not have a significant effect on migration, except for the model in column 2.

When a distinction between the LDCs and the MICs is made, the effect of precipitation anomalies is no longer significant. This result is explained when precipitation anomalies have an effect on certain groups of countries only, such as countries that are largely depending on agriculture. More about this can be found in section 7.1.3. It might as well be that the decreased sample size compared to the full sample can explain the non-significance.

In column 3 it can be seen that temperature anomalies do not have a significant effect on the bilateral migration rate in the LDCs, while it can be seen in column 5 that they do have a negative effect on migration for MICs. A one percent increase in temperature anomalies has a large effect on migration from MICs because it results in a 72 percent decrease of the bilateral migration rate. This large effect for only MICs is large enough to explain the relationship for all countries found in column 1.

Natural disasters have a different effect on the two groups of countries as well. For the LDCs, natural disasters are found to decrease migration. A one percent increase in natural disasters can reduce migration by 38 percent. Natural disasters do not have a significant impact on migration from MICs.

Overall, climate change seems to have a negative effect on migration for all countries as both temperature anomalies and natural disasters are associated with a lower bilateral migration rate. Only a decrease in precipitation results in a higher level of migration. The mainly negative relationship can be explained by the fact that climate change can make credit constraints more tight (Beine & Parsons, 2017). People that did not have a lot of resources in the first place, now have even less financial opportunities to migrate internationally. The result is a reduction in international migration when climate change becomes more severe.

In the LDCs and in the MICs, the bilateral migration rate is reduced by two different types of climate change consequences. In MICs temperature anomalies have a negative effect on the bilateral migration rate and for the LDCs natural disasters decrease the bilateral migration rate. MICs might have better prevention and mitigation systems in place that reduce the impact of natural disasters. Houses are of better quality, so will not be destroyed as easily. Also, more people in MICs might have an insurance against natural disaster costs, which makes that the population is financially less affected by natural disasters than inhabitants of the LDCs. It can be said that MICs are more resilient against natural disasters. While natural disasters often occur suddenly and have an effect over a (hopefully) shorter period of time, temperature anomalies occur gradually and over a longer period of time. This makes it harder for the affected to arm themselves against this process of climate change. Due to slowly increasing temperatures crops and people might get less productive, which causes people's financial reserves to shrink slowly. People in MICs that first were able to migrate to another country, now find themselves unable to do so due to the increased temperature anomalies. It is possible that this effect is not found in the LDCs because this type of people was never able to migrate in the first place.

For most control variables the expected sign is found. If the wage differential is larger between two countries, this has a positive effect on the migration between the two countries. The effect is larger for the LDCs, as can be seen in column 3 and 4. For the MICs, a non-significant and smaller relationship is found in column 5 and 6 respectively. Network has a robust, and positive effect on the bilateral migration rate throughout all different models. The effect is slightly larger for the MICs. For the political push factors, only a positive relationship is found for the LDCs. Distance has a negative effect on international migration between two countries. For the LDCs this effect is larger than for the MICs. Proportionally migration costs are higher from people from low-income countries compared to the rest of their income. Distance is an indication of migration costs, which explains why the effect of distance is larger for the least developing counties. The same goes for contiguity; a larger positive effect is found for the LDCs. Furthermore, colonial ties play a positive role in the migration decision for all countries combined and for the MICs, but not for the LDCs.

7.1.2 Future Predictions

To see whether climate change predictions have an effect on migration as predicted in section 4.1.2, the model is estimated with the climate change predictions included for each climate change variable. For the estimated model in Table 8 the predictions from RCP 2.6 are used, and for the estimated model in Table 9 the predictions from RCP 8.5 are used. For both models, the predictions for the period 2046 to 2065 are used.

In Table 8 and Table 9 it can be seen that climate change predictions have an effect on the bilateral migration rate. Both the predicted precipitation anomalies and the squared predicted temperature anomalies have a negative effect on the bilateral migration rate as can be seen in column 1 and 2 of Table 9. For the RCP 2.6 models, the effect of climate change predictions on the bilateral migration rate is not significant for most models. Only the models in which the predicted temperature anomalies are squared, a significant effect is found. Since the RCP 8.5 climate change predictions are more severe, the significant results for these models indicate that people respond to more extreme climate change predictions. Especially for temperature anomalies this effect seems quadratic.

In section 4.1.2 it was set out that climate change predictions can cause the bilateral migration rate to be lower when the country specific characteristics in the country of origin are less favourable than in the country of destination, and climate change is expected to have a larger effect on the country of origin. This can be the case in the sample, because OECD countries are included as destination countries, but not as countries of origin. As a result, the sample of destination countries has better country specific characteristics on average. Also, some poor countries are expected to be hit harder by climate change. Intuitively, the found negative relationship is possible when people expect climate change to exist in both the country of origin and destination. If they save money to be more resilient against climate shocks in future, this gives them less resources to migrate.

In Table 9 it can also be seen that predicted natural disasters have a positive effect on migration. People might decide to migrate, when they expect natural disasters in their country to increase, to prevent their lives to be negatively affected a natural disaster.

7.1.3 Different Country Types

To see whether climate change has a different effect on migration from different types of countries, I estimate the model for several groups of countries. The results can be found in Appendix C.3. In Table 11 a distinction between countries based on latitude is made. In column 3 and 4 the model is estimated for countries that have a latitude below the sample median, and thus have a higher temperature. In column 5 and 6 the model is estimated for countries with a latitude above the sample median. In the table it can be seen that the effect of climate change is different for the two types of countries.

On the one hand, precipitation anomalies have a large and positive effect on migration from countries with a lower temperature. A one percent increase in precipitation anomalies and squared precipitation anomalies respectively yield a 73 percent and 30.5 percent increase in the bilateral migration rate. No significant effect for countries with a low latitude is found. On the other hand, no relationship is found between temperature anomalies and migration for colder countries while there exists a significant negative relationship between temperature anomalies and migration for warm countries. This effect is equal to a 49 percent decrease and a 38 percent decrease in bilateral migration rate for a one percent increase in temperature anomalies and squared temperature anomalies respectively. Further, the effect of natural disasters also differs between the two types of countries. The effect of natural disasters on migration is negative for warm countries, but no significant effect and a positive effect are found for colder countries. Here a one percent increase in scaled natural disasters results in a 30 to 32 percent decrease in migration for countries with a high temperature and a 0 to 300 percent increase in migration for countries with a high latitude. For both types of countries sea level rise has no significant effect on the bilateral migration rate.

In Table 13 countries are divided in two groups based on their average temperature. In column 3 and 4, and 5 and 6 the model is estimated for countries with a temperature above the world median, and a temperature below the world median respectively. Since latitude is highly correlated with temperature the results are comparable to the results found in Table 11.

Again, precipitation anomalies have a positive effect on migration from colder countries only.

Now this effect is even larger: the coefficient indicates that a one percent increase in precipitation anomalies increases the bilateral migration rate with 112 percent. Temperature anomalies have a negative effect on out-migration of warmer countries, while there does not exist a relationship for countries with a temperature below the world median. Here the effect found is larger as well: a one percent increase in temperature anomalies results in a 63 percent decrease of the bilateral migration rate. Natural disasters have a negative effect on migration from warm countries only.

Overall, it can be said that climate change has a positive effect on migration from colder countries, while it has a negative effect on countries with a higher temperature. In countries with high temperatures, temperature extremes are more 'extreme' than in countries with lower temperatures. In some countries with a high temperature it already is too hot for people to work outside or crops to grow during some periods of the year. An increase in temperature will extend and intensify this period. As a result people become more credit constrained, which decreases their ability to migrate. However, in countries with a lower temperature, there does not exist such period, and people are usually richer, thus an equal increase in temperature has no impact. Further, the positive effect of precipitation anomalies on migration for colder countries might be explained by the fact that it is less costly for low temperature countries to migrate to a country that experiences less drought.

Interestingly, contradicting results are found in Table 12 when countries are divided based on their groundwater level. For countries with a low groundwater level, precipitation anomalies have a positive effect on the bilateral migration rate. For countries with a high groundwater level, there exists no relationship between precipitation and migration. However, a negative relationship between temperature anomalies and the bilateral migration rate is found.

Hence, a positive relationship between climate change and migration is found for countries with low groundwater levels and a negative relationship is found for countries with higher groundwater levels. However, the results have to be interpreted carefully, because countries with low groundwater levels likely experience more precipitation anomalies. A large occurrence makes it easier to find a significant effect. Thus, the distinction made between countries with low and high groundwater levels might result in a selection bias.

In Table 14 the model is estimated for countries of which agriculture scaled by GDP is above the world median in column 3 and 4 and below the world median in column 5 and 6. Here it can be seen that, contradictory to existing literature, no significant effects are found for all climate change variables (Cai et al., 2016; Backhaus et al., 2015). However, for the countries that have a below average level of agriculture this might be resulting from the small sample size.

The results shown in Appendix C.3 stress that climate change has a very different effect on different types of countries. As was found in section 7 climate change overall decreases migration, but here some of the climate change effects have a large positive effect on groups of countries. This emphasizes that climate change has a heterogeneous effect on migration and it is hard to predict what effect it will have in the future.

7.1.4 Robustness Check: Zero-Inflated Poisson

The bilateral migration rate is zero for 58 percent of all observations. Since the data exists out of a proportionally large amount of zeros, it is possible that the model suffers from overdispersion. To check whether the results are robust, I use a zero-inflated Poisson model. This type of model is used to estimate two processes; the bilateral migration rate that can be explained by the variables, which has a Poisson distribution and the bilateral migration rate that is zero for another reason. I expect that there is a constant amount of country-pairs of which there is no data.

I use a zero-inflated Poisson model with a constant amount of zeros and robust standard errors of which the results can be found in Table C.2. In this table, it can be seen that the estimated coefficients are very similar to the results found in Table C.1. Therefore I can conclude that the PPML model generates robust estimates.

7.2 Results Pseudo-Gravity Model without Control Variables

In Table C.4 the results of the parsimonious regression with only negative precipitation anomalies can be found. When the control variables are excluded from the model, many of the climate coefficients are no longer significant. Only the sea level interaction is significant.

A positive and significant effect of the sea level rise interacted with the population living 5 meters below sea level is found for the developing countries. However, the coefficient 2.897 found in column 3 indicates that a one percent increase can result in a 1600 percent increase in the bilateral migration rate. This result is not realistic, so the parsimonious model cannot be correct.

Probably, the different effect of sea level interaction between the model with control variables and the parsimonious model is caused by omitted variable bias. The sea level interaction heavily relies on the percentage of the population living 5 meters below sea level. Countries with similar population levels living 5 meters below sea level are more likely to be similar and geographically close. In table 4 it can be seen that there exists correlation with the wage differential and dependency rate. When these control variables are left out, their effect is absorbed by the interaction.

Overall, it can be concluded that in the case of models used in this thesis, the model with control variables probably yields the most reliable results. The R-squared of the model with control variables is much larger, thus more of the variation of the bilateral migration rate is explained by the model with control variables. Furthermore, it is likely that the model without control variables suffers from omitted variable bias.

8 Methodology Simulation

In this section, the methodology of the simulation is described. This section is structured as follows. In section 8.1, the structure of the simulation is set out. In section 8.2, the methodology of the baseline model is given. In section 8.3, the methodology of the four models based on the IPCC predictions is set out. Lastly, two other scenarios in which mitigation and adaption take place are described in section 8.4.

8.1 Basics of the Simulation

The aim of the simulation is to predict the average bilateral migration rate in the twenty-first century. In section 7.1.1 a relationship between the bilateral migration rate and temperature anomalies, precipitation anomalies, and natural disasters was found. For the simulation, I use the estimated coefficients in section 7.1.1 to predict what effect climate change will have on future migration. I use the results from the Beine and Parsons (2015) model because this model has more explanatory power about migration than the Beine and Parsons (2017) model. Also, this model is the least likely to suffer from omitted variable bias.

To begin with, I create the 53 countries of origin that are used for the analysis in section 7.1.1. For every country of origin, I create 1000 observations. The list of countries that are created can be found in Appendix B.1.1. In Figure 10 it can be seen that the analysis is based on countries of different sizes that are located on various continents.

The second step is to simulate the climate and control variables for each country of origin. I match every country of origin to its corresponding variables. In subsection 8.3.3 and subsection 8.3.2 more is explained about the simulation of the variables.

Since the simulation is based on a pseudo-gravity model, countries of destination have to be created as well. I couple every country of origin observation randomly to a country of destination. Again, for the countries of destination, the same 129 countries are used as in section 7.1.1. The countries of destination can be found in Appendix B.1.2. In Figure 11 it can be found that the countries of destination also reflect a wide variety of countries.

Afterward, the (significant) estimated coefficients from section 7.1.1 are added to the simulation. The pseudo-gravity model includes origin fixed effects and destination-time fixed effects. As a result, these coefficients are created for the simulation as well. I only re-create the destination-time fixed effects of the year 2010 because this year is closest to the years in my simulation. Hereby, I assume that the destination-time fixed effects do not change over time. In section 10.4 it is discussed whether this is a reasonable assumption.

Many variables are in used logarithmic form in the model, therefore I calculate the logarithm for all relevant variables. The logarithm of a negative number is undefined, as a result, Stata displays this as a missing value. For that reason, I replace all missing values by zero.

When all variables are created, I use the model to calculate the bilateral migration rate for each country. Here, I use the same model as used before:

$$\begin{aligned} ln(\frac{N_{ij,t}}{N_{ii,t}}) = \beta_1 ln(\frac{w_{j,t}}{w_{j,t}}) + \beta_2 ln(P_{i,t}) + \beta_3 ln(Dp_{i,t}) + \beta_4 ln(Pa_{i,t}) + \beta_5 ln(Ta_{i,t}) + \beta_6 ln(H_{i,t} \\ +\beta_7 ln(S_t * R_{i,t}) + \beta_8 ln(Nw_{ij,t}) + \beta_9 ln(D_{ij}) + \beta_{10} C_{ij} + \beta_{11} Cl_{ij} + \beta_{12} Ct_{ij} + \alpha_{j,t} + \mu_i + \epsilon_{ij,t} \end{aligned} \tag{18}$$

The pseudo-gravity model is calculated by using a pseudo-Poisson model. Consequently, the bilateral migration rate (mean) is equal to the exponent of $ln(\frac{N_{ij,t}}{N_{ii,t}})$. For every observation, I calculate the exponent of $ln(\frac{N_{ij,t}}{N_{ii,t}})$. When I have calculated the bilateral migration rate for all country-pairs, I want to calculate the sample average bilateral migration rate. Therefore, I drop out the outliers. For some country-pairs, the bilateral migration rate is equal to an extremely high number such as 951,400,000,000,000 for the country-pair Gambia to Burkina-Faso. This bilateral migration rate would indicate that 95,140,000,000,000,000 percent of the Gambia's population migrated to Burkina Faso. This creates a bias in the calculated mean. Usually, a possible solution for outliers would be to calculate median instead of the mean, but this is not possible with the data since it contains an excessive amount of zeros. Calculating the median would result in a median that is equal to zero.

For that reason, I remove the bilateral migration rate from the simulation results when it exceeds the threshold of 0.11. I use this as a threshold because in the data the maximum bilateral migration rate observed between a country-pair is equal to 0.104633. This bilateral migration rate means that around 10.5 percent of the population from Eritrea moved to Sudan in a ten year period. I use 0.11 as a threshold instead of 0.105 because it is possible that the maximum migration can get higher in the future.

Lastly, I calculate the mean of the bilateral migration rate. For the first simulation, the mean is 0.0002886, which is very close to the actual mean of 0.002961. Since I want the simulation to be as accurate as possible, I repeat the process described in this paragraph 100 times for the baseline simulation and for the four different climate scenarios.

8.2 Baseline Model

The set of 100 simulations is conducted to simulate the baseline period which ranges from 1986 to 2005. The IPCC compares the different climate change models with this period as a baseline. For example, temperature change and precipitation change are calculated compared to the 'baseline situation' from 1986 to 2005. Since I have decennial data, I use the data from the years 1990, 2000 and 2010 because the base period is roughly captured within this data.

8.2.1 Control Variables

All variables that have a significant effect on the bilateral migration rate have to be simulated for the baseline model. I start by simulating the control variables. In section 7.1.1 it can be seen that the control variables wage differential, network, distance, contiguity and colonial ties have a significant effect on the bilateral migration rate. For each of these variables, except for distance, I determine the standard deviation and mean per country separately with the use of the existing data from the baseline period.

The wage differential is normally distributed, thus for each country the variable for the wage differential is generated with a normal distribution and the country-specific mean and standard deviation. The variable network does not have a normal distribution. The variable is skewed to the right and has a log-normal distribution. Consequently, this variable is generated with a log-normal distribution with the use of the country-specific data on this variable. Lastly, contiguity and colonial ties are generated. Both variables are dummy variables, therefore I generate a random binomial number as observation for contiguity and colonial ties for each country separately. In order to do this, I have first calculated the probability of success for every country-pair.

Especially the control variable distance has an asymmetric and atypical distribution, as countries are grouped in continents. As a result, the variable sometimes has a distribution with multiple and uneven peaks. However, this varies a lot per country. Distance has a large influence on the bilateral migration rate, as can be read in section 7.1.1, so a wrongly generated variable can cause large biases. For that reason I use existing distances between the various country-pairs.

8.2.2 Climate Change Variables

For the baseline model, the climate change variables are simulated in a similar way as the control variables. Temperature anomalies, precipitation anomalies and natural disasters have a significant effect on the bilateral migration rate. For all climate change variables I generate a random variable with a normal distribution for each country of origin with the corresponding mean and standard deviation.

One of the most important effects of climate change is the sea level rise. However, in the model used in section 7.1.1 no significant relationship between the interaction with sea level rise and the population living 5 meters below sea level is found. Therefore, this variable is not used in all simulations.

8.2.3 Comparison to Actual Data

In the end, every simulation yields in around 44700 observations of the bilateral migration rate. In Appendix D.2 the Kernel density estimate of the natural logarithm of the bilateral migration rate for both the data and the first simulation is shown. Here it can be seen that, apart from a little drop around -15 for the simulation, the distribution of the bilateral migration rate is very similar.

8.3 Climate Change Simulation

In this subsection it is described how the control variables and the climate change variables are simulated for the different IPCC models.

8.3.1 IPCC Models

For all the climate change variables, I use the predictions from the Fifth Assessment Report from the IPCC. In the Fifth Assessment Report, the IPCC predicts climate change for two time periods: from 2046 to 2065 and from 2081 to 2100. Since climate change predictions are available for those two periods, I predict migration for the same time periods in this thesis. Further, the two time periods make prediction for the remainder of the twenty-first century possible because a lot of years are covered within the two time periods.

As the IPCC gives different RCPs, I predict migration for the mildest climate change scenario RCP 2.6 and for the most severe climate change scenario RCP 8.5. It is likely that climate change in future will be somewhere between the two different RCPs depending on the worldwide efforts to reduce greenhouse gas emissions. Recently, the IPCC has published a Special Report on the impacts of global warming of 1.5 °C. In this Special Report leading scientists warn about the consequences of climate change, which is greater than expected for many regions in the world (IPCC, 2018). Therefore, RCP 2.6 must be viewed as a mild, if not unrealistically positive, climate change scenario.

8.3.2 Control Variables

For the simulation I assume that the control variables do not change over time. Therefore, I keep the control variables the same as in the baseline model.

8.3.3 Climate Change

For the climate change variables temperature anomalies and precipitation anomalies the data files belonging to the Atlas of Global and Regional Climate Projections from the Fifth Assessment Report are used. The data files contain data about the precipitation and temperature change for the different models per region. In Appendix A the expected precipitation and temperature change are shown per model. As can be seen there, the temperature change is given in degrees Celsius and the precipitation change is given in percentages. The IPPC climate change predictions cover temperature change and precipitation change, but not temperature anomalies and precipitation anomalies. I assume that the variables temperature anomalies and precipitation anomalies change similarly.

Since the IPCC predictions are regional, I simulate climate change per region. For the percentage change in precipitation anomalies, a random normally distributed variable based on the mean and standard deviation found in the IPCC predictions is generated per region. The change in temperature anomalies is simulated similarly, except that I generate ten times the amount of observations for this variable. Later, I collapse these observations by ten to get the sum of temperature anomalies over ten years. This is necessary since the model used in section 7.1.1 is based on decennial data in which the temperature anomalies are added per decade instead of the yearly data as used by the IPCC.

When the change in temperature anomalies and the percentage change in precipitation anomalies are simulated per region for the different RCPs, the countries of origin that were previously created are coupled to the relevant region. At last, the change in temperature anomalies is added to temperature anomalies for each country and precipitation anomalies are multiplied by the percentage change in precipitation anomalies.

The IPCC Fifth Assessment Report does not give specific predictions for the variable natural disasters. Instead, it is stated that heavy precipitation events are likely to increase 'over many land areas' for the early 21st century and that tropical cyclone activity, heat waves, drought and extreme high sea level are 'more likely than not', 'very likely', 'likely' and 'very likely' to increase respectively (IPCC, 2014b). There are many different categories of natural disasters, which makes it hard to predict the total change in natural disasters. Overall, an increase in natural disasters is expected, but the IPCC does not give the magnitude of change.

Since it is necessary for the calculation of the bilateral migration rate to know the magnitude of change for natural disasters, I calculate the increase in natural disasters between 1980 and 2017. Between 1980 and 2017 the worldwide amount of natural disasters increased immensely. Per year, natural disasters increased by roughly 2.59 percent (Hoeppe, 2015). For the RCP 8.5 I assume that this increase continues in future, meaning that for the period 2046 to 2065 natural disasters increase by 279 percent and for the period 2081 to 2100 natural disasters increase by 885 percent compared to the baseline period. For RCP 2.6 I assume that the observed increase in natural disasters halves, so that for the period 2046 to 2065 natural disasters increase by 140 percent and for the period 2081 to 2100 natural disasters increase by 442.5 percent.

With these percentage changes for natural disasters I generate a variable for the percentage change of natural disasters with the observed percentage change as mean and a corresponding standard deviation calculated from the data from (Hoeppe, 2015). Lastly, I multiply natural disasters by the percentage change in natural disasters.

8.4 Different Scenarios

As was shown in section 4.1.2, section 4.1.3 and section 7.1.2, mitigation, adaption and climate change predictions have an effect on the bilateral migration rate. For that reason, the simulation is conducted for two different scenarios in which climate change mitigation and adaption takes place in future. The potential for adaption and mitigation is derived from the IPCC Fifth Assessment Report (2014b). In the report it is shown that the impact of climate change can be reduced between 0 and 60 percent depending on the region and risk type. Since in the report the potential level of mitigation and adaption is shown, but not the predicted level, I assume that the predicted level of climate change impact reduction is lower.

In the first scenario all countries are able to reduce the impact of climate change by 20 percent in the period 2046 to 2065 and by 40 percent in the period 2081 to 2100. In the second scenario only MICs are able to reduce the impact of climate change by 20 percent and 40 percent in 2046 to 2065 and 2081 to 2100 respectively. LDCs have less resources, and therefore I assume these countries lack the ability to keep up with the MICs in terms of mitigation and adaption. As a result, LDCs are able to reduce the impact of climate change by 10 percent in 2046 to 2065 and by 20 percent in 2081 to 2100. In order to incorporate mitigation and adaption in the simulation, the coefficient related to the climate change variables is reduced by the same percentage.

9 Results Simulation

In Table 22, Table 23 and Table 24 the results of the simulations can be found. For each box-and-whisker plot, 100 simulations per model are used. The box-and-whisker plot should be interpreted as follows. The upper whisker and lower whisker stand for the maximum and minimum average bilateral migration rate found in the simulation results respectively. The box ranges from the upper quartile to the lower quartile of the simulated bilateral migration rate, while the line within the box portraits the median. For some models, there are dots above or below the whiskers. These dots stand for outliers. In section 9.1 the results of the baseline model are discussed. In section 9.2 the results of the simulation without mitigation and adaption are discussed. Thereafter, in section 9.3 the two mitigation and adaption scenarios are elaborated on.

9.1 Baseline Model

First, the baseline model is simulated as a robustness check. When the simulation yields a similar average bilateral migration rate as is observed in the data, this means that the simulation is able to predict the average bilateral migration rate. In Figure 22 it can be seen that the simulation predicts an average bilateral migration rate of 0.0002922 for the baseline period. The mean bilateral migration rate observed in the data, shown by the red line, is 0.0002961. As can be seen in the figure, this falls within 50 percent of the observations. Also, this simulated mean falls within the 95 percent confidence interval of the average bilateral migration rate observed in the data, which is equal to [0.00024897487, 0.00034322513].

9.2 No Mitigation and Adaption

9.2.1 2046 to 2065: RCP 2.6

For the mildest climate change scenario, the average bilateral migration rate is expected to decrease to 0.0001891. This is equal to a decrease of 35 percent. In the case of the RCP 2.6 simulation, three climate change forces determine the lower average bilateral migration rate. As was described in section 2 for most countries a slight increase in precipitation is expected for RCP 2.6, since in section 7.1.1 a positive relationship between (absolute) precipitation anomalies and the bilateral migration rate was estimated. There actually exists a negative relationship between the two variables. Hence, (overall) precipitation increase causes migration to decrease. The two other climate change variables have an equal effect on the bilateral migration rate. Both temperature anomalies and natural disasters are predicted to increase for RCP 2.6. As for both variables, a negative relationship was estimated, this causes migration to decrease. Overall, the bilateral migration rate decreases as a result of all three climate change effects.

9.2.2 2046 to 2065: RCP 8.5

For the most severe climate change scenario, a more severe effect on the average bilateral migration rate is predicted. The average bilateral migration rate is expected to decrease with almost 54 percent to an average bilateral migration rate of 0.000159. Again, the same climate change effects on migration are involved. Precipitation is expected to increase for most, but not all, countries in RCP 8.5. This has a negative effect on the bilateral migration rate belonging to countries with more precipitation. Both temperature change and natural disasters are expected to increase considerably for all countries. The negative effect of the latter two climate change variables plus the mainly negative effect of the precipitation increase causes migration to decrease in most countries, which causes the average bilateral migration rate to decline.

9.2.3 2081 to 2100: RCP 2.6

For RCP 2.6 the effect of climate change on migration is not negligible. The average bilateral migration rate decreases to 0.000127, which is equal to a decrease of around 57 percent compared to the baseline situation. The substantive decrease in migration is surprising because the precipitation and temperature change for RCP 2.6 in this period seem comparable to the previous period at first sight. Temperature change is roughly similar, but precipitation change is not completely equal when one would look at it in more detail. More countries have a precipitation decrease compared to RCP 2.6 in 2046 to 2065, which causes migration for those countries to increase. However, the number of natural disasters is much higher in this period than in the previous period. Since a negative relationship between natural disasters and the bilateral migration rate was estimated in section 7.1.1, this can explain the substantive decrease of the bilateral migration rate for most countries.

9.2.4 2081 to 2100: RCP 8.5

As expected, the decrease of the average bilateral migration rate is the greatest for the RCP 8.5 model. For the most severe climate change model an average bilateral migration rate decrease of 65 percent is expected before the end of this century. Precipitation is expected to increase in some countries, but also to decrease for other countries. Therefore, it is hard to tell the overall effect of precipitation anomalies on the average bilateral migration rate for this model. Temperature anomalies and natural disasters are expected to increase to large extents. Since both variables have a negative effect on the bilateral migration rate, the average bilateral migration rate might drop to an unprecedented minimum for the given period.

9.3 Mitigation and Adaption

9.3.1 2046 to 2065: RCP 2.6

In a situation in which mitigation and adaption exist in the future, the simulation yields different results than previously found. For the mildest climate change scenario, the average migration rate is expected to be slightly lower than for the baseline model: 0.000288. This is equal to a 1.4 percent decrease. When mitigation and adaption are different for MICs and LDCs, the simulation has comparable results. Now the bilateral migration rate decreases by around 5 percent. The negative relationship between climate change and migration is largely offset by the decreased impact of climate change, and thus the decline in bilateral migration is smaller than in a situation in which mitigation and adaption do not exist.

9.3.2 2046 to 2046: RCP 8.5

For the RCP 8.5 the bilateral migration rate is expected to be slightly lower than for the baseline model. The bilateral migration rate decreases 11 percent compared to the baseline situation in the model with equal mitigation and adaption. For the simulation with unequal mitigation and adaption, the decrease is slightly smaller: 14 percent. Although mitigation and adaption cause the impact of climate change to be less severe, the increase in climate change is severe enough to have a negative effect on the bilateral migration rate in this simulation.

9.3.3 2081 to 2100: RCP 2.6

Contrary to the simulation in which there does not exist mitigation and adaption, the bilateral migration rate is expected to increase in the period 2081 to 2100 for the two mitigation and adaption simulations. In a situation in which not all countries are able to equally mitigate and adapt, the bilateral migration rate is expected to increase by 23 percent. When all countries mitigate and adapt equally, the bilateral migration rate increases even further compared to the baseline situation: by 34 percent. The increased negative effect of climate change on the bilateral migration rate is more than outweighed by the reduced impact of climate change. The bilateral migration rate increases as a result.

9.3.4 2081 to 2100: RCP 8.5

For the RCP 8.5 climate change scenario, the simulation results are similar to the RCP 2.6 simulation results. Even though climate change is more severe in this model, this effect is more than offset by the reduced impact of climate change. When MICs and LDCs have an unequal level of mitigation and adaption, the bilateral migration rate is expected to increase by 26 percent. In a situation in which all countries put in the same effort to reduce the effect of climate change, the bilateral migration rate increases by 36 percent.

The results of the simulation in which mitigation and adaption are taken into consideration, show that the bilateral migration rate is expected to change. However, the sign of this change is largely dependent on the level of climate change mitigation and adaption in the twenty-first century. In a situation in which countries try to reduce and prevent the impact of climate change drastically, the bilateral migration rate is likely to increase in the remainder of the twenty-first century. When this is not the case, the bilateral migration rate might decrease as was shown in the first simulation.

9.4 Population Growth

From the results described in this section, the effect of climate change on migration might seem clear for the twenty-first century depending on the scenario. However, it should be noted that the analysis is based on the bilateral migration rate instead of the bilateral migration. This means that the analysis is based on the percentage of inhabitants from a country of origin that migrates to a country of destination within a decade. Depending on the scenario, the simulation predicts that the percentage of people that will migrate from one country to another country will either decrease or increase. This does not predict anything about the total number of people that will migrate.

The total number of migrants depends on the initial number of inhabitants of the countries of origin. For the baseline period, the total number of people living in the countries of origin included in the sample was equal to 4,362,265,660. There is a large population growth expected in the remainder of the twenty-first century, especially for the countries in Africa. In 2055 and 2090, which are both years exactly in the middle of the two simulated periods, the sample population is expected to increase to 6,433,594,488 and to 6,748,006,523 respectively. For Africa, the sample population which was 475,582,216 in 2005, is expected to increase to 1,339,179,252 in 2055 and to 2,006,247,377 in 2090. In Appendix E.3 the sample population growth can be seen in all regions.

Therefore, it is plausible that migration itself will increase in the twenty-first century. Unfortunately, it is not possible to calculate the total migration with the model because the model works with the sample average of the bilateral migration rate. It is impossible to multiply this average with the sample population since this might lead to biases. For example, when a large country, such as China, has a very low bilateral migration rate compared to the average, the bilateral migration is biased downwards. However, since the total sample population is expected to increase by 47.5 percent in 2055 and by 54.7 percent in 2090 it is possible that even the decline in the average bilateral migration rate resulting from the simulation without mitigation and adaption is offset by the population growth.

10 Discussion

In this section, I discuss the limitations of this thesis. The section is divided into five subsections; data, methodology pseudo-gravity model, results pseudo-gravity model, methodology simulation and results from the simulation. In each subsection, I discuss the issues regarding the particular sections of my thesis.

10.1 Data

The decennial nature of the data used raises several issues. The first issue arises with intra-period migration. While the data is very useful when investigating long-term migration flows, it is not suitable for looking at short-term migration flows. Bilateral migration is calculated by taking the difference between the migration stocks in the destination countries each decade. If a migrant stays in a country of destination for a period that is shorter than ten years, he might not show up in the GBMD as a migrant since the GBMD is unable to capture intra-period migration (Coniglio & Pesce, 2015). Further, some people decide to migrate back to their country of origin. If within a decade more people move back to their country of origin from a given country of destination, this will show up as negative migration within the data. When there is negative migration, in the rare instance, this is deleted from the data. Thus, return migration is not always identifiable from the GBMD (Coniglio & Pesce, 2015).

The second issue caused by the decennial nature is that climate averages are taken over a ten year period. As a result, the climate variables are smoothed out over the period. Extremely dry and hot years are offset by colder years with more rain within the decade. Consequently, short-term climate anomalies cannot be identified from the data used for this thesis. If migration responds to short-term climate extremes that are not seen as a natural disaster, which is reasonable, this effect cannot be captured from the data (Zhang et al., 2011; Coniglio & Pesce, 2015).

Coniglio and Pesce (2015) raise a third issue that results from the decennial data. Since climate change (extremes) might happen right before the end of the decade, the migration that happens as a consequence does not always take place within the same period. Also, migration might occur before climate change actually happens, as is found in section 7.1.2. For example, people that live close to the shore might migrate before the sea level actually rises. As is stated by Coniglio and Pesce (2015) 'the timing between the occurrence of the environmental shock and the occurrence of migration flows' are not always aligned. As a result, the relationship between climate change and migration can be missed in some instances.

Furthermore, there is one other important problem with the GBMD: a lot of migration is illegal. It is difficult for countries to calculate illegal migration and as a result, many countries estimate the number of migrants. Consequently, the GBMD is largely based on estimated migration instead of real migration. When countries have estimated migration incorrectly, the GBMD contains estimation errors that can bias any further analysis conducted with the data (Gröschl & Steinwachs, 2017). The estimation of migration stock raises another minor issue. All countries calculate the migration stock within their country, but not all countries do this similarly. Most countries determine the country of origin by looking at the birth country of the migrant. However, some countries in the GBMD register the country of citizenship as the country of origin. Nevertheless, most countries use the same determination of country of origin (Berlemann & Steinhardt, 2017). Further, country of birth and country of citizenship often are equivalents, which makes this a negligible data issue.

The analyses conducted in the sections 6.1 and section 8 are based on a maximum of 53 countries of origin and 129 countries of destination. Some other countries were deleted from the sample because data from those countries was not available. As a result, the analysis is not based on all countries in the world but only on the countries included in the sample. Therefore, the results should be interpreted to be only applicable to the countries in the sample because it is possible that the countries that were deleted are fundamentally different from the countries in the sample. For example, small countries, countries with changing names and some politically unstable countries have not provided migration data for all analyzed years. Consequently, they are dropped from the sample.

Lastly, the climate change variables have some limitations. To start with, natural disasters are scarce in the data. They do not often take place. Therefore, an estimated relationship between natural disasters and migration has to be based on a small number of natural disasters. If more natural disasters would take place, the effect on migration might be different. Secondly, the variables natural disasters, precipitation anomalies and temperature anomalies are generalized for each country of origin, whereas in reality some parts of the country are differently affected than other parts of the country. From the data, it might seem that a complete country suffered from a natural disaster, while only a small region experienced the hazard. For that reason, climate change effects can be overestimated for certain countries while they are underestimated for other countries (Piguet, 2010).

10.2 Methodology Pseudo-Gravity Model

The methodology used for the pseudo-gravity model has several limitations. Firstly, I assume that OECD countries only qualify as destination countries. On the one hand, this is a reasonable assumption because OECD countries have better resources to mitigate the effects of climate change, which causes climate-induced migration to be lower. Including them would result in an (absolute) underestimation of the relationship between climate change and the bilateral migration rate. On the other hand, the distinction between OECD countries and MICs is not primarily based on the level of income, and thus resources, within the country. Some OECD countries such as Mexico, Turkey and Chile had a lower GDP per Capita than the MIC Croatia in 2005 (World Bank, 2018). Further, Argentina, Brazil and South Africa, which are seen as important upcoming economies are all included in the sample as MIC. It is possible that the OECD countries with the lowest development level have an equal, or even lower, ability to mitigate climate change effects than the MICS with the highest development level.

In my analysis, I look directly at the climate change effects instead of looking at the consequences of those effects. For example, as described in section 2.7 climate change has an effect on food security, human health and possibly on conflicts. It is possible that the consequences of climate change cause migration instead of climate change itself. Further, the same climate change effect such as a temperature increase might result in a different effect on crop yields, human health or conflicts depending on the timing and location. If indeed there exists a causal relationship between the climate change consequences and migration, and climate change does not always have the same effect on these consequences, then the variables used in my analysis do not serve as perfect proxies.

10.3 Results Pseudo-Gravity Model

In section 7.1.1 I find that sea level rise does not have a significant effect on the bilateral migration rate, but in reality, this can be different for certain countries. For example, it is expected that 20 percent of Bangladeshi land will disappear as a result of sea level rise. It is unlikely that the disappearance of land to this extent will not have an impact on international migration from Bangladesh. The non-significance of the estimated parameter for the sea level interaction can be explained by ecological fallacy. The estimated relationships explain the effect of climate change on the bilateral migration rate overall, but the effect can be different in specific countries. Moreover, the different effect of climate change on the bilateral migration rate for different types of countries is shown in section 7.1.3. Therefore, the results should be interpreted to only apply for the sample as a whole.

The insignificant effect of sea level rise on the bilateral migration rate can also be explained by the high correlation between the sea level interaction and the variable dependency. In Table 4 it can be seen that the correlation between the two variables is equal to -0.3028. This means that the effect of sea level rise might be absorbed by the variable dependency.

In this thesis, I do not investigate the effect of migration on the environment. When there exists reverse causality between climate change and migration, the results estimated in section 7.1.1 might be biased. Hence, one of my recommendations would be to look into this relationship.

10.4 Methodology Simulation

There are three minor issues with the methodology of the simulation that all result from the incorporation of climate change in the model. Firstly, for the inclusion of temperature change and precipitation change in the model, the IPCC predictions per region are used. The regional predictions are useful in determining climate change for different parts of the world but also result in one problem: some countries fall within two different regions. Especially large countries such as Brazil and Russia belong to different regions in the world. As a result, climate change is heterogeneous within the country, while it is homogeneous in my model. Consequently, for some large countries temperature and precipitation change are slightly underestimated, while for other large countries the change of those variables is slightly overestimated. However, most countries fall within one region as determined by the IPCC.

The second issue arises from the difference between temperature and precipitation with temperature and precipitation anomalies. The IPCC predicts that temperature will increase for most countries in the world and that precipitation decreases or increases depending on the region. For the simulation, I make the assumption that the temperature and precipitation anomalies change is equivalent to the temperature and precipitation change. When precipitation and temperature get a larger standard deviation as a result of climate change, it is possible that anomalies increase more than the actual temperature and precipitation. If this is the case, then precipitation anomalies and temperature anomalies are underestimated which results in either an underestimation of the bilateral migration rate or an overestimation of the bilateral migration rate for the simulated periods.

The last issue in the methodology results from the prediction of natural disasters. The IPCC indicates that natural disasters are likely to increase during the twenty-first century, but does not give a magnitude for the increase. For that reason, I have made an assumption about the percentage change of natural disasters in the future. In reality, the number of natural disasters might increase faster or slower than is assumed for this analysis. Further, in the simulation, the percentage increase in natural disasters is the same for all countries, while the increase might be heterogeneous across countries. As a result, the simulated bilateral migration rate is less precise.

10.5 Results Simulation

One of the largest limitations of the simulation is that it is based on extrapolation. This means that the simulation is based on relationships that existed in the past. To predict the effect of future climate change on the bilateral migration rate, I use the estimated coefficients of natural disasters, precipitation anomalies and temperature anomalies. In reality, the relationship between climate change and the bilateral migration rate is likely to change. Many countries are currently taking measures to mitigate the consequences of climate change (IPCC, 2014a). Hence, the effect of climate change on the bilateral migration rate is possibly larger at present times than in the future, as was shown in section 9.3.

Not only the relationship between climate change and the bilateral migration rate is assumed to stay constant over time. For the simulation, I also assume that the control variables, the country fixed effect, and the destination-time fixed effects do not change in the future. The country fixed effects and the destination-time fixed effects are likely to change in future, as those are based on country-specific conditions like immigration policies and attitude towards migration.

While it is reasonable that the control variables distance, contiguity and colonial ties will not change over time, the opposite holds for the control variables wage differential and network. The variable network is dependent on the bilateral migration rate as this variable is equal to the total migration stock within a destination country. However, it is difficult to predict how the variable network will involve in the future because the variable is not only dependent on the bilateral migration rate, but also on the population growth within the countries of origin. Also, due to the issue of ecological fallacy, it is hard to make assumptions about the 'network' of individual countries. Therefore, I have chosen to keep the variable network constant for the simulation. The same holds for the variable wage differential. It is sure that the variable wage differential will change in the future, but I cannot predict the sign and the extent of this change. For that reason, all control variables are kept constant for the simulation. For further research, I would recommend to not only use predictions about the evolution of the climate change variables but also about the evolution of the control variables.

11 Conclusion

This thesis explains and predicts the effect of climate change on migration. To do this, I have used data about climate change, migration and other important determinants of migration. I find that climate change has a heterogeneous effect on migration. For example, the magnitude and even the sign of the different climate change effects vary between agricultural countries, hot countries and countries with low groundwater. Over the whole sample, precipitation anomalies have a positive effect on migration, while temperature anomalies and natural disasters have a negative effect on migration. Overall, the relationship between climate change and migration is negative.

With the use of the estimated coefficients and the Fifth Assessment Report from the IPCC, I have simulated the bilateral migration rate for the twenty-first century. The simulation predicts that the average bilateral migration rate will decrease for both future periods if no climate change mitigation and adaption takes place. When there is climate change mitigation and adaption, the average bilateral migration rate is likely to increase for the period 2081 to 2100. However, depending on the population growth in the two periods, the total migration in the world will either increase or decrease. The model used for the simulation relies on the assumption of extrapolation for many control variables as well as for the underlying relationships between climate change and migration, hence the simulation predictions should be interpreted with caution.

Whether people migrate or not depends on a lot of underlying factors and on the opportunities people have as is shown by the effect of the different control variables on the bilateral migration rate. Sometimes people have no other choice, but to stay or to leave. In this thesis, I conclude that overall climate change does not have a positive effect on international migration. Many people, coming from the most pollutant countries, have a negative association with migration. However, migration per se, should not be seen as a negative consequence of climate change. It might very well be that no migration is even worse for large groups of people in the developing world that, as is shown in this thesis, have fewer opportunities to migrate when climate change becomes more severe. As a result of credit constraints, the poorest people might get trapped in a rapidly worsening living environment.

In December 2018 the UN Global Compact for migration was adopted by the world leaders. A compact in which climate change is mentioned as one of the causes of migration. Several developed countries have been backing out of this compact (United Nations, 2018b). In a world that is on the verge of a large climate change, it is not only important to know what effect this will have on the migration of today, but also on the migration of tomorrow.

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Appendices

A Climate Change

A.1 Sea Level Rise in 2000 to 2100

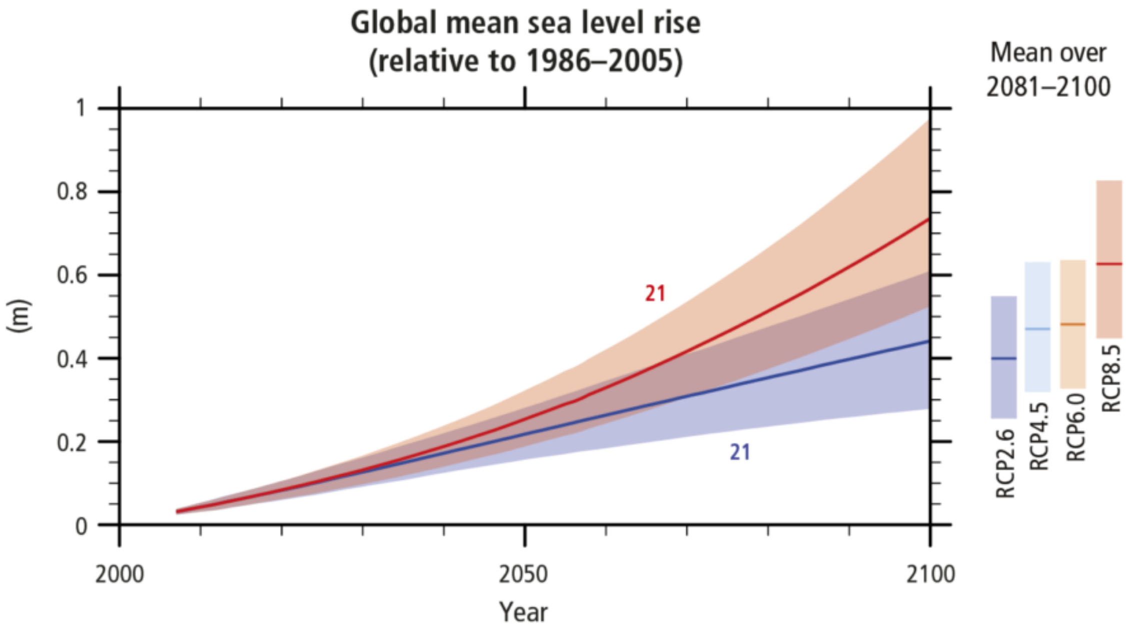


Figure 1: Sea Level Rise. Source: IPCC Fifth Assessment Report

A.2 Temperature Change RCP 2.6

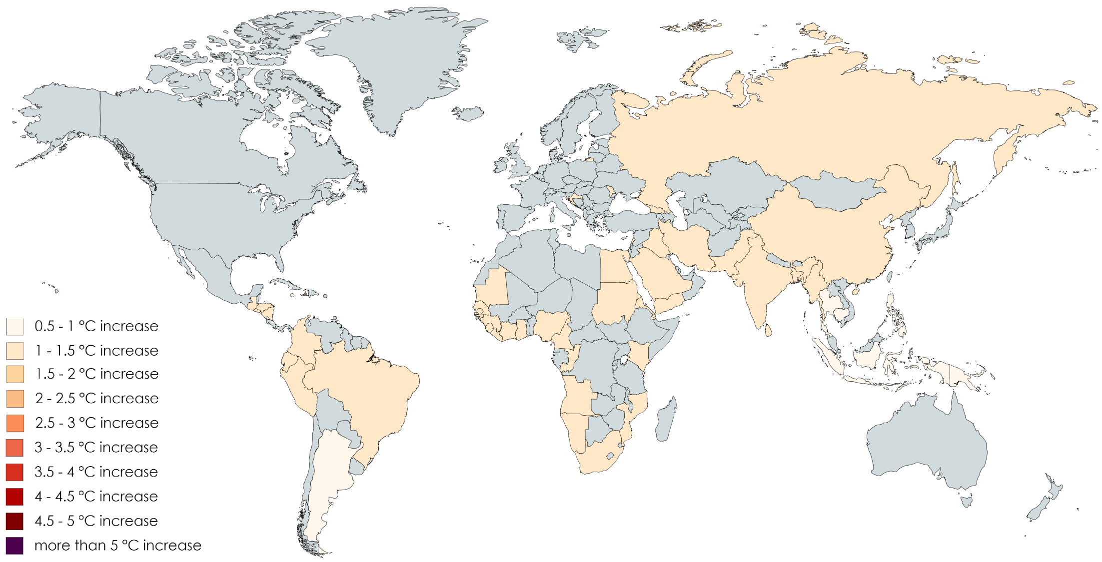


Figure 2: Temperature Change in 2046 to 2065

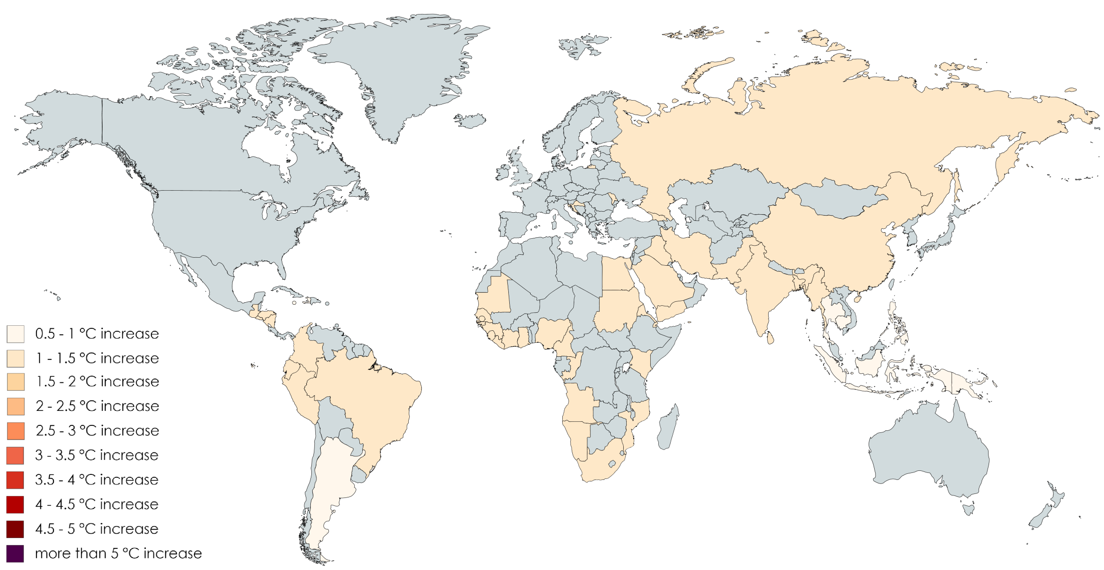


Figure 3: Temperature Change in 2081 to 2100

A.3 Temperature Change RCP 8.5

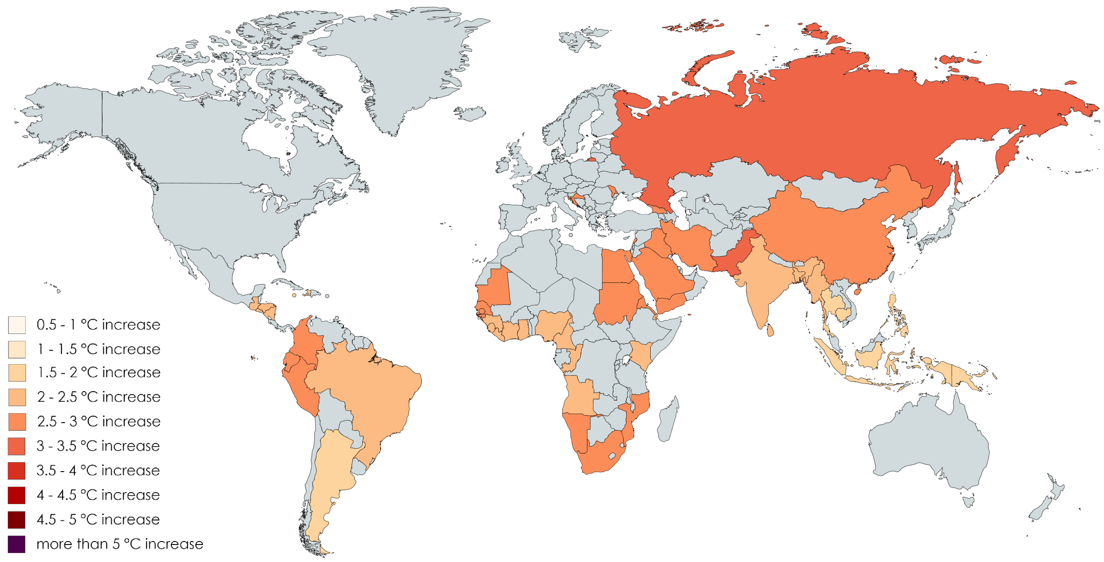


Figure 4: Temperature Change in 2046 to 2065

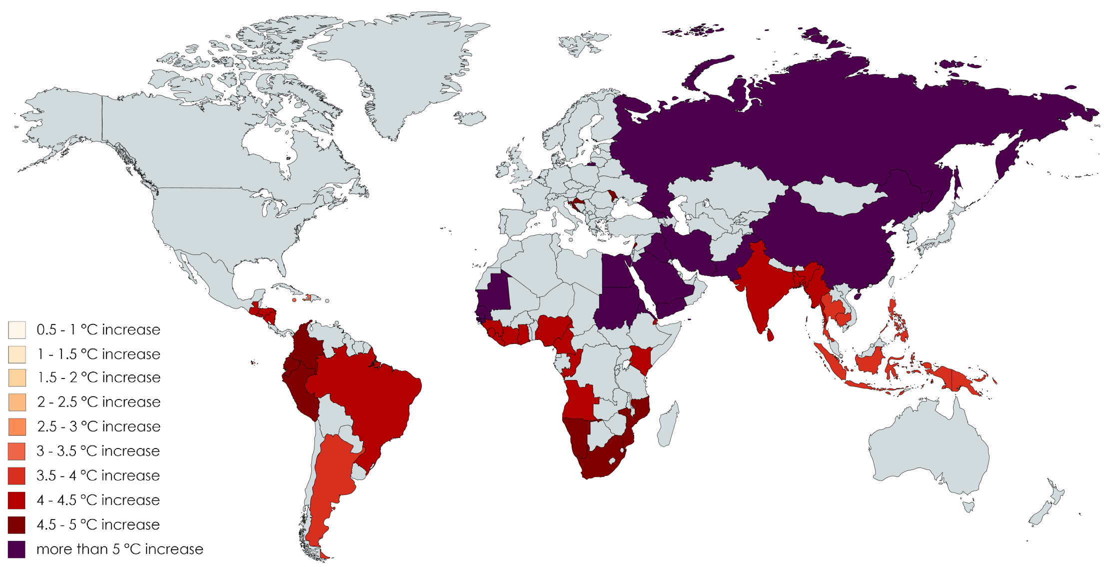


Figure 5: Temperature Change in 2081 to 2100

A.4 Precipitation Change RCP 2.6

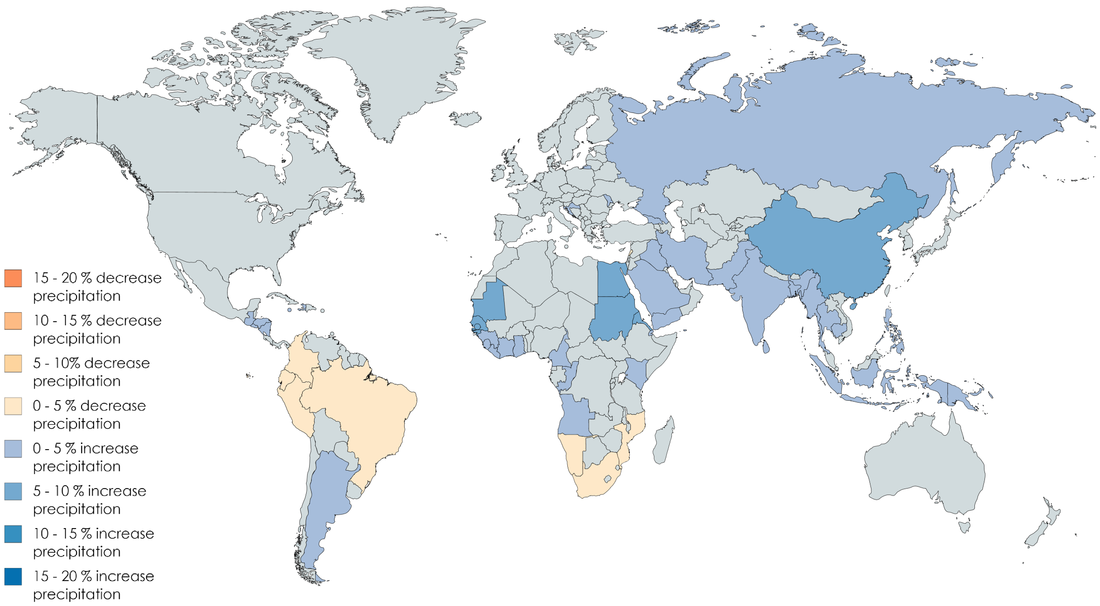


Figure 6: Precipitation Change in 2046 to 2065

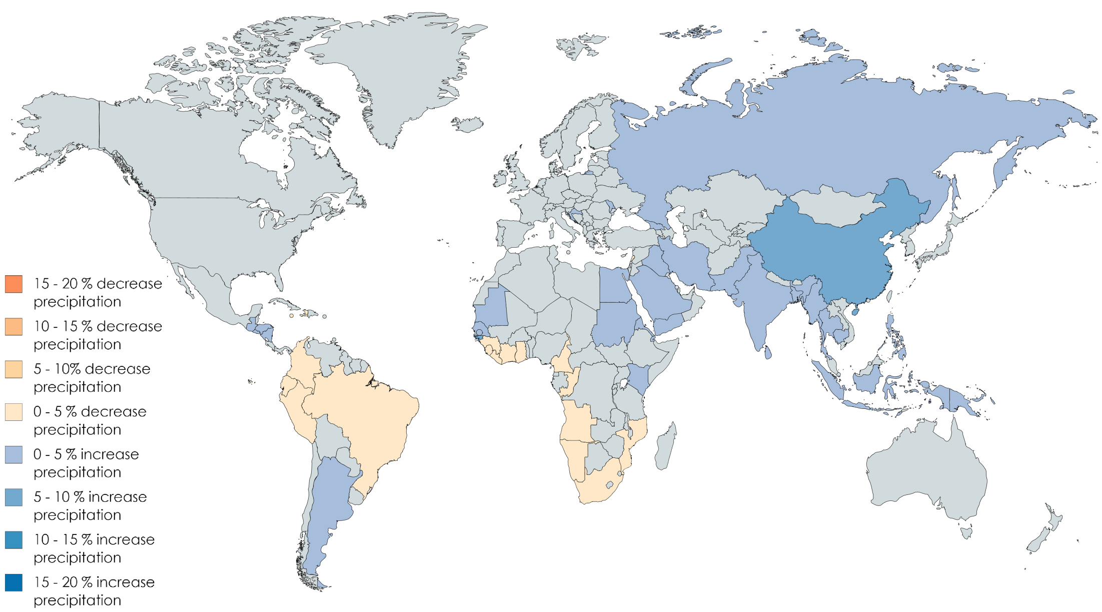


Figure 7: Precipitation Change in 2081 to 2100

A.5 Precipitation Change RCP 8.5

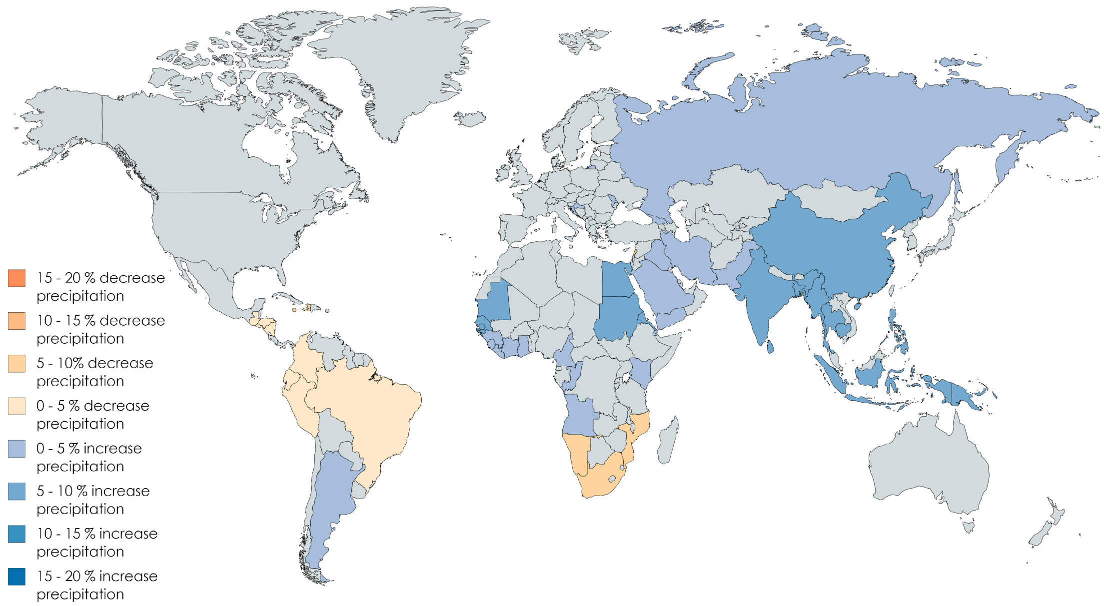


Figure 8: Precipitation Change in 2046 to 2065

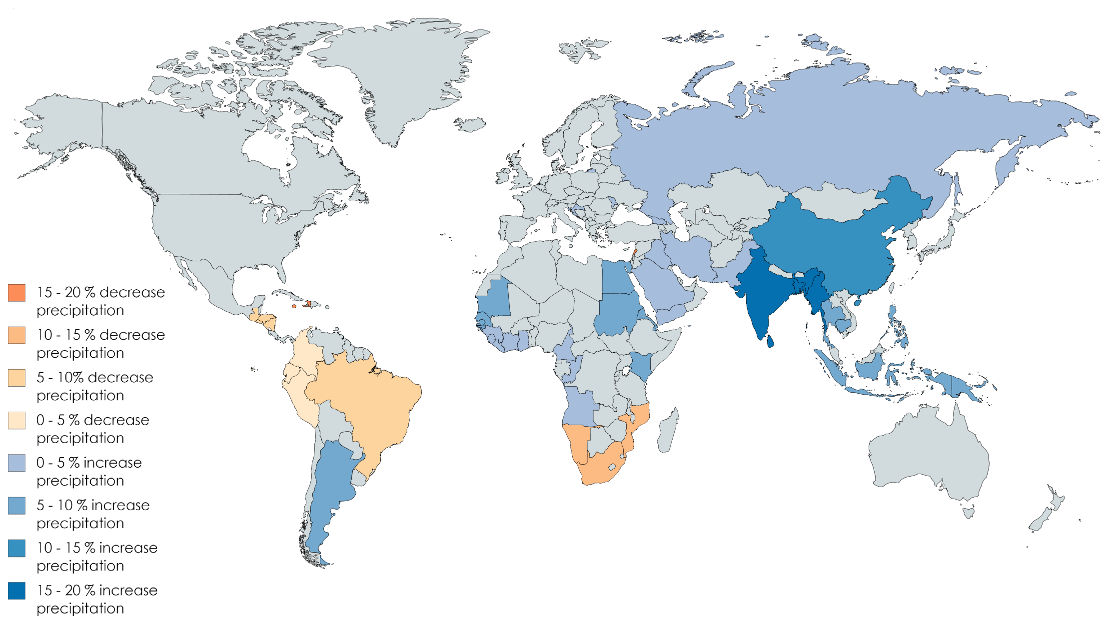


Figure 9: Precipitation Change in 2081 to 2100

B Data

B.1 List of Countries

B.1.1 Countries of Origin

OECD	Middle Income Countries	Least Developed Countries
	Argentina	Angola
	Brazil	Bangladesh
	Cameroon	Cambodia
	China	Djibouti
	Colombia	Eritrea
	Congo	Gambia
	Côte d'Ivoire	Guinea
	Croatia	Guinea-Bissau
	Ecuador	Haiti
	Egypt	Liberia
	El Salvador	Mauritania
	Georgia	Mozambique
	Ghana	Myanmar
	Guatemala	Senegal
	Honduras	Sierra Leone
	India	Solomon Islands
	Indonesia	Sudan
	Iran	Yemen
	Iraq	
	Jamaica	
	Kenya	
	Lebanon	
	Namibia	
	Nicaragua	
	Nigeria	
	Pakistan	
	Papua New Guinea	
	Peru	
	Philippines	
	Republic of Moldova	
	Russian Federation	
	Saudi Arabia	

OECD	Middle income countries	Least developed countries
	South Africa	
	Sri Lanka	
	Thailand	

B.1.2 Countries of Destination

OECD	Middle income countries	Least developed countries
Australia	Albania	Angola
Austria	Antigua and Barbuda	Bangladesh
Belgium	Argentina	Benin
Canada	Armenia	Bhutan
Chile	Aruba	Burkina Faso
Czech Republic	Bahamas	Cambodia
Denmark	Bahrain	Cape Verde
Finland	Barbados	Central African Republic
France	Belarus	Chad
Germany	Belize	Djibouti
Greece	Bolivia	Equatorial Guinea
Hungary	Brazil	Ethiopia
Iceland	Brunei Darussalam	Gambia
Ireland	Cameroon	Guinea
Israel	Congo (Brazzaville)	Guinea-Bissau
Italy	Côte d'Ivoire	Haiti
Japan	Cyprus	Lesotho
Korea (South)	Dominican Republic	Liberia
Latvia	Ecuador	Malawi
Luxembourg	Egypt	Mali
Mexico	El Salvador	Mauritania
The Netherlands	Fiji	Mozambique
New Zealand	Gabon	Myanmar
Norway	Georgia	Nepal
Poland	Guatemala	Niger
Portugal	Guyana	Rwanda
Slovakia	Hong Kong	Samoa
Spain	India	Sao Tome and Principe
Sweden	Iran	Senegal

OECD	Middle income countries	Least developed countries
Switzerland	Iraq	Sierra Leone
Turkey	Jamaica	Solomon Islands
United Kingdom	Jordan	Sudan
United States of America	Kazakhstan	Tanzania
	Kenya	Togo
	Kuwait	Uganda
	Macao	Yemen
	Malaysia	Zambia
	Mongolia	
	Namibia	
	Nicaragua	
	Nigeria	
	Oman	
	Panama	
	Papua New Guinea	
	Peru	
	Philippines	
	Qatar	
	Russian Federation	
	Saint Vincent and the Grenadines	
	Saudi Arabia	
	Singapore	
	Sri Lanka	
	Suriname	
	Tajikistan	
	Thailand	
	Timor-Leste	
	Ukraine	
	United Arab Emirates	
	Uruguay	

B.1.3 Visualized List of Countries

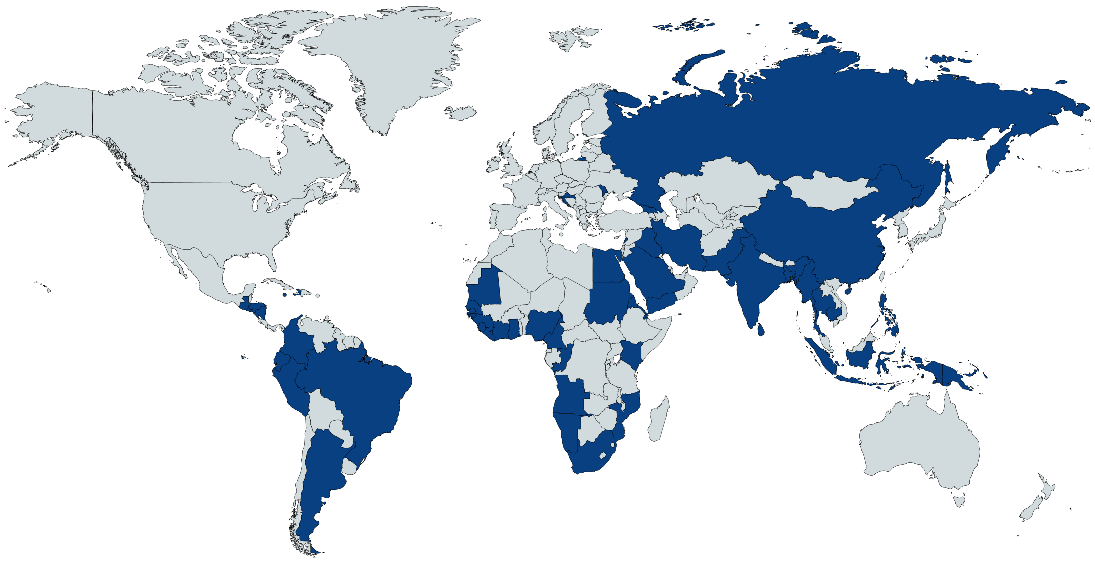


Figure 10: Countries of Origin

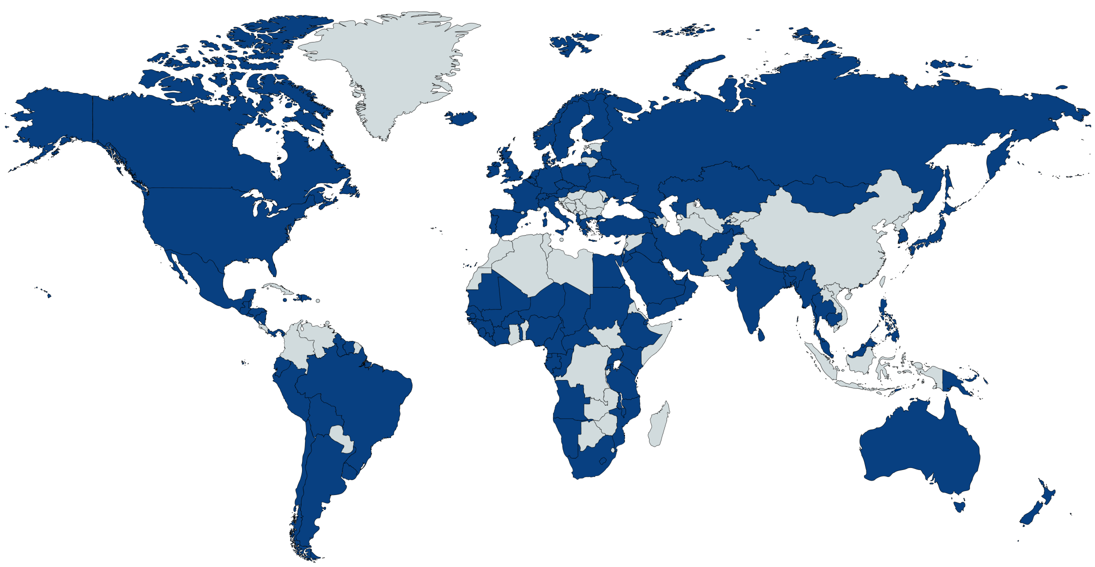


Figure 11: Countries of Destination

B.2 Descriptive Statistics

Table 1: Descriptive Statistics All Countries

Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
Bilateral Migration Rate$_{ij,t}$	10380	0.0002961	0.0024496	3.78e-10	0.104633
Migration Stock$_{i,t}$	28361	6929.484	86951.3	0	5211922
Migration$_{ij,t}$	28361	1406.373	26186.53	-1598682	1434777
Precipitation Anomalies$_{i,t}$ (cm)	28361	36.90289	71.64148	1	467.6398
Temperature Anomalies$_{i,t}$ (0.1 ° C)	28361	46.8578	25.46929	-17.09346	136.1829
Natural Disasters (scaled)$_{i,t}$	27965	1.845265	2.515874	0	17.85448
Sea Level Rise$_t$ (mm)	28361	25.06838	11.62983	16.5	45.2
Population 5m Below Sea$_{i,t}$ (percent)	28361	4.625464	5.325426	0.1589219	24.68095
Wage Differential$_{ij,t}$	26510	0.9381718	1.858345	-4.651721	5.903805
Network$_{ij,t}$	28361	5523.11	87803.92	0	5211922
Political Push Factors$_{i,t}$	27965	1.057894	1.060285	0	5
Dependency Rate$_{i,t}$	28361	75.88544	17.59383	35.59041	119.1388
Distance$_{ij}$	28361	8141.808	4471.233	180.3356	19735.32
Contiguity$_{ij}$	28361	0.0204506	0.1415383	0	1
Common Language$_{ij,t}$	28361	0.1572935	0.3640837	0	1
Colonial Ties$_{ij}$	28361	0.0083565	0.091033	0	1

Table 2: Descriptive Statistics Least Developed Countries

Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
Bilateral Migration Rate$_{ij,t}$	2801	0.0003119	0.0024829	8.13e-10	0.104633
Migration Stock$_{i,t}$	9451	3396.289	70677.95	0	4250287
Migration$_{ij,t}$	9451	562.9154	13011.49	-490108.7	546049
Precipitation Anomalies$_{i,t}$ (cm)	9451	35.36432	78.36438	1	381.7031
Temperature Anomalies$_{i,t}$ (0.1 ° C)	9451	48.70464	24.33297	14.22827	97.02333
Natural Disasters (scaled)$_{i,t}$	9451	1.115215	1.469212	0	7.66151
Sea Level Rise$_t$ (mm)	9451	25.0627	11.62696	16.5	45.2
Population 5m Below Sea$_{i,t}$ (percent)	9451	7.641538	6.440554	0.2634233	2.468095
Wage Differential$_{ij,t}$	8836	1.732597	1.695007	-2.558521	5.903805
Network$_{ij,t}$	9451	2833.374	76809.32	0	4653065
Political Push Factors$_{i,t}$	9451	0.7924029	0.6547098	0	2
Dependency Rate$_{i,t}$	9451	87.44902	12.13219	53.56207	119.1388
Distance$_{ij}$	9451	7820.93	4413.029	188.3058	19648.45
Contiguity$_{ij}$	9451	0.0168236	0.128617	0	1
Common Language$_{ij,t}$	9451	0.1542694	0.3612259	0	1
Colonial Ties$_{ij}$	9451	0.007195	0.0845221	0	1

Table 3: Descriptive Statistics Middle Income Countries

Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
Bilateral Migration Rate$_{ij,t}$	7579	0.0002903	0.0024372	3.78e-10	0.0807238
Migration Stock$_{i,t}$	18910	8695.333	93986.9	0	5211922
Migration$_{ij,t}$	18910	1827.924	30713.71	-1598682	1434777
Precipitation Anomalies$_{i,t}$ (cm)	18910	37.67185	68.02207	1	467.6398
Temperature Anomalies$_{i,t}$ (0.1 ° C)	18910	45.93476	25.97006	-17.09346	136.1829
Natural Disasters (scaled)$_{i,t}$	18514	2.21794	2.836917	0	17.85448
Sea Level Rise$_t$ (mm)	18910	25.07122	11.63157	16.5	45.2
Population 5m Below Sea$_{i,t}$ (percent)	18910	3.118065	3.871105	0.1589219	21.63699
Wage Differential$_{ij,t}$	17674	0.5410039	1.808453	-4.651721	5.359599
Network$_{ij,t}$	18910	6867.409	92784.75	0	5211922
Political Push Factors$_{i,t}$	18514	1.193421	1.193719	0	5
Dependency Rate$_{i,t}$	18910	70.1061	17.04291	35.59041	107.0591
Distance$_{ij}$	18910	8302.179	4491.572	180.3356	19735.32
Contiguity$_{ij}$	18910	0.0222634	0.1475427	0	1
Common Language$_{ij,t}$	18910	0.1588049	0.3655037	0	1
Colonial Ties$_{ij}$	18910	0.0089371	0.0941152	0	1

Table 4: Correlation Matrix

Variables		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bilateral Migration Rate$_{ij,t}$	**(1)**	1.0000							
ln(Precipitation Anomalies$_{i,t}$)	**(2)**	0.0196*	1.0000						
ln(Precipitation Anomalies squared$_{i,t}$)	**(3)**	0.0196*	1.0000*	1.0000					
ln(Temperature Anomalies$_{i,t}$)	**(4)**	0.0031	0.0283*	0.0283*	1.0000				
ln(Temperature Anomalies squared$_{i,t}$)	**(5)**	0.0009	-0.0299*	-0.0299*	0.7555*	1.0000			
ln(Natural Disasters$_{i,t}$)	**(6)**	-0.0124*	0.0028	0.0028	0.3855*	0.3262*	1.0000		
ln(Sea Level Rise$_t$ * Population 5m Below Sea$_{i,t}$)	**(7)**	0.005	-0.0845*	-0.0845*	0.1303*	0.1270*	-0.0332*	1.0000	
ln(Wage Differential$_{ij,t}$)	**(8)**	0.0208*	-0.0372*	-0.0372*	0.0338*	-0.0065*	0.1248*	-0.1199*	1.0000
ln(Network$_{ij,t}$)	**(9)**	0.0279*	-0.0341*	-0.0341*	0.1131*	0.1427*	0.1798*	-0.0878*	0.1802*
ln(Political Push Factors$_{i,t}$)	**(10)**	-0.0158*	0.0239*	0.0239*	0.1268*	0.0487*	0.2366*	0.0879*	0.0285*
ln(Dependency Rate$_{i,t}$)	**(11)**	-0.0015	-0.0957*	-0.0957*	-0.3296*	-0.4448*	-0.2299*	-0.3028*	0.3489*
ln(Distance$_{ij}$)	**(12)**	-0.0273*	0.0060*	0.0060*	-0.0274*	-0.1052*	0.0413*	0.0732*	0.0060*
Contiguity$_{ij}$	**(13)**	0.0105*	-0.0221*	-0.0221*	0.0107*	0.0233*	0.0211*	-0.0295*	-0.0231*
Common Language$_{ij,t}$	**(14)**	0.0157*	0.0262*	0.0262*	-0.0057*	-0.0990*	-0.0231*	-0.0073*	-0.0251*
Colonial Ties$_{ij}$	**(15)**	0.0195*	-0.0004	-0.0004	0.0052	0.0032	0.0044	-0.0106*	0.0643*

Variables		(9)	(10)	(11)	(12)	(13)	(14)	(15)
ln(Network$_{ij,t}$)	**(9)**	1.0000						
ln(Political Push Factors$_{i,t}$)	**(10)**	0.1135*	1.0000					
ln(Dependency Rate$_{i,t}$)	**(11)**	-0.1041*	-0.0336*	1.0000				
ln(Distance$_{ij}$)	**(12)**	-0.4397*	0.0015	0.0285*	1.0000			
Contiguity$_{ij}$	**(13)**	0.3280*	0.0184*	0.0035	-0.3201*	1.0000		
Common Language$_{ij,t}$	**(14)**	0.1650*	-0.0085	0.0936*	-0.1234*	0.0976*	1.0000	
Colonial Ties$_{ij}$	**(15)**	0.1907*	0.0086	-0.0067*	-0.0481*	0.0901*	0.0870*	1.0000

* $p<0.05$

C Results Pseudo-Gravity Model

C.1 Results Pseudo-Gravity Model with Control Variables

Table 5: Results Pseudo-Gravity Model with Control Variables

Dependent variable: Bilateral Migration Rate						
	All countries		Least developed countries		Middle income countries	
Variable	(1)	(2)	(3)	(4)	(5)	(6)
ln(Precipitation Anomalies$_{i,t}$)	0.118***		0.00205		0.0918	
	(2.59)		(0.01)		(1.61)	
ln(Precipitation Anomalies squared$_{i,t}$)		0.0452*		0.0136		0.0585**
		(1.96)		(0.18)		(1.99)
ln(Temperature Anomalies$_{i,t}$)	-0.615**		0.266		-1.262***	
	(-2.08)		(0.37)		(-3.92)	
ln(Temperature Anomalies squared$_{i,t}$)		-0.233		0.130		-0.194
		(-1.23)		(0.24)		(-0.76)
ln(Natural Disasters$_{i,t}$)	-0.480***	-0.279**	-0.476**	-0.479**	-0.0951	-0.0914
	(-3.43)	(-2.12)	(-2.19)	(-2.19)	(-0.49)	(-0.57)
ln(Sea Level Rise$_t$ * Population 5m Below Sea$_{i,t}$)	-1.478	-2.695**	-3.833	-3.727	-0.876	-1.709
	(-1.22)	(-2.32)	(-0.91)	(-0.89)	(-0.67)	(-1.34)
ln(Wage Differential$_{ij,t}$)	0.327*	0.616***	0.813*	0.859**	0.140	0.414*
	(1.67)	(3.63)	(1.79)	(2.03)	(0.54)	(1.66)
ln(Network$_{ij,t}$)	0.408***	0.425***	0.424***	0.424***	0.500***	0.513***
	(11.59)	(12.27)	(11.51)	(11.59)	(12.49)	(12.91)
ln(Political Push Factors$_{i,t}$)	0.0121	0.191	0.561**	0.574**	-0.200	-0.00418
	(0.09)	(1.56)	(2.37)	(2.44)	(-1.50)	(-0.03)
ln(Dependency Rate$_{i,t}$)	0.153	1.230	-0.249	-0.184	2.717**	4.608***
	(0.17)	(1.10)	(-0.12)	(-0.08)	(2.54)	(3.20)
ln(Distance$_{ij}$)	-0.624***	-0.656***	-0.976***	-0.974***	-0.396***	-0.431***
	(-6.36)	(-7.04)	(-6.85)	(-6.82)	(-3.87)	(-4.37)
Contiguity$_{ij}$	1.611***	1.548***	2.180***	2.181***	0.549**	0.570**
	(7.14)	(7.02)	(6.56)	(6.56)	(2.30)	(2.37)
Common Language$_{ij,t}$	0.0777	0.0390	0.0609	0.0602	0.203	0.111
	(0.62)	(0.32)	(0.30)	(0.30)	(1.15)	(0.65)
Colonial Ties$_{ij}$	0.677***	0.701***	0.694	0.694	0.560**	0.620**
	(3.38)	(3.50)	(1.58)	(1.57)	(2.37)	(2.57)
Origin FE	Yes	Yes	Yes	Yes	Yes	Yes
Destination-year FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.870	0.863	0.977	0.977	0.877	0.861
Constant	-9.560***	-13.10***	-3.750	9.043	-19.32**	-28.02***
	(-2.64)	(-2.76)	(-0.38)	(0.47)	(-2.07)	(-2.83)
Number observations	15019	15359	4207	4207	9694	10021

t statistics in parentheses, * p<0.10, ** p<0.05, *** p<0.01

Table 6: Results Pseudo-Gravity Model with Control Variables: Positive Precipitation Anomalies

Dependent variable: Bilateral Migration Rate						
	All countries		Least developed countries		Middle income countries	
Variable	(1)	(2)	(3)	(4)	(5)	(6)
ln(Precipitation Anomalies$_{i,t}$)	0.138		0.427**		0.165	
	(1.39)		(2.10)		(1.23)	
ln(Precipitation Anomalies squared$_{i,t}$)		0.171		0.38		0.222
		(1.11)		(1.59)		(0.94)
ln(Temperature Anomalies$_{i,t}$)	1.428***		3.417***		-0.173	
	(2.96)		(2.77)		(-0.16)	
ln(Temperature Anomalies squared$_{i,t}$)		-0.105		-0.176		0.03688
		(-0.49)		(-0.42)		(0.12)
ln(Natural Disasters$_{i,t}$)	0.540**	-0.217	0.117	-0.379	0.429	-0.0163
	(1.98)	(-1.55)	(0.30)	(-1.63)	(1.41)	(-0.09)
ln(Sea Level Rise$_t$ * Population 5m below sea$_{i,t}$)	-4.899**	-2.959***	-12.15***	-0.0428	4.411	-2.409
	(-2.00)	(-2.59)	(-2.82)	(-0.01)	(0.83)	(-1.52)
ln(Wage Differential$_{ij,t}$)	-0.0766	0.622***	-1.204*	0.780**	-0.379	0.495*
	(-0.28)	(3.60)	(-1.93)	(2.15)	(-0.69)	(1.87)
ln(Network$_{ij,t}$)	0.378***	0.421***	0.475***	0.424***	0.397***	0.507***
	(9.37)	(12.26)	(11.09)	(11.60)	(5.04)	(12.90)
ln(Political Push Factors$_{i,t}$)	-0.137	0.171	-0.437	0.576**	-0.405**	-0.0518
	(-0.76)	(1.36)	(-1.37)	(2.47)	(-2.09)	(-0.38)
ln(Dependency Rate$_{i,t}$)	-0.284	0.944	0.252	-0.820	1.919	3.402**
	(-0.23)	(0.88)	(0.06)	(-0.38)	(1.03)	(2.38)
ln(Distance$_{ij}$)	-0.838***	-0.661***	-1.086***	-0.977***	-0.901***	-0.440***
	(-6.68)	(-7.08)	(-5.50)	(-6.82)	(-4.03)	(-4.41)
Contiguity$_{ij}$	1.050***	1.542***	1.170***	2.173***	0.244	0.577**
	(4.67)	(7.04)	(3.16)	(6.56)	(0.68)	(2.36)
Common Language$_{ij,t}$	0.335**	0.0461	-0.0624	0.0711	0.678***	0.111
	(2.34)	(0.38)	(-0.34)	(0.35)	(2.97)	(0.65)
Colonial Ties$_{ij}$	0.783***	0.728***	0.883	0.683	0.420	0.664***
	(2.93)	(3.69)	(1.15)	(1.53)	(1.34)	(2.77)
Origin FE	Yes	Yes	Yes	Yes	Yes	Yes
Destination-year FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.926	0.857	0.971	0.977	0.956	0.85
Constant	-8.843	-13.21***	40.65*	-7.752	-28.80**	-20.86**
	(-1.29)	(-2.89)	(1.67)	(-0.74)	(-2.46)	(-1.99)
Number observations	7339	15359	2216	4207	4437	10021

t statistics in parentheses, * p<0.10, ** p<0.05, *** p<0.01

Table 7: Results Pseudo-Gravity Model with Control Variables: Type Natural Disaster

Dependent variable: Bilateral Migration Rate						
	All countries		Least developed countries		Middle income countries	
Variable	(1)	(2)	(3)	(4)	(5)	(6)
ln(Precipitation Anomalies$_{i,t}$)	0.0908**		-0.0992		0.118***	
	(2.40)		(-0.18)		(2.61)	
ln(Precipitation Anomalies squared$_{i,t}$)		0.0400*		-0.246		0.0474*
		(1.96)		(-1.22)		(1.89)
ln(Temperature Anomalies$_{i,t}$)	-0.723***		1.102		-1.163***	
	(-2.85)		(0.78)		(-3.32)	
ln(Temperature Anomalies squared$_{i,t}$)		-0.244		1.939**		-0.0446
		(-1.38)		(2.09)		(-0.21)
ln(Natural Disasters affected by climate change$_{i,t}$)	-0.166	-0.114	-0.0764	-0.486	0.0141	-0.235
	(-1.03)	(-0.72)	(-0.14)	(-1.36)	(0.05)	(-0.81)
ln(Natural Disasters not affected by climate change$_{i,t}$)	0.127	0.233	0.0528	0.699	-0.0359	0.408
	(0.92)	(1.52)	(0.10)	(1.20)	(-0.14)	(1.50)
ln(Sea Level Rise$_t$*Population 5 m Below Sea$_{i,t}$)	-1.113	-2.281**	-5.801	-12.93	-0.943	-1.216
	(-1.05)	(-2.10)	(-0.65)	(-1.37)	(-0.64)	(-0.82)
ln(Wage Differential$_{ij,t}$)	0.275	0.426**	0.646	-1.018	0.0553	0.439
	(1.34)	(2.10)	(0.41)	(-0.95)	(0.17)	(1.42)
ln(Network$_{ij,t}$)	0.411***	0.415***	0.407***	0.408***	0.473***	0.474***
	(14.36)	(14.41)	(9.99)	(10.11)	(13.20)	(12.75)
ln(Political Push Factors$_{i,t}$)	-0.137	-0.131	0.496*	0.223	-0.352**	-0.321**
	(-1.08)	(-1.01)	(1.71)	(1.09)	(-2.41)	(-2.27)
ln(Dependency Rate$_{i,t}$)	-0.355	-0.311	-1.427	-0.367	1.471	0.719
	(-0.42)	(-0.36)	(-0.71)	(-0.16)	(1.32)	(0.63)
ln(Distance$_{ij}$)	-0.735***	-0.700***	-0.943***	-0.946***	-0.614***	-0.554***
	(-7.71)	(-8.07)	(-5.17)	(-5.27)	(-6.03)	(-6.01)
Contiguity$_{ij}$	1.029***	1.087***	1.306***	1.330***	0.662***	0.761***
	(6.35)	(7.05)	(3.72)	(3.79)	(3.06)	(3.52)
Common Language$_{ij}$	0.0179	-0.0567	0.159	0.172	0.0431	-0.0562
	(0.14)	(-0.50)	(0.64)	(0.70)	(0.25)	(-0.37)
Colonial Ties$_{ij}$	0.824***	0.879***	0.531	0.508	0.796***	0.846***
	(4.15)	(4.32)	(1.00)	(0.93)	(3.22)	(3.35)
Origin FE	Yes	Yes	Yes	Yes	Yes	Yes
Destination-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-2.845	2.857	21.62	50.67	-15.42**	-15.86**
	(-0.45)	(0.41)	(0.52)	(1.24)	(-2.27)	(-2.34)
Number observations	12752	12904	3215	3215	8522	8672

t statistics in parentheses, * p<0.10, ** p<0.05, *** p<0.01

Table 8: Results Pseudo-Gravity Model with Control Variables: Predictions Future RCP 2.6 2046 to 2065

Dependent variable: Bilateral Migration Rate						
	All countries		Least developed countries		Middle income countries	
Variable	(1)	(2)	(3)	(4)	(5)	(6)
ln(Precipitation Anomalies$_{i,t}$)	0.0350		-0.166		0.0498	
	(0.53)		(-0.63)		(0.69)	
ln(Precipitation Anomalies squared$_{i,t}$)		0.0539*		0.0328		0.0811***
		(1.89)		(0.34)		(2.68)
ln(Predicted Precipitation Anomalies$_{i,t}$)	0.0410		0.0162		0.0825	
	(0.70)		(0.24)		(1.31)	
ln(Predicted Precipitation Anomalies squared$_{i,t}$)		0.000646		-0.0408		-0.00218
		(0.03)		(-1.26)		(-0.10)
ln(Temperature Anomalies$_{i,t}$)	19.34		85.04*		17.11	
	(1.38)		(1.92)		(1.31)	
ln(Temperature Anomalies squared$_{i,t}$)		0.273		-0.264		0.752**
		(1.07)		(-0.24)		(2.43)
ln(Predicted Temperature Anomalies$_{i,t}$)	-20.71		-86.63*		-18.75	
	(-1.42)		(-1.88)		(-1.38)	
ln(Predicted Temperature Anomalies squared$_{i,t}$)		-0.448***		0.367		-0.701***
		(-2.93)		(0.46)		(-4.30)
ln(Natural Disasters$_{i,t}$)	0.494	-0.545	1.369	1.076	0.972	-1.185
	(0.70)	(-0.80)	(1.02)	(0.99)	(1.33)	(-1.55)
ln(Predicted Natural Disasters$_{i,t}$)	-0.955	0.120	-2.141	-1.512	-0.948	0.887
	(-1.38)	(0.18)	(-1.60)	(-1.47)	(-1.40)	(1.23)
ln(Sea Level Rise$_t$*Population 5 m Below Sea$_{i,t}$)	-1.641	-2.758**	-17.08**	-4.509	-3.403**	-1.573
	(-1.17)	(-2.12)	(-2.30)	(-1.04)	(-2.22)	(-1.16)
ln(Predicted Sea Level Rise$_t$*Population 5 m Below Sea$_{i,t}$)	0.167	0.726***	-0.00264	0.220	0.454	1.057***
	(0.73)	(2.78)	(-0.01)	(0.70)	(1.54)	(3.73)
ln(Wage Differential$_{ij,t}$)	0.476**	0.358*	0.662	0.732	0.417	0.174
	(2.29)	(1.84)	(0.76)	(1.55)	(1.62)	(0.72)
ln(Network$_{ij,t}$)	0.360***	0.422***	0.467***	0.428***	0.440***	0.514***
	(11.34)	(12.41)	(10.48)	(11.71)	(11.68)	(13.10)
ln(Political Push Factors$_{i,t}$)	-0.0131	0.0170	0.741**	0.540**	-0.274**	-0.295**
	(-0.09)	(0.12)	(2.53)	(2.10)	(-2.01)	(-2.15)
ln(Dependency Rate$_{i,t}$)	-0.180	0.140	1.537	-0.276	2.454**	2.834***
	(-0.19)	(0.16)	(0.60)	(-0.11)	(2.00)	(2.72)
ln(Distance$_{ij}$)	-0.970***	-0.682***	-0.909***	-0.972***	-0.749***	-0.494***
	(-9.15)	(-7.02)	(-4.81)	(-7.01)	(-6.63)	(-4.80)
Contiguity$_{ij}$	1.686***	1.549***	2.326***	2.187***	0.520**	0.382
	(7.77)	(6.94)	(6.46)	(6.44)	(2.29)	(1.59)
Common Language$_{ij}$	-0.0671	0.0390	-0.147	0.118	-0.0128	0.176
	(-0.45)	(0.32)	(-0.57)	(0.55)	(-0.07)	(1.09)
Colonial Ties$_{ij}$	0.609*	0.726***	0.641	0.631	0.505*	0.618**
	(1.92)	(3.54)	(1.10)	(1.41)	(1.68)	(2.51)
Origin FE	Yes	Yes	Yes	Yes	Yes	Yes
Destination-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-0.820	-9.779***	19.47	-3.085	-10.16	-24.96***
	(-0.17)	(-2.61)	(1.19)	(-0.27)	(-1.50)	(-5.06)
Number observations	11158	15359	3185	4207	6991	10021

t statistics in parentheses, * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 9: Results Pseudo-Gravity Model with Control Variables: Predictions Future RCP 8.5 2046 to 2065

Dependent variable: Bilateral Migration Rate						
	All countries		Least developed countries		Middle income countries	
Variable	(1)	(2)	(3)	(4)	(5)	(6)
ln(Precipitation Anomalies$_{i,t}$)	0.261**		0.0766		0.0559	
	(1.96)		(0.30)		(0.37)	
ln(Precipitation Anomalies squared$_{i,t}$)		0.0863**		0.0610		0.0559
		(2.01)		(0.58)		(1.18)
ln(Predicted Precipitation Anomalies$_{i,t}$)	-0.200*		-0.298*		0.0414	
	(-1.82)		(-1.67)		(0.34)	
ln(Predicted Precipitation Anomalies squared$_{i,t}$)		-0.0283		-0.0999		0.0126
		(-0.81)		(-1.51)		(0.36)
ln(Temperature Anomalies$_{i,t}$)	-1.456		1.574		0.0213	
	(-0.35)		(0.21)		(0.00)	
ln(Temperature Anomalies squared$_{i,t}$)		0.0485		0.288		0.302
		(0.22)		(0.24)		(0.99)
ln(Predicted Temperature Anomalies$_{i,t}$)	0.796		-0.537		-1.160	
	(0.17)		(-0.07)		(-0.22)	
ln(Predicted Temperature Anomalies squared$_{i,t}$)		-0.336***		0.131		-0.471***
		(-2.78)		(0.15)		(-3.45)
ln(Natural Disasters$_{i,t}$)	-1.894***	-1.330**	-3.231**	-1.784	-0.769	-1.382*
	(-2.72)	(-1.98)	(-2.50)	(-1.59)	(-1.10)	(-1.83)
ln(Predicted Natural Disasters$_{i,t}$)	1.387**	0.890	2.680**	1.325	1.462**	1.048
	(2.05)	(1.30)	(2.20)	(1.21)	(2.15)	(1.35)
ln(Sea Level Rise$_t$*Population 5 m Below Sea$_{i,t}$)	0.142	-1.745	-7.794*	-5.136	-3.175**	-0.0861
	(0.10)	(-1.46)	(-1.73)	(-1.29)	(-2.05)	(-0.06)
ln(Predicted Sea Level Rise$_t$*Population 5 m Below Sea$_{i,t}$)	-0.259	-0.00777	-0.728	-0.776**	0.0278	0.147
	(-0.99)	(-0.03)	(-1.63)	(-2.01)	(0.09)	(0.40)
ln(Wage Differential$_{ij,t}$)	0.347	0.326	0.355	0.577	0.114	0.0755
	(1.52)	(1.63)	(0.68)	(1.33)	(0.33)	(0.29)
ln(Network$_{ij,t}$)	0.354***	0.419***	0.440***	0.426***	0.453***	0.511***
	(11.17)	(11.97)	(10.55)	(11.80)	(10.91)	(12.83)
ln(Political Push Factors$_{i,t}$)	-0.00444	0.0166	0.831***	0.792***	-0.242*	-0.280**
	(-0.03)	(0.12)	(3.19)	(2.94)	(-1.83)	(-2.07)
ln(Dependency Rate$_{i,t}$)	0.0741	-0.0201	2.332	0.523	0.581	2.633**
	(0.07)	(-0.02)	(1.12)	(0.23)	(0.41)	(2.31)
ln(Distance$_{ij}$)	-0.771***	-0.668***	-1.038***	-0.960***	-0.438***	-0.462***
	(-6.10)	(-7.02)	(-5.33)	(-6.65)	(-3.09)	(-4.55)
Contiguity$_{ij}$	1.802***	1.526***	2.227***	2.165***	0.159	0.463*
	(7.41)	(6.85)	(6.39)	(6.96)	(0.63)	(1.91)
Common Language$_{ij}$	0.107	0.0524	0.0841	0.0653	0.207	0.125
	(0.67)	(0.44)	(0.34)	(0.31)	(1.04)	(0.76)
Colonial Ties$_{ij}$	0.877***	0.722***	0.854*	0.771*	0.612**	0.649***
	(3.81)	(3.68)	(1.72)	(1.76)	(2.41)	(2.81)
Origin FE	Yes	Yes	Yes	Yes	Yes	Yes
Destination-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-12.79**	-9.544**	-13.04	-7.368	-14.46*	-27.43***
	(-2.11)	(-2.37)	(-1.33)	(-0.64)	(-1.77)	(-2.98)
Number observations	10621	15359	3280	4207	6326	10021

t statistics in parentheses, * p<0.10, ** p<0.05, *** p<0.01

C.2 Results Pseudo-Gravity Model with Control Variables: Zero-Inflation

Table 10: Results Pseudo-Gravity Model with Control Variables: Zero-Inflation

Dependent variable: Bilateral Migration Rate						
	All countries		Least developed countries		Middle income countries	
Variable	(1)	(2)	(3)	(4)	(5)	(6)
ln(Precipitation Anomalies$_{i,t}$)	0.118***		0.00202		0.0918	
	(2.59)		(0.01)		(1.61)	
ln(Precipitation Anomalies squared$_{i,t}$)		0.0452*		0.0136		0.0585**
		(1.96)		(0.18)		(1.99)
ln(Temperature Anomalies$_{i,t}$)	-0.615**		0.266		-1.262***	
	(-2.08)		(0.37)		(-3.92)	
ln(Temperature Anomalies squared$_{i,t}$)		-0.233		0.130		-0.194
		(-1.23)		(0.24)		(-0.76)
ln(Natural Disasters$_{i,t}$)	-0.480***	-0.279**	-0.476**	-0.479**	-0.0952	-0.0914
	(-3.43)	(-2.12)	(-2.19)	(-2.19)	(-0.49)	(-0.57)
ln(Sea Level Rise$_t$ * Population 5m Below Sea$_{i,t}$)	-1.478	-2.694**	-3.831	-3.727	-0.875	-1.709
	(-1.22)	(-2.32)	(-0.91)	(-0.89)	(-0.67)	(-1.34)
ln(Wage Differential$_{ij,t}$)	0.327*	0.616***	0.813*	0.859**	0.140	0.414*
	(1.67)	(3.63)	(1.79)	(2.03)	(0.53)	(1.66)
ln(Network$_{ij,t}$)	0.408***	0.425***	0.424***	0.424***	0.500***	0.513***
	(11.59)	(12.27)	(11.50)	(11.59)	(12.49)	(12.91)
ln(Political Push Factors$_{i,t}$)	0.0121	0.191	0.561**	0.574**	-0.200	-0.00419
	(0.09)	(1.56)	(2.37)	(2.44)	(-1.50)	(-0.03)
ln(Dependency Rate$_{i,t}$)	0.153	1.230	-0.250	-0.184	2.717**	4.607***
	(0.17)	(1.10)	(-0.12)	(-0.08)	(2.54)	(3.20)
ln(Distance$_{ij}$)	-0.624***	-0.656***	-0.976***	-0.974***	-0.396***	-0.431***
	(-6.36)	(-7.04)	(-6.85)	(-6.82)	(-3.87)	(-4.37)
Contiguity$_{ij}$	1.611***	1.548***	2.181***	2.181***	0.549**	0.570**
	(7.14)	(7.02)	(6.56)	(6.56)	(2.30)	(2.37)
Common Language$_{ij,t}$	0.0777	0.0390	0.0609	0.0601	0.203	0.111
	(0.62)	(0.32)	(0.30)	(0.30)	(1.15)	(0.65)
Colonial Ties$_{ij}$	0.677***	0.701***	0.694	0.694	0.560**	0.620**
	(3.38)	(3.50)	(1.57)	(1.57)	(2.37)	(2.57)
Origin FE	Yes	Yes	Yes	Yes	Yes	Yes
Destination-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-9.075**	-12.78**	2.366	1.878	-20.98**	-31.00***
	(-2.64)	(-2.76)	(-0.38)	(0.47)	(-2.07)	(-2.83)
Constant inflated	-51.69***	-51.69***	-50.53***	-50.53***	-49.56***	-51.69***
	(-4265.64)	(-4320.08)	(-2181.89)	(-2181.89)	(-3485.63)	(-3698.82)
Number observations	18808	19174	6386	6386	12422	12788

t statistics in parentheses, * p<0.10, ** p<0.05, *** p<0.01

C.3 Results Pseudo-Gravity Model with Control Variables: Different Country Types

Table 11: Results Pseudo-Gravity Model with Control Variables: Latitude

Dependent variable: Bilateral Migration Rate						
	All countries		Below median latitude		Above median latitude	
Variable	(1)	(2)	(3)	(4)	(5)	(6)
ln(Precipitation Anomalies$_{i,t}$)	0.118***		0.0197		0.548***	
	(2.59)		(0.42)		(3.49)	
ln(Precipitation Anomalies squared$_{i,t}$)		0.0452*		0.0245		0.266**
		(1.96)		(0.96)		(2.48)
ln(Temperature Anomalies$_{i,t}$)	-0.615**		-0.667**		-0.399	
	(-2.08)		(-2.02)		(-0.78)	
ln(Temperature Anomalies squared$_{i,t}$)		-0.233		-0.476**		-0.968
		(-1.23)		(-2.03)		(-1.60)
ln(Natural Disasters$_{i,t}$)	-0.480***	-0.279**	-0.383**	-0.345**	0.523	1.394**
	(-3.43)	(-2.12)	(-2.44)	(-2.20)	(0.78)	(2.12)
ln(Sea Level Rise$_t$*Population 5 m Below Sea$_{i,t}$)	-1.478	-2.695**	-0.476	-1.141	1.427	4.430
	(-1.22)	(-2.32)	(-0.37)	(-0.87)	(0.39)	(0.82)
ln(Wage Differential$_{ij,t}$)	0.327*	0.616***	0.525***	0.578***	-0.808**	-1.171*
	(1.67)	(3.63)	(2.71)	(2.95)	(-2.01)	(-1.84)
ln(Network$_{ij,t}$)	0.408***	0.425***	0.303***	0.303***	0.489***	0.531***
	(11.59)	(12.27)	(8.18)	(8.19)	(10.55)	(9.92)
ln(Political Push Factors$_{i,t}$)	0.0121	0.191	-0.0843	-0.107	-0.00181	0.473**
	(0.09)	(1.56)	(-0.41)	(-0.53)	(-0.01)	(2.17)
ln(Dependency Rate$_{i,t}$)	0.153	1.230	0.0694	-0.0853	-2.726	-8.489**
	(0.17)	(1.10)	(0.07)	(-0.08)	(-1.34)	(-2.44)
ln(Distance$_{ij}$)	-0.624***	-0.656***	-1.219***	-1.219***	-0.115	-0.262*
	(-6.36)	(-7.04)	(-8.72)	(-8.75)	(-0.84)	(-1.93)
Contiguity$_{ij}$	1.611***	1.548***	2.194***	2.195***	0.125	-0.0588
	(7.14)	(7.02)	(9.74)	(9.73)	(0.48)	(-0.22)
Common Language$_{ij}$	0.0777	0.0390	0.358**	0.354**	0.618**	0.482*
	(0.62)	(0.32)	(2.36)	(2.35)	(2.05)	(1.83)
Colonial Ties$_{ij}$	0.677***	0.701***	0.894***	0.885***	0.0195	0.270
	(3.38)	(3.50)	(4.09)	(4.08)	(0.06)	(0.81)
Origin FE	Yes	Yes	Yes	Yes	Yes	Yes
Destination-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-9.560***	-13.10***	-2.832	-2.057	-8.622	14.27
	(-2.64)	(-2.76)	(-0.56)	(-0.36)	(-0.86)	(1.04)
Number observations	15019	15359	10090	10090	4098	4426

t statistics in parentheses, * p<0.10, ** p<0.05, *** p<0.01

Table 12: Results Pseudo-Gravity Model with Control Variables: Groundwater level

Dependent variable: Bilateral Migration Rate						
	All countries		Low groundwater		High groundwater	
Variable	(1)	(2)	(3)	(4)	(5)	(6)
ln(Precipitation Anomalies$_{i,t}$)	0.118***		0.405***		0.0207	
	(2.59)		(3.36)		(0.39)	
ln(Precipitation Anomalies squared$_{i,t}$)		0.0452*		0.204***		0.0469
		(1.96)		(3.56)		(1.62)
ln(Temperature Anomalies$_{i,t}$)	-0.615**		-0.136		-1.208***	
	(-2.08)		(-0.34)		(-3.18)	
ln(Temperature Anomalies squared$_{i,t}$)		-0.233		-0.246		-0.475**
		(-1.23)		(-0.66)		(-2.10)
ln(Natural Disasters$_{i,t}$)	-0.480***	-0.279**	-0.366	-0.332	-0.0559	-0.0967
	(-3.43)	(-2.12)	(-1.12)	(-0.91)	(-0.28)	(-0.68)
ln(Sea Level Rise$_t$*Population 5 m Below Sea$_{i,t}$)	-1.478	-2.695**	-1.923	-1.699	-2.055	-1.992
	(-1.22)	(-2.32)	(-0.64)	(-0.52)	(-1.27)	(-1.42)
ln(Wage Differential$_{ij,t}$)	0.327*	0.616***	0.415	0.624	0.249	0.241
	(1.67)	(3.63)	(1.02)	(1.40)	(1.17)	(1.17)
ln(Network$_{ij,t}$)	0.408***	0.425***	0.394***	0.417***	0.448***	0.433***
	(11.59)	(12.27)	(8.40)	(8.91)	(11.23)	(11.52)
ln(Political Push Factors$_{i,t}$)	0.0121	0.191	-0.139	-0.141	0.152	0.382**
	(0.09)	(1.56)	(-0.60)	(-0.54)	(0.95)	(2.48)
ln(Dependency Rate$_{i,t}$)	0.153	1.230	-2.653	-2.995	1.809	3.732***
	(0.17)	(1.10)	(-1.53)	(-1.48)	(1.56)	(2.75)
ln(Distance$_{ij}$)	-0.624***	-0.656***	-0.698***	-0.920***	-0.621***	-0.616***
	(-6.36)	(-7.04)	(-3.83)	(-5.50)	(-5.64)	(-6.36)
Contiguity$_{ij}$	1.611***	1.548***	1.772***	1.637***	0.936***	1.044***
	(7.14)	(7.02)	(5.64)	(5.06)	(3.41)	(3.85)
Common Language$_{ij}$	0.0777	0.0390	0.236	0.286	-0.00583	-0.134
	(0.62)	(0.32)	(1.28)	(1.47)	(-0.04)	(-0.96)
Colonial Ties$_{ij}$	0.677***	0.701***	0.494	0.506*	0.675***	0.731***
	(3.38)	(3.50)	(1.61)	(1.64)	(2.89)	(2.98)
Origin FE	Yes	Yes	Yes	Yes	Yes	Yes
Destination-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-9.560***	-13.10***	8.723	11.95	-12.87***	-23.35***
	(-2.64)	(-2.76)	(0.72)	(0.98)	(-2.64)	(-4.08)
Number observations	15019	15359	5352	5543	8941	9109

t statistics in parentheses, * p<0.10, ** p<0.05, *** p<0.01

Table 13: Results Pseudo-Gravity Model with Control Variables: Temperature

Dependent variable: Bilateral Migration Rate						
	All countries		Temperature above world median		Temperature below world median	
Variable	(1)	(2)	(3)	(4)	(5)	(6)
ln(Precipitation Anomalies$_{i,t}$)	0.118***		0.0268		0.751**	
	(2.59)		(0.58)		(2.26)	
ln(Precipitation Anomalies squared$_{i,t}$)		0.0452*		0.0318		0.0662
		(1.96)		(1.24)		(0.58)
ln(Temperature Anomalies$_{i,t}$)	-0.615**		-0.995***		-0.375	
	(-2.08)		(-2.60)		(-0.96)	
ln(Temperature Anomalies squared$_{i,t}$)		-0.233		-0.696**		-0.319
		(-1.23)		(-2.46)		(-0.67)
ln(Natural Disasters$_{i,t}$)	-0.480***	-0.279**	-0.289*	-0.216	-0.612	0.0834
	(-3.43)	(-2.12)	(-1.68)	(-1.26)	(-1.34)	(0.19)
ln(Sea Level Rise$_t$*Population 5 m Below Sea$_{i,t}$)	-1.478	-2.695**	-0.201	-1.282	4.392	-0.435
	(-1.22)	(-2.32)	(-0.15)	(-0.92)	(1.16)	(-0.11)
ln(Wage Differential$_{ij,t}$)	0.327*	0.616***	0.410**	0.504**	-0.0882	0.227
	(1.67)	(3.63)	(2.02)	(2.45)	(-0.28)	(0.53)
ln(Network$_{ij,t}$)	0.408***	0.425***	0.289***	0.288***	0.492***	0.521***
	(11.59)	(12.27)	(7.91)	(7.89)	(10.82)	(10.23)
ln(Political Push Factors$_{i,t}$)	0.0121	0.191	0.108	0.0780	-0.135	0.251
	(0.09)	(1.56)	(0.57)	(0.42)	(-0.78)	(1.42)
ln(Dependency Rate$_{i,t}$)	0.153	1.230	0.671	0.406	-1.599	-2.800
	(0.17)	(1.10)	(0.57)	(0.34)	(-1.06)	(-1.06)
ln(Distance$_{ij}$)	-0.624***	-0.656***	-1.281***	-1.282***	-0.100	-0.206*
	(-6.36)	(-7.04)	(-9.26)	(-9.33)	(-0.94)	(-1.87)
Contiguity$_{ij}$	1.611***	1.548***	1.983***	1.980***	0.176	0.0746
	(7.14)	(7.02)	(8.56)	(8.50)	(0.65)	(0.27)
Common Language$_{ij}$	0.0777	0.0390	0.190	0.186	0.801***	0.631**
	(0.62)	(0.32)	(1.26)	(1.24)	(2.86)	(2.55)
Colonial Ties$_{ij}$	0.677***	0.701***	0.765***	0.755***	0.217	0.477
	(3.38)	(3.50)	(3.19)	(3.19)	(0.65)	(1.47)
Origin FE	Yes	Yes	Yes	Yes	Yes	Yes
Destination-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-9.560***	-13.10***	-4.917	-2.064	-20.53**	-5.265
	(-2.64)	(-2.76)	(-0.90)	(-0.37)	(-2.35)	(-0.48)
Number observations	15019	15359	10056	10056	4115	4450

t statistics in parentheses, * p<0.10, ** p<0.05, *** p<0.01

Table 14: Results Pseudo-Gravity Model with Control Variables: Agriculture

Dependent variable: Bilateral Migration Rate						
	All countries		Agriculture above world median		Agriculture below world median	
Variable	(1)	(2)	(3)	(4)	(5)	(6)
ln(Precipitation Anomalies$_{i,t}$)	0.118***		-0.0925		0.627	
	(2.59)		(-1.63)		(.)	
ln(Precipitation Anomalies squared$_{i,t}$)		0.0452*		-0.0476		0.300
		(1.96)		(-1.32)		(.)
ln(Temperature Anomalies$_{i,t}$)	-0.615**		0.200		0.314	
	(-2.08)		(0.54)		(.)	
ln(Temperature Anomalies squared$_{i,t}$)		-0.233		0.132		-0.536
		(-1.23)		(0.40)		(.)
ln(Natural Disasters$_{i,t}$)	-0.480***	-0.279**	0.458	0.464	-2.657	-2.043
	(-3.43)	(-2.12)	(1.26)	(1.23)	(.)	(.)
ln(Sea Level Rise$_t$*Population 5 m Below Sea$_{i,t}$)	-1.478	-2.695**	0.549	0.349	0.376	0.255
	(-1.22)	(-2.32)	(0.31)	(0.20)	(.)	(.)
ln(Wage Differential$_{ij,t}$)	0.327*	0.616***	-0.233	-0.136	-1.285	-1.511
	(1.67)	(3.63)	(-0.75)	(-0.41)	(.)	(.)
ln(Network$_{ij,t}$)	0.408***	0.425***	0.397***	0.414***	0.452	0.452
	(11.59)	(12.27)	(12.13)	(12.46)	(.)	(.)
ln(Political Push Factors$_{i,t}$)	0.0121	0.191	0.149	0.182	-1.459	-1.296
	(0.09)	(1.56)	(1.12)	(1.36)	(.)	(.)
ln(Dependency Rate$_{i,t}$)	0.153	1.230	2.421	2.557	3.616	2.859
	(0.17)	(1.10)	(1.20)	(1.07)	(.)	(.)
ln(Distance$_{ij}$)	-0.624***	-0.656***	-0.740***	-0.852***	-0.446	-0.446
	(-6.36)	(-7.04)	(-6.00)	(-6.66)	(.)	(.)
Contiguity$_{ij}$	1.611***	1.548***	0.946***	0.827***	0.506	0.506
	(7.14)	(7.02)	(4.63)	(4.00)	(.)	(.)
Common Language$_{ij}$	0.0777	0.0390	0.223	0.265	0.318	0.318
	(0.62)	(0.32)	(1.39)	(1.57)	(.)	(.)
Colonial Ties$_{ij}$	0.677***	0.701***	0.0677	0.119	1.059	1.059
	(3.38)	(3.50)	(0.28)	(0.48)	(.)	(.)
Origin FE	Yes	Yes	Yes	Yes	Yes	Yes
Destination-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-9.560***	-13.10***	-22.67***	-23.59**	-39.59	-30.94
	(-2.64)	(-2.76)	(-2.74)	(-2.28)	(.)	(.)
Number observations	15019	15359	8331	8506	3524	3524

t statistics in parentheses, * p<0.10, ** p<0.05, *** p<0.01

C.4 Results Pseudo-Gravity Model without Control Variables

Table 15: Results Pseudo-Gravity Model without Control Variables

Dependent variable: Bilateral Migration Rate						
	All countries		Least developed countries		Middle income countries	
Variable	(1)	(2)	(3)	(4)	(5)	(6)
ln(Precipitation Anomalies$_{i,t}$)	0.0616		0.00343		0.0731	
	(1.25)		(0.04)		(1.32)	
ln(Precipitation Anomalies squared$_{i,t}$)		0.0216		0.0128		0.0269
		(0.91)		(0.27)		(1.02)
ln(Temperature Anomalies$_{i,t}$)	0.188		0.148		0.205	
	(1.05)		(0.38)		(1.09)	
ln(Temperature Anomalies squared$_{i,t}$)		0.149		0.301		0.180
		(0.78)		(0.74)		(0.84)
ln(Natural Disasters$_{i,t}$)	0.0939	0.0173	0.0568	0.0492	0.108	0.0187
	(0.84)	(0.15)	(0.23)	(0.2)	(0.90)	(0.15)
ln(Sea Level Rise$_t$ * Population 5m Below Sea$_{i,t}$)	1.582	0.296	2.897*	3.271*	-0.116	-1.343
	(1.08)	(0.2)	(1.68)	(1.83)	(-0.05)	(-0.64)
Origin FE	Yes	Yes	Yes	Yes	Yes	Yes
Destination-year FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.409	0.409	0.223	0.225	0.477	0.461
Constant	-23.92***	-19.90***	-35.55***	-44.67***	-20.09***	-16.89***
	(-4.93)	(-4.41)	(-3.01)	(-3.10)	(-2.98)	(-2.76)
Number observations	46542	48142	11122	11122	32823	34449

t statistics in parentheses, * p<0.10, ** p<0.05, *** p<0.01

Table 16: Results Pseudo-Gravity Model without Control Variables: Positive Precipitation

Dependent variable: Bilateral Migration Rate						
	All countries		Least developed countries		Middle income countries	
Variable	(1)	(2)	(3)	(4)	(5)	(6)
ln(Precipitation Anomalies$_{i,t}$)	0.0192		-0.0353		0.0386	
	(0.12)		(-0.21)		(0.19)	
ln(Precipitation Anomalies squared$_{i,t}$)		0.246		0.406		0.297
		(1.41)		(1.55)		(0.17)
ln(Temperature Anomalies$_{i,t}$)	-0.316		-0.446		-0.0795	
	(-0.69)		(-0.43)		(-0.15)	
Ln(Temperature Anomalies squared$_{i,t}$)		0.0458		0.0623		0.122
		(0.22)		(0.15)		(0.59)
ln(Natural disasters$_{i,t}$)	0.0427	0.0324	-0.0996	0.0573	0.123	0.0379
	(0.23)	(0.29)	(-0.28)	(0.24)	(0.53)	(0.31)
ln(Sea Level Rise$_t$ * Population 5m Below Sea$_{i,t}$)	5.346*	0.531	3.869	3.930**	10.31*	-1.872
	(1.90)	(0.36)	(1.38)	(2.05)	(1.78)	(-0.89)
Origin FE	Yes	Yes	Yes	Yes	Yes	Yes
Destination-year FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.444	0.417	0.418	0.244	0.531	0.473
Constant	-33.41***	-22.19***	-46.43**	-46.65***	-52.99***	-17.74***
	(-3.37)	(-4.52)	(-2.13)	(-3.28)	(-2.73)	(-2.91)
Number observations	21539	48142	5464	11122	14323	34449

t statistics in parentheses, * p<0.10, ** p<0.05, *** p<0.01

C.5 Results Pseudo-Gravity Model without Control Variables: Different Country Types

Table 17: Results Pseudo-Gravity Model without Control Variables: Type Natural Disaster

Dependent variable: Bilateral Migration Rate						
	All countries		Least developed countries		Middle income countries	
Variable	(1)	(2)	(3)	(4)	(5)	(6)
ln(Precipitation Anomalies$_{i,t}$)	0.125		0.0306		0.105	
	(1.45)		(0.29)		(1.19)	
ln(Precipitation Anomalies squared$_{i,t}$)		0.0457		0.0184		0.0393
		(1.10)		(0.38)		(0.89)
ln(Temperature Anomalies$_{i,t}$)	-0.614		0.276		-0.563	
	(-1.24)		(0.30)		(-1.04)	
ln(Temperature Anomalies squared$_{i,t}$)		0.181		0.202		0.306
		(0.54)		(0.28)		(0.87)
ln(Natural Disasters affected by climate change$_{i,t}$)	-0.267	-0.248	0.281	0.270	-0.633**	-0.742**
	(-1.22)	(-1.11)	(0.87)	(0.85)	(-2.11)	(-2.44)
ln(Natural Disasters not affected by climate change$_{i,t}$)	0.128	0.169	0.190	0.193	0.0961	0.152
	(0.67)	(0.85)	(0.90)	(0.93)	(0.38)	(0.56)
ln(Sea Level Rise$_t$*Population 5 m Below Sea$_{i,t}$)	-1.749	-1.513	1.817	1.898	-1.577	-0.768
	(-0.85)	(-0.78)	(0.77)	(0.79)	(-0.63)	(-0.33)
Origin FE	Yes	Yes	Yes	Yes	Yes	Yes
Destination-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-4.276	-13.20	-22.30***	-22.64***	-9.434	-20.71*
	(-0.33)	(-1.38)	(-3.04)	(-2.74)	(-0.58)	(-1.76)
Number observations	20084	20250	5400	5400	12925	13090

t statistics in parentheses, * p<0.10, ** p<0.05, *** p<0.01

Table 18: Results Pseudo-Gravity Model without Control Variables: Latitude

Dependent variable: Bilateral Migration Rate						
	All countries		Below median latitude		Above median latitude	
Variable	(1)	(2)	(3)	(4)	(5)	(6)
ln(Precipitation Anomalies$_{i,t}$)	0.0616		0.0698		0.0525	
	(1.25)		(1.30)		(0.43)	
ln(Precipitation Anomalies squared$_{i,t}$)		0.0216		0.0278		0.0101
		(0.91)		(1.09)		(0.16)
ln(Temperature Anomalies$_{i,t}$)	0.188		0.240		-0.567	
	(1.05)		(1.32)		(-1.50)	
ln(Temperature Anomalies squared$_{i,t}$)		0.149		0.241		0.381
		(0.78)		(0.91)		(1.39)
ln(Natural Disasters$_{i,t}$)	0.0939	0.0173	0.198	0.102	-0.0962	-0.0612
	(0.84)	(0.15)	(1.43)	(0.70)	(-0.57)	(-0.40)
ln(Sea Level Rise$_t$*Population 5 m Below Sea$_{i,t}$)	1.582	0.296	2.020	1.838	-2.022	-2.571
	(1.08)	(0.20)	(1.31)	(1.17)	(-0.45)	(-0.98)
Origin FE	Yes	Yes	Yes	Yes	Yes	Yes
Destination-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-23.92***	-19.90***	-25.30***	-25.01***	-22.58**	-28.59***
	(-4.93)	(-4.41)	(-4.87)	(-4.56)	(-1.97)	(-3.87)
Number observations	46542	48142	30385	30713	12928	14149

t statistics in parentheses, * p<0.10, ** p<0.05, *** p<0.01

Table 19: Results Pseudo-Gravity Model without Control Variables: Groundwater

Dependent variable: Bilateral Migration Rate						
	All countries		Low groundwater		High groundwater	
Variable	(1)	(2)	(3)	(4)	(5)	(6)
ln(Precipitation Anomalies$_{i,t}$)	0.0616		0.0332		0.0682	
	(1.25)		(0.28)		(1.07)	
ln(Precipitation Anomalies squared$_{i,t}$)		0.0216		-0.00737		0.0212
		(0.91)		(-0.14)		(0.71)
ln(Temperature Anomalies$_{i,t}$)	0.188		-0.0617		0.189	
	(1.05)		(-0.15)		(1.03)	
ln(Temperature Anomalies squared$_{i,t}$)		0.149		-0.305		0.158
		(0.78)		(-0.90)		(0.72)
ln(Natural Disasters$_{i,t}$)	0.0939	0.0173	0.0394	0.0230	0.0456	-0.0181
	(0.84)	(0.15)	(0.15)	(0.10)	(0.39)	(-0.14)
ln(Sea Level Rise$_t$*Population 5 m Below Sea$_{i,t}$)	1.582	0.296	-0.125	-1.957	0.999	2.718
	(1.08)	(0.20)	(-0.06)	(-1.05)	(0.47)	(1.22)
Origin FE	Yes	Yes	Yes	Yes	Yes	Yes
Destination-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-23.92***	-19.90***	-14.36	-19.50***	-23.41***	-29.18***
	(-4.93)	(-4.41)	(-1.18)	(-3.11)	(-3.63)	(-4.24)
Number observations	46542	48142	13763	14309	28503	29600

t statistics in parentheses, * p<0.10, ** p<0.05, *** p<0.01

Table 20: Results Pseudo-Gravity Model without Control Variables: Temperature

Dependent variable: Bilateral Migration Rate						
	All countries		Temperature above world median		Temperature below world median	
Variable	(1)	(2)	(3)	(4)	(5)	(6)
ln(Precipitation Anomalies$_{i,t}$)	0.0616		0.0565		0.208	
	(1.25)		(1.10)		(1.54)	
ln(Precipitation Anomalies squared$_{i,t}$)		0.0216		0.0213		0.0360
		(0.91)		(0.87)		(0.55)
ln(Temperature Anomalies$_{i,t}$)	0.188		0.233		-0.602*	
	(1.05)		(1.27)		(-1.68)	
ln(Temperature Anomalies squared$_{i,t}$)		0.149		0.220		0.252
		(0.78)		(0.84)		(1.03)
ln(Natural Disasters$_{i,t}$)	0.0939	0.0173	0.164	0.0699	-0.0937	-0.0821
	(0.84)	(0.15)	(1.20)	(0.49)	(-0.51)	(-0.51)
ln(Sea Level Rise$_t$*Population 5 m Below Sea$_{i,t}$)	1.582	0.296	2.165	1.959	-7.759*	-3.913
	(1.08)	(0.20)	(1.44)	(1.28)	(-1.85)	(-1.42)
Origin FE	Yes	Yes	Yes	Yes	Yes	Yes
Destination-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-23.92***	-19.90***	-25.70***	-25.24***	18.06	-32.40***
	(-4.93)	(-4.41)	(-5.04)	(-4.70)	(0.83)	(-4.13)
Number observations	46542	48142	31918	32248	11417	12662

t statistics in parentheses, * p<0.10, ** p<0.05, *** p<0.01

Table 21: Results Pseudo-Gravity Model without Control Variables: Agriculture

Dependent variable: Bilateral Migration Rate						
	All countries		Agriculture above world median		Agriculture below world median	
Variable	(1)	(2)	(3)	(4)	(5)	(6)
ln(Precipitation Anomalies$_{i,t}$)	0.0616		0.153		0.0667	
	(1.25)		(1.63)		(0.78)	
ln(Precipitation Anomalies squared$_{i,t}$)		0.0216		0.0467		0.00279
		(0.91)		(1.04)		(0.07)
ln(Temperature Anomalies$_{i,t}$)	0.188		0.427**		-0.387	
	(1.05)		(1.99)		(-1.33)	
ln(Temperature Anomalies squared$_{i,t}$)		0.149		0.494		-0.161
		(0.78)		(1.47)		(-0.42)
ln(Natural Disasters$_{i,t}$)	0.0939	0.0173	0.241	-0.178	-0.00233	0.0358
	(0.84)	(0.15)	(0.72)	(-0.53)	(-0.02)	(0.28)
ln(Sea Level Rise$_t$*Population 5 m Below Sea$_{i,t}$)	1.582	0.296	4.437	4.143	-2.406	-3.310
	(1.08)	(0.20)	(1.63)	(1.34)	(-0.46)	(-1.10)
Origin FE	Yes	Yes	Yes	Yes	Yes	Yes
Destination-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-23.92***	-19.90***	-27.21***	-49.35**	-26.54**	-29.17***
	(-4.93)	(-4.41)	(-5.78)	(-2.23)	(-2.05)	(-3.38)
Number observations	46542	48142	20447	21550	16223	16576

t statistics in parentheses, * p<0.10, ** p<0.05, *** p<0.01

D Methodology Simulation

D.1 Mean-Variance ln(Bilateral Migration Rate)

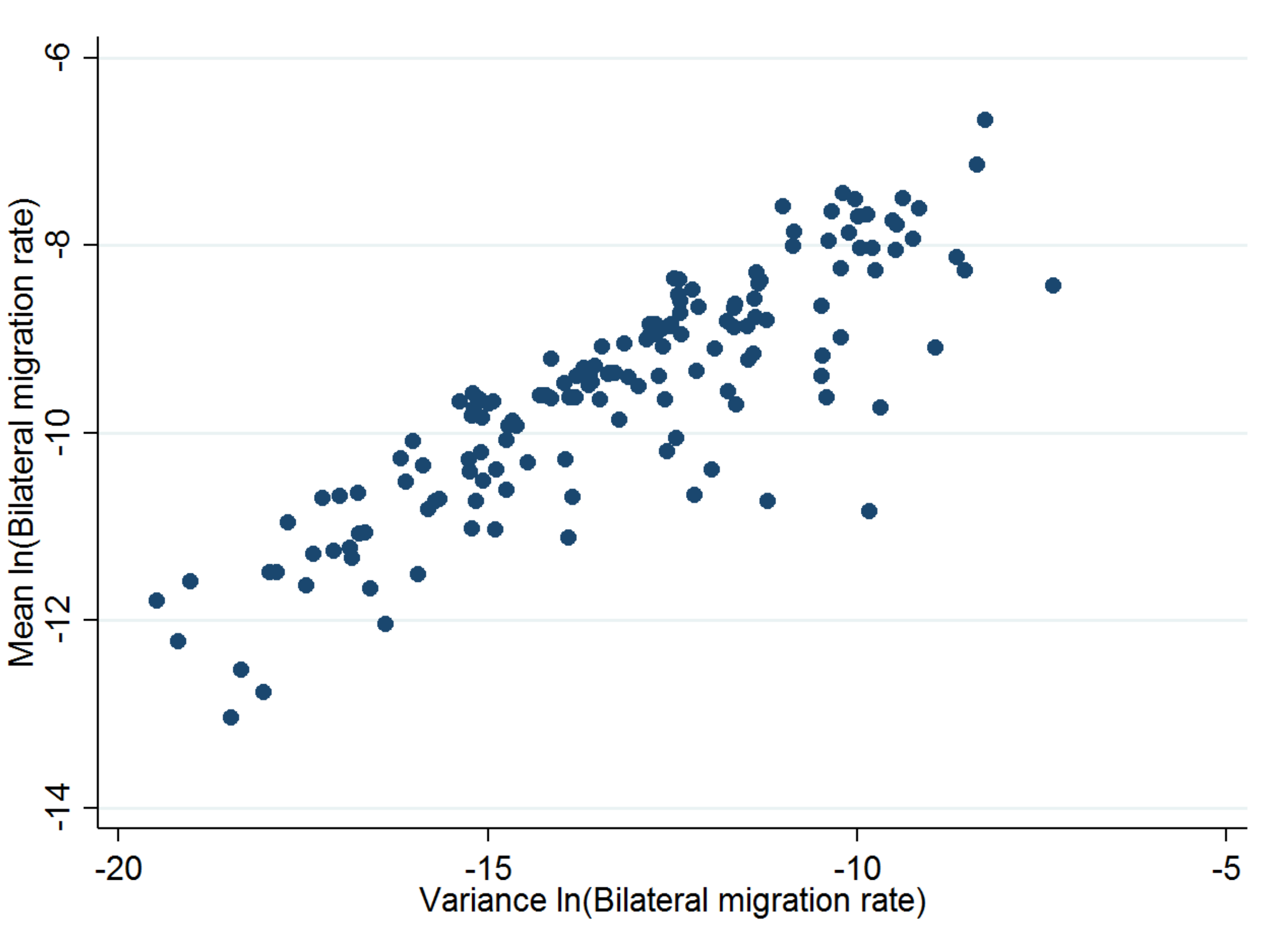


Figure 12: Mean-Variance ln(Bilateral migration rate)

D.2 Kernel Density Estimate

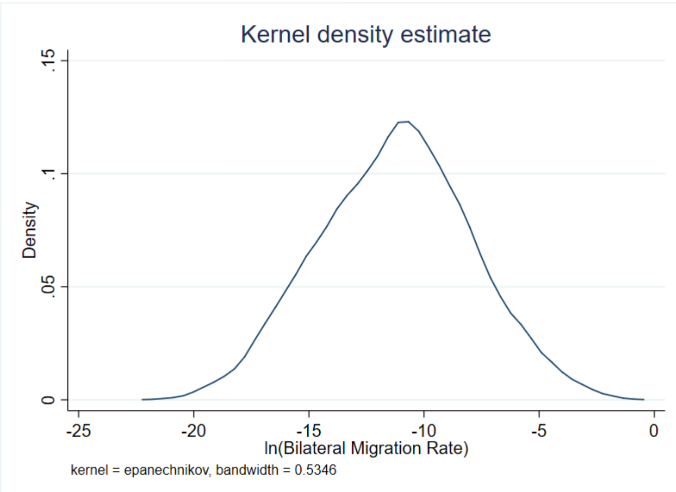


Figure 13: Data

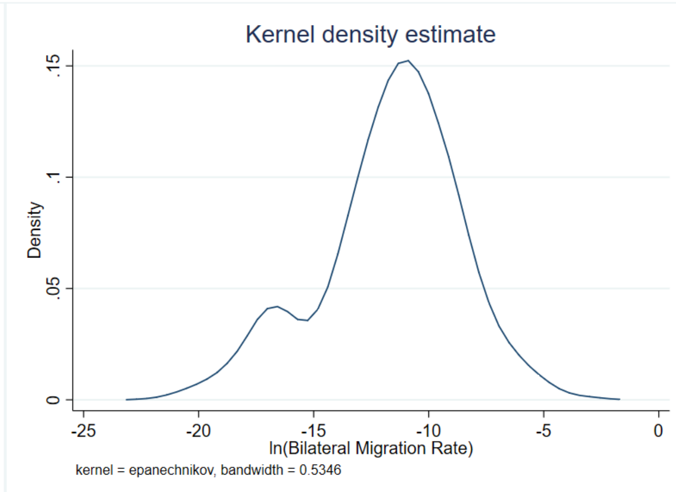


Figure 14: Simulation

E Results Simulation

E.1 Results Simulation

Table 22: Results Simulation No Mitigation and Adaption

Type of Model	Observations	Mean	Standard Deviation	Minimum	Maximum
Baseline Model	100	0.0002922	0.000012	0.0002632	0.0003263
RCP 2.6 2046-2065	100	0.0001891	0.0000181	0.0001495	0.000225
RCP 8.5 2046-2065	100	0.0001592	0.0000145	0.0001281	0.0001998
RCP 2.6 2081-2100	100	0.0001269	0.0000128	0.0000991	0.0001644
RCP 8.5 2081-2100	100	0.0001019	0.0000102	0.0000804	0.000128

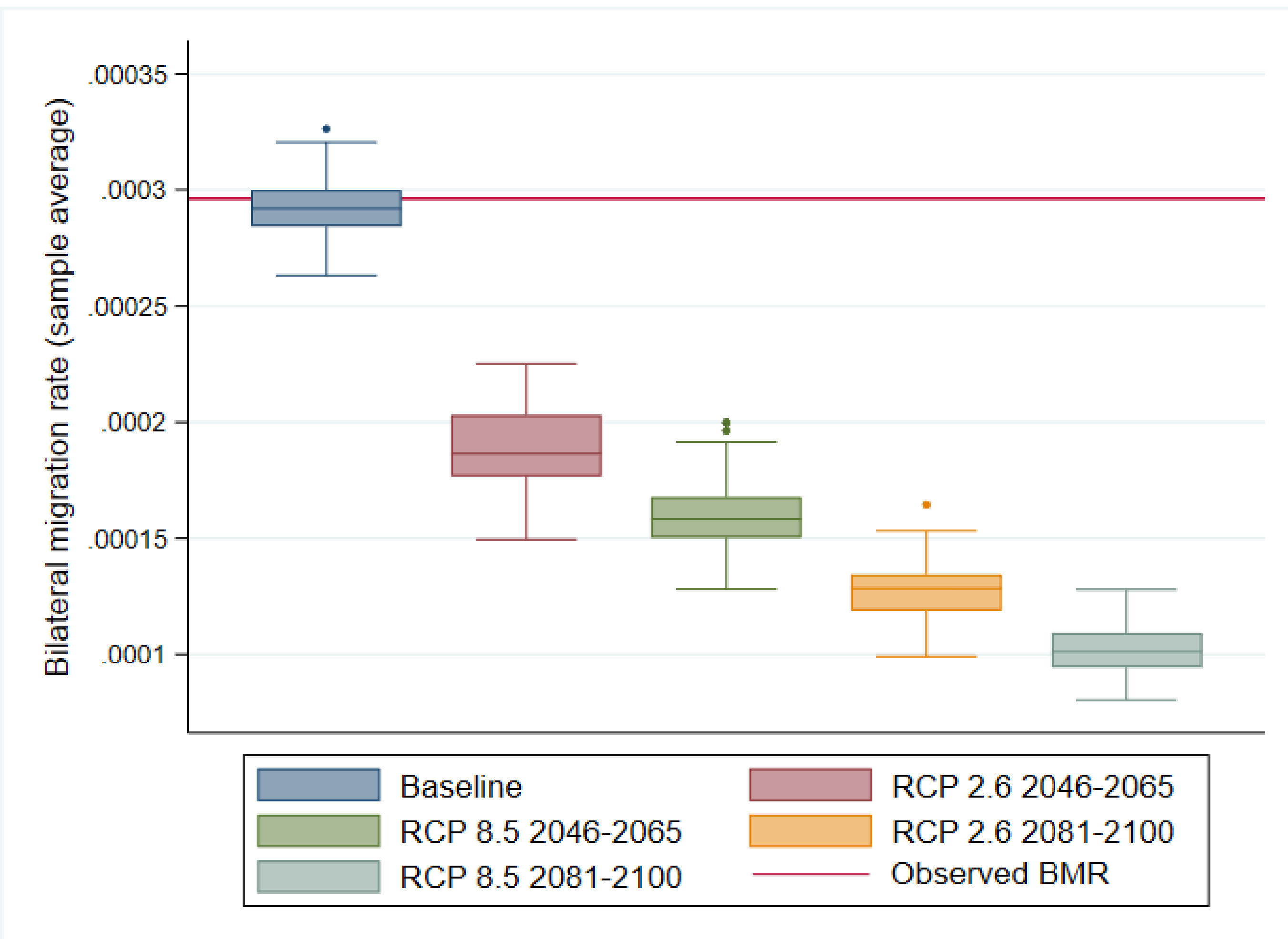


Table 23: Results Simulation Mitigation and Adaption

Type of Model	Observations	Mean	Standard Deviation	Minimum	Maximum
Baseline Model	100	0.0002922	0.000012	0.0002632	0.0003263
RCP 2.6 2046-2065	100	0.000288	0.0000229	0.0002381	0.0003438
RCP 8.5 2046-2065	100	0.0002604	0.0000163	0.0002102	0.0003031
RCP 2.6 2081-2100	100	0.0003923	0.0000216	0.0003487	0.0004713
RCP 8.5 2081-2100	100	0.0003985	0.0000238	0.0003511	0.0004773

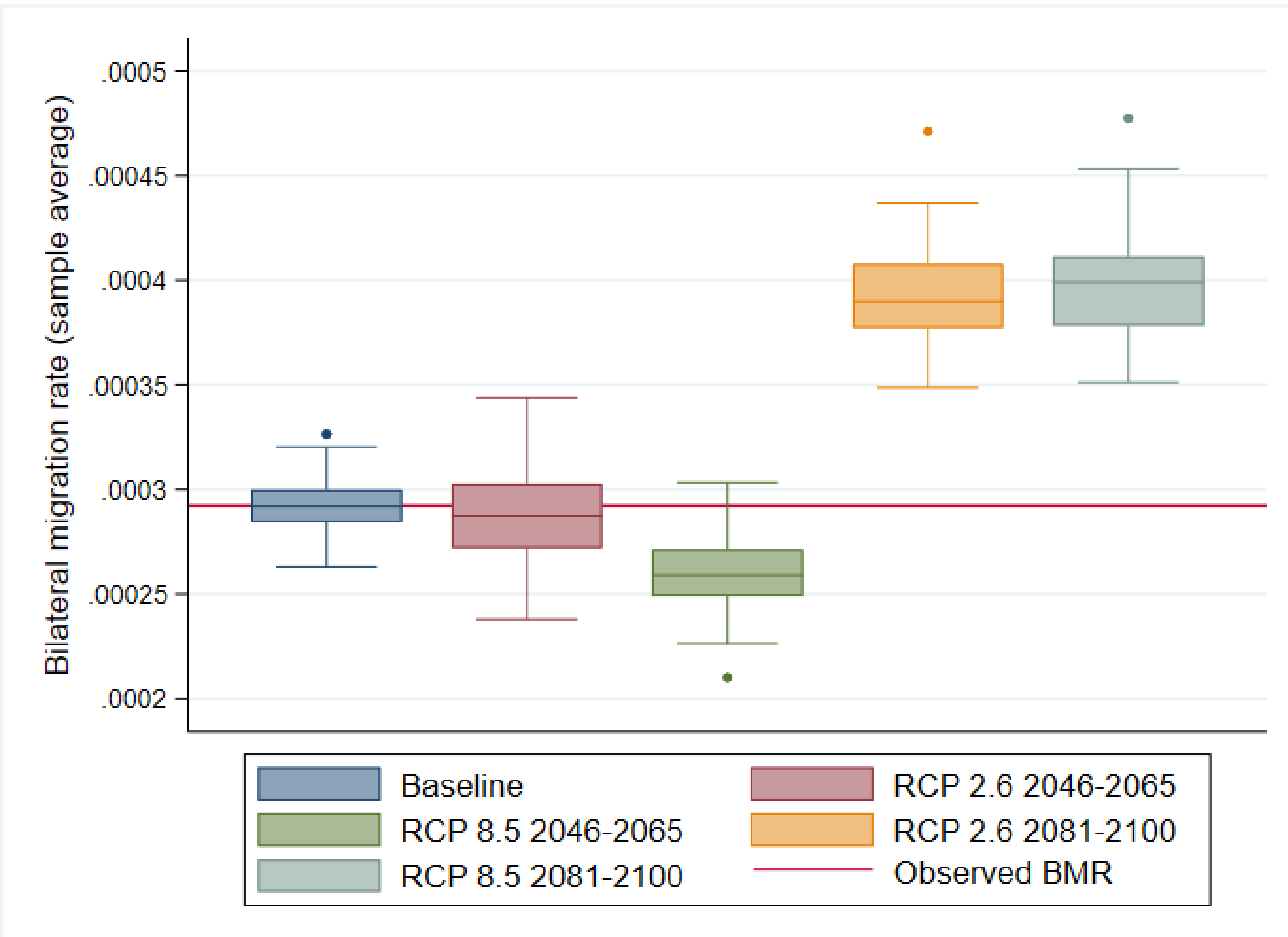
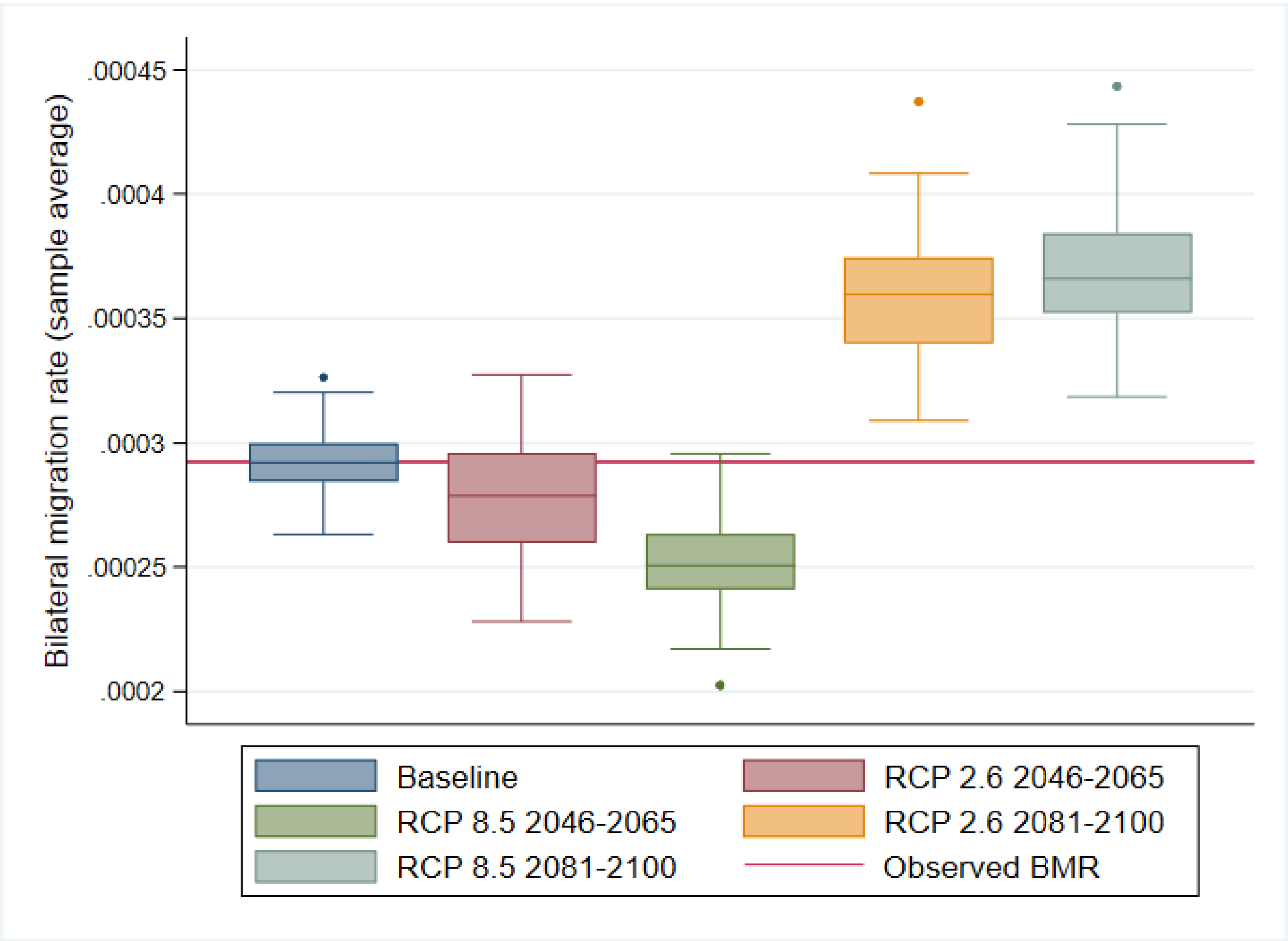


Table 24: Results Simulation Mitigation and Adaption Different for LDCs and MICs

Type of Model	Observations	Mean	Standard Deviation	Minimum	Maximum
Baseline Model	100	0.0002922	0.000012	0.0002632	0.0003263
RCP 2.6 2046-2065	100	0.0002776	0.0000229	0.0002281	0.0003263
RCP 8.5 2046-2065	100	0.0002523	0.0000171	0.0002025	0.0002956
RCP 2.6 2081-2100	100	0.0003584	0.0000243	0.0003089	0.0004372
RCP 8.5 2081-2100	100	0.0003695	0.0000243	0.0003184	0.00044333



E.2 Calculation Confidence Interval Bilateral Migration Rate

$$0.0002961 + 1.96 * (\frac{0.0024496}{\sqrt{10380}}) = 0.00034322513 \tag{19}$$

$$0.0002961 - 1.96 * (\frac{0.0024496}{\sqrt{10380}}) = 0.00024897487 \tag{20}$$

E.3 Population Growth

		Sample Population (millions)		
Region	Subregion	2005	2055	2090
Total		4,362.266	6,433.594	6,748.007
Africa		475.582	1,339.179	2,006.247
	East Africa	61.724	188.747	276.517
	Middle Africa	40.692	152.181	260.517
	Northern Africa	107.690	247.538	323.893
	Southern Africa	50.853	78.789	83.104
	Western Africa	214.624	671.926	1,062.216
Asia		3,373.165	4,459.335	4,145.125
	Eastern Asia	1,321.623	1,328.501	1,072.519
	Southern Asia	1,531.406	2,308.341	2,205.641
	South-Eastern Asia	440.165	628.440	617.383
	Western Asia	79.970	194.052	249.582
Europe		4.378	3.349	2.658
Latin America and the Caribbean		354.580	481.547	447.482
	Caribbean	12.008	16.812	15.070
	Central America	31.878	56.688	59.319
	South America	310.694	408.047	373.094
Oceania		10.942	18.875	21.980
Russia		143.618	131.310	124.513