FIW – Working Paper

FIW Working Paper N° 190
December 2018

Earthquakes and Economic Growth

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Natural disasters are known to have devastating immediate impacts, but their long-run effect on economic growth is not well understood. For the natural hazard of earthquakes, this paper provides the first global empirical study on this topic that applies a measure of the exogenous physical hazard responsible for earthquake impacts, earthquake ground shaking. I exploit the random within-country year-to-year variation of shaking to identify the causal effect of earthquakes on economic growth. To construct a panel dataset with country-year observations of earthquake exposure and socioeconomic variables, I combine the universe of relevant earthquake ground shaking data from 1973 to 2015 with country-level World Bank indicators. I find negative long-run growth impacts for an average country comparable with recent findings for climate related natural disasters. A typical earthquake reduces GDP per capita by 1.6% eight years later, with substantial heterogeneity by country categories. In particular, low and middle-income countries experience the greatest long-run economic damages while high-income countries may even experience some positive "building back better" effects. Based on an analysis of alternative spatial aggregation approaches, I find earthquake impacts are driven by local high-intensity events rather than spatially diffuse exposure to lower intensity shaking.

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The Research Centre International Economics FIW is a project of WIFO, wiiw and WSR on behalf of the Federal Ministry for Digital and Economic Affairs. The FIW cooperation with Austrian Universities is supported by the Federal Ministry of Education, Science and Research.

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This version: November 11, 2018
The most recent version is available at slackner.com/eeg

Abstract

Natural disasters are known to have devastating immediate impacts, but their long-run effect on economic growth is not well understood. For the natural hazard of earthquakes, this paper provides the first global empirical study on this topic that applies a measure of the exogenous physical hazard responsible for earthquake impacts, earthquake ground shaking. I exploit the random within-country year-to-year variation of shaking to identify the causal effect of earthquakes on economic growth. To construct a panel dataset with country-year observations of earthquake exposure and socioeconomic variables, I combine the universe of relevant earthquake ground shaking data from 1973 to 2015 with country-level World Bank indicators. I find negative long-run growth impacts for an average country comparable with recent findings for climate-related natural disasters. A typical earthquake reduces GDP per capita by 1.6% eight years later, with substantial heterogeneity by country categories. In particular, low and middle-income countries experience the greatest long-run economic damages while high-income countries may even experience some positive "building back better" effects. Based on an analysis of alternative spatial aggregation approaches, I find earthquake impacts are driven by local high-intensity events rather than spatially diffuse exposure to lower intensity shaking.

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[†]I am grateful to my advisors John Mutter, Douglas Almond, Michael Oppenheimer, and Art Lerner-Lam. I also want to thank Geoffrey Heal, Rodrigo Soares, George Deodatis, Donald Davis, Jeffrey Shrader, Suresh Naidu, Timothy Foreman, Jesse Anttila-Hughes, Amir Jina, Anouch Missirian, Markus Riegler, Tatyana Deryugina and other participants of the 2018 Heartland Environmental and Resource Economics Workshop at Illinois, my paper discussant Saudamini Das at the 2018 World Congress of Environmental and Resource Economists, seminar participants at Columbia University, and many students and alumni of the Columbia University Sustainable Development PhD program for valuable feedback and discussions on this paper.

1 Introduction

Earthquakes and other natural disasters cause considerable destruction and tremendous human suffering every year. For any given natural hazard type, population growth and urbanization will further increase their impacts in the future. The number of climate-related extreme events is also likely to increase with climate change. It will therefore become even more relevant in the future than it is already today to understand the immediate and long-run impacts of natural disasters. Earthquakes are a natural hazard with almost no warning time. In some regions of the world with well developed warning systems, a couple of minutes of warning is possible in the best case scenarios. But in many cases, especially in poor regions of the world, no warning exists. This fact is a major reason for why earthquakes are the most fatal natural hazard type, and they are particularly fatal in low-income countries (Wallemacq and House, 2018). They are not only a global concern in terms of capital destruction and human casualties, but they can also affect institutions (Belloc et al., 2016) and impact inequality within and across countries. Earthquakes and other natural disasters impose a disproportionately large burden on poor countries (Wallemacq and House, 2018), which can contribute to non-converging GDP per capita trajectories between rich and poor countries.

With this work, I provide the first global empirical study on the long-run economic impacts of earthquakes that utilizes a disaster measure which represents the exogenous physical hazard of earthquake ground shaking. This paper has three main contributions. First, I identify and quantify the long-run impacts of earthquakes on economic growth on a global level and with respect to countries' income categories. These quantifications can aid in a better understanding of long-run impacts of earthquakes, which is important for decision making on disaster planning and preparation. A significant long-run impact on GDP per capita suggests that earthquakes can be an essential component in determining growth in countries that are repeatedly exposed to strong earthquakes. Second, earthquakes provide the unique opportunity to study economic shocks through a completely exogenous natural experiment and hence provide a cleaner identification than previous literature on other types of shocks. Earthquakes are not predictable, and unlike climate-related hazards, they are not significantly affected by society. This paper therefore contributes to the general literature on long-run impacts of macroeconomic shocks such as fiscal shocks (Cerra and Saxena, 2008; Reinhart and Rogoff, 2009; Romer and Romer, 2010), civil war (Cerra and Saxena, 2008), and climate-related shocks (Dell et al., 2012; Hsiang and Jina, 2014). Third, this paper also provides a measurement and spatial methods contribution. I improve earthquake exposure measurement by using exogenous physical hazard data instead of endogenous direct impact data. I also improve on the exogenous earthquake measure by using quantifications of surface shaking exposure, the immediate cause of earthquake impacts, instead of earthquake magnitude, which only correlates with impacts through the surface phenomenon of ground shaking. Connected to the measurement of natural hazard exposure is the choice of a spatial data aggregation approach. Calculating an admin-region level exposure from gridded natural hazard data requires to apply a spatial aggregation approach, which always implies certain assumptions (e.g. about non-linearities). Since high-resolution gridded data is still relatively new, there is no standard method yet on how to choose spatial aggregation approaches. I contribute to filling this gap in the literature by explicitly discussing and comparing different spatial aggregation approaches. I show that the choice of the spatial aggregation approach is indeed highly relevant.

While the immediate impacts of natural disasters are undoubtedly negative, some studies have suggested that they have no or even positive long-run effects on the economy through technological upgrading and increased economic activity from rebuilding efforts (Albala-Bertrand, 1993; Skidmore and Toya, 2002). A standard Solow-Swan model would predict a return to the previous trend after a disaster exposure through temporarily increased growth rates. Davis and Weinstein (2002) find indeed that long-run city size is robust to large temporary shocks, suggesting a temporarily increased growth rate which offsets the negative impacts. Nevertheless, Hornbeck and Keniston (2017) present evidence for a creative destruction effect after the Boston fire of 1872 leading to a long-run positive net impact on land value. Agrawal (2011) argues that disasters are a natural reset button which can allow the transition to an alternative social trajectory. A transition to a better social trajectory might not always be possible though.

Many studies based on macro and micro-level empirical analyses as well as theoretic models have presented evidence that low-income populations affected by disasters are subject to particular constraints that can affect their recovery. Crespo Cuaresma et al. (2008) find that only rich countries benefit from capital upgrading after a natural disaster and Hallegatte and Dumas (2009) suggest that natural disasters may be an explanation for poverty traps, when disaster damages exceed the reconstruction capacity of the affected economy. However, the dynamics of how a country can get locked into a low-level equilibrium after a natural disaster are complicated. Based on data for Vietnam, Noy and Vu (2010) show that disasters have net negative impacts on the affected regions but that relatively more destructive than lethal events have less negative effects, suggesting a form of "reconstruction boom". De Mel et al. (2011) find that grants allocated to microenterprises in Sri Lanka were effective in supporting recovery after the 2004 tsunami, concluding that lack of access to capital inhibits the recovery process. However, McSweeney and Coomes (2011) demonstrate that even poor communities can in some cases benefit in the long-run from a disaster.

The empirical literature on the global impacts of natural disasters on long-run economic productivity is full of studies that use endogenous or suboptimal disaster exposure measures. This body of literature is relatively young and the methodology is still developing. The exisiting inconsistent results in the literature are therefore not surprising, with studies suggesting large negative, no, or even positive effects as well as disagreements about potential heterogeneities in the effects (Hsiang and Jina, 2014; Felbermayr and Gröschl, 2014). Skidmore and Toya (2002) conducted the first empirical study on the long-run growth impacts of natural disasters. However, the study is based on cross-country regression analyses, which suffer from endogeneity biases. Other studies have addressed this issue by utilizing panel datasets to be able to make conclusions about causality (e.g. Raddatz, 2007; Crespo Cuaresma et al., 2008; Cavallo et al., 2013). The applied disaster exposure measures have usually been based on the EM-DAT disaster database[1], either using the number of events or the reported damages. However, disaster impact data is endogenous, whereas an exogenous measure for the intensity of the natural hazard is required for an unbiased estimation. A number of publications have pointed out the shortcomings of using the EM-DAT database for studying long-run impacts (Noy, 2009; Felbermayr and Gröschl, 2014; Hsiang and Jina, 2014). To overcome these shortcomings, Felbermayr and Gröschl (2014) develop a database of disaster exposure that is based on geophysical measures of the natural hazard and apply it in a panel data analysis of long-run growth impacts. However, to accomplish the extensive task of creating country-level exposure variables for five different types of natural hazards they apply very simplified approaches for measuring the individual natural hazards. For the case of earthquakes, for example, they use an approach based on magnitude which is not a good proxy for surface shaking - the actual cause of earthquake impacts (Lackner, 2018b).

Considering the exogenous physical hazard is crucial to accurately identify the long-run growth impacts of natural disasters. It is therefore necessary to sufficiently take into account the specific geophysical characteristics and spatial patterns of the individual natural hazard types. Before combining various types of natural hazards in one study on natural disasters, it is therefore advisable to first study hazards individually. Besides prudence of applying sound scientific geophysical measures for the natural hazards, studying different

[1]The EM-DAT International Disaster Database contains reported information on events that exceed certain impact thresholds and is maintained by the Centre for Research on the Epidemiology of Disasters (CRED).

hazard types separately also has an additional advantage. The mechanisms of how disasters affect economies in the long-run might be specific or at least correlated to the hazard type. Studying them separately can help to identify these differences. There are several reasons for how the natural hazard type can be a determinant of mechanisms and thus of long-run impacts. First, different types of natural hazards might have systematic differences in what kind of immediate impacts they cause (e.g. a flooded house vs. losing the roof in a storm). The long-run impacts could therefore also differ for different types of events. Second, different hazards have inherently different warning times. Cyclones, for example, come with a couple of days of warning, while earthquakes have a maximum warning time of a couple of minutes in the best case scenarios. Last minute (or rather last day) measures that are possible for cyclones (e.g. evacuation or boarding up windows) will never be able to completely prevent impacts, but they do have the potential to significantly change not just the size but also the nature of direct impacts, thus resulting in potentially systematic long-run differences in growth impacts. The lack of warning for earthquakes, for example, makes them particularly deadly. Earthquakes therefore have relatively more human capital impacts than capital impacts compared to storms. Furthermore, the spatial pattern of the natural hazard are specific to the hazard type. This study will show evidence that spatially more concentrated impacts might be responsible for most of the long-run impacts of earthquakes. If this holds in general for natural disasters, the spatial pattern of a hazard has a significant relationship with long-run impacts.

While climate-related natural hazards are intensely studied in the literature, geologic natural hazards have received less attention. An increasing body of literature examines how different climate variables affect economic outcomes by taking advantage of exogenous variation over time within a given spatial unit (Dell et al., 2014). Hsiang and Jina (2014) provide a comprehensive analysis of the long-run growth impacts of cyclones and Dell et al. (2012) have investigated the role of temperature shocks in determining growth. No comparable study on the long-run growth impacts of earthquakes exists so far. Only relatively few empirical studies have analyzed the long-run impacts of earthquakes on GDP or other welfare-related economic variables. Except for some local case studies (e.g. Gignoux and Menéndez, 2016; Kirchberger, 2017), all empirical studies on the subject are not earthquake specific but consider a range of different natural disasters. No global study on long-run impacts of earthquakes on economic growth (or other macroeconomic variables) has utilized a quantification of surface shaking for the natural hazard of earthquakes. While earthquake magnitude is commonly used to quantify the exogenous natural hazard, it has been shown that it is not a good proxy for surface shaking and is therefore a suboptimal measure (Lackner, 2018b). With this work I also demonstrate that using a measure that is based on ground shaking instead of magnitude is crucial for identifying long-run impacts.

I exploit the random within-country variation of earthquake shaking over years to identify the causal effect of earthquakes on economic growth. Lackner (2018a) introduces a dataset which represents the universe of global relevant earthquake shaking for 1973-2015. Here, I combine this dataset with World Bank indicators to construct a panel dataset with annual country level earthquake exposure linked with economic variables. Based on the results in Lackner (2018b), I use peak ground acceleration (PGA) to quantify ground shaking. I particularly investigate potential heterogeneities in the effects as well as non-linearities. Furthermore, I assess the relevance of spatially diffuse nuisance exposure compared to spatially concentrated high level exposure by applying different spatial aggregation approaches for the natural hazard.

I find significant global net long-run economic growth impacts with substantial heterogeneities in the effects. Eight years later an average (non-zero) earthquake exposure reduces GDP per capita by 1.6%, a 90% percentile exposure even by 3.8%. However, low-income countries are strongly negatively affected while high-income countries might even be able to benefit from "building back better" effects. I simulate alternative GDP per capita trajectories without earthquakes for low and lower-middle income countries and compare them to their actual trajectories. This comparison reveals that GDP per capita among all low and lower-middle income countries would have been on average 2.4% higher in 2015 if earthquakes would not have had a negative effect on their economic growth in the preceeding four decades. Among regularly exposed countries of this group of countries, the difference between actual and simulated GDP per capita is even 7.7%. Furthermore, I find that localized disaster events are the drivers behind impacts compared to more widespread nuisance exposure.

2 Theoretical Framework

We can start with a simple growth model to illustrate the theoretical relationship between natural disasters and economic growth. The following Cobb-Douglas production function describes economic output Y as a function of labor L and capital K.

$$Y = AL^{\beta}K^{\alpha} \tag{1}$$

Denoting level variables in capital letters and per capita variables in lower caps, we can rewrite this in per capita terms.

$$y = AL^{\beta-1}K^{\alpha} \tag{2}$$

If the production function has constant returns to scale ($\beta + \alpha = 1$), we can simplify this equation.

$$y = Ak^{\alpha} \tag{3}$$

The change in the capital-labor ratio k is assumed to be defined by the savings function $s()$, population growth n, and depreciation d.

$$\Delta k = s(y) - (n + d)k \tag{4}$$

In this model the steady-state would be characterized by a growth rate of per capita output y that is equal to the growth of the total factor productivity A. In a model like this, a natural disaster should merely reduce capital. This would set the economy back in its development path, but it would experience higher growth rates and return to its original trend.

Natural disasters - and earthquakes in particular - are actually often used to illustrate a sudden reduction in capital in neo-classical growth models. A mystical earthquake is supposed to open up the earth and almost surgically take out capital without affecting the economy in any other way. Unfortunately, this is not how earthquakes work and my empirical analysis does not confirm such a return to trend. Poverty traps might be responsible for why a reduction in capital through a disaster could be detrimental for an already poor country. Poverty traps are represented by S-shaped curves of next period's capital as a function of current capital. This is usually argued to result from an S-shaped savings curve. But there are many more pathways of how earthquakes can affect long-run growth even in a simple model like this.

Earthquakes don't just destroy capital, they kill people and affect human capital in many ways. After an earthquake labor is likely less efficient since employees might miss work, are distracted during work, need to move and find new jobs, and know-how might be lost. Capital, on the other hand, might not just be destroyed but also experience higher depreciation rates after a disaster. The misallocation of human capital in the immediate aftermath of a natural disaster is actually an infamous phenomenon. Replacement of equipment and infrastructure might be subject to different constraints and the availability of loans as well as social, political, and legal frameworks can be significantly changed compared to before the event (Belloc et al. (2016) show that earthquakes can affect institutions). A disaster can essentially introduce frictions into the economy in numerous ways. In our model, this could mean that the population growth rate n or the depreciation rate d are endogenous and subject to the state of the economy which could be affected by a disaster.

A permanent increase in n or d would imply a new steady state with the same growth rate as before, but the event would shift down the trajectory of the GDP per capita level. Depending on the growth rate θ of the total factor productivity, this shift can either imply an actual reduction of the GDP per capita level, or just a growth rate below θ for a number of periods until the new steady state is established. The long-run GDP per capita level trajectory would be lower but parallel to the counterfactual trajectory without the disaster.

Furthermore, a natural disaster might change how effectively capital or labor can be employed for production and thus change the output elasticities of capital or labor (α and β), resulting in decreasing returns to scale. Equation 3 would no longer hold, since it depends on the assumption of constant returns to scale.

Finally, a disaster could also change the growth rate θ of the total factor productivity A and hence also change the steady state accordingly. After a disaster it is likely that investments in research and development are reduced and risk aversion by entrepreneurs could be increased. This would result in a reduction of technological growth θ and therefore also a reduction in GDP per capita growth. If this change is temporary, the change in the GDP per capita trajectory is equivalent as in the example of an increase in population growth n or depreciation rate d. In the case of a permanent change in θ it would also imply a reduced steady state growth rate of GDP per capita.

Country characteristics such as culture, geography, or income category could affect which of these discussed changes would be experienced by an economy and to what extend. It is therefore not straightforward to conclude how earthquakes would affect economic productivity in the long-run.

3 Data

For this study, a panel dataset of country-year observations of shaking and economic variables is constructed. The dataset can be considered to contain the universe of global relevant ground shaking for the years 1973 - 2015. Since the shaking data is restricted to these years, and at least eight lags - as well as three leads - of shaking will be included in the analysis the dataset for the analysis spans the 32 years from 1981 to 2012. The availability of economic

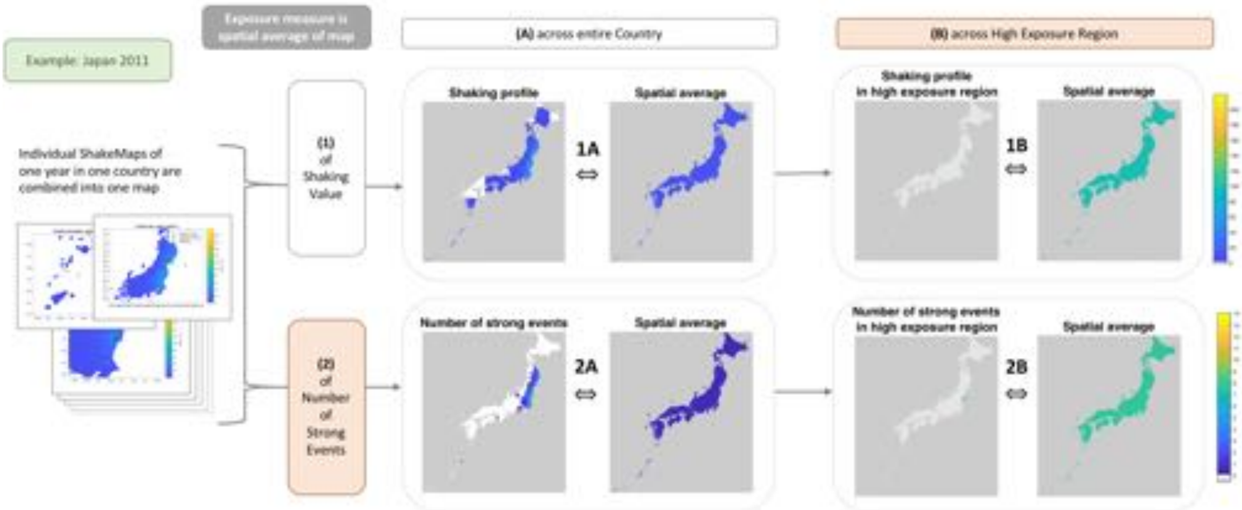

Figure 1: Data processing. Illustration of how the data is processed to calculate four different annual country-level exposure measures. Among those measures Exposure 2B is the best proxy for whether a "disaster" event occurred. It is used as the default measure in this study. Other literature so far has primarily relied on the simple spatial average (Exposure 1A), which implies a linear relationship between the physical measure and long-run growth impacts.

data restricts the number of countries included in the dataset. The final dataset includes 195 countries. Four different natural hazard exposure variables are calculated and evaluated. The four exposure variables are based on different spatial aggregation approaches and are illustrated in Figure 1. Summary statistics of the data are provided in the appendix.

Earthquake Shaking Data

The shaking data is based on some 14,000 USGS ShakeMaps (Wald et al., 1999) from individual earthquakes which have been combined into one dataset (Lackner, 2018a). The dataset can be considered to contain the universe of global relevant ground shaking for the years 1973 - 2015. The individual ShakeMaps are compiled into one dataset, which is applied to calculate annual country level shaking exposure variables for the years 1973 - 2015. Peak ground acceleration (PGA) maps are here used for the analysis. PGA is commonly used in earthquake engineering and has been shown to perform well in explaining earthquake impacts at an event level compared to other earthquake shaking quantifications with good data availability (Lackner, 2018b). For each country, two different types of annual maps of earthquake exposure are produced. First, annual shaking grids representing the **(1) shaking value** are created by calculating the maximum PGA value in a grid cell over the respective year. The second type of annual maps displays the number of earthquakes that exceeded a threshold of 10%g in the respective location and year, thus representing the **(2) number of strong events**. Each of the two annual grids has a resolution of 1/120 x 1/120 of a degree[2]. Examples of such maps are illustrated in Figure 1. Global maps of the annual averages over 1973-2015 of the shaking value maps and the number of events maps are provided in Figure 14 and Figure 2 respectively.

Other Data

The GPW gridded population data (CIESIN et al., 2005; CIESIN, 2016c) is used to generate annual population maps for each country at a resolution of 1/120 of a degree. For the years without GPW data I estimate population numbers by assuming an exponential growth model (consistent with the GPW model approach). The GPW national identifier grid (CIESIN, 2016b) is used to define the country shapes for the 241 countries represented in the data. Moreover, The GPW land area grid (CIESIN, 2016a) is used to assign an area size in square kilometer to each grid cell.

The World Bank indicator NY_GDP_PCAP_KD for "GDP per capita (constant 2010 US$)"[3] is used as the main outcome variable of interest. Also the World Bank indicators for fertility rates, under 5-years child mortality, displacement, and growth of the three different economic sectors [4] are obtained and used in the empirical analysis. Each country is assigned to an income category according to the World Bank classifications from 2015[5]. The World Bank Gross National Income indicator NY.GNP.PCAP.CD (GNI per capita, Atlas method current US$) from 2015 is used to assign an income category to each country. For countries with a missing value for the year 2015, the most recent available data point of the indicator is used. Countries with a GNI per capita below $1,026 are categorized as low-income economies. Between $1,026 and $4,035 they are defined as lower middle-income economies, and between $4,036 and $12,475 as upper middle- income economies. High-income economies are defined as those countries which have a GNI per capita above $12,476.

[2] The same resolution as the GPW population (CIESIN, 2016c) data.

[3] All World Bank data has been downloaded using the wbopendata tool for Stata. https://datahelpdesk.worldbank.org/knowledgebase/articles/889464 (accessed on 4/10/17)

[4] Those indicators are: SP_DYN_TFRT_IN "Fertility rate, total (births per woman)"; SH_DYN_MORT "Mortality rate, under-5 (per 1,000 live births)"; VC_IDP_TOTL_HE " Internally displaced persons (number, high estimate)" in the analysis the indicator is divided by the total population; NV_AGR_TOTL_KD_ZG "Agriculture, value added (annual % growth)"; NV_SRV_TETC_KD_ZG "Services, etc., value added (annual % growth)"; NV_IND_TOTL_KD_ZG "Industry, value added (annual % growth)".

[5] http://databank.worldbank.org/data/download/site-content/OGHIST.xls (accessed on 8/21/2018).

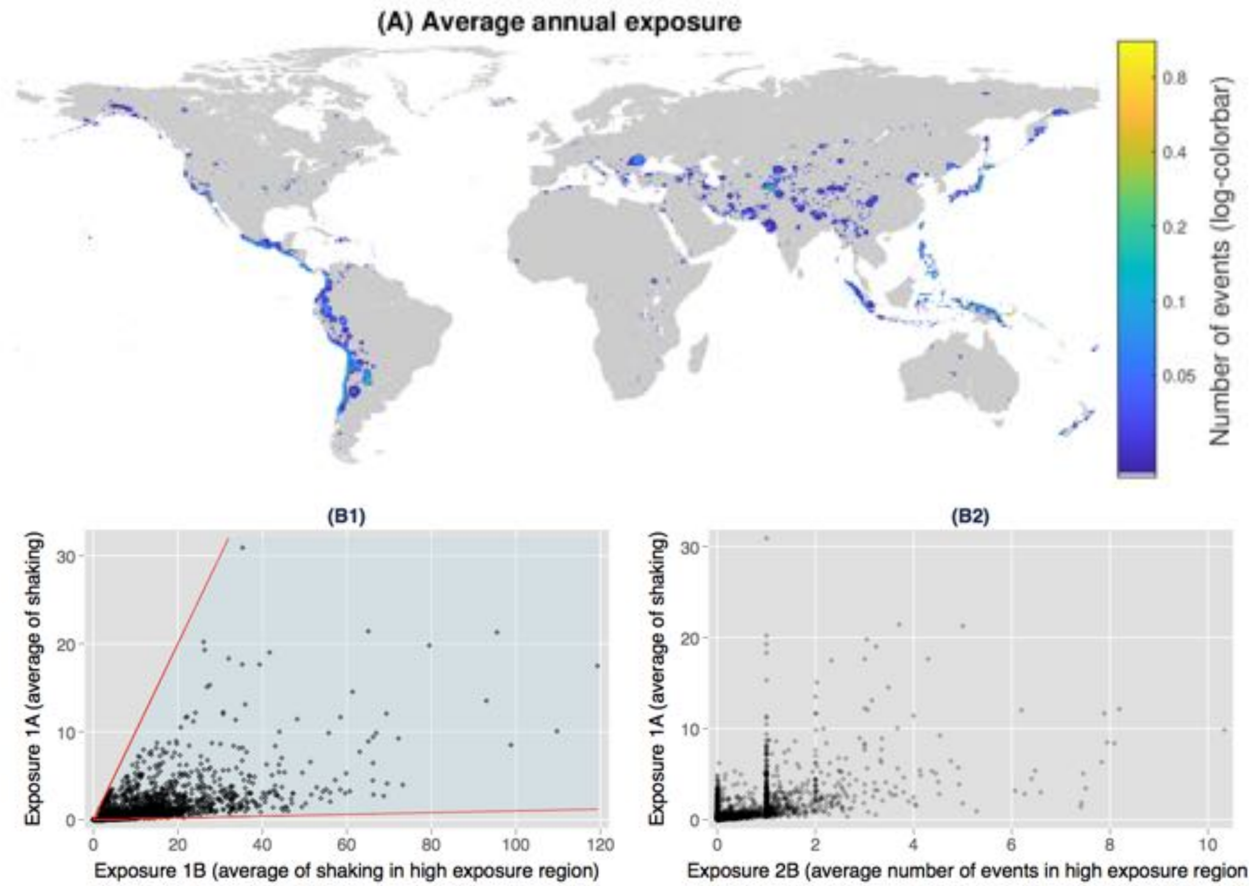

Figure 2: Overview of the exposure data. Panel (A) displays the average of the annual exposure maps that are used to calculate exposures 2A and 2B. It shows the average annual number of events with shaking above the threshold of 10%g PGA based on the years 1973 - 2015. Panel (B) compares the different country-level exposure measures. The relationship between exposure 1A and 1B (which is restricted by an upper and lower bound in red) in panel (B1) illustrates that the spatial average is not always a good proxy for whether a disaster event occurred. This becomes even more obvious in panel (B2), which compares exposure 1A and 2B.

4 Spatial Aggregation of the Natural Hazard Data

Economic growth data is independent of country size and a single-valued annual exposure measure that is also independent of country size is therefore needed. Hsiang and Jina (2014) use the spatial average to aggregate wind speeds to a country-level variable to be able to link the geophysical measurements with the economic measurements. This has two caveats. It requires the assumption that long-run impacts increase in a linear manner with the geophysical hazard, and it introduces a form of measurement error.

While a linear relationship between the geophysical hazard and long-run impacts might hold for the case of cyclone wind speeds, we can not necessarily assume the same for earthquake shaking (measured by PGA). Previous results on the correlation between PGA and impacts at an event level don't refute that this might also be true for PGA, but they also show that the ability to explain direct impacts for the spatial average decreases with an increase in the area size considered (Lackner, 2018b). This suggest that small regions of high intensity shaking are responsible for the bulk of damages and lower shaking values are not that relevant. Nevertheless, other research (Shoaf et al., 1998) has found that injuries in the 1994 Californian Northridge earthquake increased in an approximately linear manner with PGA. However, even if direct impacts are linearly affected by shaking, this does not necessarily imply that a linear relationship applies for the long-run impacts on GDP per capita. If the entire country is exposed to a uniform very low shaking value this might have very different impacts than if only a very small part of the country is exposed to very strong shaking, but the two scenarios could have the same spatial average exposure. The spatial average alone can not tell us if an event that we would consider a "disaster" actually occurred. The approach of Hsiang and Jina (2014) suggests that the occurrence of a "disaster" is not necessarily relevant, but that a large spatial extent of low valued hazard exposure adds up to similar impacts as a smaller spatial extent of a high valued exposure. On the other hand, it might be true that a local high intensity event with a clustering of direct impacts is necessary to be disruptive enough to the economy to affect growth in a significant way.

The difference between the physics of cyclones and earthquakes might affect how well of a proxy the spatial average is, for whether a (local) high intensity event (a "disaster") occurred. Cyclones are spatially larger phenomena than earthquakes and cyclone exposure is concentrated in coastal regions in the tropics and mid latitudes (Hsiang and Jina, 2014). For any specific year, the regions within a country that experience positive cyclone wind speeds tend to be connected due to physics behind how and where cyclones form and travel. Earthquakes on the other hand occur primarily along plate boundaries, which also tend to be along coastlines, but the "earthquake history" is less concentrated than the "cyclone climate". Hsiang and Jina (2014) term the average annual pixel exposure to cyclone wind speeds as the *cyclone climate*. In a similar way we can define the *earthquake shaking history*, which is illustrated in Figure 14[6]. Figure 2 provides an overview of the regions that have experienced shaking above 10%g PGA. It is probably more common for earthquake shaking exposure maps of a country to exhibit relatively large (often disconnected) areas of low valued exposure than it is for cyclone wind speed exposure maps. The fact that a wind-speed threshold defines whether a cyclone is classified as a cyclone, while no such threshold exists for earthquakes is also partially responsible for this.

Relatively large spatial exposure of a country to positive cyclone wind speeds likely correlates well with the maximum exposure (grid cell with the highest value in that year). This correlation is not particularly strong for earthquakes. Whether the impacts of the natural hazard are linear or whether local high intensities are the drivers of impacts, might not matter much for applying spatial averages in the case of cyclones since the spatial average is probably a good proxy for whether a (local) "disaster" occurred. For earthquakes on the other hand, the spatial average might not be appropriate if high intensities are the main source of long-run impacts.

The second issue with the use of the spatial average is that it introduces a form of measurement error due to the differences in land use in different countries and the spatial differences across events and countries. Individual natural disasters (no matter if earthquake or cyclone) can differ a lot in how much they overlap with densely populated or capital intense areas. Individual countries also vary a lot in how much of their territory is made up by unpopulated, rural, or urban regions. For example Hong Kong has essentially no unpopulated regions and a large share of the entire territory is urban while Russia has large unpopulated regions and only a relatively small part of the country is urban. For any given non-zero exposure calculated by the spatial average, it is relatively save to assume that an event actually hit populated regions in the case of Hong Kong, but a large uncertainty exists about whether this is the case for Russia. From a data perspective, the variance of the shaking will be negatively correlated with the size of the country. This is not necessarily a major concern, but it does introduce noise into the data. If the impacts don't increase in a linear manner with the natural hazard as discussed above, this will also have an additional impact on the difference between small and large countries, since the spatial mean of shaking

[6]In theory the term earthquake shaking climate could be used, but since earthquakes are not a climate phenomenon and past shaking is not equal to future earthquake risk. To avoid misinterpretation, I have therefore chosen the term earthquake shaking history. For a map of the maximum exposure experienced see also Figure 15.

is a better proxy for whether a "disaster" occurred for a small country than it is for a large country.

Definition of the exposure measure

I compare four different definitions of annual earthquake exposure which are illustrated in Figure 1. They are furthermore calculated across different interest areas (defined by population distribution) across the country as well as the entire country. The populated part of the country is used as the default area definition of a country.

As discussed before, two different types of annual exposure maps are produced from the shaking data: **(1) shaking value** maps, and **(2) number of strong events** maps. Each of the two types of annual maps are aggregated in two ways, as the spatial average **(A) across the country**, and **(B) across the high exposure region** which is defined as the (spatial) 1% of the country with the highest exposure in the respective year. The four different measures are therefore labelled 1A, 1B, 2A, and 2B. The second version of each component (2 and B) both give more emphasis to stronger shaking and thus are a better measure for whether a more local strong disaster event occurred compared to more widespread nuisance exposure. In the case of non-linearities these measures are assumed to perform better than the spatial average in identifying impacts. Measure 2B is used as the default exposure measure.

Restricting to only 1% of the country, but still considering the variable as a representation of the exposure of the entire country is not a major concern for several reasons. First, it has been repeatedly emphasized in the literature that natural hazard zones tend to also often be economically attractive regions such as coastlines and are thus often densely populated. This is also true for earthquakes, which is easy to see from a comparison of hazard maps and population maps (e.g Figure 14 and Figure 27). It will therefore be uncommon that a high exposure in 1% of the country will have only hit sparsely populated regions. This is particularly true for the baseline case which only considers the populated regions of each country. Second, if a high exposure is observed in the strongest 1% of a country it is unlikely that the rest of the country was untouched by earthquake shaking. This is because (i) the spatial extent of strong events can be quite large and even the area exposed to at least 90% of the maximum shaking is on average 171 square kilometers (Lackner, 2018a), and (ii) earthquakes occur in clusters and have aftershocks that - while spatially close - are usually not at the exact same location.

The difference between the physics of cyclones and earthquakes might affect how well of a proxy the spatial average is, for whether a (local) high intensity event (a disaster) occurred. To investigate this, Panel B1 in Figure 2 compares the averages over the entire (populated) country with the average restricted to the strongest 1% region. The average shaking is restricted by an upper bound (it can not be larger than the average in the strongest 1%) and a lower bound (1% of the average shaking in the strongest 1%), which are depicted by the red lines. The two variables do not show a strong linear relationship (the correlation is 0.6), suggesting that the overall spatial average is not a particularly good proxy for whether a localized high intensity event occurred. For cyclones this correlation could be significantly higher and the spatial average might thus be a reasonable proxy for whether a disaster event occurred. However, given this relationship for earthquakes, if impacts are not linear, a measure that summarizes the occurrence of strong shaking would be better suited than the average over all shaking values. For this study, I therefore also create the number of events maps to calculate exposure measures from. The average over these maps can be considered an estimate for the spatial extent of strong shaking in the given year and country.

The spatial average approach is here extended by not just calculating spatial averages over the entire country but also with respect to different spatial definitions of "the country". Hsiang and Jina (2014) omit Alaska from the calculation of the spatial average for the United States, presumably because it is largely unpopulated. However, they do not apply a similar approach for other sparsely populated regions of the world (e.g. Russia). To apply a more systematic approach, I will define unpopulated regions for each country and omit those[7] from the calculation of the spatial average in the *populated* part of the country. Details on how these areas are defined can be found in Appendix B. A threshold of 1 person per square kilometer is used in the default specification. While a population weighted exposure would be a solution for the heterogeneity issue of how different events actually affect society, it would introduce endogeneity into the measure since it is very likely that population density responds to natural hazard risks. However, I assume that it is unlikely that an otherwise favorable location would be completely unpopulated due to such a risk.

5 Empirical Framework

I exploit the random within-country variation of earthquake shaking over years to identify the causal effect of earthquakes on economic productivity. The empirical approach is similar to Hsiang and Jina (2014). An impulse-response function of growth (calculated as the first

[7]This includes most but not all of Alaska for the US.

differences of log GDP per capita $Y_{i,t} = ln(GPD_{i,t}) - ln(GPD_{i,t-1}))$ to earthquake shaking exposure S for up to k lags is applied, while accounting for country i as well as year t specific differences by including country and year fixed effects (γ_i and δ_t). Additionally a country-specific linear time trend is included which accounts for country-specific rates of capital and human capital accumulation.

$$Y_{i,t} = \gamma_i + \delta_t + \eta_i t + \sum_{\tau=0}^{k} \beta_\tau S_{i,t-\tau} + \epsilon_{i,t} \tag{5}$$

The error terms are allowed to be serially correlated within a country for up to 10 years and spatially correlated across countries within the same year for up to 1000km (Hsiang, 2010). The coefficients β can be summed up to calculate the cumulative reduction (in percent) of GDP per capita after j years.

$$\Omega_j = \sum_{\tau=0}^{j} \beta_\tau \tag{6}$$

The results will focus on these cumulative impacts on GDP per capita Ω_j. A lag length k of eight years is used in the standard specification which is much shorter than the 20 years considered by Hsiang and Jina (2014). However, the shorter time period of the earthquake panel data does not allow for a similar number of lags. Furthermore, leads of shaking for up to three years are included.

To distinguish between the impacts on different groups of countries the shaking exposure is interacted with a dummy variable for the different groups.

$$Y_{i,t} = \gamma_i + \delta_t + \eta_i t + \sum_{\tau=0}^{k} \beta_{\tau,c(i)} S_{i,t-\tau} \times D_{c(i)} + \epsilon_{i,t} \tag{7}$$

This approach allows for a different response to shaking exposure for different groups $c(i)$ of countries. Countries are classified by income category, size of populated area, whether they experience earthquakes on a regular basis, and population density in populated regions. An overview of the number of countries in each group is provided in Table 1 in the appendix.

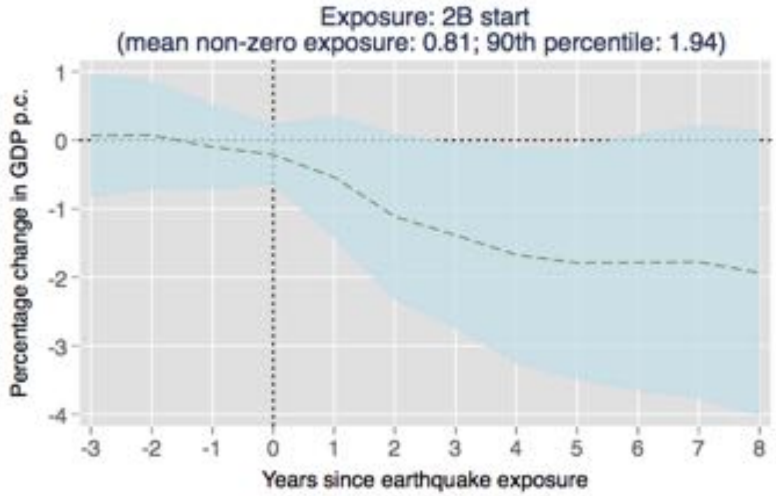

Figure 3: The cumulative impact of earthquake exposure on GDP per capita. A 95% confidence interval is included and the dotted zero-line represents the previous baseline trend (N = 5586). Growth drops in the years following an exposure. While growth recovers after a few years, earthquakes still have negative long-run effects on the level of GDP per capita after 8 years.

6 Results

To discuss the results, we will focus on plotting the cumulative impacts Ω_1 through Ω_8 of earthquake shaking exposure on GDP per capita describing the percentage deviation from the pre-disaster baseline trend. Result tables with the β_τ coefficent estimates are reported in the appendix. Additionally to the lags, also the cumulative coefficients of the leads are included (Ω_{-1} through Ω_{-3}). A 95% confidence interval is plotted with the coefficients. For examples of the time-series of GDP per capita growth and the different shaking exposure variables of individual countries see Figures 23 - 25 in the appendix.

Global Average Impact of Earthquakes

I will first discuss the results from the model with the default specifications. Figure 3 presents the results from the model described by Equation 5 with eight lags and three leads and applying the earthquake exposure measure 2B (the average number of events with PGA $\geq$ 10%g in the most exposed 1% of the country) with respect to only the populated part of each country. The plotted estimates describe the marginal response of GDP per capita to an increase in the exposure measure 2B. The results suggest that earthquakes cause significant long-run impacts on GDP per capita even eight years after an exposure. We observe a significant drop in GDP per capita in the years after an earthquake exposure compared to

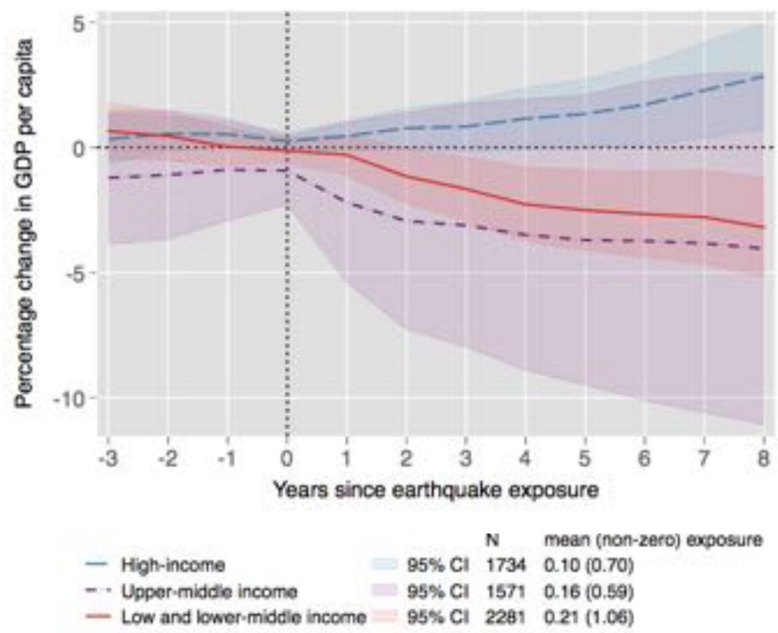

Figure 4: The impulse response to earthquake exposure by income categories. Low-income countries are significantly affected by earthquake exposure while high-income countries are potentially even able to experience building back better effects.

the baseline trend representing the counterfactual without an earthquake exposure. After about 5 years the drop seems to stabilize but not return to the baseline trend (at least not by year 8). The leads are not significant, which suggests that the model is well specified. Varying the number of leads and lags does not affect the results in a significant way (see Figure 31). The shaking in unpopulated regions of countries should not matter much in determining impacts, shaking exposure variables based on only the populated part of each country are therefore used as the default. The results based on the entire country are reported in Figure 33.

An earthquake that exposes 1% of a country to a shaking of at least 10%g is estimated to cause a reduction in GDP per capita eight years later by almost 2%. An average non-zero exposure would suggest a reduction of GDP per capita by 1.6% after eight years, a 90th percentile non-zero exposure by 3.8%, and a 99th percentile exposure by even 10.2%. These results represent a global net average of impacts across all countries. However, since disasters can have a stimulating effect on the economy in certain circumstances, it is possible that heterogeneities in the effects exist.

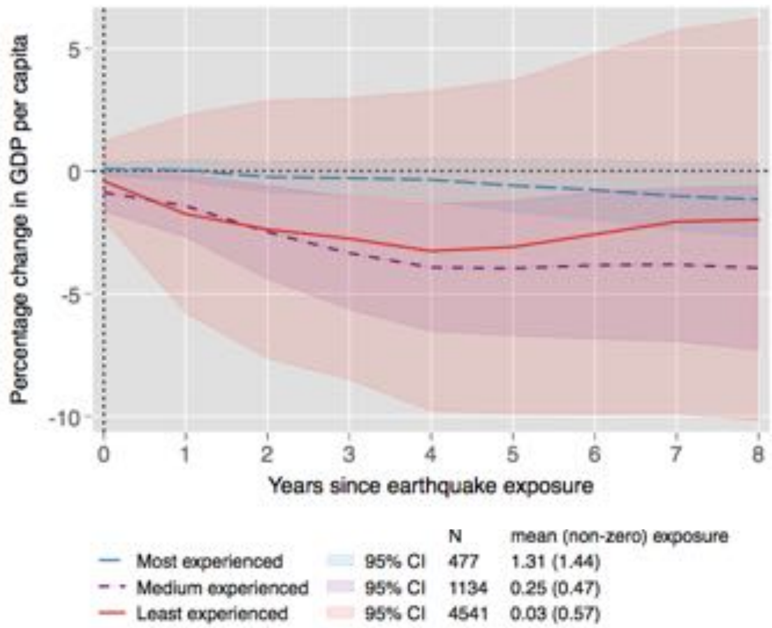

Figure 5: The impulse response to exposure differentiated by country experience with earthquakes. The results suggests that adaptation is effective in preventing at least some of the long-run impacts of earthquakes.

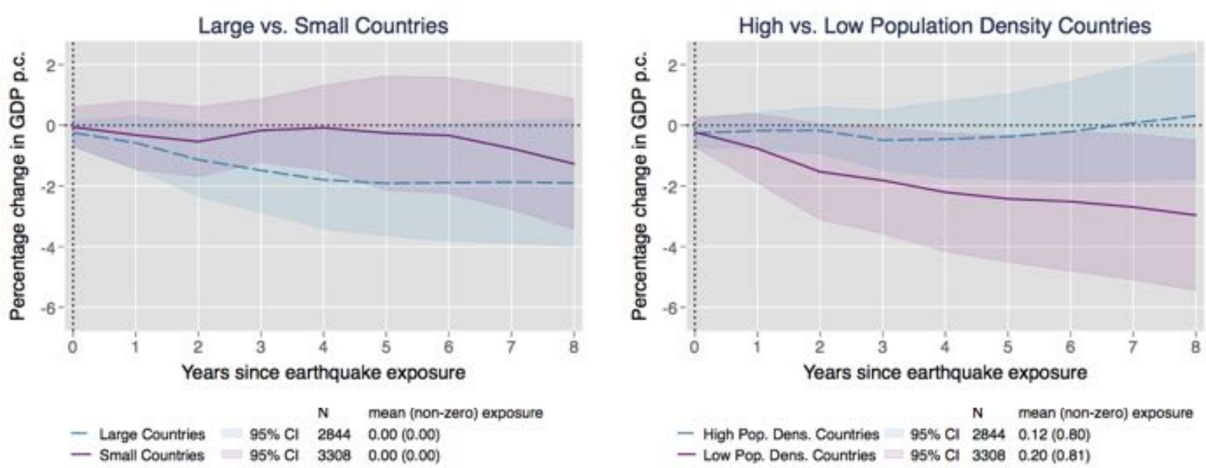

Figure 6: The impulse response to exposure differentiated by country size (left) and country population density (right).

Heterogenous Response

Creative destruction and building back better are often argued to cause positive effects after a disaster. While the results here suggest that the global net effects are negative, it is possible that certain countries are actually able to faire better in the long-run or have neutral long-run effects under favorable circumstances. As the next step, we therefore consider the model described by Equation 7 which allows for a country category specific response by interacting the exposure measure with a country category dummy.

A primary concern is that low-income countries might not be able to take advantage of the creative destruction and building back better opportunities that an extreme event can offer. The results from the model with country income category specific effects are shown in Figure 4. Low-income and lower middle-income category countries are combined in the lowest category. The results show that this category of countries is driving the average global impacts of earthquakes. While upper middle-income countries have a similar estimated GDP per capita trajectory, their estimates are not significant. High-income countries seem to experience neutral or potentially even positive "building back better" effects starting about 6 years after an exposure.

These results have shown that country income-level clearly matters for long-run impacts of earthquakes. However, there are two distinct paths of how higher-income can affect these impacts; a reactive and a proactive one. First, high-income countries may be able to take advantage of opportunities that open up after a disaster. This reactive response can support growth in way that low-income countries might not be able to achieve. Second, it is relatively cheaper for high-income countries to invest in defense mechanisms and they are therefore more likely to proactively invest in infrastructure that can prevent major impacts in the case of an event. This pathway is not increasing growth after an exposure, but preventing a drop of growth that would occur in less prepared countries.

A natural next step is therefore to investigate if adaptation to earthquakes is effective in preventing negative impacts. Figure 5 presents the differential response by country's earthquake experience. The group of most exposed countries is here defined by a median exposure of measure 2B of 0.25 or greater. This group contains 14 countries. The medium exposed countries are defined by having at least every second year some earthquake shaking within the populated region of the country. This is the same as a median exposure of measure 1A above 0. The point estimates confirm smaller impacts for countries with the most earthquake experience. This suggests that adaptation to earthquakes is effective in preventing at least some of the long-run impacts of earthquakes. The estimates of the

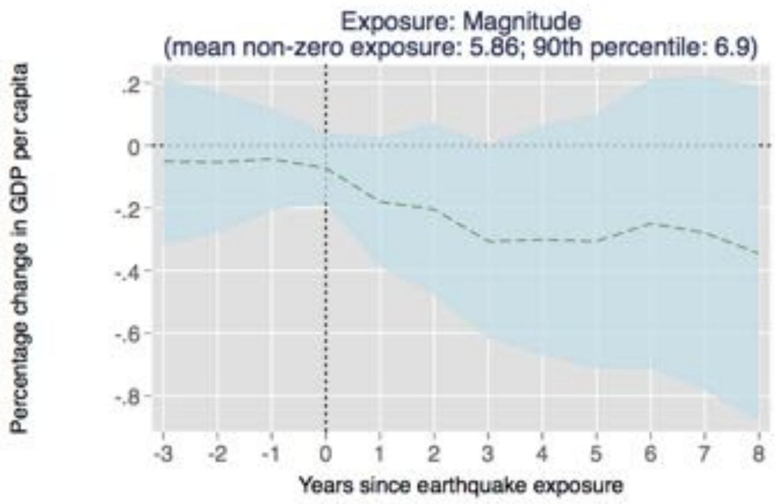

Figure 7: The results for a simple magnitude approach, where each countries annual earthquake exposure is defined as the maximum magnitude of an earthquake in the country.

countries with less earthquake experience is much noisier, due to the lower number of positive exposures.

The panels of Figure 6 present the results for more country category specific effects, other than income. They illustrate the different impulse response functions of particular groups of countries. Separating the smallest countries (smaller than 12,000km^2) from the rest shows that the small countries are not driving the overall results. Surprisingly, countries that have lower population densities in their populated regions seem to be driving the overall average impacts. This could be due to the fact that more urban countries might be more resilient and better equipped for recovery. The population density threshold to distinguish between the two groups of countries is here chosen as 100 people per square kilometer.

The Importance of the Measure

Applying an appropriate measure for the exposure to the natural hazard in the empirical analysis, is crucial for several reasons. First, the measure is supposed to actually represent the exogenous physical hazard of interest. Exposure measures based on direct impacts or even population weighted measures of the physical hazard introduce potential endogeneity and might bias the estimator. Nevertheless, also physical measures that are related to but don't actually represent the physical phenomenon of interest are suboptimal. Figure 7 illustrates the value of applying a quantification of earthquake shaking instead of magnitude to identify impacts. It provides the results for a simple magnitude approach, applying a similar model as before, but using the maximum magnitude of the earthquakes with epicenter within the country in a given year as the annual earthquake exposure. This approach ignores where and what kind of shaking occurs. This approach results in no significant long-run impacts. Using actual shaking data is therefore crucial for identifying the impacts of earthquakes.

Second, the chosen spatial aggregation approach needs to consider potential non-linearities in the impacts. To be better able to identify whether the occurrence a "disaster" event occurred, various exposure measures were defined. Using the two different maps - (1) the shaking profile, and (2) the number of strong events - with each two aggregation approaches - (A) across the country, and (B) across the 1% highest exposure region - resulted in four different annual country-level earthquake exposure measures. The results of the model with the default specifications are illustrated in Figure 30. For all four exposure definitions GDP per capita experiences a drop compared to its baseline trend in the years after an earthquake exposure. The better performance of the exposure measures 1B and 2B, which focus on shaking in the high-exposure region suggests that localized strong events might be driving the impacts opposed to widespread lower level exposure. Since the four panels of Figure 30 stem from four different exposure measures, the y-axes of the individual graphs can not be directly compared. Each panel therefore also displays the average and 90th percentile exposure among all non-zero exposures.

To allow for a direct comparison of the implied effects of the four exposure measures the results are applied to the shaking observed in the dataset and plotted in Figure 34. The Figure shows the distribution of expected impacts for each of the four exposure measures given that a non-zero exposure occurs. Using the simple spatial average approach (1A) would result in underestimating the long-run impacts of earthquakes compared to using an approach that focuses on the high intensity exposure (e.g. 2B). While an average non-zero exposure in the model with measure 2B is estimated to result in a reduction of GDP per capita by 1.6% after eight years, the same model with exposure 1A suggests a reduction by only 0.3% eight years after an average non-zero exposure.

Potential Mechanisms

To investigate potential mechanisms we can apply the model to different output variables. Figure 8 compares the impacts on the three different economic sectors: services, industry, and agriculture. The results suggest that primarily the services and industry sector are affected. Figure 9 distinguishes again by country income category and reveals that these impacts are primarily born by low and lower-middle income countries.

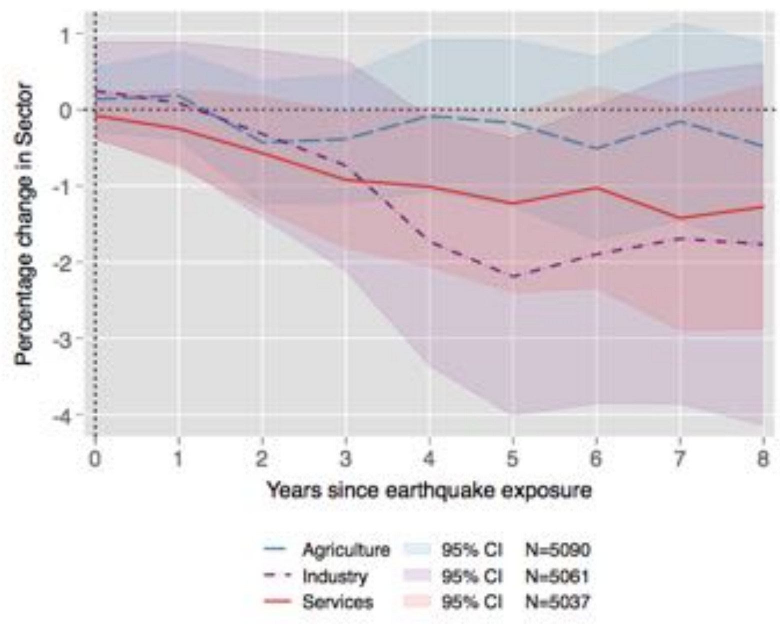

Figure 8: The impact of earthquake shaking exposure on the three different economic sectors.

A similar approach with fertility rates (births per woman) as outcome suggests on average an increase in fertility rates that starts a couple of years delayed after an exposure. By year eight after the earthquake exposure this increase seems to return back o the original equilibrium. Figure 10 displays the estimates of the coefficients β_τ for the global average model as well as for the model with income-category specific responses. This reveals that the significant increase in fertility rates only holds for the group of low and lower-middle income countries.

A variable that is particularly interesting to consider for investigating long-run human capital impacts is the percentage of internally displaced people. The impacts on displacement are illustrated in Figure 36. On average we observe a significant increase in the percentage of internally displaced people. If we consider the income-category specific results, we find that the estimates for low and middle-income countries are actually less significant while still being positive with about the same magnitude.

If we consider the outcome of mortality of under-5-year-old children, the model suggests a not significant increase which is driven by low and lower-middle income countries. What is particularly interesting is the large increase of the confidence interval in the year of the exposure compared to the other years. This likely stems from data quality issues that are heightened in years of disasters. Disasters are known to make data collection hard and regular reporting of indicators can be noisier in years of disasters. Since disaster fatality

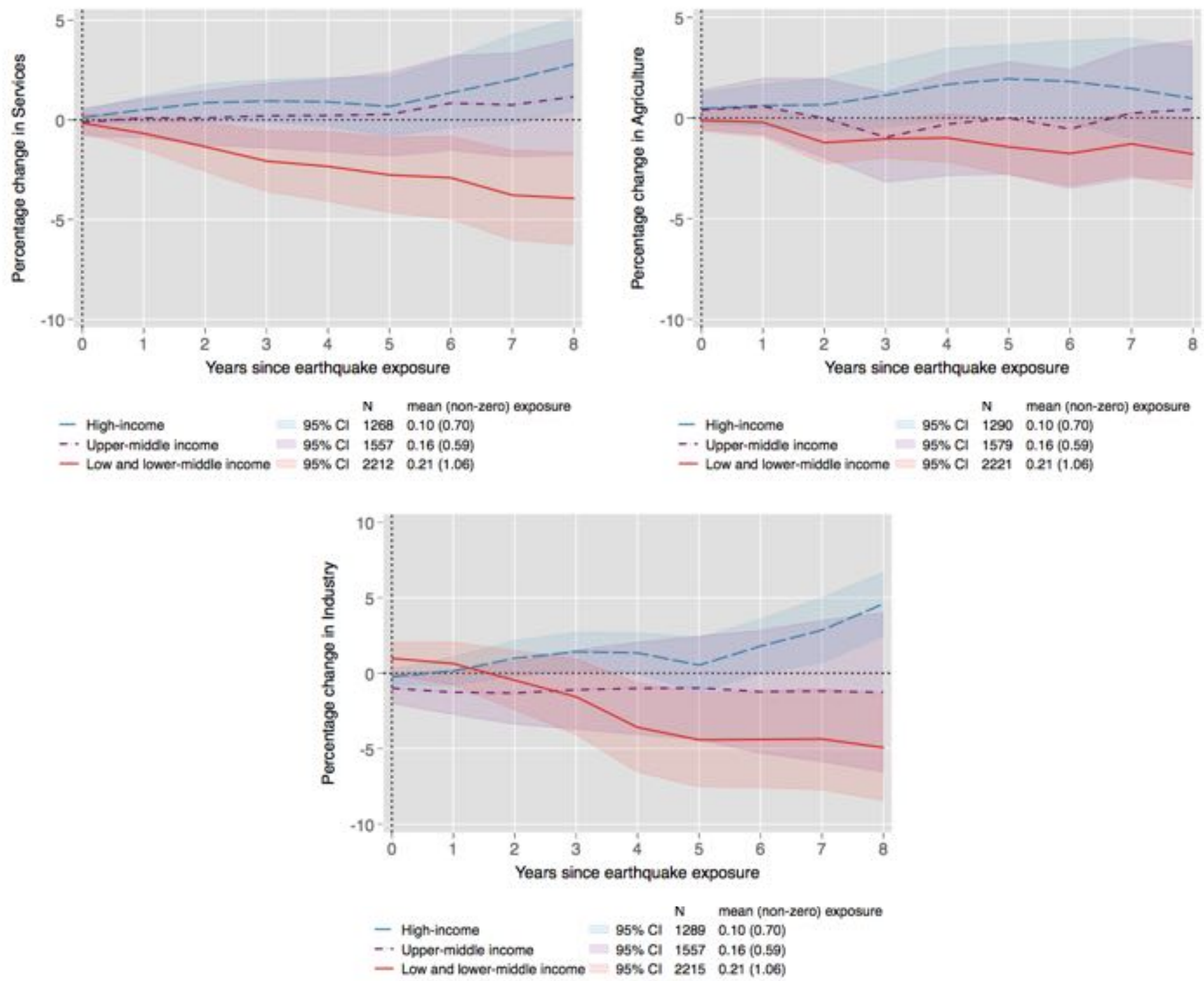

Figure 9: The impulse response of the individual sectors to earthquake exposure by income categories. Low and lower-middle income category countries are most affected across all sectors, with the strongest impacts in the service and industry sectors.

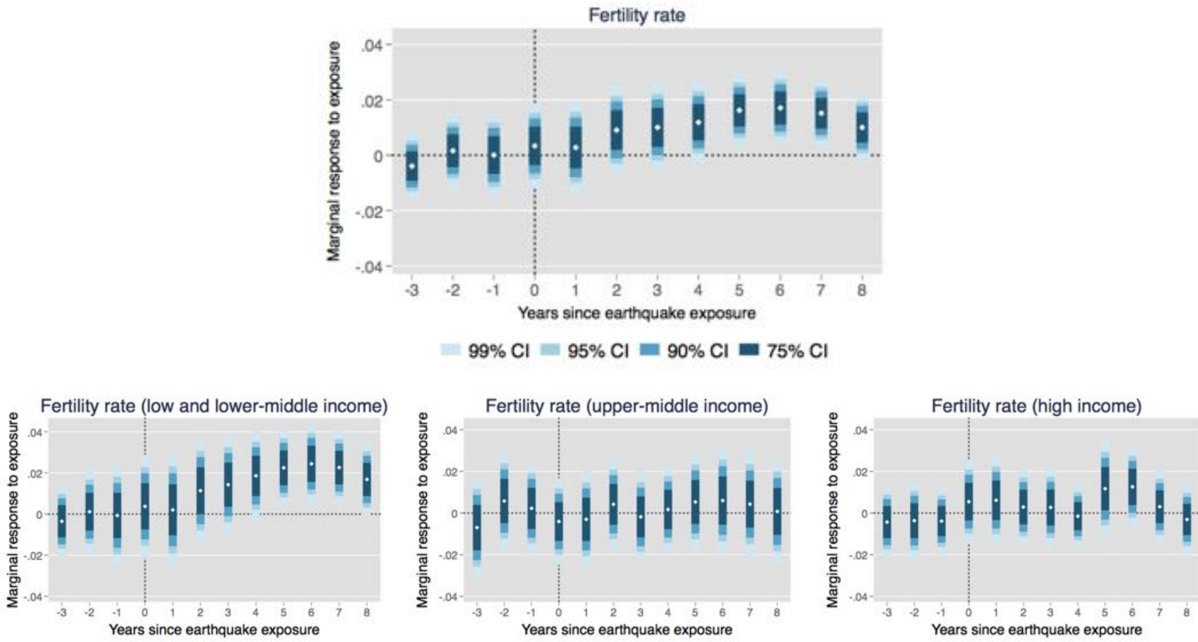

Figure 10: The impact of earthquake shaking exposure on fertility rate as a global average (top) and by country-income categories (bottom).

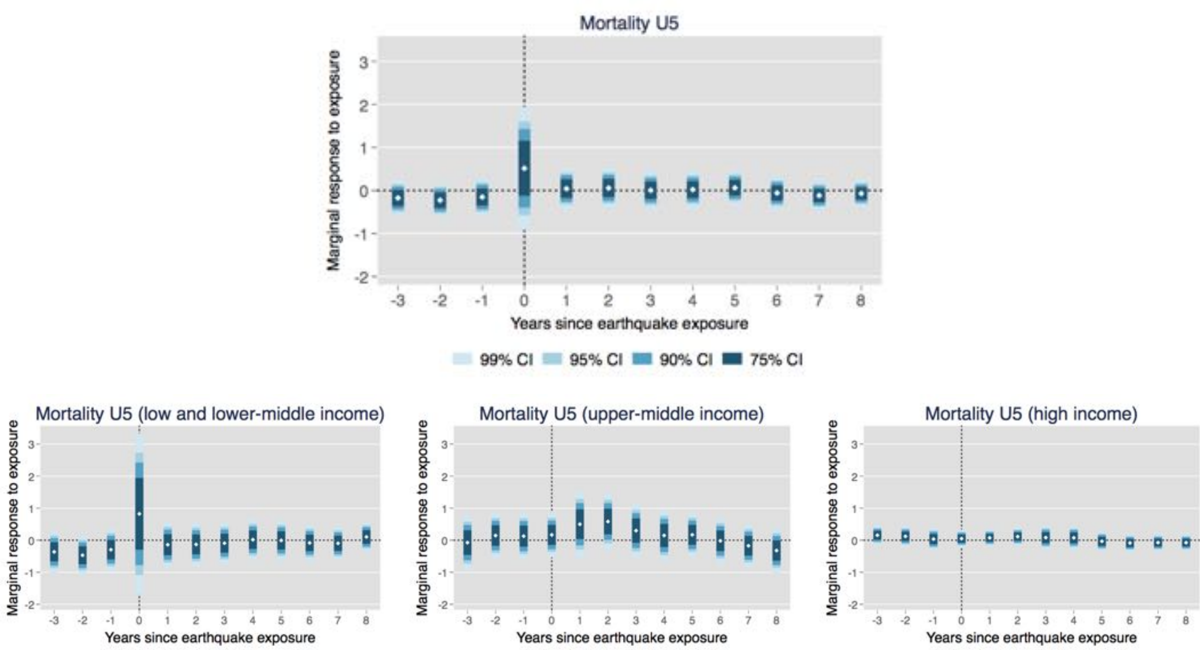

Figure 11: The impact of earthquake shaking exposure on mortality of under-5-year old children as a global average (top) and by country-income categories (bottom).

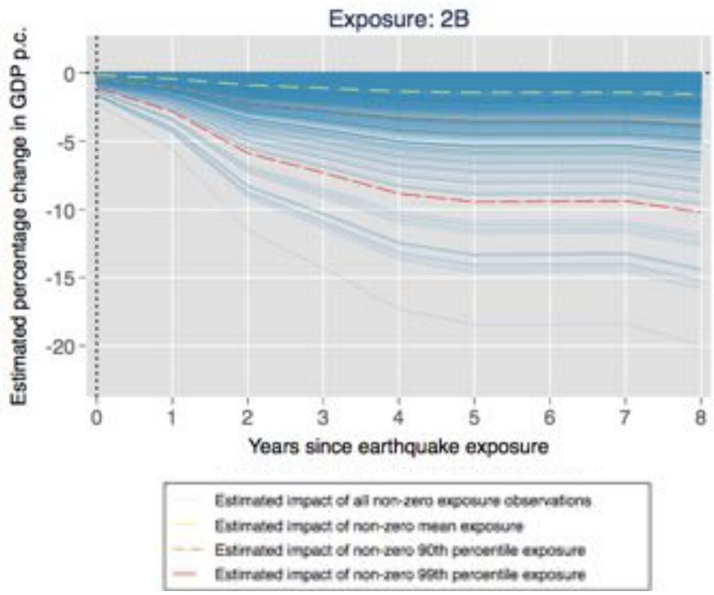

Figure 12: Distribution of expected impacts.

numbers are infamously unreliable, the noisier response of under-5 mortality can be a direct result of noisier data on under-5 mortality in those years.

Simulating Alternative Trajectories

We can illustrate the distribution of expected impacts by applying the model results to the earthquake exposure observations in the dataset. Figure 12 presents this visualization for the standard model representing the global average impacts.

To illustrate the impact that earthquakes have had on low-income countries, I simulate alternative GDP per capita trajectories without earthquake impacts. Using the results from the model with income-category specific impulse response functions, I calculate the estimated GDP per capita without the earthquake effect.

$$\overline{GDP}_{i,t} = GDP_{i,0} * \prod_{j=1}^{t} (1 + \widetilde{Y}_{i,j} - \sum_{\tau=0}^{k} \widetilde{\beta}_{\tau,c(i)} S_{i,t-\tau} \times D_{c(i)}) \tag{8}$$

$$\widetilde{Y}_{i,j} = \widetilde{\gamma}_i + \widetilde{\delta}_t + \widetilde{\eta}_i t + \sum_{\tau=0}^{k} \widetilde{\beta}_{\tau,c(i)} S_{i,t-\tau} \times D_{c(i)} \tag{9}$$

Examples for a number of those simulations are shown in Figure 13. The simulated alternative trajectories $\overline{GDP}_{i,t}$ are plotted together with the model estimates with earthquakes

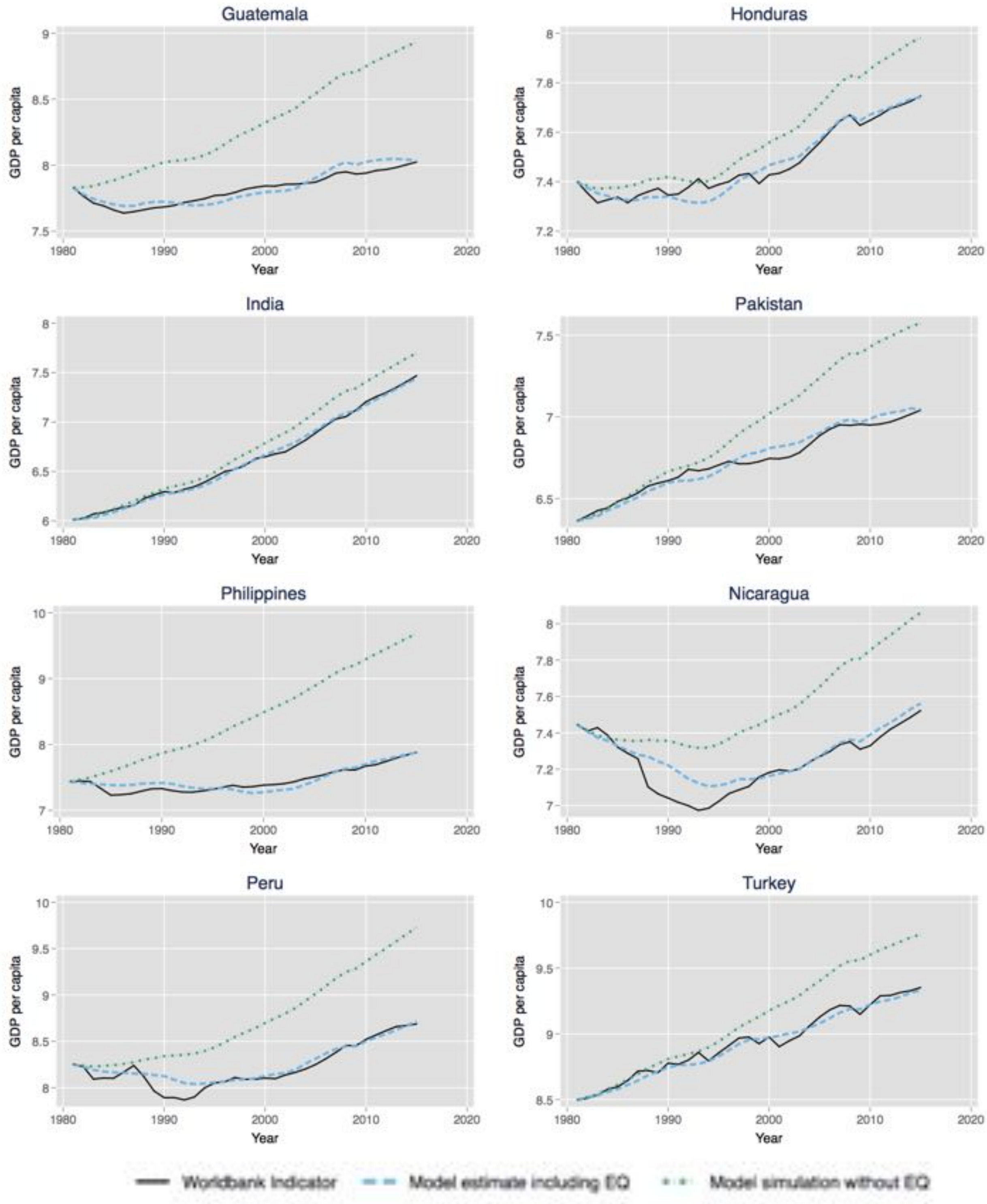

Figure 13: Examples of simulation results for alternative GDP per capita trajectories.

$\widetilde{GDP}_{i,t}$ and the actual GDP per capita World Bank indicators. These simulations reveal that average GDP per capita in low and lower-middle income countries would have been 2.4% higher in 2015 if earthquakes would not have affected these countries in the previous four decades. If we only consider countries that are regularly exposed to earthquakes within this group of countries, this difference is even 7.7% with a maximum difference above 30%.

Population Exposure

Population exposure is a crucial factor for determining impacts, but population is also endogenous to society. Population can respond to natural hazard risk and it is likely that more urban regions are relatively better prepared for natural disasters. This can make population exposure correlated with resilience. Furthermore, the quality of population data is correlated with countries' income categories. Since the spatial resolution of population data is on average higher in high-income countries, the high exposure measures will have a bias towards high-income countries. Given that this study has found systematically different responses for rich and poor countries, this can cause biased result. Nevertheless, we can still consider population as an alternative or additional exposure measure in the model (see Figure 38).

Population as alternative exposure measure to shaking, does not result in significant impacts. We can use the following model to include population exposure additionally with shaking.

$$Y_{i,t} = \alpha + \gamma_i + \delta_t + \eta_i t + \sum_{\tau=0}^{k} \beta_{S,\tau} S_{i,t-\tau} + \sum_{\tau=0}^{k} \beta_{P,\tau} P_{i,t-\tau} + \epsilon_{i,t} \tag{10}$$

This approach reveals that shaking exposure is driving the results and not population exposure. Population exposure in this combined model even appears to affect growth positively in the long-run. This could be an artifact of the data quality issue overemphasizing exposure of high-income countries.

Instead of using population exposure explicitly, we can use a higher threshold than 1 person per square kilometer to define the included regions of each country. I additionally consider population density thresholds of 10, and 100 people per square kilometer. Figure 39 displays the results for increasing thresholds for exposure measure 1A and 2B. Again, emphasizing higher population density regions does not result in smaller confidence intervals. This can have several reasons. Population density might just not be a good predictor for vulnerability, or data quality issues favoring high-income countries could bias the results.

Alternative Empirical Approach

An alternative to the distributed lag model, is an approach following the method according to Jordà (2005). In this alternative approach that is here applied as a robustness check, the impulse response coefficient β_τ in each period is estimated through a separate regression.

$$Y_{i,t} = \gamma_i + \delta_t + \eta_i t + \beta_\tau S_{i,t-\tau} + \epsilon_{i,t} \tag{11}$$

This approach would usually require to include not only the shaking in period τ but also before up to the number of periods for which an autocorrelation in the shaking data exists. However, the earthquake exposure measures 2B as well as 1A are not autocorrelated. this is confirmed by showing that the β coefficient in the following model is not significantly different from zero.

$$S_{i,t} = \gamma_i + \beta S_{i,t-1} + \epsilon_{i,t} \tag{12}$$

The results are displayed in Figure 32 and confirm the pattern observed in the distributed lag model. GDP per capita growth is significantly decreased in the first few years after an earthquake exposure. It recovers after that, but does not experience a period of increased growth that would offset the long-term effect on GDP per capita.

Another alternative would be a multidimensional exposure approach that incorporates several different exposure definitions. Similar to including population exposure with the shaking measure, we can also combine two different shaking measures (1A and 2B) in one model.

$$Y_{i,t} = \alpha + \gamma_i + \delta_t + \eta_i t + \sum_{\tau=0}^{k} \beta_{1A,\tau} S(1A)_{i,t-\tau} + \sum_{\tau=0}^{k} \beta_{2B,\tau} S(2B)_{i,t-\tau} + \epsilon_{i,t} \tag{13}$$

Applying this approach confirms again that exposure measure 2B is preferred. While the estimates suggest a negative and significant response to the shaking exposure 2B, the estimates for the measure 1A are not significant (see Figure 37).

7 Conclusion and Discussion

This work is the first global empirical study on the long-run impacts of earthquakes on GDP per capita growth that utilizes a measure based on ground shaking. Peak ground acceleration data from USGS ShakeMaps are utilized to calculate different annual country level exposure measures. I evaluate four different approaches to aggregate all earthquake ShakeMaps of one year within one country into one variable. The four approaches are based on (1) maps of the maximum shaking value over time, and (2) maps of the number of earthquakes above a threshold, which are each aggregated as spatial average (A) across the entire (populated) country, and (B) across the 1% region of the country with the highest exposure. The simple spatial average (1A) implies a linear relationship between PGA and impacts. This means that spatially diffuse low-level exposures should have the same long-run impacts as more concentrated high intensity events as long as they have the same spatial average. This approach is particularly compared to the measure (2B) which is the best proxy among the four measures for whether a more localized disaster event occurred.

For all four measures, earthquakes are found to have a negative overall impact on GDP per capita even eight years after an exposure. The results suggest that a measure that is a better proxy for whether disaster event occurred compared to spatially large low-level exposure is best suited to estimate long-run impacts. While growth rates seem to stabilize after a few years, the lost growth is not recovered by year eight. This implies a permanent reduction in GDP per capita level in the long-run. The results from the default exposure measure (2B), the spatial average of the number of strong events in the most exposed 1% of the country, suggest that an average exposure (among non-zero exposures) results in a GDP per capita of 1.7% below the baseline trend and a 90th percentile exposure results in a reduction by about 3.8% after eight years. Using instead the simple spatial average approach (1A) would result in underestimating the long-run impacts of earthquakes.

The results suggest that the impacts are primarily incurred by low and middle-income category countries and that high income countries are potentially even able to experience positive "building back better" effects. This difference can be caused by a number of different factors. First, it is relatively cheaper for high-income countries to invest in defense mechanisms and they are therefore more likely to be better prepared for earthquakes. Comparing countries with different earthquake experience levels suggests that adaptation is indeed effective in reducing impacts. Second, liquidity constraints and institutions that may correlate with a country's income category might be responsible for ineffective preparation and could make it harder for low-income countries to take advantage of creative destruction and building back better opportunities after an earthquake. Finally, lower level of preparation for low-income countries compared to high-income countries can also affect the nature of impacts incurred. Earthquakes are much more deadly in low-income countries than in high-income countries. It is conceivable that earthquakes have a relatively larger impact on human capital than capital for low-income countries than high-income countries not just in terms of direct impacts, but also for long-term impacts.

The results show that the choice of the disaster measure is crucial. The geophysical natural hazard as well as potential non-linearities in impacts with regard to space and intensity need to be considered to be able to accurately determine long-run impacts of natural hazards. A comparison with an approach, that only uses magnitude and epicenter to quantify the earthquake exposure, reveals that using actual shaking data is crucial to identify the impacts of earthquake exposure.

Also the spatial aggregation approach applied to summarize the natural hazard is found to be highly relevant. The results suggest that impacts are primarily driven by (local) high intensity events and less by spatially large exposure to lower intensity shaking. Using a simple spatial average of shaking across the entire country (Exposure 1A) instead of other measures that put more emphasis on disaster events opposed to nuisance exposure, would therefore result in underestimating the overall impact on GDP per capita. Furthermore, I show that the spatial average is also not a good proxy in the case of earthquakes for whether a local "disaster" event occurred, but it might be for other natural hazard types. If such a relationship doesn't exist and disaster events are the drivers behind impacts, then the use of the spatial average is not adequate. For the case of cyclones Hsiang and Jina (2014) only include wind speeds from cyclones, but not from weaker storms. This implies that a maximum wind speed strong enough to receive the classification "cyclone" had to occur. For earthquakes no such intensity thresholds exist. Additionally, cyclone exposure maps compared to earthquake shaking exposure maps have a spatially larger and more connected pattern. This implies that using the spatial average for the natural hazard of cyclones will be a relatively good proxy for whether a high intensity exposure occurred. We can conclude that the geophysical differences between different natural hazard types might require a systematically different approach to aggregate the spatial exposure maps to the unit of observation (country).

There are several reasons for why the more local high intensity exposure would result in higher impacts than spatially larger low-level exposure. First, the direct damages due to the physical hazard might just not be linear, which is the least interesting scenario. Second, the accumulation of big damages concentrated in a spatially small region might exceed the local resilience capacity. This can be interpreted as affected business being harmed further by decreased demand and unreliable supply-chains. Furthermore, households would not just be affected themselves, but also their local social-safety network would be impaired. The third and most concerning option is that large disaster events might trigger a misallocation of resources. After such an event there are often large spendings on reconstruction and financial aid for affected people. However, these spendings are often ad-hoc, not well planned, and can be highly political. This can result in inefficiencies in the economy. Furthermore, displaced population might also result in misallocation of human resources. Finally, adaptation (or preparation) might be very effective for low-level exposure, but less so for high intensity exposure.

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A Data

A.1 Shaking Data

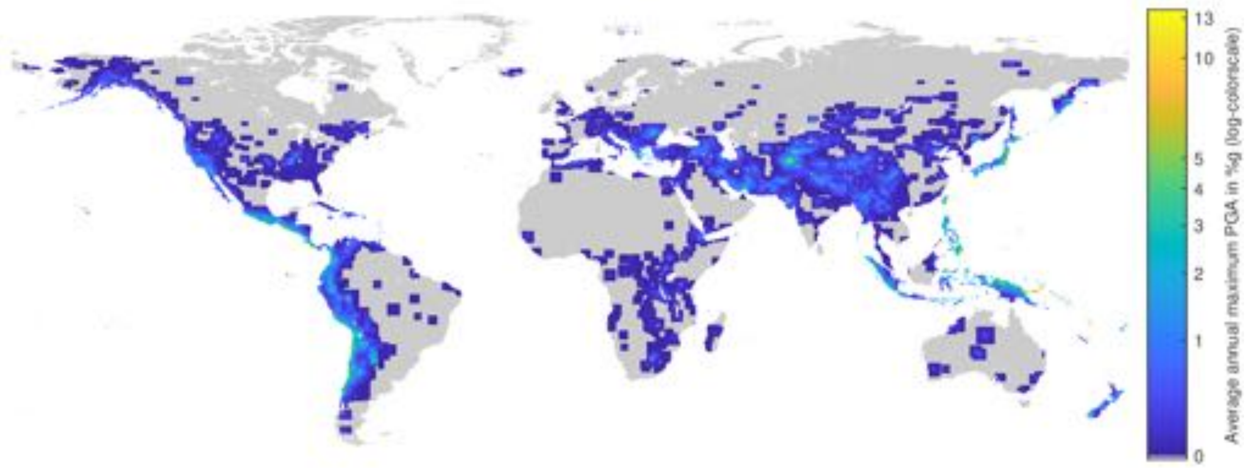

Figure 14: *Earthquake shaking history.* The average annual pixel exposure to maximum PGA within a year based on the years 1973 - 2015. Figure adapted from Lackner (2018a).

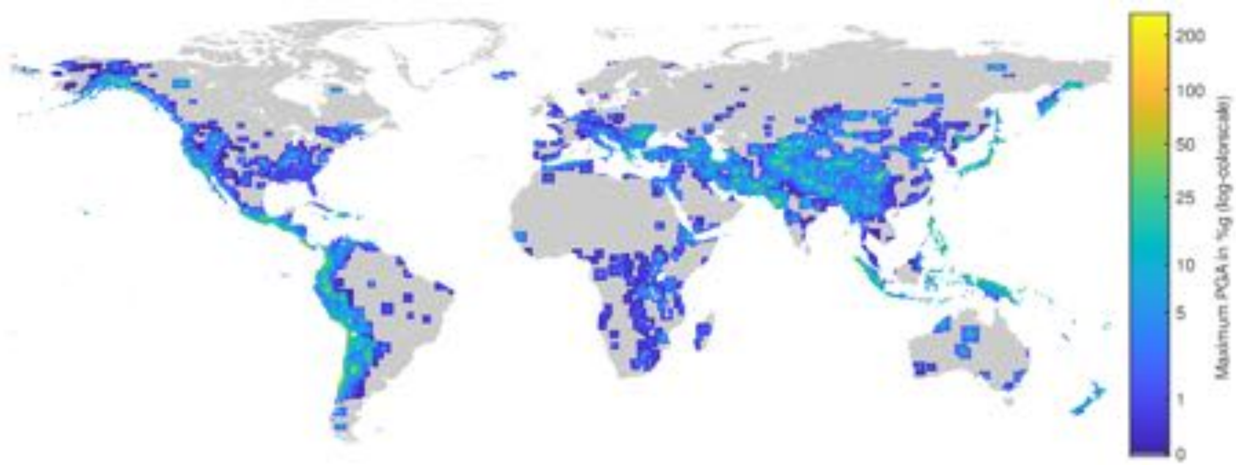

Figure 15: Maximum earthquake shaking (PGA) experienced in the time period 1973 - 2015. Figure adapted from Lackner (2018a).

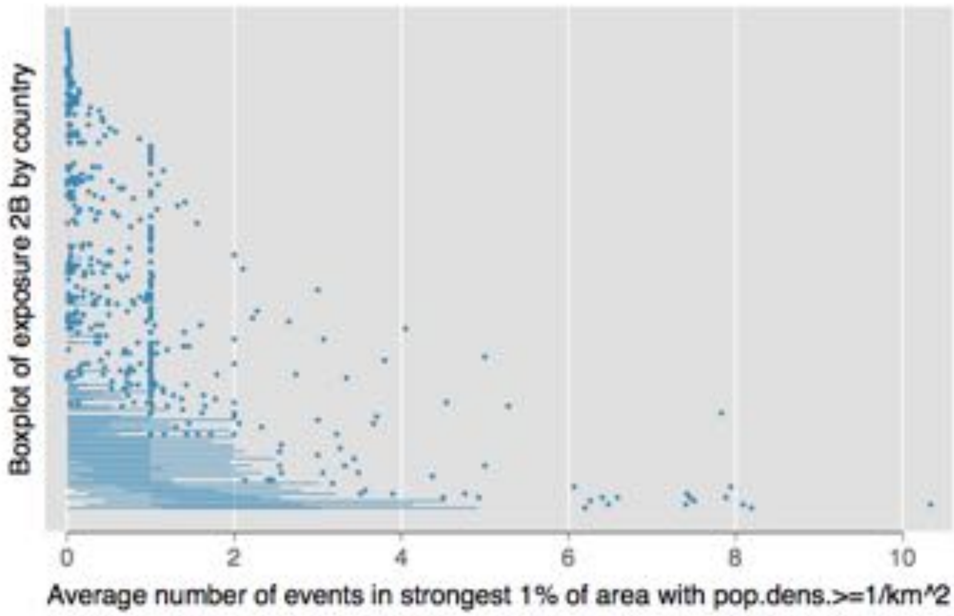

Figure 16: Exposure 2B summarized by country. The countries are sorted by the mean, and the median is marked in red.

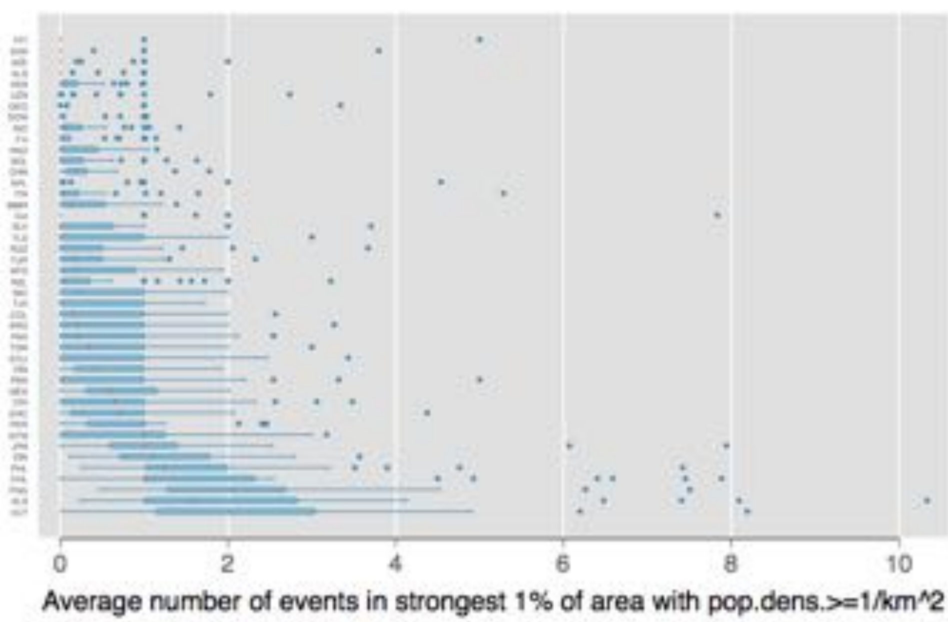

Figure 17: Exposure 2B summarized by country (strongest third by mean exposure). The countries are sorted by the mean, and the median is marked in red.

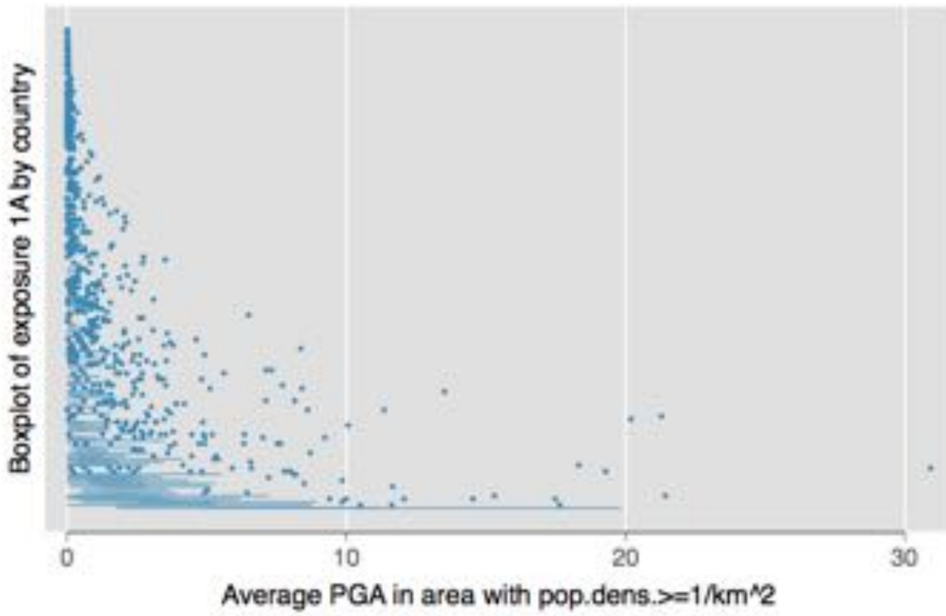

Figure 18: Exposure 1A summarized by country. The countries are sorted by the mean, and the median is marked in red.

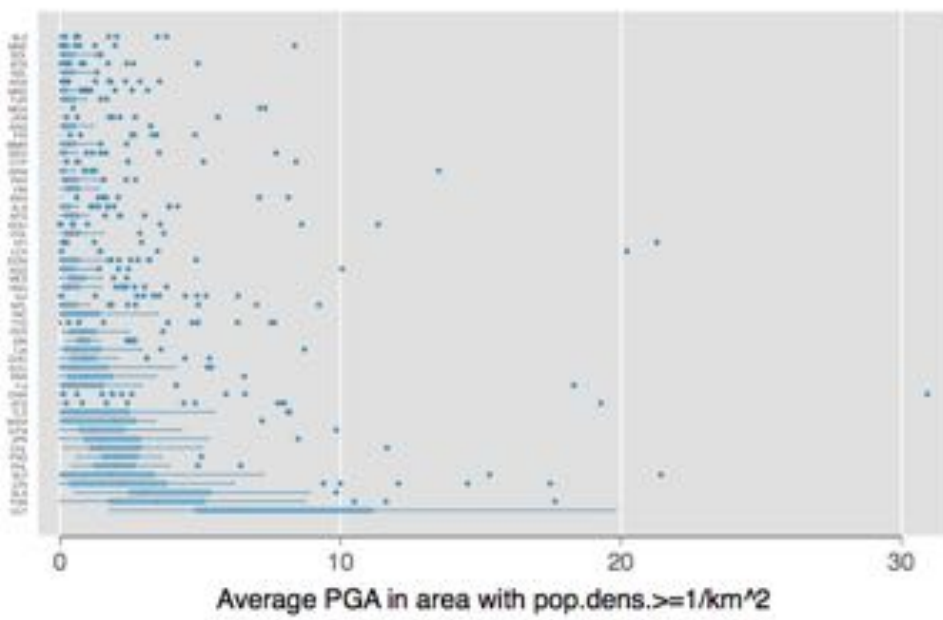

Figure 19: Exposure 1A summarized by country (strongest third by mean exposure). The countries are sorted by the mean, and the median is marked in red.

A.2 Shaking Data Relative to GDP per capita data

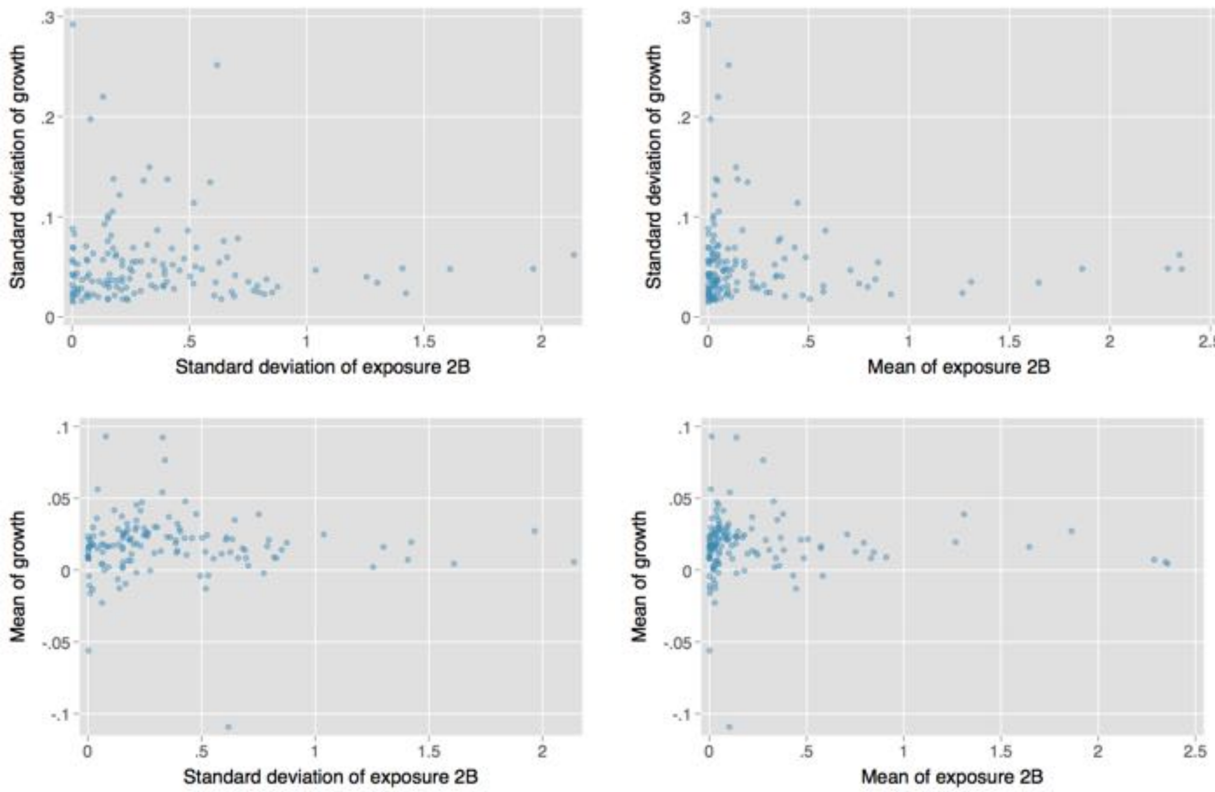

Figure 20: Cross-section comparison of shaking and GDP per capita data. Only countries that experienced some shaking at some point in 1973-2015 are included.

A.3 Shaking Data Relative to Country Size

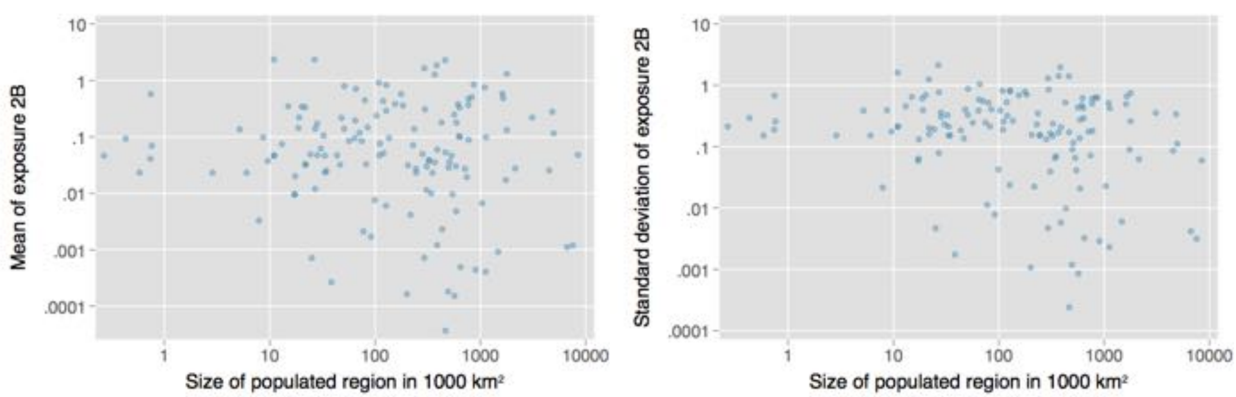

Figure 21: Mean and standard deviation of exposure 2B compared to country size.

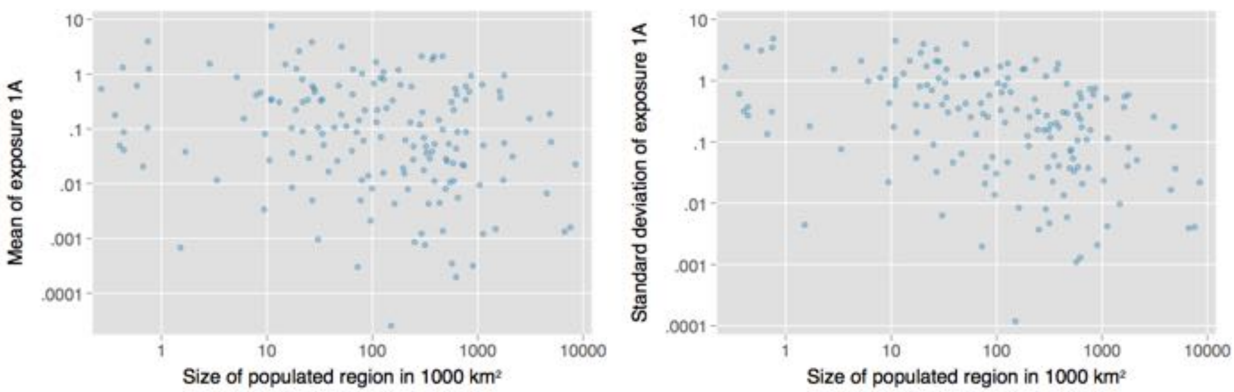

Figure 22: Mean and standard deviation of exposure 1A compared to country size.

A.4 Country Categories

Table 1: Number of countries by category. Low and lower middle income countries are combined under the category "Low", "Middle" represents upper-middle income countries, and high income countries are under "High". Countries with a populated region above 12,000km^2 are defined as "Large" and below as "Small". A country is categorized as mostly "rural", if less than 10% of the populated region of the country is classified as urban, otherwise it is defined as mostly "urban". Regular exposure is defined as having at least every second year some earthquake shaking within the populated region of the country.

Income:	Low		Middle		High		
Regular exposure:	No	Yes	No	Yes	No	Yes	Total
Small & rural	4	1	1	0	4	0	10
Small & urban	4	1	10	1	16	0	32
Large & rural	31	11	21	17	24	6	110
Large & urban	19	9	4	1	8	2	43
Total	58	22	36	19	52	8	195

	Low	Middle	High	Total
Rural	47	39	34	120
Urban	32	16	26	75
Total	80	55	60	195

Table 2: Comparison of income and rural/urban category.

A.5 Country Table

ISO	Population 2010	Size km^2	Income Category	Exposure>0 2B	Exposure>0 1A	Average Exposure 2B	Average Exposure 1A	N
AFG	27972688	615	1	7	10	0.175	0.446	10
AGO	21237666	1123	3	2	5	0.001	0.002	27
ALB	2902724	28	3	7	17	0.167	0.465	32
ARE	8318172	80	4	0	7	0.000	0.013	32
ARG	41233048	1644	3	24	30	0.490	0.342	32
ARM	2962260	28	2	0	7	0.000	0.142	22
ATG	87233	0	4	1	6	0.031	0.645	32
AUS	22160438	6659	4	8	16	0.001	0.001	32
AUT	8397575	82	4	0	4	0.000	0.018	32
AZE	9094761	85	3	4	11	0.222	0.323	22
BDI	9452047	25	1	1	6	0.001	0.039	32
BEL	10939421	31	4	3	4	0.052	0.071	32
BEN	9505804	116	1	0	0	0.000	0.000	32
BFA	15636110	276	1	0	0	0.000	0.000	32
BGD	151554464	136	2	9	19	0.122	0.284	32
BGR	7408050	111	3	4	12	0.071	0.152	32
BHR	1261235	1	4	0	0	0.000	0.000	32
BHS	360830	3	4	0	2	0.000	0.016	32
BIH	3835747	51	3	1	3	0.059	0.048	18
BLR	9489284	205	3	0	0	0.000	0.000	22
BLZ	322093	22	3	2	9	0.002	0.228	32
BMU	63954	0	4	0	0	0.000	0.000	32
BOL	9920137	565	2	17	30	0.284	0.358	32
BRA	198601200	4509	3	12	17	0.034	0.009	32
BRB	279566	0	4	0	1	0.000	0.065	32
BRN	392514	3	4	0	0	0.000	0.000	32
BTN	736045	33	2	4	8	0.110	0.281	32
BWA	2046384	316	3	0	2	0.000	0.001	32
CAF	4430974	434	1	2	3	0.001	0.003	32
CAN	34125688	7545	4	10	20	0.001	0.002	32
CHE	7822896	38	4	1	9	0.000	0.017	32

CHL	17013772	384	4	31	32	1.921	2.121	32
CHN	1340929408	4816	3	32	32	0.241	0.176	32
CIV	20130852	208	2	0	0	0.000	0.000	32
CMR	20602916	466	2	1	4	0.000	0.002	32
COD	65941280	2142	1	16	23	0.033	0.039	32
COG	4070046	341	2	1	2	0.013	0.006	32
COL	45917352	772	3	22	27	0.436	0.515	32
COM	698695	2	1	0	2	0.000	0.051	32
CPV	490379	4	2	0	0	0.000	0.000	32
CRI	4545482	51	3	21	29	0.870	3.390	32
CUB	11308133	110	3	3	9	0.039	0.128	32
CYP	1103685	9	4	4	6	0.132	0.600	32
CZE	10508937	77	4	1	2	0.001	0.002	22
DEU	80437552	351	4	9	14	0.024	0.032	32
DJI	830290	22	2	3	7	0.164	0.804	22
DMA	71167	1	3	3	7	0.094	1.583	32
DNK	5551081	28	4	0	0	0.000	0.000	32
DOM	9903514	48	3	9	12	0.230	0.694	32
DZA	36036236	641	3	16	19	0.083	0.091	32
ECU	14935110	177	3	16	24	0.622	1.215	32
EGY	82045288	389	2	4	8	0.080	0.068	32
ERI	4690643	120	1	1	6	0.111	0.122	19
ESP	46586372	500	4	8	13	0.030	0.033	32
EST	1330938	26	4	0	0	0.000	0.000	17
ETH	87566800	1131	1	8	12	0.132	0.063	31
FIN	5339493	186	4	0	0	0.000	0.000	32
FJI	859952	19	3	15	22	0.243	1.546	32
FRA	62973492	545	4	6	12	0.010	0.011	32
FSM	103619	1	2	2	7	0.068	0.164	26
GAB	1543459	244	3	0	0	0.000	0.000	32
GBR	62715984	217	4	4	6	0.006	0.010	32
GEO	4252194	65	3	7	13	0.232	0.513	32
GHA	24329752	233	2	0	0	0.000	0.000	32
GIN	11010809	246	1	0	0	0.000	0.000	26
GMB	1688395	11	1	0	1	0.000	0.036	32
GNB	1634913	33	1	1	1	0.031	0.109	32

GNQ	728269	27	4	1	2	0.016	0.007	32
GRC	11180620	128	4	29	30	0.789	1.103	32
GRD	104677	0	3	0	2	0.000	0.118	32
GTM	14734288	108	2	22	30	0.770	1.446	32
GUY	753420	151	3	0	3	0.000	0.000	32
HKG	7029610	1	4	0	0	0.000	0.000	32
HND	7508378	103	2	13	28	0.211	0.719	32
HRV	4317262	57	4	1	2	0.055	0.017	17
HTI	9994086	27	1	1	3	0.312	1.356	16
HUN	10013906	92	4	0	0	0.000	0.000	21
IDN	241611072	1781	2	32	32	1.490	1.054	32
IMN	84327	1	4	0	0	0.000	0.000	28
IND	1231035776	3103	2	29	32	0.231	0.166	32
IRL	4618034	46	4	0	0	0.000	0.000	32
IRN	74249696	1617	3	32	32	0.533	0.482	32
IRQ	30864562	283	3	7	27	0.047	0.120	32
ISL	318042	64	4	3	4	0.106	0.044	32
ISR	7427880	17	4	1	5	0.012	0.131	32
ITA	59587236	298	4	17	20	0.188	0.173	32
JAM	2741253	11	3	2	6	0.062	0.412	32
JOR	6519336	44	3	2	4	0.048	0.130	32
JPN	127319800	370	4	32	32	1.426	2.031	32
KAZ	16320494	1786	3	5	18	0.055	0.040	22
KEN	40323128	495	2	1	4	0.000	0.010	32
KGZ	5500651	184	2	12	20	0.350	0.739	26
KHM	14375530	117	2	0	0	0.000	0.000	19
KIR	102648	0	2	0	0	0.000	0.000	32
KNA	52352	0	4	1	4	0.031	0.389	32
KOR	49091296	99	4	2	4	0.009	0.010	32
KWT	3057938	17	4	0	2	0.000	0.046	17
LAO	6269441	229	2	4	10	0.074	0.089	28
LBN	4342056	10	3	2	3	0.067	0.145	24
LBR	3960370	96	1	0	1	0.000	0.003	32
LBY	6265393	649	3	0	1	0.000	0.004	12
LCA	177397	1	3	1	3	0.031	0.785	32
LKA	20201312	43	2	0	0	0.000	0.000	32

LSO	1995910	31	2	0	1	0.000	0.001	32
LTU	3122520	64	4	0	0	0.000	0.000	17
LUX	503178	3	4	0	0	0.000	0.000	32
LVA	2091658	63	4	0	0	0.000	0.000	17
MAC	525615	0	4	0	0	0.000	0.000	30
MAR	32119360	368	2	3	5	0.047	0.052	32
MDA	4081576	33	2	0	0	0.000	0.000	17
MDG	21079532	590	1	1	3	0.002	0.009	32
MDV	332575	0	3	0	0	0.000	0.000	11
MEX	118571232	1102	3	31	32	0.731	0.578	32
MHL	52428	0	3	0	0	0.000	0.000	31
MKD	2060944	24	3	1	7	0.032	0.247	22
MLI	15168350	623	1	0	1	0.000	0.000	32
MLT	412064	0	4	0	0	0.000	0.000	32
MMR	51745844	634	2	19	25	0.366	0.448	32
MNE	621835	13	3	0	3	0.000	0.000	15
MNG	2713779	1040	2	4	15	0.009	0.011	31
MOZ	24344118	714	1	2	4	0.036	0.030	32
MRT	3587857	438	2	0	0	0.000	0.000	32
MUS	1247951	2	3	0	1	0.000	0.001	32
MWI	14749303	71	1	2	2	0.158	0.111	32
MYS	28118926	323	3	2	10	0.013	0.038	32
NAM	2186576	569	3	2	4	0.000	0.000	32
NER	16295290	544	1	0	0	0.000	0.000	32
NGA	159201776	902	2	1	1	0.001	0.000	32
NIC	5736502	119	2	19	27	0.471	0.937	32
NLD	16629343	35	4	2	4	0.034	0.068	32
NOR	4888253	252	4	0	2	0.000	0.001	32
NPL	26910844	128	1	9	16	0.184	0.560	32
NRU	10025	0	4	0	0	0.000	0.000	5
NZL	4369026	155	4	20	24	0.413	0.331	32
OMN	2952761	163	4	0	12	0.000	0.004	32
PAK	169987664	829	2	26	31	0.504	0.469	32
PAN	3620576	66	3	15	28	0.525	1.222	32
PER	29374292	864	3	31	32	0.937	1.013	32
PHL	93038912	294	2	32	32	1.724	2.057	32

PLW	20470	0	3	0	0	0.000	0.000	21
PNG	6847870	463	2	32	32	2.381	2.161	32
POL	38577052	308	4	16	16	0.020	0.025	22
PRI	3709671	8	4	1	6	0.004	0.475	32
PRT	10586773	47	4	3	6	0.016	0.025	32
PRY	6211218	201	3	1	3	0.000	0.021	32
PSE	4060158	6	2	1	1	0.056	0.361	18
QAT	1765586	9	4	0	0	0.000	0.000	12
ROU	20295866	235	3	1	3	0.031	0.022	22
RUS	143156704	8448	3	21	23	0.069	0.031	23
RWA	10306503	22	1	2	2	0.044	0.109	32
SAU	28094192	1747	4	3	8	0.023	0.015	32
SDN	36113540	1475	2	1	1	0.001	0.002	32
SEN	12961487	196	1	0	1	0.000	0.026	32
SGP	5078962	0	4	0	1	0.000	0.055	32
SLB	526177	27	2	22	22	2.229	3.962	22
SLE	5772308	73	1	0	1	0.000	0.000	32
SLV	6034468	20	2	12	28	0.341	2.795	32
SRB	7295157	75	3	3	5	0.108	0.127	17
SSD	10054238	624	1	0	0	0.000	0.000	4
STP	170880	1	2	0	0	0.000	0.000	12
SUR	518196	56	3	0	0	0.000	0.000	32
SVK	5406667	32	4	0	0	0.000	0.000	20
SVN	2054012	19	4	2	2	0.082	0.090	17
SWE	9382756	293	4	1	1	0.001	0.002	32
SWZ	1193056	17	2	1	1	0.013	0.011	32
SYC	93081	0	4	0	0	0.000	0.000	32
TCD	11891536	688	1	0	0	0.000	0.000	32
TGO	6375346	57	1	0	0	0.000	0.000	32
THA	66690020	511	3	3	8	0.033	0.022	32
TJK	7580690	80	2	13	24	0.426	1.055	27
TKM	5055420	466	3	5	7	0.053	0.110	25
TLS	1059016	15	2	5	9	0.462	1.711	13
TON	103947	1	3	20	28	0.615	3.870	31
TTO	1328095	5	4	5	8	0.183	1.124	32
TUN	10639451	127	2	2	5	0.007	0.019	32

TUR	72316648	770	3	24	29	0.413	0.370	32
TUV	9827	0	3	0	0	0.000	0.000	22
TZA	45654440	775	1	9	11	0.126	0.120	24
UGA	33133356	206	1	3	6	0.043	0.083	30
UKR	45647772	586	2	1	2	0.027	0.020	25
URY	3371396	69	4	0	0	0.000	0.000	32
USA	309920832	4964	4	32	32	0.106	0.058	32
UZB	27687404	428	2	4	16	0.078	0.044	25
VCT	109316	0	3	0	2	0.000	0.067	32
VEN	28998782	592	3	17	22	0.169	0.183	32
VNM	88344488	326	2	2	6	0.004	0.011	28
VUT	236299	11	2	32	32	2.449	7.546	32
WSM	186029	3	2	1	20	0.033	1.750	30
YEM	23592026	309	2	2	10	0.009	0.098	22
ZAF	51638656	532	3	30	31	0.051	0.049	32
ZMB	13919025	743	2	9	22	0.008	0.018	32
ZWE	13968325	388	1	1	8	0.000	0.011	32
ANR	83128	0	4	0	0	0.000	0.000	32
ESH	514220	94	2	0	0	0.000	0.000	32
KOS	1764580	11	2	1	4	0.083	0.320	12

Table 3: List of countries in the data set. The table displays the population of the country in 2010, the size of the country area (in km^2) with a population density of 1 person per square kilometer or greater, the income category of the country (1 - low income, 2 - lower middle income, 3 - upper middle income, 4 - high income), The number of years with earthquake exposure greater than zero and the average exposure both for measure 1A and 2B, and the number of years with sufficient GDP per capita data to be included in the regressions.

A.6 Country-level time-series examples

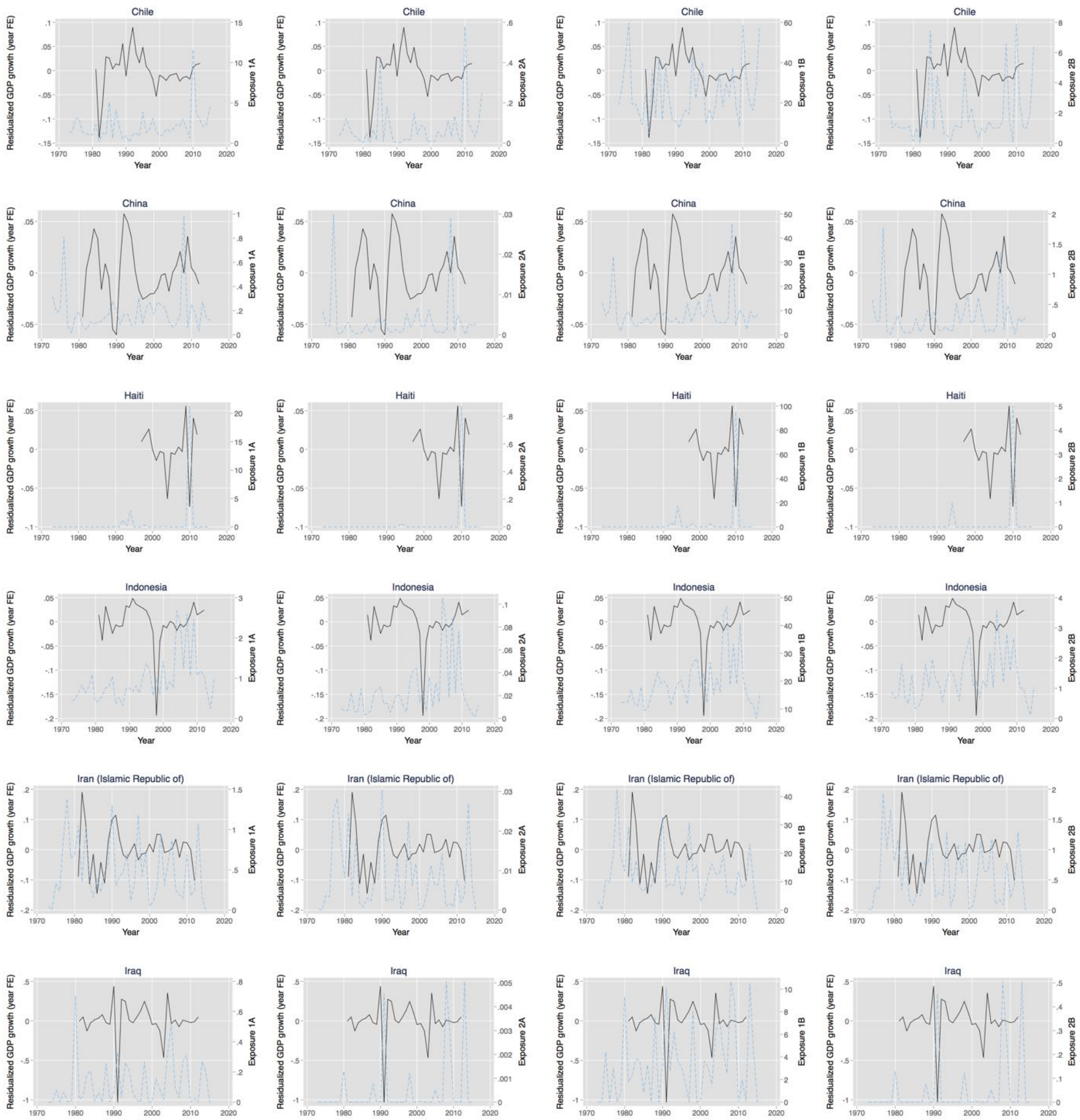

Figure 23: Examples (part 1) of country time series for growth of GDP per capita (black) and exposure (blue). The residual growth after controlling for global year and country fixed effects as well as a country-specific linear time trend is shown. Shaking is restricted to the populated regions of each country.

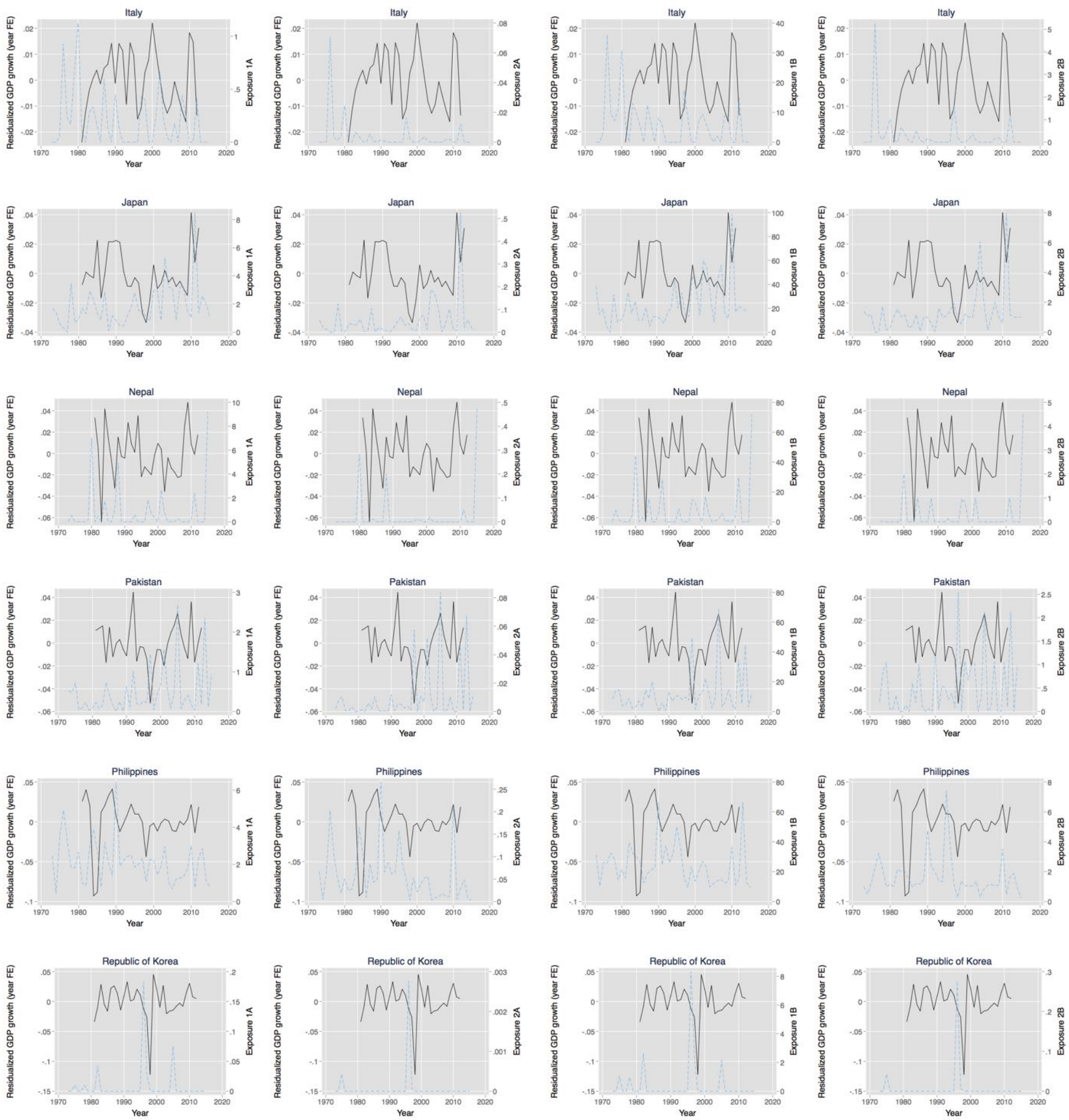

Figure 24: Examples (part 2) of country time series for growth of GDP per capita (black) and exposure (blue). The residual growth after controlling for global year fixed effects as well as a country-specific linear time trend is shown. Shaking is restricted to the populated regions of each country.

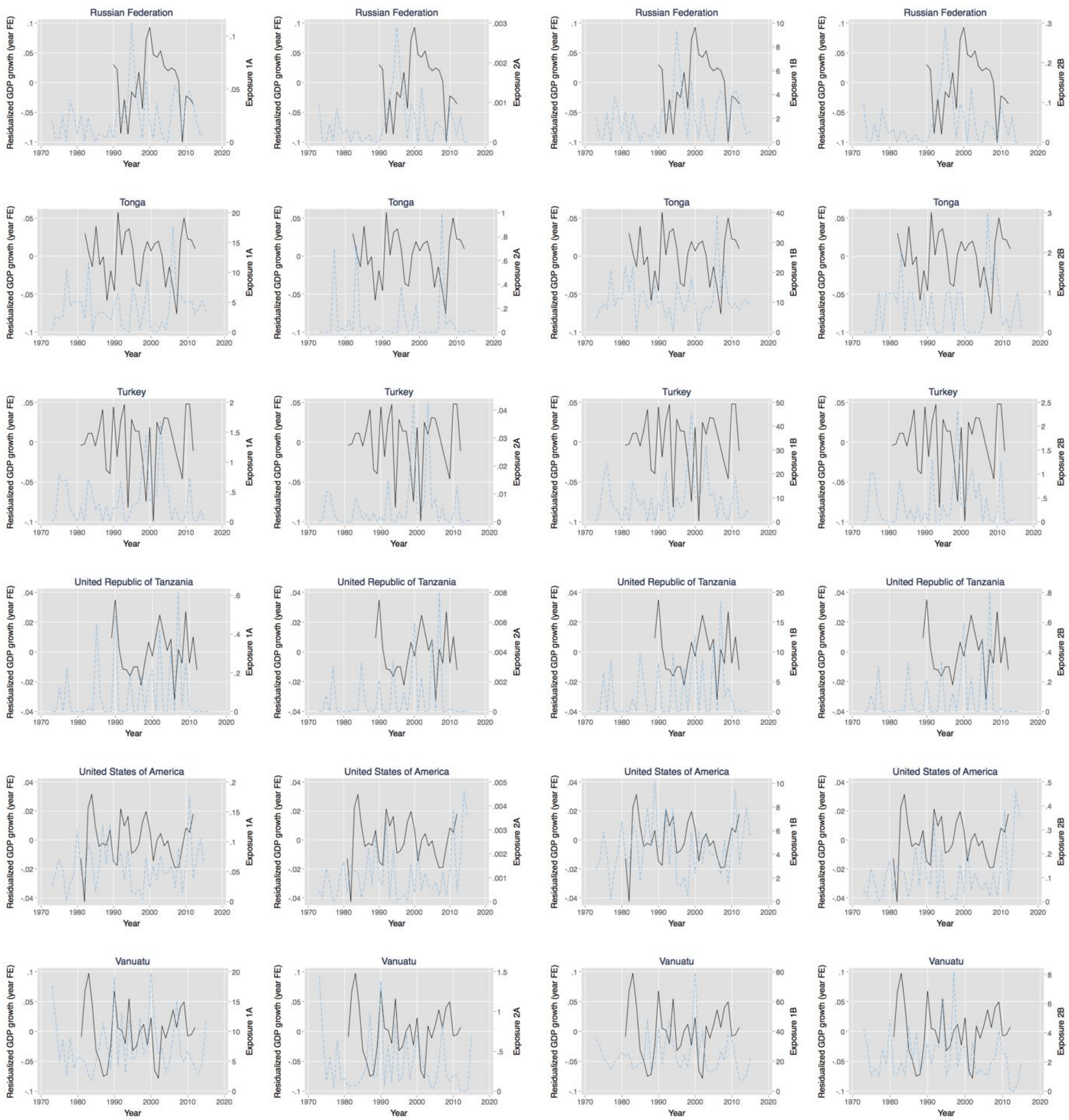

Figure 25: Examples (part 3) of country time series for growth of GDP per capita (black) and exposure (blue). The residual growth after controlling for global year fixed effects as well as a country-specific linear time trend is shown. Shaking is restricted to the populated regions of each country.

B Populated Area Definition

The empirical analysis requires to identify populated and unpopulated areas. Additionally, I also calculate country-specific urban/rural area definitions. For simplicity and to avoid potential issues with inconsistent area definitions, these areas are here defined based on the population data from 2010 and the same areas are used across years. This provides the benefit of time-invariant spatial definitions for these classifications.[8] The GPW data is based on the smallest available unit of an administrative or census region for which population data is available. The spatial size of these units varies significantly across countries and thus affects the data quality. The data does, therefore, not always show zero population for unpopulated areas. The population density threshold for distinguishing whether a grid cell is considered *populated* or unpopulated is defined as one person per km^2. To distinguish between rural and urban country-specific population density thresholds are determined. No global standard definition of "urban" and "rural" exists and it has been argued that rurality (or urbanity) should be considered a gradient and not a dichotomy (Chomitz et al., 2005). Nevertheless, for the application here a discrete distinction is necessary to calculate a rural and an urban exposure to shaking. Official country statistics usually provide a national definition for distinguishing between rural and urban regions. These definitions are seldom exclusively based on population density, but commonly include absolute population thresholds for settlements, infrastructure network connectivity, and economic activity. If population density thresholds are used as a criterion, they take on a wide range of different values (between 150 to 1,500 people per km^2) in different countries[9]. The choice of an appropriate threshold depends on national characteristics. For the application here the average population density in the populated region of each country is calculated and a country-specific threshold is defined by adding one third of the standard deviation of the population density grid cells in the populated area.

Since the GPW population grid is derived by area-weighting admin-unit population counts, high population density numbers are more common in countries with highly disaggregated population data (small admin-units). To prevent this from strongly affecting the calculation of the standard deviations, all grid cells in a country that have a population density above 1500 people per km^2 are combined into one observation with population density $d \geq 1500$ and area a. This observation is then split up into n observations with population density d and area $\frac{a}{n}$ such that $\frac{a}{n}$ is equal to the average grid cell size in the country. This is only done for the calculation of the standard deviation of population density within a country. The threshold 1500 is chosen, since it is the largest commonly used population density threshold in the literature to classify urban population.

[8]While population numbers did change over time and certain grid cells should probably be considered to have switched their classifications over the years, the range of years that will be included in the regression analysis is not extensive enough that this measurement error problem would outweigh the benefit of a time-invariant definition.

[9]http://blogs.worldbank.org/sustainablecities/what-does-urban-mean (accessed 4/10/17)

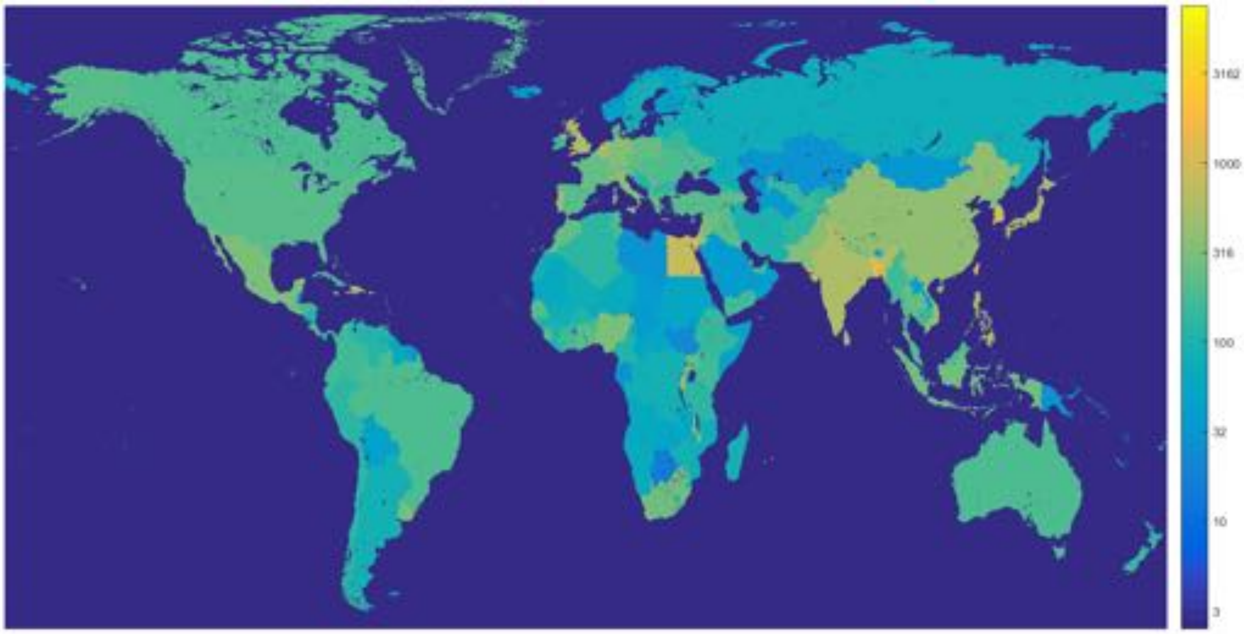

Figure 26: Country-specific thresholds of population density (people per km^2) to distinguish between rural and urban.

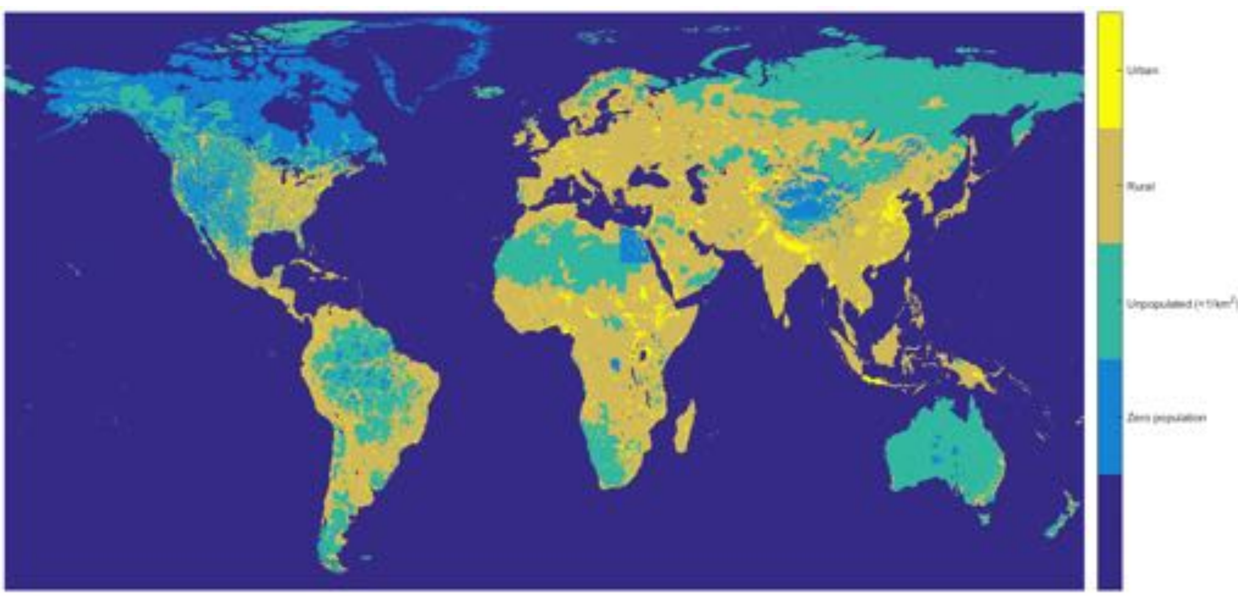

Figure 27: Country specific classification into urban, rural and unpopulated. Zero population also belongs to the category *unpopulated* in the empirical analysis.

The actual country-specific *urban* threshold is then defined as the minimum population density which is greater or equal to the calculated threshold (mean + std/3), if there is at least one grid cell with that density in the country. Figure 26 summarizes the urban thresholds for all countries and Figure 27 provides the map of the different classifications for one country. When considering Figure 27 it is important to keep in mind that the definitions of urban and rural are country specific. Finally, Figure 28 compares the respective area definitons with overall country size.

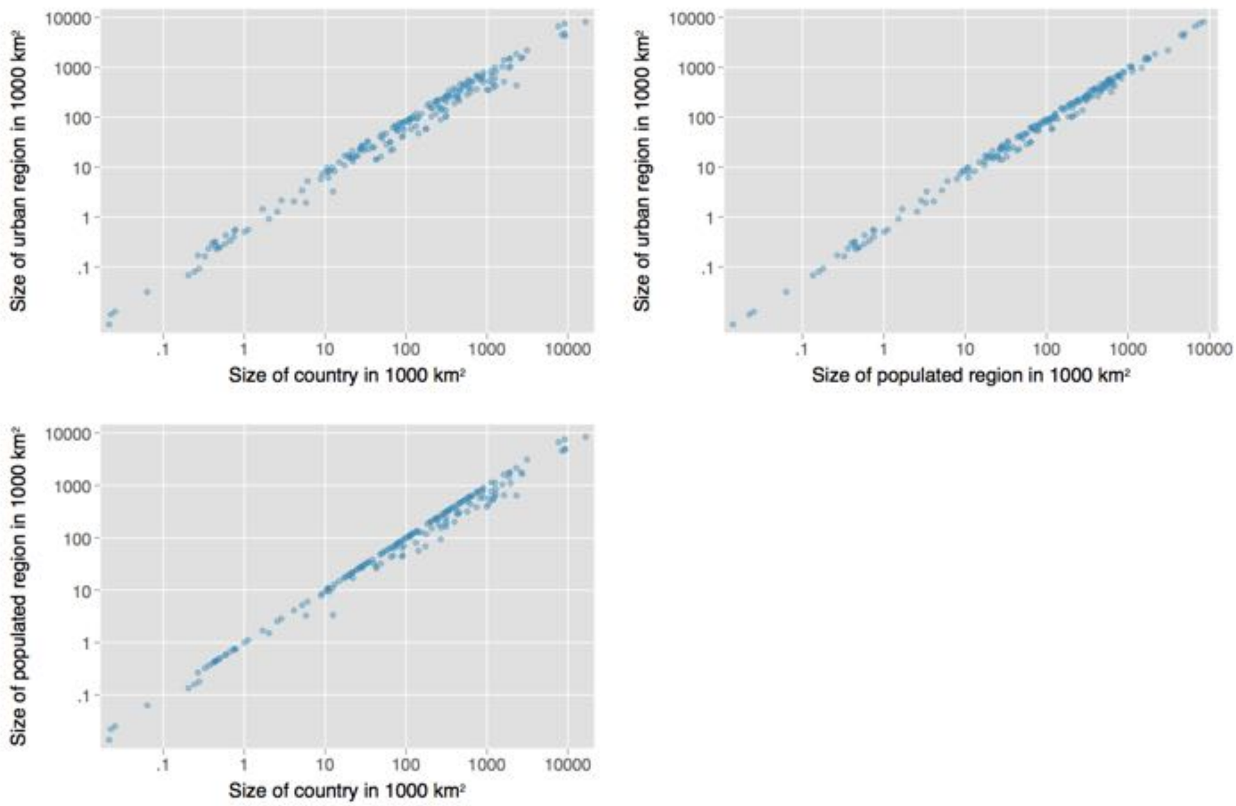

Figure 28: Comparison of size of entire country, populated region, and urban region.

An alternative to country-specific definitions of urban areas, is to use global population thresholds. Figure 29 displays the population of the world according to uniform population density thresholds. Namely, the thresholds 0, 1, 10, 100, and 1000 people per square kilometer are considered and displayed.

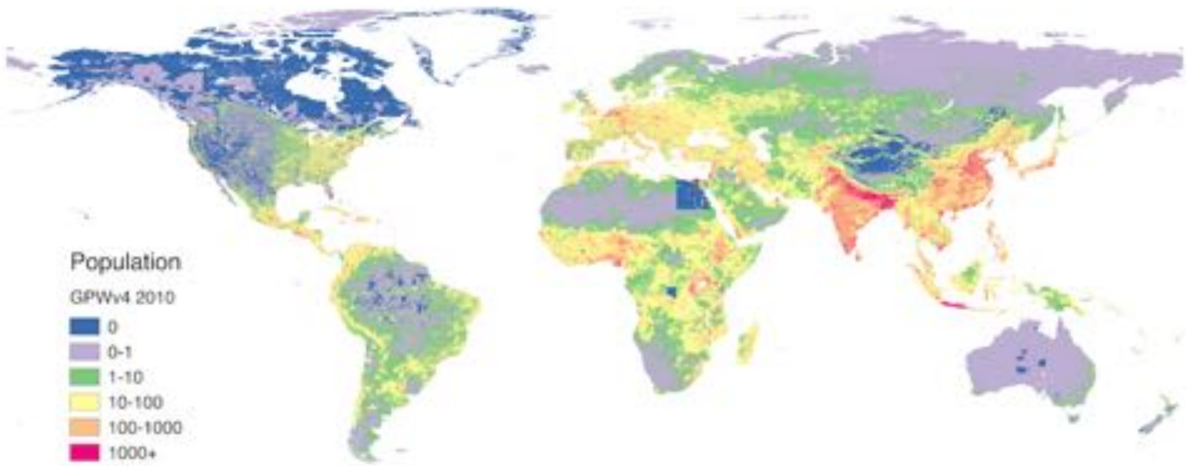

Figure 29: Population distribution by global population density thresholds in terms of people per square kilometer.

VARIABLES	(1) 2B	(2) 1B	(3) 2A	(4) 1A
F1shaking	0.0011	-0.0000	-0.0144	-0.0002
	(0.0014)	(0.0001)	(0.0118)	(0.0006)
F2shaking	0.0017	-0.0001	-0.0217	-0.0008
	(0.0016)	(0.0001)	(0.0106)	(0.0005)
F3shaking	-0.0000	-0.0002	-0.0100	-0.0006
	(0.0017)	(0.0001)	(0.0102)	(0.0005)
shaking	-0.0021	-0.0003	-0.0214	-0.0009
	(0.0022)	(0.0002)	(0.0141)	(0.0007)
L1shaking	-0.0033	-0.0003	-0.0159	-0.0006
	(0.0027)	(0.0002)	(0.0167)	(0.0011)
L2shaking	-0.0058	-0.0004	-0.0149	-0.0005
	(0.0021)	(0.0002)	(0.0142)	(0.0008)
L3shaking	-0.0027	-0.0004	-0.0100	-0.0007
	(0.0014)	(0.0001)	(0.0113)	(0.0007)
L4shaking	-0.0029	-0.0003	-0.0150	-0.0013
	(0.0023)	(0.0002)	(0.0235)	(0.0014)
L5shaking	-0.0012	-0.0000	0.0007	-0.0004
	(0.0017)	(0.0001)	(0.0122)	(0.0006)
L6shaking	0.0001	0.0001	0.0151	0.0006
	(0.0017)	(0.0001)	(0.0125)	(0.0007)
L7shaking	0.0001	0.0001	0.0063	0.0007
	(0.0016)	(0.0001)	(0.0130)	(0.0007)
L8shaking	-0.0016	-0.0001	0.0045	0.0003
	(0.0014)	(0.0001)	(0.0120)	(0.0006)
Observations	5,586	5,586	5,586	5,586
R-squared	0.1197	0.1218	0.1179	0.1181
year FE	X	X	X	X
country FE	X	X	X	X
country time trend	X	X	X	X

Error terms are spatially correlated within one year across countries for up to 1000km and serially correlated within one country across years for up to 10 years.
The dependent variable is the first difference of log GDP per capita.

Table 4: Regression results of the β coefficients from the main model for the four different shaking exposure definitions.

C Additional Results Tables and Figures

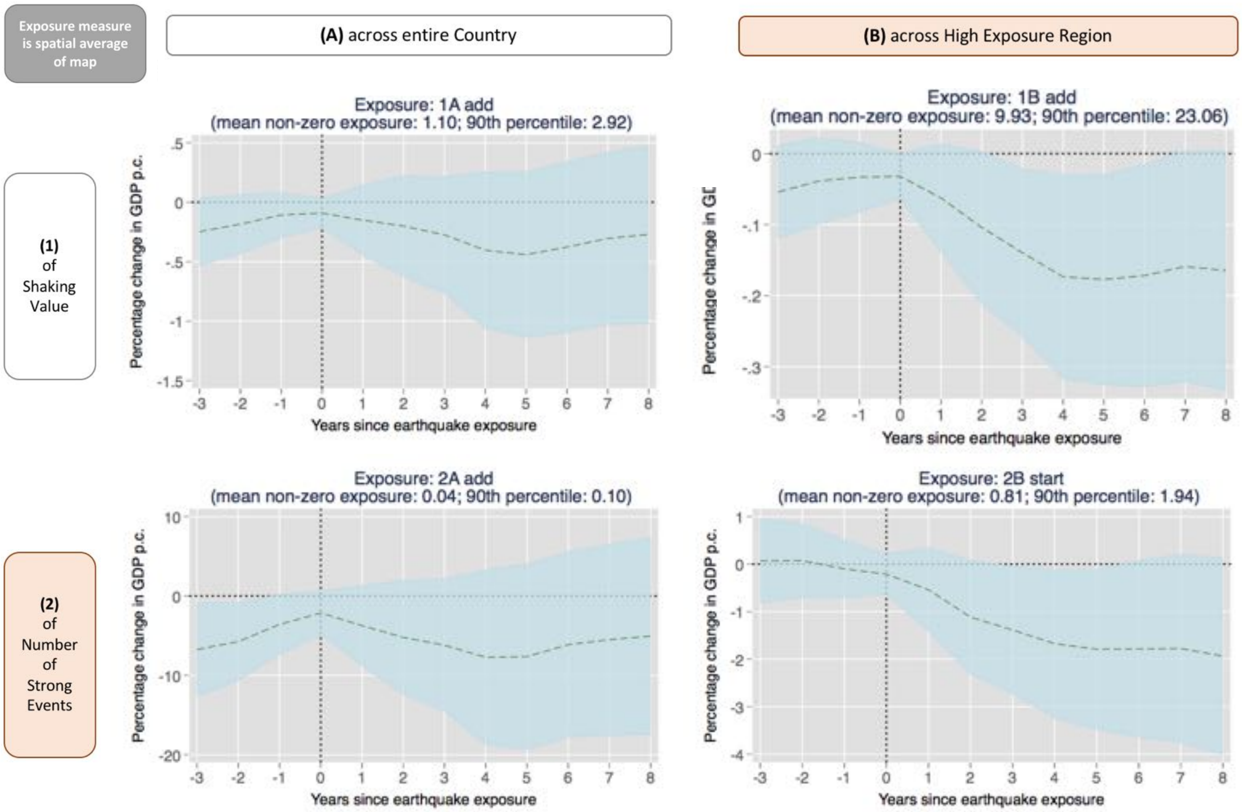

Figure 30: The cumulative impact of earthquake exposure on GDP per capita for all four different exposure definitions. A 95% confidence interval is included and the dashed zero-line represents the previous baseline trend. For all four measures we observe negative impacts on GDP per capita, but the two measures that only consider shaking in the high-intensity region display a better performance. Using a simple spatial average of shaking across the entire country (Exposure 1A) instead of other measures that put more emphasis on disaster events compared to nuisance exposure, can result in underestimating the overall impact on GDP per capita. (N = 5586)

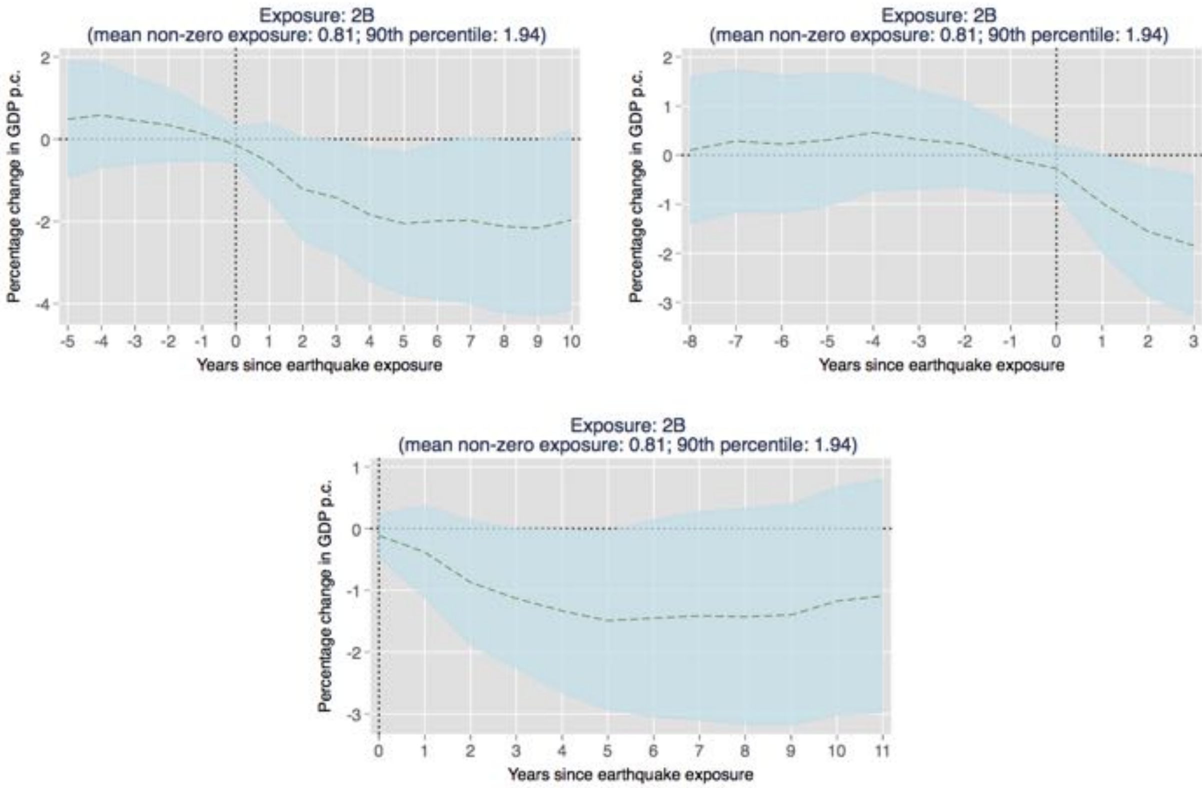

Figure 31: Results from the standard model with varying numbers of leads and lags.

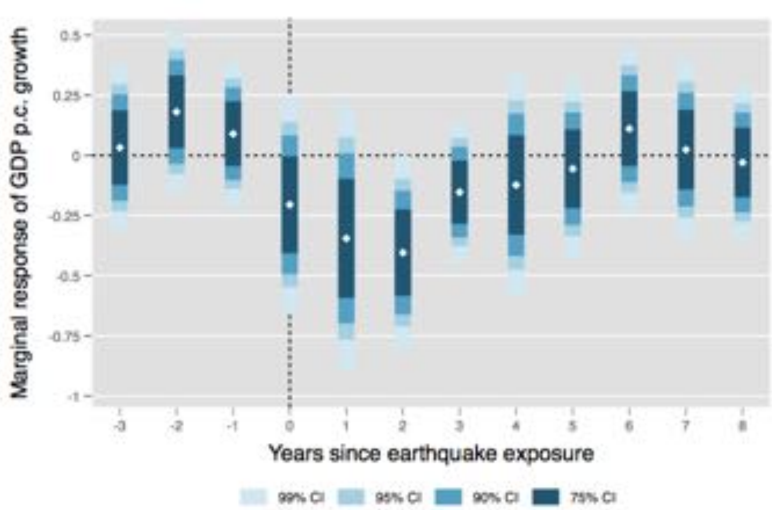

Figure 32: The impulse response from the alternative empirical approach according to the method of Jordà (2005).

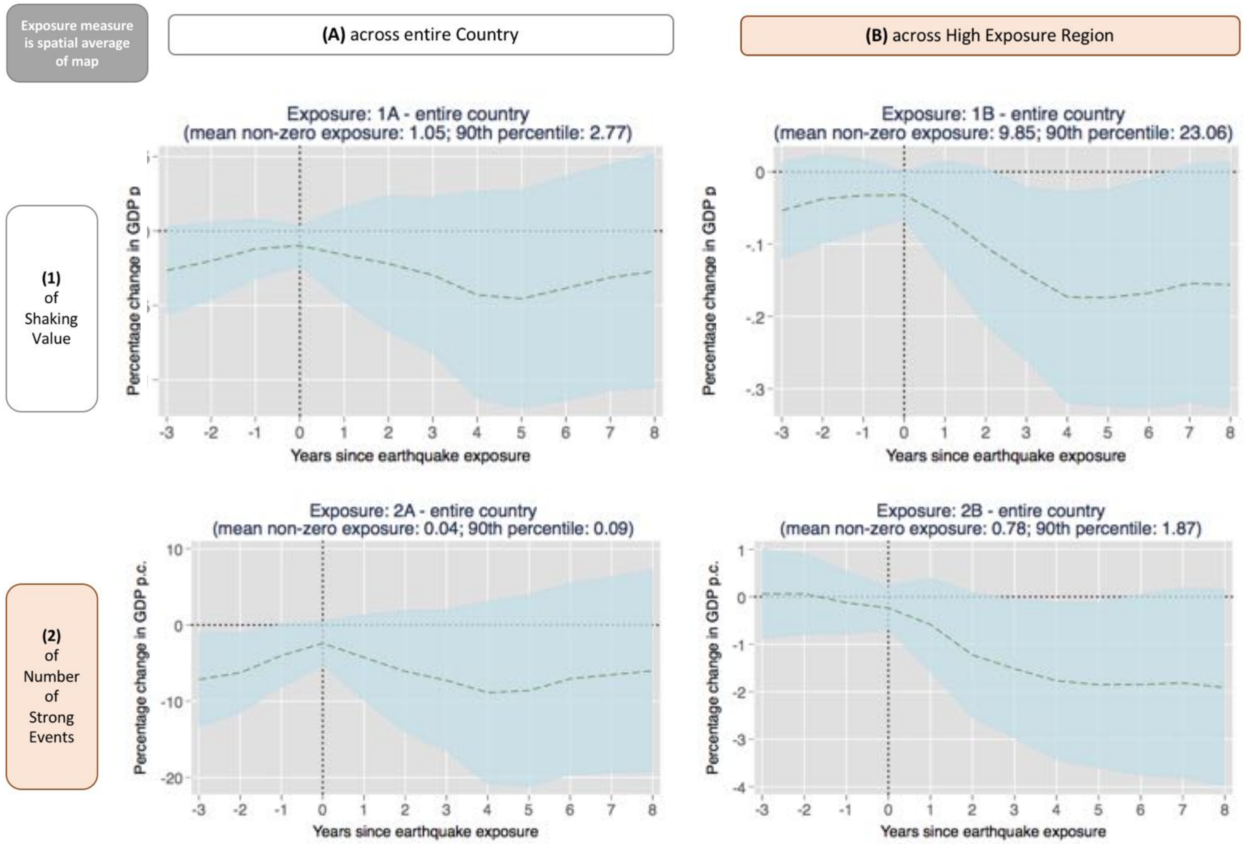

Figure 33: Results based on exposure measures calculated with respect to the entire country including unpopulated regions.

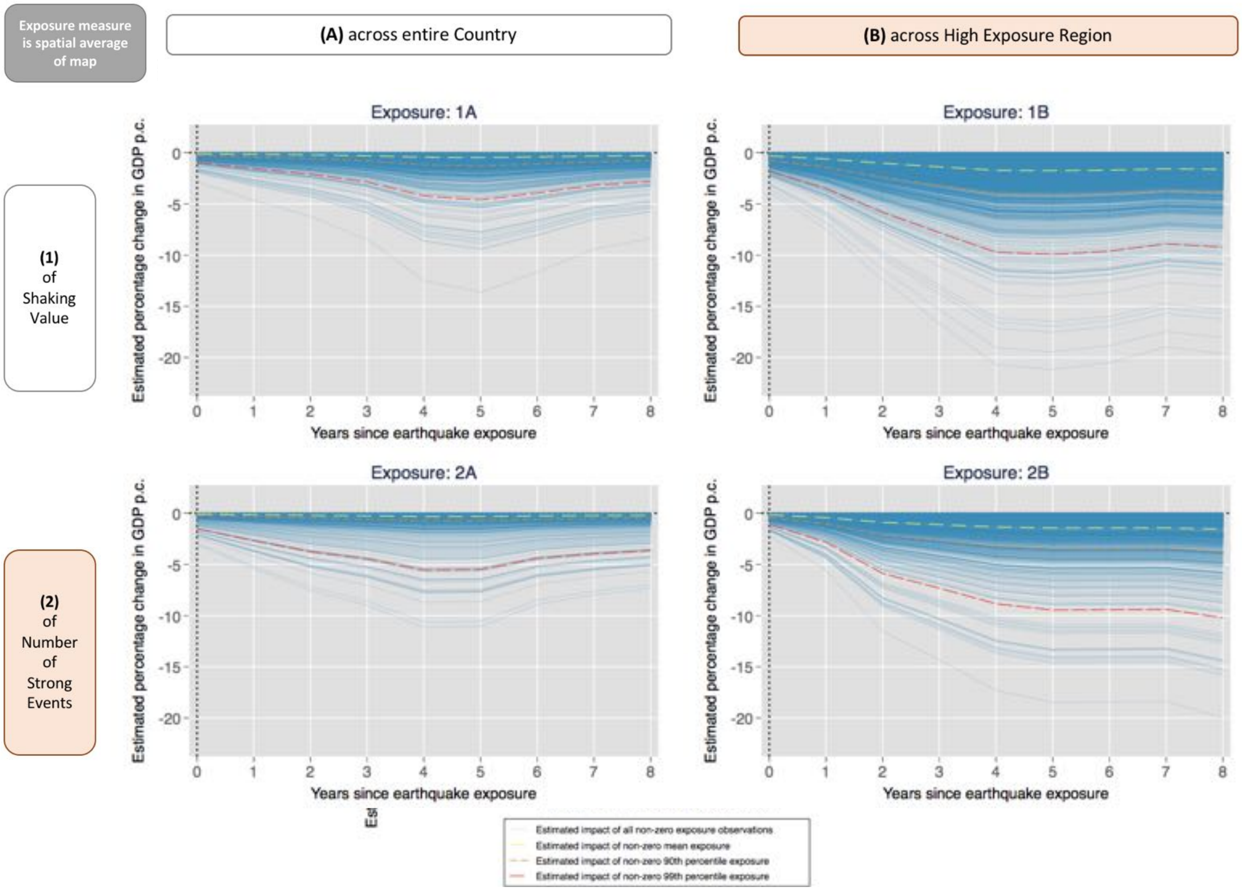

Figure 34: Distribution of expected impacts by exposure measures. Applying the model output on the exposure variables in the data set allows to directly compare the implied impacts of the different measures in terms of change in GDP per capita. The use of the simple spatial average (exposure 1A) would result in underestimating the total impacts due to non-linearities in the effects.

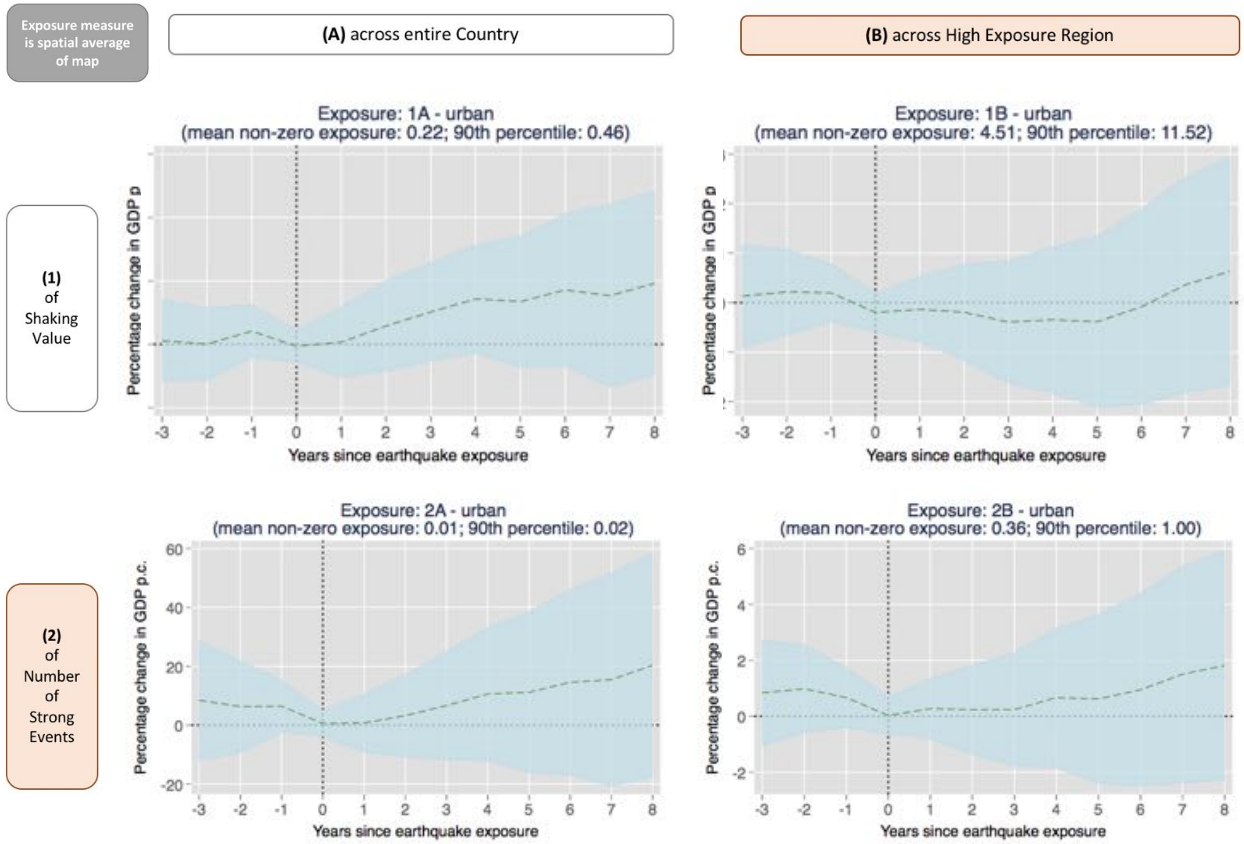

Figure 35: Results based on exposure measures calculated with respect to only the urban regions of each country. The results are not significant under this specification. This could be due to the fact that more rural countries are actually faring worse after an earthquake exposure and they would actually receive lower exposure measures under this specification.

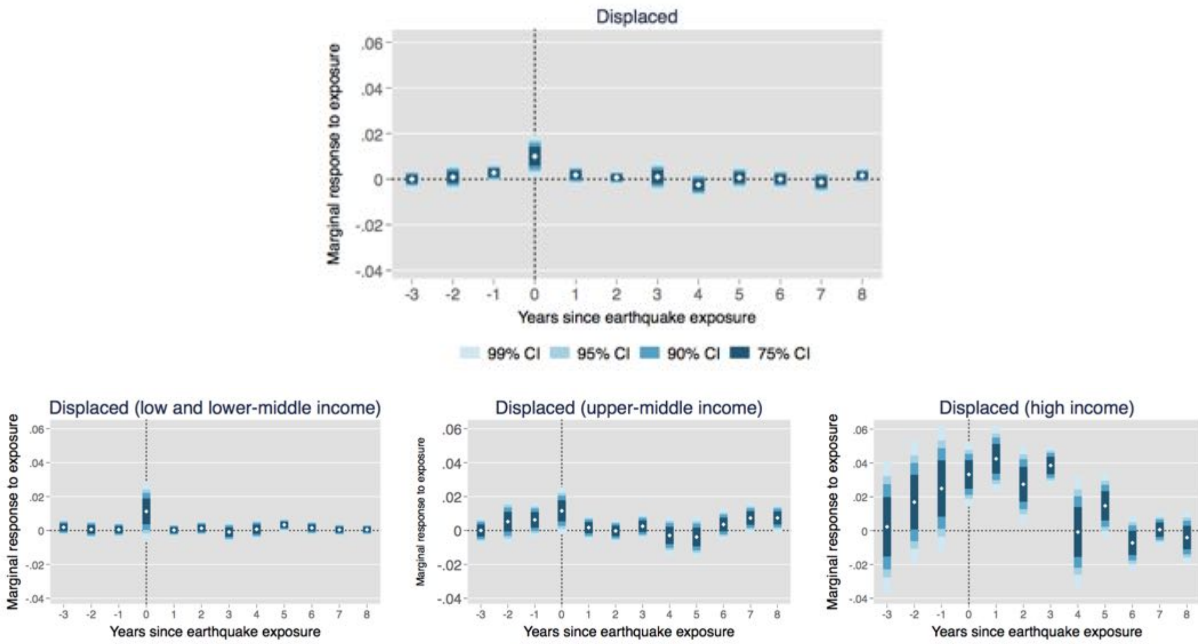

Figure 36: The impact of earthquake shaking exposure on displacement (percentage of internally displaced people of total population) as a global average (top) and by country-income categories (bottom).

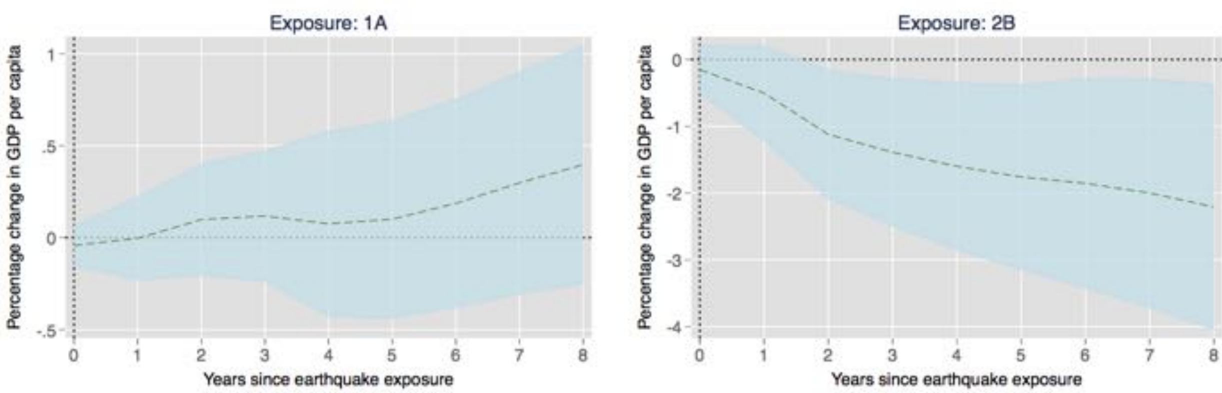

Figure 37: Results from multidimensional exposure approach

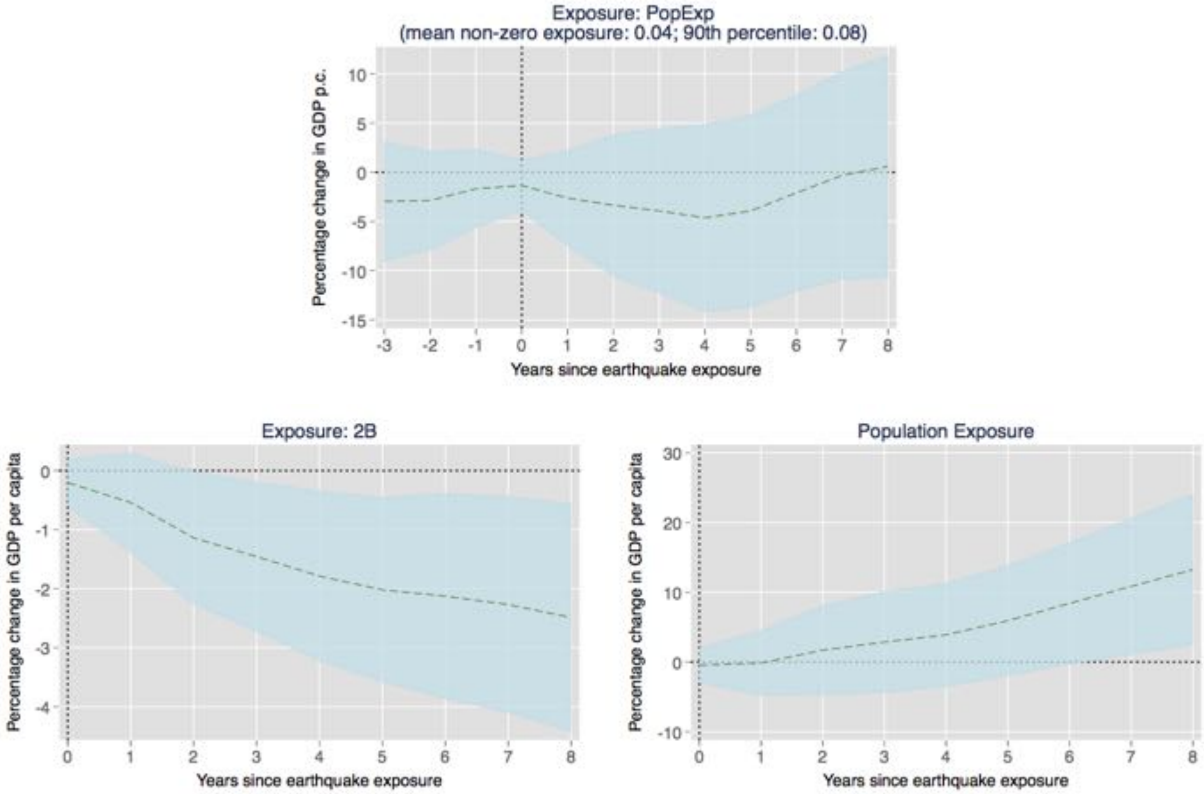

Figure 38: Population as alternative (top) and additional (bottom) exposure measure.

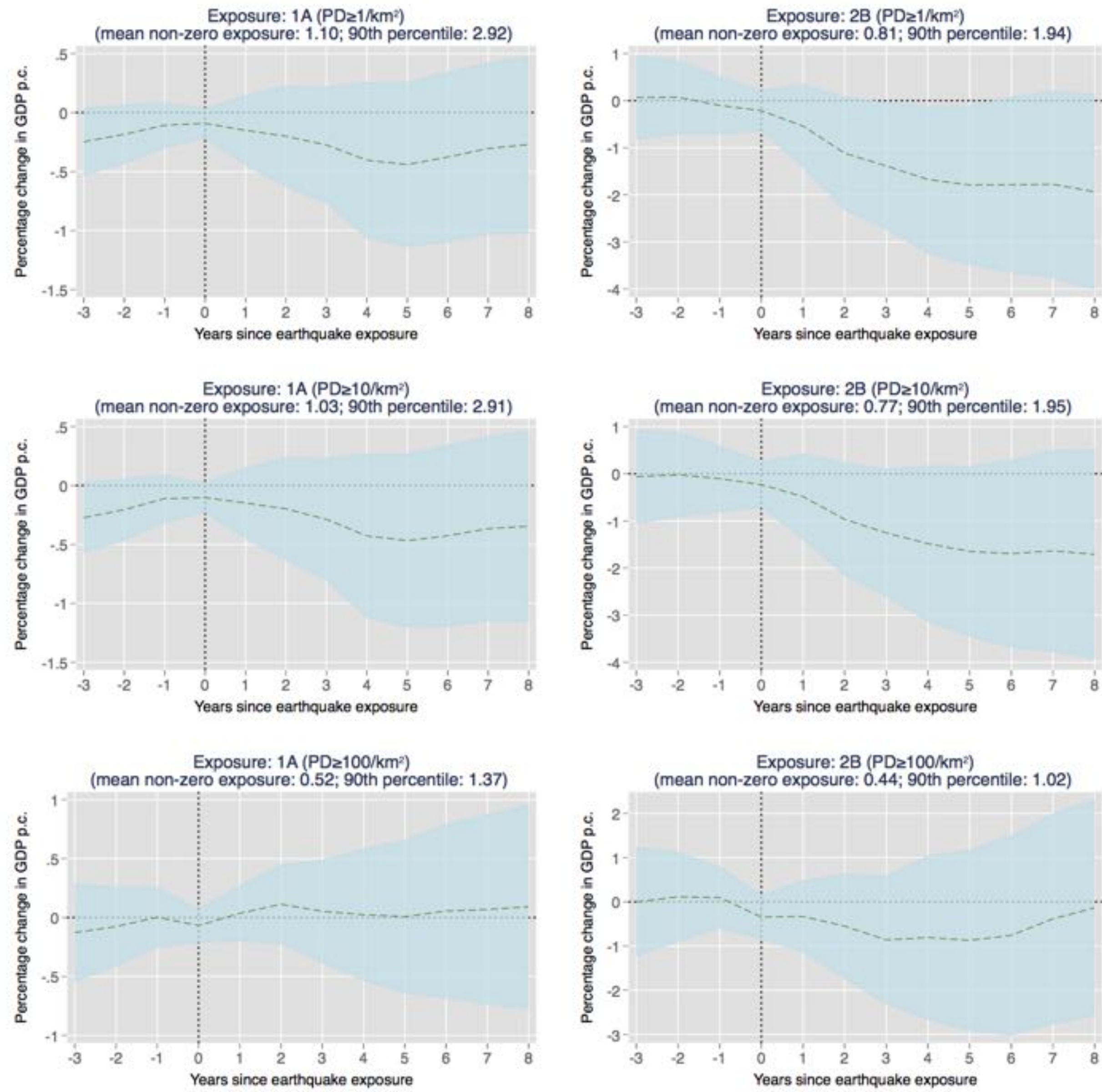

Figure 39: Comparing the model results for exposure measures 1A (left column) and 2B (right column) for increasing population density thresholds of the considered areas.