Abstract

Natural disasters are known to have devastating immediate impacts. However, the long-run impacts of natural disasters on economic productivity are not yet well enough understood and some studies have even suggested positive impacts. Hsiang and Jina (2014) argue that the inconsistent results in the literature might be due to not sufficiently taking into account the physical nature of the hazard. They provide a comprehensive study of the long-run growth impacts of cyclones and find significant sizable negative impacts, but they do not consider other types of natural hazards. This study finds comparable negative impacts on growth for the natural hazard of earthquakes. In particular, the results suggest that 8 years later an average (non-zero) exposure reduces GDP per capita by 1.9%. Additionally, the inherent spatial patterns of the different natural hazard types are found to have important implications for the spatial aggregation approach. I construct a panel dataset of country-year observations of earthquake shaking and economic variables from 1973 to 2015. The data is applied in an econometric analysis to exploit the random within-country variation of shaking over years to identify the causal effect of earthquakes on economic growth. Comparing with an approach that uses magnitude, reveals that using actual shaking data is crucial to identify the impacts of earthquake exposure. In contrast to the findings of Hsiang and Jina (2014) on cyclones the results here suggest that (i) the impacts on growth are primarily incurred by low and middle-income countries and that (ii) high-income countries are potentially even able to experience positive “building back better” effects. Moreover, impacts are primarily driven by (local) high intensity events and not by spatially large exposure to lower intensity shaking. This study concludes that different natural hazard types might require systematically different approaches in how they are integrated in a quantitative model to study impacts, due to the geophysical differences between them.
1 Introduction

Estimates of the economic impacts of natural disasters are often connected to large uncertainties. Estimates of direct impacts of a natural disaster are often calculated in the immediate aftermath of an event (e.g., the USGS PAGER system, Jaiswal and Wald, 2013) and they are commonly used to help decision makers to channel resources for response. Nevertheless, even direct impact estimates are always subject to a high degree of uncertainty and no comprehensive methodology for estimating direct losses at a high accuracy is available at this point. When looking at the long-run indirect impacts this uncertainty is even higher and some studies even suggest that natural disasters can have positive net outcomes by creative destruction and building back better arguments (Albala-Bertrand, 2006; Skidmore and Toya, 2002).

A possible explanation for the inconsistent findings in the past literature on the long-term impacts of natural disasters on economic growth are methodological issues. Skidmore and Toya (2002) conducted the first empirical study on the long-run impacts of natural disasters and find that climatic disasters (particularly floods) are positively correlated with growth, whereas geologic disasters, such as earthquakes, are negatively correlated with growth. However, the study is based on cross-country regression analyses, which suffer from endogeneity biases. Other studies that utilize panel datasets find negative impacts, particularly for developing countries (Cuaresma, 2008; Noy, 2009), or no significant impacts (Cavallo et al., 2013). However, the choice of the disaster measure is still a general weakness in the relevant literature dealing with long-run impacts of natural hazards. Hsiang and Jina (2014) provide a detailed discussion of the literature on how natural disasters affect economic growth. They stress the importance of using a continuous disaster measure that reflects the exogenous natural hazard exposure and not endogenous impact data. Skidmore and Toya (2002) for example merely use the total number of events without regard to the size of the natural hazard. Another common approach is the use of EM-DAT disaster impact data (Centre for Research on the Epidemiology of Disasters - CRED, 2014) to assign a size to each event (particularly when natural disasters are studied without distinguishing between the different natural hazard types). This is problematic not only because the data is self-reported and therefore not consistent across events and countries, but also because it is endogenous impact data instead of an exogenous physical measure.

Hsiang and Jina (2014) have emphasized the importance of applying exogenous physical measures of the natural hazard. For the case of cyclones, they employ a measure of cyclone intensities characterized by peak wind speeds and conduct an empirical econometric analysis to estimate the long-run impacts on economic growth. Their results suggest significant sizable impacts of cyclones on income even 20 years after an event occurred. Their work is the first empirical analysis of global disaster impacts on growth that uses a comprehensive approach to measure the physical hazard and thus does not suffer from the endogeneity issues of impact data. However, it is not yet understood if similar impacts can be expected for other natural hazard types than cyclones.

Since we do not yet understand well enough if different natural hazard types affect economies in systematically different ways, this work here will apply a similar approach as Hsiang and Jina (2014), but for evaluating the long-run impacts of earthquakes instead of cyclones. Furthermore, I will assess the validity of the underlying assumptions of the spatial data aggregation approach chosen by Hsiang and Jina. In particular, Hsiang and Jina
assume a linear relationship between the physical hazard and long-run impacts. This suggests that a spatially large low level exposure has the same impacts as a spatially smaller high level exposure. Such a relationship does not necessarily hold for other natural hazard types. It might in fact not even hold for cyclones, but the spatial pattern inherent to cyclones could make that an irrelevant concern. Nevertheless, it might be an important concern for other natural hazard types, such as earthquakes.

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 (Kirchberger, 2017; Gignoux and Menéndez, 2016), all empirical studies on the subject are not earthquake specific but consider a range of different natural disasters. So far there has been no global study on long-run impacts of earthquakes on economic growth (or other macro-level variables) that utilizes a quantification of surface shaking for the natural hazard of an earthquake. 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 therefore a suboptimal measure (Lackner, 2017).

Other literature on growth impacts of natural disasters have often combined different disaster types without distinguishing between them. But different types of natural hazards might have systematic differences in what kind of impacts they cause. The long-run impacts could therefore also differ for different types of events. 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 impacts, thus resulting in potentially systematic long-run differences in growth impacts. Furthermore, the spatial pattern of the natural hazard are specific to the hazard type. It is conceivable that the long-term impacts have a significant relationship to the spatial pattern of a hazard for example through concentration of impacts.

I construct a panel dataset with annual country level exposure linked with economic variables from a dataset of global earthquake shaking which can be considered the universe of relevant earthquake shaking for 1973-2015 which was introduced by Lackner (2018). Based on the results in Lackner (2017) peak ground acceleration (PGA) is here used to quantify ground shaking. The random within-country variation of earthquake shaking over years is exploited to identify the causal effect of earthquakes on economic growth. Special consideration is given to the spatial aggregation approach and the implied assumptions.

2 Data

For this study, a panel dataset of country-year observations of shaking and economic variables is constructed. 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 (2018). 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 data restricts the number of countries included in the dataset. The final dataset includes 195 countries.
Spatial aggregation of the natural hazard data

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, 2017). For each country two different types of annual maps of earthquake exposure are produced. First, annual shaking grids (the shaking profile) at a 1/120 of a degree resolution are created by calculating the maximum PGA value in a grid cell over the respective year. The second type of annual maps are at the same resolution but displaying the number of earthquakes that exceeded a threshold of 10%g in the respective location, thus representing the number of strong events. Examples of such maps are displayed in Figure 1.

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. First, it requires the assumption that impacts increase in a linear manner with the geophysical hazard. While this might be the case for 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 impacts for the spatial average decreases with an increase in the area size considered (Lackner, 2017)². This suggest that small regions of high intensity shaking are responsible for the bulk of damages and lower shaking values

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1The same resolution as the GPW population data (Center for International Earth Science Information Network - CIESIN - Columbia University, 2016a).
2It is important to note that this is partially a data quality issue, since individual ShakeMaps are usually (somewhat arbitrarily) cutoff before shaking completely attenuates.
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 term impacts on GDP. 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 cannot 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 2. Figure 3 additionally provides an overview of the regions that have

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3The use of the maximum wind speed over the course of a year is, however, argued with the potential relevance of critical thresholds.

4In 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 Figure 16 in the appendix.
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. 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-term impacts.

The second issue with the use of the spatial average is that it introduces 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 is a better proxy for whether a “disaster” occurred for a small country than it is for a large country.

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, Figure 4 compares the averages over the entire (populated) country with

Figure 3: High intensity exposure. The average annual number of events with shaking above the threshold of 10%g PGA based on the years 1973 - 2015. Figure adapted from Lackner (2018).
Figure 4: Comparing average shaking with the average in the strongest 1% region. The average shaking in the entire (populated) country is restricted by an upper (it can not be larger than the average in the strongest 1%) and a lower (1% of the average shaking in the strongest 1%) boundary, which are depicted by the red lines.

the average restricted to the strongest 1% region. The two variables do not show a strong linear relationship, suggesting that the overall spatial average is not a 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 maps that summarize the number of events that exceeded a PGA threshold of 10%g on a grid cell level. Similar spatial averages as for the shaking maps are calculated. The averages over these maps can be considered an estimate for the spatial extent of strong shaking in the given year and country.

Here, the spatial average approach will be 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 from the calculation of the spatial average in the populated part of the country. Moreover, the populated part of a country can be separated into urban and rural and separate average exposure variables are also calculated for those regions. 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.

To be better able to distinguish whether a “disaster” event occurred, I also calculate the spatial mean within the strongest 1% area of the different regions of interest. Using the two different maps - (1) the shaking profile, and (2) the number of strong events - with each two aggregation approaches - (A) across the entire country, and (B) across the 1% highest

\[^{5}\text{This includes most but not all of Alaska for the US.}\]
exposure region - results in four different annual country-level earthquake exposure measures. These measures are illustrated in Figure 1. This approach is applied separately for the entire country as well as only the populated/rural/urban regions of the country. The baseline case will use the populated part of each country as the area of the country to be considered.

Population and area definitions

The GPW gridded population data (Center for International Earth Science Information Network - CIESIN - Columbia University et al., 2005; Center for International Earth Science Information Network - CIESIN - Columbia University, 2016a) 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 estimated population numbers by assuming an exponential growth model (consistent with the GPW model approach). The GPW national identifier grid (Center for International Earth Science Information Network - CIESIN - Columbia University, 2016b) is used to define the country shapes for the 241 countries represented in the data. Moreover, The GPW land area grid (Center for International Earth Science Information Network - CIESIN - Columbia University, 2016c) is used to assign an area size in square kilometer to each grid cell.

The empirical analysis requires to identify rural, urban, and unpopulated areas. 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. 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. 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.

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.

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.

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 5 summarizes the urban thresholds for all countries and Figure 6 provides the map of the different classifications for one country. When considering Figure 6 it is important to keep in mind that the definitions of urban and rural are country specific.

Country level economic data

The main objective of this work is to identify the impact of earthquake shaking on economic growth. The most commonly used variable to represent economic productivity is the Gross Domestic Product (GDP). The World Bank indicator NY_GDP_PCAP_KD for “GDP per capita (constant 2010 US$)”\textsuperscript{8} is used as the main outcome variable of interest. Also the

\textsuperscript{8}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)
Figure 6: Country specific classification into urban, rural and unpopulated. Zero population also belongs to the category unpopulated in the empirical analysis.

World Bank indicators for growth of the different sectors \(^9\) are obtained and used in the empirical analysis.

3 Empirical approach

The random within-country variation of earthquake shaking over years will be exploited to identify the causal effect of earthquakes on economic productivity. The empirical approach is very similar to [Hsiang and Jina (2014)]. An impulse-response function of growth (calculated as the first 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 as well as year specific differences by including country and year fixed effects \((\gamma_i, \delta_t)\).

\[
Y_{i,t} = \alpha + \gamma_i + \delta_t + \sum_{\tau=0}^{k} \beta_{\tau} S_{i,t-\tau} + \epsilon_{i,t}
\]

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 \(\beta\) can be summed up to calculate the cumulative reduction (in percent) of GDP after \(j\) years.

\[
\Omega_j = \sum_{\tau=0}^{j} \beta_{\tau}
\]

The results will focus on these cumulative impacts on GDP \(\Omega_j\). A lag length \(k\) of eight years is used in the standard specification which is much shorter than the 20 years considered

\(^9\)Those indicators are: 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)”.
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.

\[ Y_{i,t} = \alpha + \gamma_i + \delta_t + \sum_{\tau=0}^{k} \beta_{\tau,c(i)} S_{i,t-\tau} \times D_{c(i)} + \epsilon_{i,t} \]  

This approach allows for a different response to shaking exposure for different groups \( c(i) \) of countries. Countries are broken up by income category, whether the populated area of the country is larger than 12,000 km\(^2\), whether they experience earthquakes on a regular basis, and if more than 10\% of the populated area is urban or not. An overview of the number of countries in each group is provided in Table 1 in the appendix.

Unlike Hsiang and Jina (2014) no country specific-time trend is included, since the smaller sample size (the cyclone data covers 59 years compared to 43 years for the earthquake data) would result in an overfitting of some of the models. For comparison the results of the main model are also provided with a country specific linear time trend.

4 Results

The results compare four different definitions of annual earthquake exposure. Two main components are used to define and calculate the four measures:\footnote{The four main exposure measures are all defined on only the populated regions of each country. For simplicity the populated regions of each country are referred to as the entire country. A gridcell is defined as populated if it has a population density of at least one person per square kilometer, based on the GPWv4 gridded population data.}

- The first component is about the variable displayed in the annual exposure maps.
  - 1 - Shaking value is the maximum shaking\footnote{Shaking is measured by peak ground acceleration (PGA) measured in \%g.} per gridcell and year.
  - 2 - Number of strong events is the number of events above a threshold of 10\%g per gridcell and year.

- The second component defines the spatial aggregation approach.
  - A - Spatial average across entire country
  - B - Spatial average across high exposure region which is defined as the (spatial) 1\% of the country with the highest exposure in the given year.

The four different measures are therefore labelled 1A, 1B, 2A, and 2C in Figure 7. 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.

The main results are summarized in Figure 7. It plots the cumulative impacts \( \Omega_1 \) through \( \Omega_8 \) of earthquake shaking exposure on GDP per capita in terms of percentage deviation from
Figure 7: The cumulative impact of earthquake exposure on GDP per capita for 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 significant negative impacts on GDP. 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. (N = 5586)
Figure 8: Results from the model with exposure 2B and increased number of leads and lags. (N = 4922)

the pre-disaster baseline trend. For all four exposure definitions GDP experiences a significant drop compared to its baseline trend in the years after 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 narrower confidence intervals as well as the stronger overall impact in 2B suggest that localized strong events might be driving the impacts, compared to widespread lower level exposure. The leads show significant effects for all of the four exposure measures except 2B. There are two possible explanations for this: (i) small aftershocks after a big event are causing an autocorrelation in the exposure data, which is less the case for 2B because of how the measure is designed, and (ii) improvements in the coverage of ShakeMaps over time for smaller events introduce an artificial time trend in the data that is expected to be strongest for exposure measure 1A and weakest for 2B.

Since the four panels of Figure 7 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. The results from the exposure being calculated as the average number of events in the strongest 1% region imply a reduction of GDP by 1.9% 8 years later for the average exposure (if a positive exposure occurs) and by about 4% for a 90th percentile exposure. The results for the exposure being defined as the spatial average of shaking imply reductions of GDP 8 years later by only 0.3% and 0.7% for an average exposure and a 90th percentile exposure respectively. To allow direct comparison of the model results from Figure 7, the results are applied to the shaking observed in the dataset and plotted in Figure 9. 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) might result in underestimating the long-term impacts of earthquakes compared to using an approach that focuses on the high intensity exposure (e.g. 2B).

Varying the number of leads and lags does not affect the results in a significant way.
Figure 9: The distribution of impacts that can be expected for the different 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.
Figure 10: Results for model with additional country-specific linear time trend.
Figure 11: The impulse response to exposure in mostly urban countries compared to mostly rural countries. A country is defined as mostly urban if 10% or more of the populated regions are urban.

Figure 12: The impulse response to exposure in “large” compared to “small” countries. A country is here defined as small if its populated area is smaller than 12,000km$^2$.

Neither does including a country-specific time trend (see Figure 10). 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, only the urban part of each country, and population weighted measures are reported in Figures 23 - 25 in the appendix.

For examples of the time-series of GDP per capita growth and the different shaking exposure variables of individual countries see Figures 26 - 28 in the appendix. For the remainder of this section we will focus on the average number of events with PGA$\geq 10%g$ in the strongest 1% of the populated part of each country.

The results from the model described by Equation 3 are shown in Figures 11 - 14. They illustrate the different impulse response functions of particular groups of countries. We find that rural countries experience stronger impacts than urban countries. Separating the smallest countries (smaller than 12,000km$^2$) from the rest shows that the small countries are not driving the overall results. Countries that are regularly exposed to shaking and therefore should have more experience with earthquakes exhibit for the first four years after the exposure a slower decline of GDP per capita with respect to its baseline trend. After that until
Figure 13: The impulse response to exposure in regularly exposed countries compared to not regularly exposed countries. Regular exposure is defined as having at least every second year some earthquake shaking within the populated region of the country.

Figure 14: The impulse response to exposure for countries with different income levels. Regularly exposed countries compared to not regularly exposed countries. Regular exposure is defined as having on average at least every second year some earthquake shaking within the populated region of the country.
Figure 15: The results for a simple magnitude approach, where each country's annual earthquake exposure is defined as the maximum magnitude of an earthquake with its epicenter within the country. Year eight these countries keep experiencing a decline while countries that are not regularly exposed seem to potentially recover. Separating the countries by income-level reveals that the long-term impacts are mostly experienced by low and middle income countries, while high-income countries show almost no significant impact or even a slight increase starting about 6 years after an exposure.

Finally, to show the value of the approach applied in this work, Figure 15 provides the results for a simple magnitude approach. In this case, the common use of magnitude to measure the size of earthquake exposure is evaluated by 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. We can see that this results in no significant impacts. Using actual shaking data is therefore crucial for identifying the impacts of earthquakes.

5 Conclusion

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 has been utilized to calculate different annual country level exposure measures. I have evaluated 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 that spatially large nuisance exposure should have the same long-term impacts as more local high intensity events. This approach is particularly compared to the measure (2B) which is the best proxy for whether a more localized disaster event occurred.

For all four measures, earthquakes are found to have a significant negative overall impact on GDP per capita even 8 years after an exposure. The results suggest that a measure that is a better proxy for whether disaster event occurred compared is best suited to estimate
long-term impacts. In particular the exposure based on the spatial average of the number of strong events in the most exposed 1% of the country (exposure measure 2B) performed best. An average exposure (among non-zero exposures) results in a GDP per capita of 1.9% below the baseline trend and a 90th percentile exposure results in a reduction by about 4%. Using instead the simple spatial average approach (1A) might result in underestimating the long-term impacts of earthquakes.

The results show that the spatial aggregation approach to summarize the natural hazard is highly relevant. They suggest that impacts are primarily driven by (local) high intensity events and less by spatially large exposure to lower intensity shaking. This is in contradiction to the assumptions by [Hsiang and Jina (2014)](https://www.authors.com) for using a simple spatial aggregation approach for cyclone wind speeds. However, the spatial average might be a good proxy for whether a local “disaster” event occurred for the natural hazard of cyclones, but it is not for earthquakes. 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).

Unlike the findings of [Hsiang and Jina (2014)](https://www.authors.com) the results here 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.

A comparison with an approach, that only uses magnitude and epicenter to quantify the earthquake exposure, shows that using actual shaking data is crucial to identify the impacts of earthquake exposure.

**Appendix**

![Figure 16: Maximum earthquake shaking (PGA) experienced in the time period 1973 - 2015. Figure adapted from Lackner (2018).](https://example.com/figure16.png)
Figure 17: Comparison of size of entire country, populated region, and urban region.

Figure 18: Mean and standard deviation of exposure compared to country size.
**Figure 19:** Exposure summarized by country. The countries are sorted by the mean, and the median is marked in red.

**Figure 20:** Exposure summarized by country (strongest third by mean exposure). The countries are sorted by the mean, and the median is marked in red.
**Figure 21:** Exposure summarized by country (middle third by mean exposure). The countries are sorted by the mean, and the median is marked in red.

**Figure 22:** Exposure summarized by country (weakest third by mean exposure). The countries are sorted by the mean, and the median is marked in red.
<table>
<thead>
<tr>
<th>Regular exposure:</th>
<th>Low</th>
<th>Middle</th>
<th>High</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Small &amp; rural</td>
<td>4</td>
<td>1</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Small &amp; urban</td>
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<td>1</td>
<td>10</td>
<td>1</td>
</tr>
<tr>
<td>Large &amp; rural</td>
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<td>11</td>
<td>21</td>
<td>17</td>
</tr>
<tr>
<td>Large &amp; urban</td>
<td>19</td>
<td>9</td>
<td>4</td>
<td>1</td>
</tr>
<tr>
<td>Total</td>
<td>58</td>
<td>22</td>
<td>36</td>
<td>19</td>
</tr>
</tbody>
</table>

**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 12,000km² 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.

**Figure 23:** Results based on exposure measures calculated with respect to the entire country.
Figure 24: Results based on exposure measures calculated with respect to only the urban regions of each country.
Figure 25: Results based on exposure measures calculated by population weighting.
Figure 26: 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 fixed effects is shown. Shaking is restricted to the populated regions of each country. For each country four different approaches to aggregate the annual shaking map are displayed: the spatial average of PGA, the spatial average of the number of events with PGA ≥ 10%g, as well as these two approaches applied on only the strongest 1% of the populated regions of the country.
Figure 27: 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 is shown. Shaking is restricted to the populated regions of each country. For each country four different approaches to aggregate the annual shaking map are displayed: the spatial average of PGA, the spatial average of the number of events with PGA $\geq 10\%g$, as well as these two approaches applied on only the strongest 1% of the populated regions of the country.
Figure 28: 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 is shown. Shaking is restricted to the populated regions of each country. For each country four different approaches to aggregate the annual shaking map are displayed: the spatial average of PGA, the spatial average of the number of events with PGA $\geq 10\%g$, as well as these two approaches applied on only the strongest 1% of the populated regions of the country.

References


Cavallo, E., S. Galiani, I. Noy, and J. Pantano (2013). Catastrophic natural disasters and


