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Hurricanes, Economic Growth and Transmission Channels

Empirical Evidence for Developed and Underdeveloped Countries

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Abstract

While the short-term growth consequences of natural disasters are comparatively well studied, there is little knowledge how disasters affect long-run growth. Based on truly exogenous storm indicators, derived from a meteorological database, we show that the growth effects of tropical storms go well beyond the short-term perspective. These negative growth effects of hurricanes are especially pronounced in underdeveloped countries which have comparatively little possibilities to protect against storm consequences. We show that the negative growth effects in underdeveloped countries are amplified by an increase in net fertility and a decrease in educational efforts in the aftermath of occurring hurricanes.

JEL-Codes: Q540.

Keywords: economic growth, natural disasters, tropical storms, transmission channels.

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1. Introduction

Although natural disasters have always affected life on planet earth, only recently economists have started analyzing the effects of natural disasters on economic development. This rising interest in the growth effects of natural disasters was triggered by the expectation that the ongoing process of global warming increases the frequency or at least the severity of certain types of natural hazards and extreme weather events. Under a warming climate, extreme temperatures and precipitation events are expected to increase (Banholzer, Kossin and Donner 2014). The same holds true for the length, frequency and/or intensity of heat waves (IPCC 2013). For other natural hazards such as tropical storms the picture is yet less clear (see e.g. Callaghan and Power 2010, Grinsted, Moore and Jevrejeva 2012, Wang and Lee 2008, Thomas 2014), as tropical storms become natural disasters typically only when making landfall and global warming tends to affect tropical cyclone tracks (Murakami and Wang 2010).

Most of the existing literature on the growth effects of natural disasters is concerned with the short-term growth impact of natural disasters (see, e.g., Raddatz 2007, Noy 2009, Felbermayr and Gröschl 2014). In their comprehensive analysis of the short-term effects of different sorts of natural disasters Felbermayr and Gröschl (2014) conclude that the effect of natural disasters on short-term economic growth is ”naturally negative”. Much less attention has been devoted to the question whether natural disasters have medium- and long-term growth effects. The likely reason for the strong focus on short-term growth effects is that according to standard neoclassical growth theory a natural disaster has no effect on long-run per-capita GDP. Interpreting a disaster as a shock on a country's capital stock (or population), this shock leads to a negative (positive) effect on per-capita income in the short-run. As a consequence of a temporarily rising per-capita savings rate the capital stock will rise to its intial per-capita level, leaving the economy without a long-term growth effect.

However, the view that natural disasters leave long-term growth unaffected might be wrong. Many natural disasters occur quite often in certain regions. As mentioned earlier, within the ongoing process of global warming the frequency and/or severity of certain types of natural hazards and extreme weather events will likely further increase. Repeatedly occurring disasters might prevent that countries reach their long-term equilibrium. Moreover, the implicit assumption of neoclassical growth theory that individual saving behavior, education decisions or fertility remain unaffected by disasters is unlikely to hold in reality (see e.g. Berlemann, Steinhardt and Tutt 2015 or Berlemann and Wenzel 2016).

Only recently, empirical research on the long-run growth effects of natural disasters intensified. However, as Noy and duPont (2016) argue, the existing empirical evidence is yet inconclusive. In their literature review, Cavallo and Noy (2011) come to the conclusion "A further significant lacuna in the current state of our knowledge is the absence of any agreement regarding the long-run effects of these disasters". One might suspect that three reasons are responsible for the relatively mixed picture. First, it seems to be questionable to treat all (climatic) disasters as homogenous, as one might easily imagine different disasters to affect economic development differently. Second and even more problematic, inappropriate measurement of natural disaster severity might have contributed to the yet ambiguous results (see also Cavallo and Noy 2011). The vast majority of existing studies relies on data from the EM-DAT database.[1] As Strobl (2012) argues, the EM-DAT data was collected from various different sources and thus is likely contaminated with measurement error since the reporting sources differ in their motives, methodologies and quality of reporting disaster damages. Moreover, using the EM-DAT disasters intensity indicators likely leads to an endogeneity problem in growth regressions as (i) the monetized damage of a disaster and (ii) insurance coverage and thus the probability of inclusion into the database depend on per capita GDP, the dependent variable in growth regressions (Felbermayr and Gröschl 2014). Third, the typically employed approach to study the effect of natural disasters in Barro-type regressions is likely inadequate. When adding a disaster variable to a set of likely determinants of economic to the estimation equation the estimation approach likely suffers from multicollinearity as the long-term effect of natural disasters on economic growth must be transmitted through at least one channel (the so-called ”overcontrolling problem” (Dell, Jones and Olken 2014). Fourth, the effects of natural disasters on long-term growth might depend on the level of development of a country, as highly developed countries can protect themselves much better against the consequences of natural disasters than less developed countries (Skidmore and Toya 2007).

In this paper we contribute to the literature by studying the short-, medium- and long-run growth effects of one disaster type, tropical storms, systematically within a unified panel estimation approach. Instead of using EM-DAT data we rely on truly exogenous meteorological storm data to construct appropriate hurricane indicators. Moreover, we avoid the mentioned overcontrolling problem by using a two-way fixed effects estimation approach without possibly multicollinear control variables. Our analysis shows that tropical storms in fact affect economic growth negatively both in the short- and the long-run. In order to understand the mechanics behind these effects we also study a number of channels through which tropical storms might affect growth figures. We find that saving rates, education, fertility and the government share in the gross domestic product, which all have a significant impact on economic growth, also react to tropical storms and thereby influence the long-run development of the afflicted countries. We also show that it is in fact important to distinguish between countries on different levels of development. While both well- and underdeveloped countries

[1] For more information on the EM-DAT database see: http://www.emdat.be/.

suffer from negative growth effects of hurricanes, the effects are systematically larger in comparatively poor countries. Our empirical analysis reveals that this finding is to a significant extent due to differing reactions of the population to tropical storms in developed and underdeveloped countries.

The remainder of the paper is organized as follows. In the second section, we review the literature on growth effects of tropical storms. Section three outlines the estimation approach and presents and describes the employed data. Section four is concerned with identifying basic growth determinants in our panel dataset. Section five delivers and discusses the estimation results for growth effects of hurricanes. Section six deals with an empirical analysis of possible transmission channels through which tropical storms affect economic growth. The final section summarizes and draws some conclusions.

2. Related Literature

In the following we summarize briefly the most closely related literature. We thereby concentrate on the literature studying potential growth effects of tropical storms. Transmission channels have yet rarely been discussed in the related literature. We later report some related findings in the context of the presentation and discussion of our estimation results for possible transmission channels in Section 6.

In general, the number of papers which has investigated the growth effects of natural disasters is relatively small. Thus, only a few papers have yet systematically examined the case of hurricanes; most of them deal with short-term consequences of tropical storms. Loayza et al. (2012) study the effects of various types of natural disasters on economic growth within a five-year period observations panel estimation approach based on the EM-DAT database. The authors find no systematic effect of storms on economic growth, neither in the full nor in the development country sample. However, storms tend to affect agricultural growth negatively and industrial growth positively in developing countries. Strobl (2012) studies the growth impact of hurricanes in the Central American and Caribbean regions. In order to do so he applies a wind field model to hurricane data to construct an exogenous indicator of destructiveness. Strobl (2012) finds hurricanes to have a significantly negative effect on economic growth, which is, however, very short-lived. Strobl (2011) delivers a methodologically similar analysis for a highly developed country. In his study of the the growth impact of hurricanes on U.S. coastal counties he finds significantly negative effects of hurricanes. However, these effects do not turn out to be economically strong enough to be reflected in national economic growth rates. As both studies focus on certain regions it is somewhat unclear whether the results can be generalized. Felbermayr and Gröschl (2014) study the growth effects of various types of natural disasters based on data on their physical strength. Using a dynamic panel regression approach for a sample of

108 countries and the time period of 1979 to 2010, the authors find strong empirical evidence in favor of the hypothesis that natural disasters affect short-term economic growth negatively. Especially storms turn out to have strong negative growth effects. These effects turn out to be especially pronounced in non-democratic countries and in countries with low degrees of trade and financial openness.

Interestingly enough, the pioneer paper on the growth effects of natural disasters by Skidmore and Toya (2002) for a long period of time was the only paper studying the long-term effects on natural disasters in general. The paper is based on the earlier discussed EM-DAT data and employs a cross-section approach by regressing the average real growth rate over the period of 1960 to 1990 on a set of control variables and the number of natural disasters occurring throughout the same period. The authors classify all disaster types into climatic and geologic disasters and find a statistically significant positive effect of climatic disasters on economic growth. The effect of geologic disasters tends to be negative, however is statistically insignificant in most cases. While the study by Skidmore and Toya (2002) was the first comprehensive study of the long-term growth effects of natural disasters, the analysis suffers from the earlier described endogeneity problem.

To the best of our knowledge the only existing study concerned with the long-term growth effects of tropical storms is the analysis by Hsiang and Jina (2014). The authors make use of panel data covering 110 countries and the time period of 1950 to 2008 and also control for spatial effects which might play a significant role in the case of hurricanes. As Felbermayr and Gröschl (2014) the authors make use of storm severity data from a meteorological database to prevent endogeneity problems and also deal with multicollinearity issues adequately. Hsiang and Jina (2014) find tropical storms to exert a systematically negative effect on economic growth, both in the short- and in the long-run, using a wide variety of stability tests. However, as the paper focuses on uncovering the growth effects of tropical storms, the transmission aspect is not discussed in detail.

3. Estimation Strategy and Data

3.1. Basic Estimation Approach

As outlined in the introduction, we are interested in both, the effects of tropical storms on economic growth and, given these effects exist, the channels through which hurricanes affect economic growth. Moreover, we are interested in the question whether the growth effects of tropical storms differ between underdeveloped and developed countries. In order to study these issues, we proceed in three steps in our empirical analysis.

In the first step (see section 4) we estimate a standard growth model based on a large (unbalanced) annual panel data set. As determinants of economic growth we thereby concentrate on the core set of explanatory variables as they result from neoclassical growth theory. Basically, we estimate a panel regression of the type

$$\ln GDP_{t,i} - \ln GDP_{t-1,i} = \alpha_i + \delta \cdot \ln X_{t-1,i} + \epsilon_{t,i} \quad (1)$$

where $lnGDP_{t,i}$ is the natural logarithm of the per capita gross domestic product in country i at time t, α_i are country fixed effects controlling for countries' differing institutions, cultures and geographies, $X_{t-1,i}$ is a vector of one period lagged control variables and $\epsilon_{i,t}$ is the unexplained residual.

In the second step of our analysis (section 5) we study whether tropical storms have an influence on economic growth. Most previous empirical studies rely on Barro regressions (see e.g. Barro 1991, Mankiw, Romer and Weil 1992, and Islam 1995) to uncover the growth effects of natural disasters. This approach consists of employing the baseline model of economic growth from equation (1) and adding a disaster indicator to the regression equation

$$\ln GDP_{t,i} - \ln GDP_{t-1,i} = \alpha_i + \delta \cdot \ln X_{t-1,i} + \gamma \cdot H_{t,i} + \epsilon_{t,i} \quad (2)$$

with $H_{t,i}$ being an indicator of disaster (here: hurricane) severity in country i and period t.[2] The studies employing this approach then argue that only if the estimated coefficient of the disaster indicator turns out to be significantly different from zero, natural disasters have a systematic growth effect. However, this approach is problematic because of at least two reasons.

First, the included control variables themselves might be (and quite likely are) endogenous to natural disasters. As Dell, Jones and Olken (2014) argue, including possibly endogenous control variables leads to an over-controlling problem. One might illustrate the over-controlling problem at the example of investments. Whenever natural disasters have a direct or an indirect impact on investments, the estimated coefficient for the disaster indicator in a Barro regression might be insignificant as the effect of disasters is already captured by the investment coefficient. Whenever natural disasters in fact have a medium- or long-term effect on economic growth, this effect must work through certain transmission channels with the traditional control variables in growth regressions being the most likely candidates. Thus, the Barro regression approach is at least not unproblematic. We therefore follow the approach chosen by Hsiang and Jina (2014) to exclude all control variables from the regression equation and to estimate the effects of hurricanes in a two-way fixed effects panel model.[3]

[2]The disaster indicator can also enter the estimation equation with a time lag.
[3]While doing so seems to be the most reliable approach, we nevertheless also present the results of the

Second, simply adding the contemporaneous or a lagged value of the hurricane indicator is not suitable to learn about the medium- and long-term effects of natural disasters. A disaster occurring at time t will likely affect economic growth in the contemporaneous period, but might have also an effect over various future periods. Thus, in order to learn about the full impact of natural disasters, it is necessary to estimate the contemporaneous and the lagged effects of disasters on economic growth. We therefore estimate the model

$$\ln GDP_{t,i} - \ln GDP_{t-1,i} = \alpha_i + \beta_t + \sum_{j=0}^{J} \left(\gamma_j \cdot H_{t-j,i} \right) + \epsilon_{t,i} \tag{3}$$

with β_t being time fixed effects. J defines the maximal number of periods a hurricane is allowed to influence future economic growth. In line with Hsiang and Jina (2014) we then calculate the cumulative effect of a hurricane on economic growth as

$$GCUM_J = \sum_{j=0}^{J} \gamma_j \tag{4}$$

In the third and final step of our analysis (section 6) we study through which channels natural disasters have an impact on economic growth. We thereby concentrate on the control variables we identify as significant determinants of economic growth in the first step of our analysis. Again, we employ two-way fixed effects estimations to analyze the impact of tropical storms on the identified growth determinants

$$\ln X_{t,i} = \alpha_i + \beta_t + \sum_{j=0}^{J} \left(\gamma_j \cdot H_{t-j,i} \right) + \epsilon_{t,i} \tag{5}$$

We then evaluate the cumulative effect of a hurricane on the referring growth determinant

$$XCUM_J = \sum_{j=0}^{J} \gamma_j \tag{6}$$

In order to estimate the described models we need macroeconomic data (GDP, control variables) and an appropriate indicator of hurricane severity. We discuss the data sources and deliver some descriptive statistics on the employed data sources separately in the following.

earlier described Barro regression approach (see equation (2)) as additional evidence.

3.2. Macroeconomic Data

The left-hand variable in the first and second step of our analysis is the real per-capita growth rate of the gross domestic product. We construct this variable from GDP per capita in constant prices of 2005 (RGDPNA) as provided in the Penn World Tables Version 8.0 (PWT 8.0, see Feenstra, Inklaar and Timmer 2015).

Table 1: Data Sources and Descriptive Statistics

Variable	Source	Mean	Std. Dev.	Min	Max
Growth of real GDP per capita (RGDPNA, 2005 const. prices)	PWT 8.0	0.035	0.069	-1.082	0.724
Log of current GDP, output side (current PPP)	PWT 8.0	10,006	2,106	3,965	16,257
Investment share of real GDP per capita (RGDPL, % of GDP)	PWT 8.0	0.198	0.114	0.006	1.396
Government share of real GDP per capita (RGDPL, % of GDP)	PWT 8.0	0.199	0.117	0.011	1.439
Net fertility rate (calculated)	WDI	3.816	1.579	1.065	7.795
Average years of secondary schooling, linear interpolated	Barro & Lee (2010)	5.134	3.051	0.024	12.726

The empirical growth literature has considered numerous different potential growth determinants. The core set of control variables used in growth regressions (and especially in the earlier described Barro Regressions) consists of a number of variables which can directly be derived from theoretical models of economic growth such as the initial level of per-capita GDP, the saving rate (or, closely related, the investment share of GDP), population growth (or net fertility), the level of education and the total government share in GDP. In our subsequent empirical analysis, we concentrate on these control variables as they are available for a large number of developed and underdeveloped countries. While the empirical growth literature has studied numerous additional factors such as e.g. formal and informal institutions, we refrain here from considering these factors as the referring data is only available for much less countries and considerably shorter periods of time.

For the initial level of GDP per capita we use current GDP (output side, current PPP) as provided in the Penn World Tables Version 8.0. Data for the investment share of real GDP per capita and the government share of real GDP per capita were also extracted from Penn World Tables. Net fertility comes from the World Development Indicators Database. As indicator for education we use the average years of secondary schooling (linear interpolated) as extracted from Barro and Lee (2010).

Table 1 summarizes the data sources and delivers some descriptive statistics on the employed variables. Altogether, our unbalanced panel dataset consists of data from 130 countries and covers the years of 1960 to 2002. The number of years included into the estimations differs in between 12 and 43.

3.3. Best Track Data of Hurricanes

Besides macroeconomic data, we need an appropriate indicator of hurricane occurrence and destructiveness. Hurricanes are a specific and highly destructive form of storms.[4] They belong to the storm class of cyclones, which are defined as areas of low atmospheric pressure, characterized by rotating winds. As a consequence of the Coriolis effect, cyclones rotate counterclockwise in the Northern and clockwise in the Southern Hemisphere. Depending on their region of origin, cyclones are classified as tropical or extratropical. Tropical cyclones develop between 5 and 20 degrees latitude and thus over warm water. On the contrary, extratropical cyclones have cool central cores as they typically form between 30 and 70 degrees latitude in association with weather fronts. The two types of cyclones can have quite similar destructive effects, however, they differ in their source of energy and their structure. Tropical cyclones derive their energy from warm ocean water and heat of rising air which condenses and forms clouds. Extratropical cyclones derive their energy from the temperature difference of airmasses on both sides of a front.

According to the National Oceanic and Atmospheric Administration (NOAA) tropical cyclones with a maximum sustained wind of 38 mph (61 km/h) or less are called ”tropical depressions”. Whenever a tropical cyclone reaches winds of at least 39 mph (63 km/h) they are typically called ”tropical storms”. At this stage they are also assigned a name. If maximum sustained winds reach 74 mph (119 km/h), the cyclone is called a hurricane, whenever it developed in the North Atlantic Ocean, the Northeast Pacific Ocean east of the dateline or the South Pacific Ocean east of 160°E. In other regions the terms ”typhoon” (Northwest Pacific Ocean west of the dateline), ”severe tropical storm” (Southwest Pacific Ocean west of 160°E or Southeast Indian Ocean east of 90°E), and ”severe cyclonic storm” (North Indian Ocean) are common. In the Southwest Indian Ocean the terminology sticks to the simple term ”tropical cyclone”.

Hurricanes (or more general tropical cyclones) are further classified according to their wind speed. This is often done by employing the Saffir Simpson Scale (see Table 2).[5] The Saffir Simpson Hurricane Wind Scale is a 1 to 5 rating based on the hurricane’s intensity. This scale only addresses the wind speed and does not take into account the potential for other hurricane-related impacts such as storm surge and rainfall-induced floods. Earlier versions of this scale, known as the “Saffir Simpson Hurricane Scale”, also incorporated these categories, however, often led to quite subjective and sometimes implausible categorizations of occurring storms. In order to reduce public confusion and to provide a more scientifically defensible scale, the storm surge ranges, flooding impact and central pressure statements were removed from the Saffir Simpson Scale and only peak winds are now employed.

The hurricane indicator, we employ in our empirical analysis, is based on data from a meteorological database: the Best Track Dataset of tropical cyclones provided jointly

[4]The following expositions are primarily based on Keller and DeVecchio (2012).

[5]The scale is named after its inventors, the wind engineer Herb Saffir and the meteorologist Bob Simpson.

Table 2: Saffir Simpson Hurricane Wind Scale

Category	Sustained Winds	Types of Damage Due to Hurricane Winds
1	74-95 mph 64-82 kt 119-153 km/h	Very dangerous winds will produce some damage: Well-constructed frame homes could have damage to roof, shingles, vinyl siding and gutters. Large branches of trees will snap and shallowly rooted trees may be toppled. Extensive damage to power lines and poles likely will result in power outages that could last a few to several days.
2	96-110 mph 83-95 kt 154-177 km/h	Extremely dangerous winds will cause extensive damage: Well-constructed frame homes could sustain major roof and siding damage. Many shallowly rooted trees will be snapped or uprooted and block numerous roads. Near-total power loss is expected with outages that could last from several days to weeks.
3	111-129 mph 96-112 kt 178-208 km/h	Devastating damage will occur: Well-built framed homes may incur major damage or removal of roof decking and gable ends. Many trees will be snapped or uprooted, blocking numerous roads. Electricity and water will be unavailable for several days to weeks after the storm passes.
4	130-156 mph 113-136 kt 209-251 km/h	Catastrophic damage will occur: Well-built framed homes can sustain severe damage with loss of most of the roof structure and/or some exterior walls. Most trees will be snapped or uprooted and power poles downed. Fallen trees and power poles will isolate residential areas. Power outages will last weeks to possibly months. Most of the area will be uninhabitable for weeks or months.
5	157 mph or higher 137 kt or higher 252 km/h or higher	Catastrophic damage will occur: A high percentage of framed homes will be destroyed, with total roof failure and wall collapse. Fallen trees and power poles will isolate residential areas. Power outages will last for weeks to possibly or higher months. Most of the area will be uninhabitable for weeks or months.

Source: http://www.nhc.noaa.gov/aboutsshws.php

by the National Oceanic and Atmospheric Administration (NOAA), the Tropical Prediction Center (Atlantic and eastern North Pacific hurricanes) and the Oceanography Center / Joint Typhoon Warning Center (Indian Ocean, western North Pacific, and Oceania hurricanes).[6] The advantage of this database is its worldwide coverage. The Best Track dataset provides data on the position of tropical cyclone centers in 6-hourly intervals[7] in its geographic coordinates, the measured maximal sustained wind speed in knots,[8] central surface pressure data in millibar and the Saffir Simpson Hurricane Wind Scale rating of the referring storm interval. The data is collected post-event from different sources like reconnaissance aircraft, ships and weather satellites.

Most of the time, hurricanes are located over the open sea. While tropical cyclones might cause some damage there, e.g. at oil platforms or ships, the referring storm periods are a thread to life and/or wealth for only a minimal fraction of the population. We therefore concentrate on storm periods occurring over land masses. Most of these storm periods are located in coastal areas. This is due to the fact that tropical cyclones rapidly diminish when a cyclone's eye passes land masses. Atop land masses a storm lacks moisture and heat provided by the ocean. As a consequence it quickly loses power and starts diminishing. However, as the destructive power of a tropical cyclone goes

[6]The dataset was downloaded from the Unisys Weather Hurricane Data Archive at: http://weather.unisys.com/hurricane/index.php. For our purposes we used the tracking information files for each single hurricane provided in the annual storm tracking data.

[7]The data is recorded on a daily basis at 6am, 12am, 6pm and 12pm.

[8]The database contains the average maximum sustained wind speed at 10 metres above the earth's surface over a one minute time span anywhere within the tropical cyclone.

well beyond a cyclone's center we follow Yang's (2005) proposal to include all 6-hourly storm intervals with a Saffir-Simpson grading whose centers pass a country's borders up to a 160 kilometer distance (for a graphical illustration see Figure 1). This buffer zone might be justified by the typical structure of tropical cyclones. Its strongest winds are located in the eyewall, a ring of tall thunderstorms located around the cyclone's eye. The eye is the calmest part of the tropical cyclone with a typical diameter of in between 32 and 64 kilometers. Around the eyewall and arranged like a spiral, there are curved rainbands producing heavy rain, wind and tornadoes. The destructive winds and rains of a tropical cyclone affect a wide area. Hurricane winds may extend to more than 242 kilometers from the eye of a large tropical cyclone. Because this extension may vary considerably from case to case, a cautious buffer of 160 kilometers seems to be reasonable.

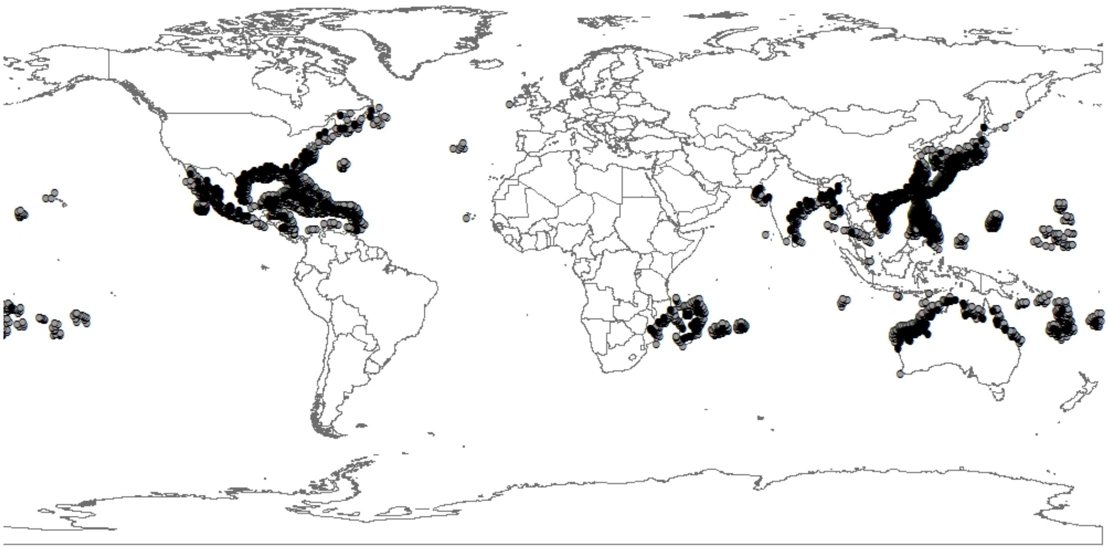

Figure 1: Relevant 6-hourly Storm Periods

Using the described Best Track Dataset we construct two different hurricane indicators: The first indicator (*SNO*) is the annual sum of all six-hourly storm intervals with a Saffir-Simpson grading whose centers pass a country's borders up to a 160 kilometer distance. Note that this indicator is not a pure frequency indicator of hurricanes, as it bases on the number of six-hourly storm periods. Thus, storms which are located over landmasses for longer periods of time have a higher impact on the indicator than quickly decaying hurricanes. Moreover, more severe hurricanes are also more likely to exist for longer periods of time. For reasons of simplicity, we nevertheless refer to this indicator as "storm number indicator" in the following.

The second hurricane indicator, we calculate for our empirical analysis, incorporates storm severity more explicitly by using maximum wind speed. For our purpose we compute the indicator as the annual sum of the maximum sustained wind speed of all six-hourly storm intervals whose centers pass a country's borders up to a 160 kilometer distance. We refer to this indicator as "wind speed indicator" in the following (*SWIND*).

4. Determinants of Economic Growth

We start out our empirical analysis with estimating the fixed effects baseline growth model from equation (1) for the whole country sample.[9] The estimation results are summarized in Table 3. In the upper part of the table we show the estimated coefficients, in the middle part we report basic regression statistics and the lower part summarizes some further test results. In the upper part, we report the estimated coefficients (column 2), the standardized coefficients (column 3) and the standard errors (column 4). As the Wooldridge test indicates, the growth regression suffers from autocorrelated residuals. To solve this problem and to correct for possible heteroscedasticity we calculate HAC standard errors[10] (column 5) and report the referring p-values of t tests (column 6). The Hausman test indicates that estimating a fixed effects model rather than relying on a random effects model is adequate.

We find all five included control variables to have statistically significant and economically meaningful effects on the rate of real per-capita economic growth. As (neoclassical) growth theory predicts, the initial level of GDP has a highly significant negative effect on economic growth. Higher investment shares of GDP (and thus higher saving rates) turn out to affect economic growth positively. Again, the effect turns out to be highly significant. Education has also a positive impact on economic growth, however, the effect is only significant at the 90% confidence level. Countries with higher government shares turn out to have highly significantly lower economic growth. Finally, net fertility affects economic growth negatively. Again, the effect is highly significant. Altogether, our fixed effects panel regression model thus delivers highly reasonable results for all included control variables. In the third step of our analysis, when considering the channels through which tropical storms affect economic growth, we base our models on these findings.

[9]The results of the Phillips Perron panel unit root tests indicate that all employed time series are stationary when including an intercept. For the test results see the Appendix.
[10]See Newey and West (1987).

Table 3: Baseline Estimation Results: Determinants of Economic Growth

	Country fixed effects model				
	coefficient	**std. coefficient**	**s.e.**	**HAC s.e.**	**p-value**
Control variables:					
lag(lncgdpo, 1)	-0.032	-1.062	0.003	0.008	0.000***
lag(lnis, 1)	0.011	0.103	0.002	0.003	0.000***
lag(lneduavg2i, 1)	0.007	0.125	0.002	0.003	0.053*
lag(lngs, 1)	-0.010	-0.082	0.002	0.002	0.000***
lag(lnfertn, 1)	-0.038	-0.279	0.005	0.014	0.006***
Regression statistics:					
no. of observations	5,496				
no. of countries	130				
F-Value	39.61***				
adj. R-square	0.035				
Hausman test:	$\chi^2 = 162.703, df = 5, p = 0.000$				
Wooldridge test:	$\chi^2 = 28.926, p = 0.000$				

Notes: Dependent variable: wr gdppwtna. ***, **, * indicate statistical significance at the 1%, 5%, 10% level. Country fixed effects included, but not reported. We report the results of the Hausman test for superiority of a random effects model and the results of the Wooldridge test for serial correlation in FE panels.

5. Growth Effects of Tropical Storms

In the next step of our analysis we study the growth effects of tropical storms. In order to do so, we estimate the two-way fixed effects model from equation (3). As we have no information whether hurricanes affect economic growth only contemporaneously or over numerous years we estimate the model for values of J ranging in between 0 and 20. Instead of reporting the full estimation results for every single estimation we show a graphical representation of the estimated cumulative coefficient and the referring 90% confidence interval. The confidence intervals are again based on HAC standard errors (Newey and West 1987). Moreover, as hurricanes might affect not only the country where they occur but also the surrounding regions we account for spatial correlation of the error terms by employing the procedure proposed in Conley (1999).[11] We follow the proposal of Hsiang and Jina (2014) to correct for autocorrelation up to a distance of 1,000 km which roughly equals twice the diameter of a tropical storm and also equals the average inland distance a hurricane travels over landmasses.

In a first step, we estimate the cumulative effects of hurricanes on economic growth in the full country sample. The results are summarized in Figure 2. The left part of the figure shows the results for the storm number indicator (SNO), the right part displays the results for the wind speed indicator (SWIND). Both indicators deliver

[11]We implemented an adapted version of the Conley correction procedure proposed in Fetzer (2015).

almost the same results. The estimated cumulative effect is negative for all considered time-horizons and in general increases in absolute size when allowing for more long-lasting effects. For values of J exceeding four the cumulative coefficients turn always out to be significant.

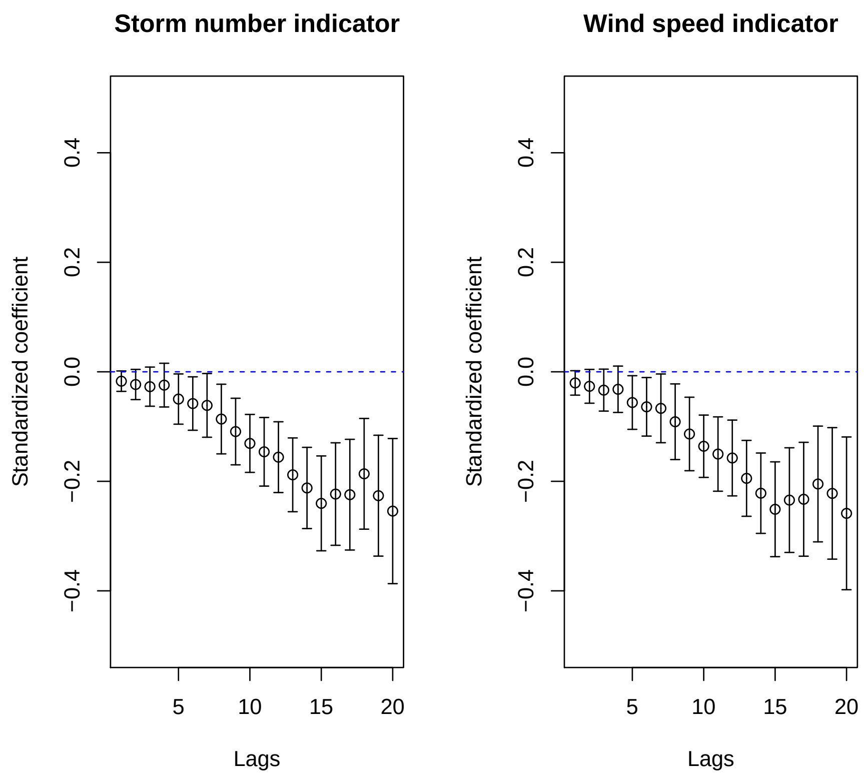

Figure 2: Effect of Tropical Storms on Economic Growth (Full Country Sample, Twoway FE Panel Regression)

Figure 3 shows the results we receive when employing the full set of control variables in our estimation approach. Again, the estimation results are similar for both hurricane indicators. In comparison to the case without (possibly endogenous) controls the results become less clearcut. For values of J below 12 years the estimation results become insignificant.[12] However, for $12 \leq J \leq 20$ we still find significantly negative cumulative growth effects of hurricanes.

Altogether, while our estimation approach differs in some details from the one employed in Hsiang and Jina (2014), we broadly find a similar qualitative result: tropical storms tend to have long-lasting negative effects on economic growth. As our sample consists of countries on quite different levels of development it is an intriguing question whether the detected negative long-term growth effects occur to the same extent in developed and in less developed countries. To shed light on this issue we subdivide

[12] All graphs show 90% confidence bands.

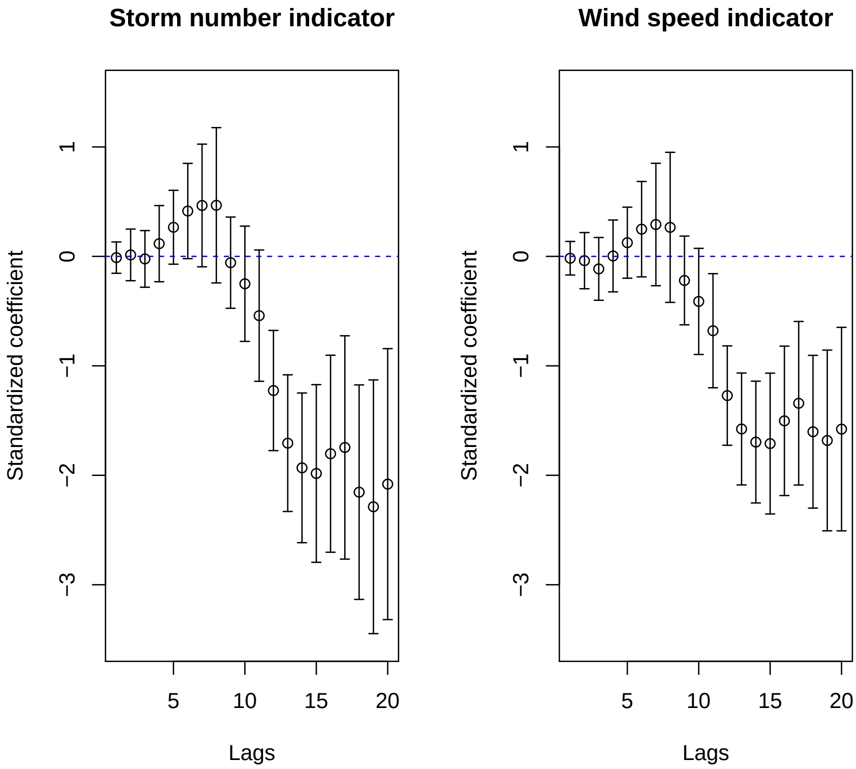

Figure 3: Effect of Tropical Storms on Economic Growth (Full Country Sample, Twoway FE Panel Regressions with Control Variables)

the sample countries into two subgroups of developed and underdeveloped countries. In order to do so we employ the World Bank classification of country groups and sort all high and upper middle income countries into the group of developed countries and the lower middle and low income countries into the group of underdeveloped countries.[13] We then repeat our estimations for the two country groups and both hurricane indicators. The results for the estimations without economic control variables are shown in Figure 4.

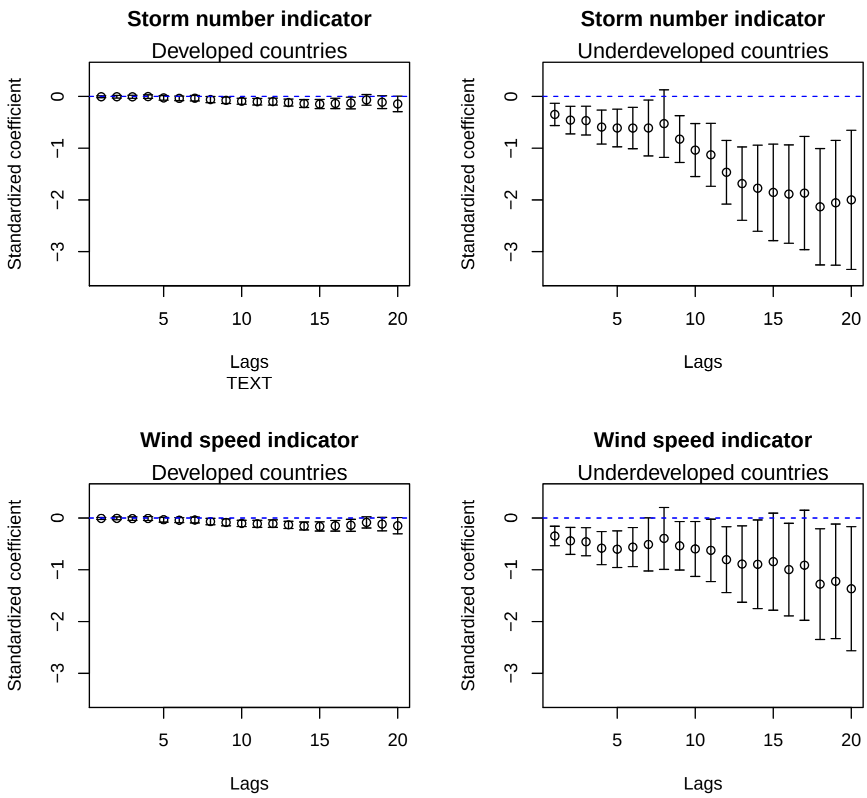

Figure 4: Effect of Tropical Storms on Economic Growth for Country Subsamples (Twoway FE Panel Regressions)

The left part of Figure 4 shows the results for the group of developed countries. For both hurricane indicators we find a similar pattern. While the cumulative coefficients are always negative, they are insignificant for evaluation periods below 8 years and of more than 17 years. However, the results indicate that even in developed countries, tropical storms leave their traces in medium- and long-term growth patterns.

The right part of Figure 4 displays the effects for underdeveloped countries. Obviously, hurricanes have much more pronounced negative growth effects in these coun-

[13]We group the countries according to their World Bank classification in the first year they turn up in the dataset. Whenever the classification changes directly in the second year we used the second year classification. The group of developed countries consists of 58 countries, the one of underdeveloped countries includes 107 countries. While it would be interesting to study more country groups, doing so is infeasible as tropical storms do not occur at all in many sample countries.

tries. However, the confidence bands for this country group are also comparatively large. Nevertheless, for the huge majority of evaluation periods, the estimated cumulative effect is significantly negative. With the exception of an evaluation period of six years, all cumulative effects are significantly negative for the storm number indicator. And even when employing the wind speed indicator in only three evaluation periods the effect remains marginally insignificant.

When using the full set of control variables (see Figure 5) we end up with the same qualitative findings. In general, the inclusion of control variables decreases the significance of the effects of tropical storms on economic growth. In the light of the earlier discussed over-controlling problem, this finding is reasonable. We still find more pronounced negative growth effects for countries on lower levels of development. Moreover, the cumulative effects turn out to be significant in much more cases in this country group.

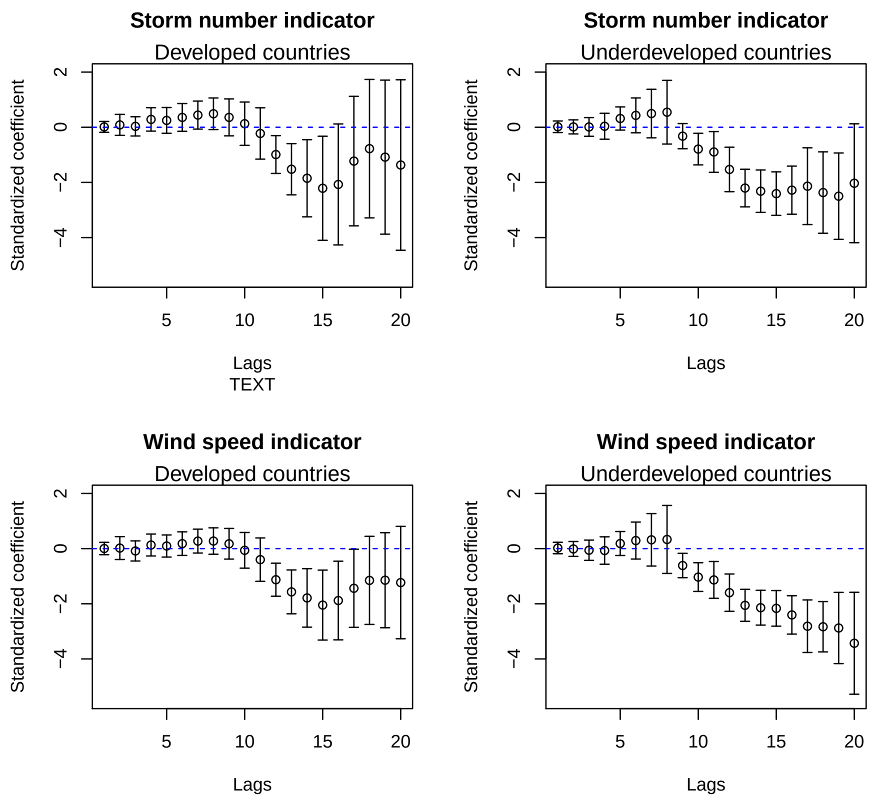

Figure 5: Effect of Tropical Storms on Economic Growth for Country Subsamples (Twoway FE Panel Regressions with Control Variables)

The second step of our empirical analysis leads us to conclude that tropical storms tend to exert negative medium- and long-term effects on economic growth in both, developed and underdeveloped countries. However, the presented empirical evidence also points into the direction that underdeveloped countries tend to suffer more from the consequences of occurring hurricanes.

6. Transmission Channels

As mentioned earlier, possible transmission channels have yet rarely been discussed within empirical studies of the effects of natural disasters (and especially tropical stroms) on economic growth.[14] When thinking about the channels through which natural disasters might affect long-term economic growth it is reasonable to start out with considering factors which play a decisive role in theoretical models of economic growth. We base our subsequent analysis on the results of the first step of our empirical analysis in which we identified a number of determinants of economic growth such as the investment share of GDP, net fertility, education and the government share in GDP.[15] While these factors are mostly assumed to be constant parameters in model of economic growth, they might be affected by the occurrence of natural disasters. In the third and final step of our empirical analysis we therefore turn to the question, through which channels tropical storms affect long-run economic growth. As outlined in Section 3 our estimation approach consists of estimating two-way fixed effects models (see equation 5) for the four discussed possible transmission channels separately. Due to space restriction we thereby concentrate on the more advanced wind speed indicator (SWIND).[16] As the empirical analysis presented in section 5 showed, the growth effects of tropical storms differ to quite some extent between developed and underdeveloped countries. Thus, the reaction of the growth determinants on tropical storms likely also differ. Thus, instead of study the channels in the full country sample here in length we directly turn to an analysis of the reaction of growth determinants in the two earlier defined country subsamples.[17]

We start our analysis with the savings/investment channel. In the neoclassical growth model of a closed economy (and most of its successors) the saving rate has a positive impact on per-capita GDP as only the portion of GDP which is not consumed can be invested. In open-economy growth models investments can also be financed by foreign saving; however, still domestic saving can be thought of playing an important role for feeding domestic investments. For individuals, saving is typically a means of consumption smoothing. Naturally, the amount of saving will increase with a corresponding increase in life expectation. Whenever natural disasters pose a risk to life, this likely increases consumption and depresses saving. However, the theory of precautionary saving argues that saving does not only serve to spread income over the life cycle, but might also serve as insurance against uncertain events (Lusardi 1998). In

[14]Two noteworthy exceptions are Skidmore and Toya (2002) and, more recently, Berlemann and Wenzel (2016).

[15]While one might speculate about additional possible transmission channels, we concentrate on the four mentioned channels in the subsequent analysis due to data availability.

[16]The results for the storm number indicator (SNO), which are available from the authors on request, turn out to be very similar.

[17]The results for the full country sample are available from the authors on request.

this context, Roson, Calzadilla and Pauli (2005) argue that individuals might react to natural disasters by increasing their savings. Based on a theoretical model of constant absolute risk aversion, Freeman, Keen and Mani (2003) show that the optimal amount of precautionary saving depends positively on expected loss, and thus on both the disaster probability and disaster loss. Natural disasters might increase expected losses and thus increase precautionary saving. This effect should be the more pronounced for more risk-averse individuals (Fuchs-Schündeln and Schündeln 2005). However, it is also possible that precautionary saving is reduced as a consequence of natural disasters. Often individuals who have suffered from catastrophic losses are supported or even compensated by state institutions, private donations or international aid. All these forms of support decrease the incentives for accumulating one's own precautionary savings. This phenomenon is also known as the Samaritans Dilemma (Buchanan 1975, Coate 1995) or the Charity Hazard (Raschky and Weck-Hannemann 2007, Dobes, Jotzo and Stern 2014). Individuals might also be forced to reduce saving for a certain period of time in response to natural disasters, due to increases in expenditures (e.g., for repairs or replacements) or negative income shocks. The scarce existing empirical evidence yet displays no clear picture. Skidmore and Toya (2002) do not find a significant reaction of investments in the aftermath of natural disasters. However, in their panel analysis of the effects of droughts, Berlemann and Wenzel (2016) find the macroeconomic saving rate to decrease after drought events. In line with this finding, the study of micro-behavior of Berlemann, Steinhardt and Tutt (2015) finds reduced savings among individuals which were directly affected with a flood event when compared to unaffected individuals.

Our estimation results for the sample of developed countries are displayed in the left part of Figure 6, those for the underdeveloped countries in the right part of the same figure. The displayed results indicate that, if at all, the effect of tropical storms on the investment share of GDP is positive for both country samples. For the group of developed countries the reaction of the investment share is comparatively small. In the developed countries we find the cumulative effect on saving to be significantly positive for evaluation periods of six up to 13 years. When considering more than 13 years, the effect renders insignificant again. For underdeveloped countries we find a similar pattern; however, the estimated coefficients are much larger but also come with much larger confidence bands. Moreover, the reaction in underdeveloped countries follows immediately after the storm event as all cumulative coefficients (with the exception of the one for 5 years) until an evaluation period of 13 years turn out to be significantly positive. In the very long-run, the cumulative coefficient is typically insignificant.

Altogether the presented empirical evidence for the investment/savings channel points into the direction that in both developed and underdeveloped countries we observe a temporary post-hurricane increase in investments. This finding is in line with the idea of increased precautionary saving. While we cannot judge which sorts of investments are made, one might suspect that in the light of the earlier detected negative long-term growth effects of hurricanes the investments especially in the underdeveloped countries primarily aim at rebuilding and replacing destroyed capital rather than increasing the long-term capital stock.

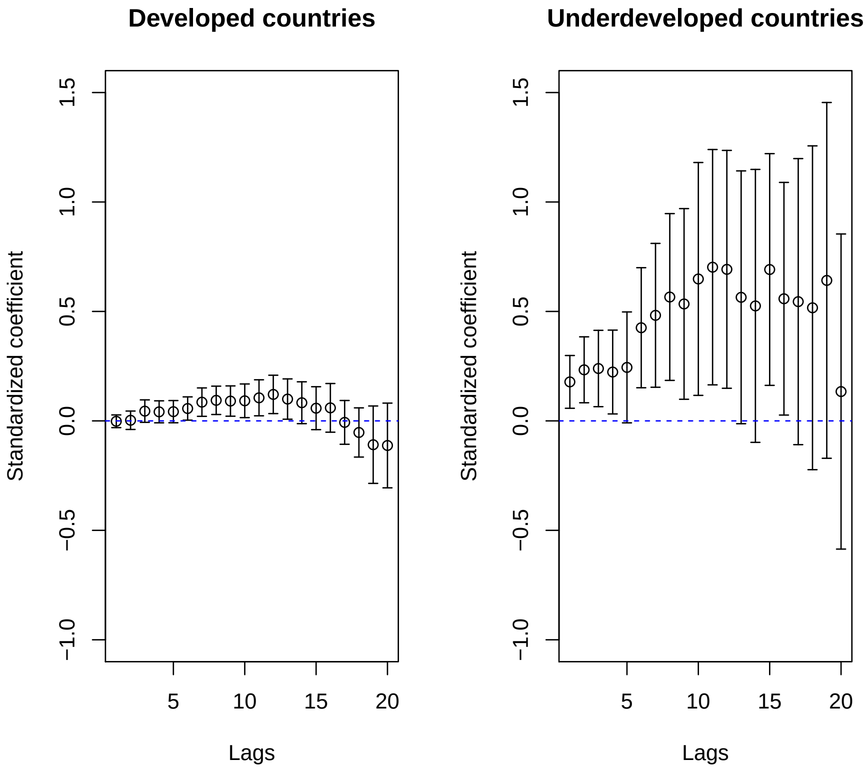

Figure 6: Effect of Tropical Storms on Saving Rate for Country Subsamples (Twoway FE Panel Regressions)

The second channel we consider is fertility. An increasing likelihood of the occurrence and/or severity of natural disasters might decrease the incentives to make the long-term investments required to raise a family. At least parts of the population might get the impression that the environment becomes too dangerous to raise children. Disasters might cause disruptions in family life, e.g. by causing the death or injuries of family members (especially children), by destroying houses or causing individuals to lose their jobs (Lin 2010). All these issues might contribute to lower fertility in the aftermath of disasters. However, especially in less developed countries, children are a means of smoothing consumption over time (Guarcello, Mealli and Rosati 2010). Whenever households experience losses of income and/or wealth, the birth of additional children can, at least in the medium- and long-run, help the parents to enhance their financial situation, e.g. by generating supplemental income or taking over roles in family life which allows both parents to be part of the labor force.[18] Whenever disaster risk

[18] In their empirical analysis of fertility trends in the United States, Jones and Tertilt (2008) present strong

poses not only a threat to income and wealth but also to life, parents might choose to increase their number of children as an insurance against child mortality (Schultz 1997). Boldrin and Jones (1992) argue within a theoretic framework that parents in general procreate because the children care about their old parents' utility, and thus provide them with old age transfers. This motive is especially pronounced in the absence of social security systems.[19] The scarce empirical literature, which is primarily concerned with comparatively poor countries, supports the hypothesis that disasters tend to increase fertility. In their empirical analysis of the December 2004 Indian Ocean Tsunami Nobles, Frankenberg and Thomas (2014) find a subsequent increase in fertility in the affected region. Finlay (2009) studies the fertility reaction after three huge earthquakes in India, Pakistan and Turkey and again reports long-lasting increases of fertility rates. Skidmore and Toya (2002) report the same result for climatic disasters. For geologic disasters the effect has the opposite sign but is insignificant.

Figure 7 shows the results for the fertility channel. Again we show the results for the developed countries in the left and those for the underdeveloped countries in the right part of the figure. Obviously, the reaction to tropical storms differs systematically between the two country groups after five years. In the very short-run, in both country groups the cumulative effect on net fertility is negative but insignificant. However, after roughly five years, the effects in the two country groups start do develop into different directions. For developed countries net fertility further decreases and the cumulative effect becomes significant. This result indicates that in comparatively rich countries the confrontation with disasters tends to disrupt the confidence to bring children into the world and raise them under the more risky circumstances. Interestingly enough, we find just the opposite long-term effect in the group of underdeveloped countries. Here, the cumulative effect on net fertility becomes significantly positive in the long-run, a finding which is in line with the earlier cited empirical studies by Finlay (2009) and Skidmore and Toya (2002). One might suspect that in comparatively poor countries in fact decide to have more children as an insurance against higher child mortality and to ensure old-age income transfers in the absence of systems of social security, as it is typical for underdeveloped countries.

A third channel through which disasters might affect economic growth is education. Again, two different reactions are possible. On the one hand, natural disasters tend to reduce the expected return to physical capital, which should increase the incentive to invest in human capital (Skidmore and Toya 2002). On the other hand, whenever disaster risk also increases mortality, the return of educational investments decreases and makes human capital accumulation less attractive (Checchi and Garcia-Penalosa

support for the hypothesis that poorer households have more children.

[19] Boldrin, De Nardi and Jones (2005) deliver empirical evidence in favor of the hypothesis that countries with low levels of social security have higher rates of fertility.

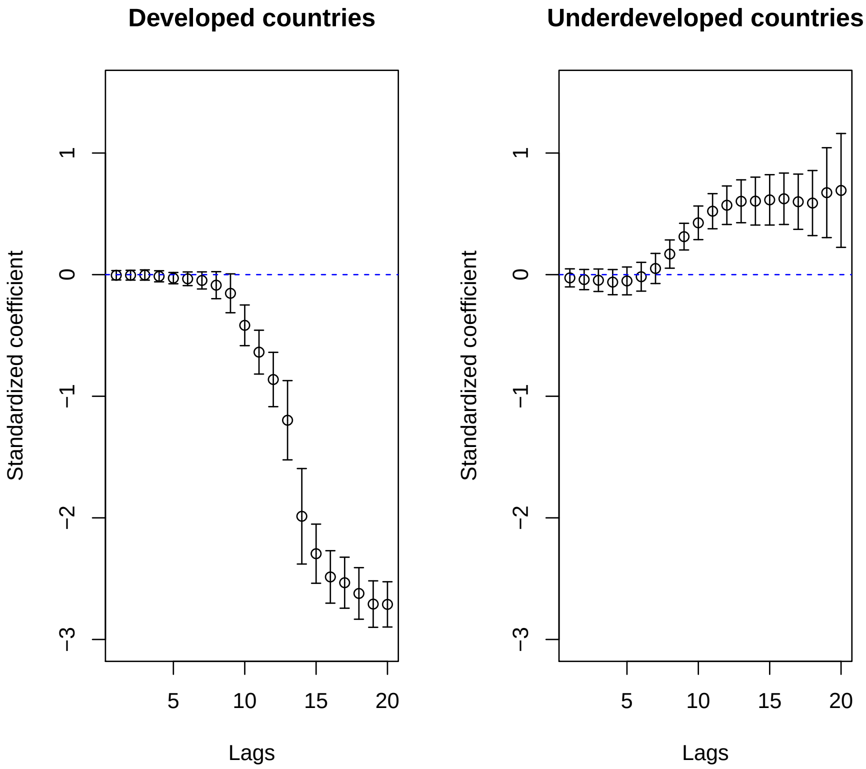

Figure 7: Effect of Tropical Storms on Fertility for Country Subsamples (Twoway FE Panel Regressions)

2004). Moreover, natural disasters might also have negative effects of human capital accumulation via decreasing educational attainment, e.g. in consequence of evacuations, increasing drop-out rates or school switching (Sacerdote 2012). The available empirical evidence on the effects of natural disasters on education are yet inconclusive. Alderman, Hoddinott and Kinsey (2006) study the effect of droughts on human capital formation in rural Zimbabwe and find a significantly negative effect on the number of completed school grades. Alston and Kent (2006) study the drought impact in secondary education access in Australia's rural and remote areas based on interviews and find evidence that droughts decrease human capital formation on the level of primary as well as on high schools. Cuaresma (2010), based on a sample of 80 countries over the period of 1980 to 2000, finds geologic disasters to depress secondary school enrollment while no such effect exists for climatic disasters. Kim (2010) studies the effect of two droughts in Cameroon and Burkina Faso based on a combination of survey and EMDAT data. While he finds a significantly negative effect of the 1990 drought on primary school completion in Cameroon, the effect for the 1988 drought in Burkina Faso turns out to be insignificant.[20] When analyzing data for more than 100 years from Guatemala, Pörtner (2009) finds disasters to increase education efforts.

Figure 8 displays the results for the education channel. As before we show the results for the developed countries in the left and those for the underdeveloped countries in the right part of the figure. Again we find a systematically different reaction on tropical storms in both country groups. In the sample of comparatively rich countries the cumulative effect on education is positive for all evaluation periods and it becomes significant when including at least 5 years. As the developed countries own much more physical capital and thus also have a much higher potential of capital destruction, the relative return to human capital tends to increase in these countries, thereby increasing the incentive to invest in further education. For underdeveloped countries we find just the opposite effect. The cumulative effect of tropical storms on education are negative over all evaluation periods up to 17 years and then become marginally insignificant. The fact that even in the very first years after the natural disaster occurred we already observe a significantly negative effect on education is likely due to decreasing educational attainment as a direct consequence of the occurring hurricanes. As the population in underdeveloped countries typically have a much worse and more disaster-prone infrastructure, school buildings and public transportation are more likely affected. Throughout reconstruction of their homes, children are less likely going to school. The fact that even in the medium- and long-run educational efforts decrease might be the consequence of the fact that tropical storms pose a higher risk to life in underdeveloped countries. As a consequence to the more uncertain return to

[20] Kim (2010) also shows that wild fires in Mongolia reduced the probability to complete secondary school significantly.

education, educational efforts might be reduced.

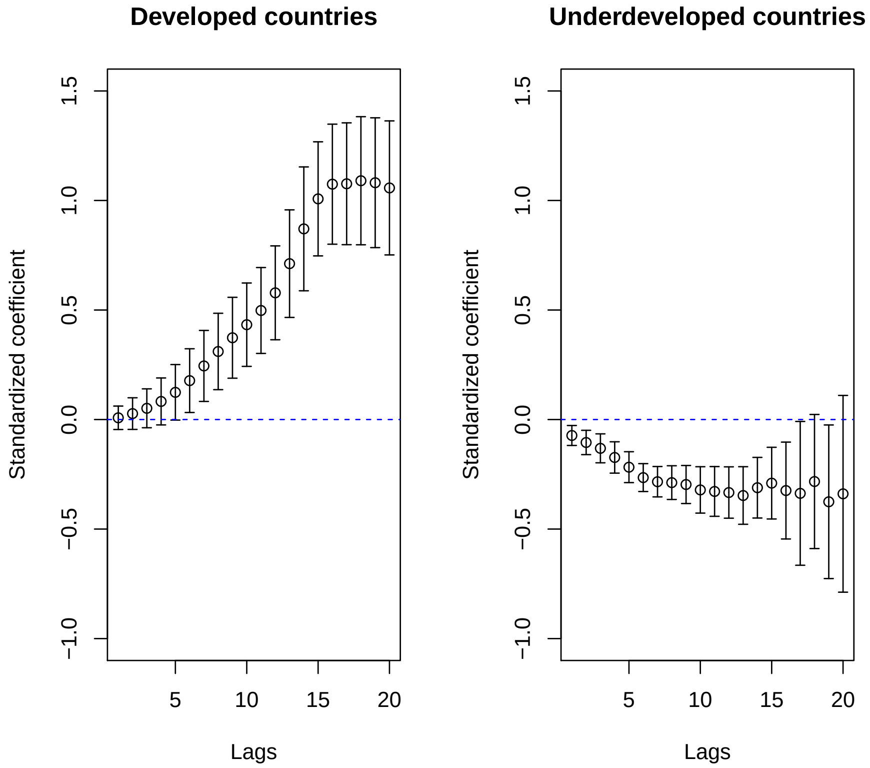

Figure 8: Effect of Tropical Storms on Education for Country Subsamples (Twoway FE Panel Regressions)

Finally, a channel through which natural disasters might affect economic growth is the government share. Again, two different scenarios might occur. On the one hand, governments might be tempted to increase spending for emergency help, to invest in rebuilding infrastructure or storm proof buildings (Fidrmuc, Ghosh and Yang 2015). All these efforts likely increase the government share in GDP. We might expect that we observe a rise in the government share especially in comparatively rich countries which have the opportunity to increase the tax burden to finance the described measures. On the other hand governments might be unable to finance additional spending as the natural disaster has a negative effect on economic activity and thus also on the volume of income and commercial taxes. Especially in comparatively poor countries such a lack of financial resources might be relevant (Linneroth-Bayer and Mechler 2007). Systematic empirical studies on the reaction of the government share on natural disasters are - to the best of our knowledge - yet unavailable.

Figure 9 shows the estimation results for the effect of tropical storms on the government share. In fact, we find a significant increase in the government share for the group of developed countries. However, the cumulative effect becomes significant not before 7 years. Thus it is quite unlikely that the results for the developed countries are driven

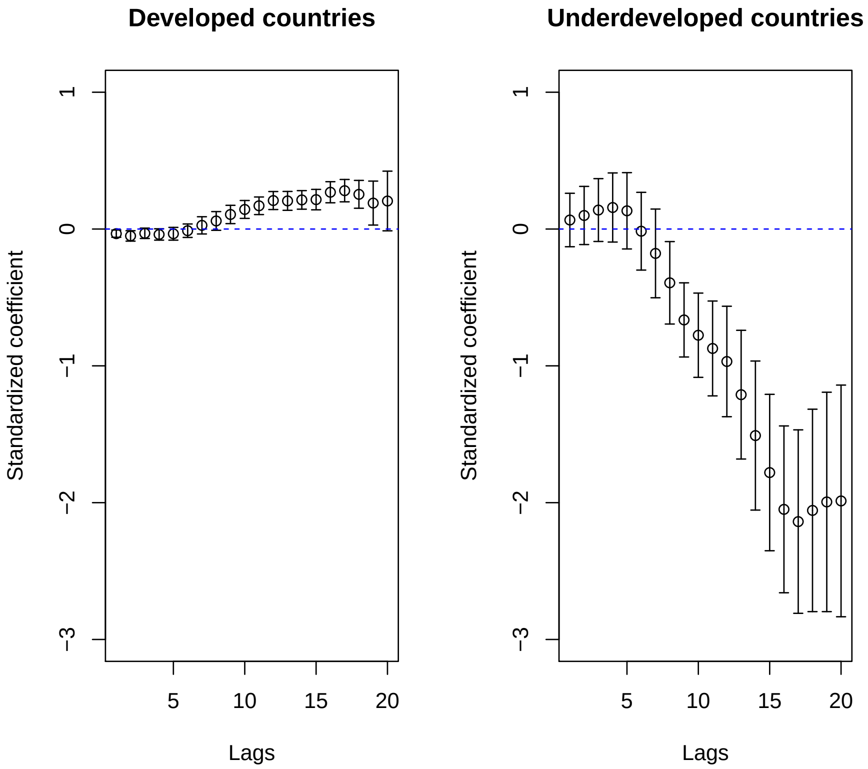

Figure 9: Effect of Tropical Storms on Government Share for Country Subsamples (Twoway FE Panel Regressions)

by quick post-disaster help for the affected population. The necessity for post-disaster government help in high-income countries in general is not too large due to typically high insurance coverages. Thus, the medium- and long-term increase in the government share in the aftermath of hurricanes is more likely due to government efforts to rebuild the public infrastructure and/or to make it less disaster-prone. In the group of less developed countries we find positive (but insignificant) cumulative coefficients in the first years after hurricanes occurred. However, in the medium- and long-run the government share in GDP tends to erode in this country group. The short-term increase in the government share is most likely due to short-term disaster help. However, as our previous results indicated, the growth effects of natural disasters in underdeveloped countries are strongly negative. As a consequence, tax income likely erodes, thereby providing little room for government action in the medium- and long-term perspective.

7. Conclusions

Based on truly exogenous storm indicators, derived from a meteorological database, we show that the growth effects of tropical storms go well beyond the short-term perspective. We find a significant long-term impact of tropical storms on economic growth for both well developed and underdeveloped countries. However, the effect turns out to be much larger in the group of underdeveloped countries. To a significant extent, this is due to the fact that poorer countries often cannot afford to implement costly protective measures which would help to keep the direct costs of natural disasters low. Our study of the channels through which tropical storms might influence long-term growth reveals that the disastrous effects in countries on low levels of development are likely amplified by changes in economic behavior of the afflicted population. In comparatively poor countries net fertility tends to increase in the aftermath of hurricane events whereas education efforts tend to decline. Both effects depress long-term economic growth. These results might be helpful in implementing more effective post-disaster management strategies for underdeveloped countries.

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A. Results Panel Unit Root Tests

Table 4: Phillips Perron Unit Root Test

wr gdppwtna	lnfertn	lneduavg2i	lngs	lnis	
lag (1)	140.1958	5.1773	47.3369	1,6811	14.4775
	(0.0000)	(0.0000)	(0.0000)	(0.0464)	(0.0000)
lag (2)	140.3037	2.5547	33.5091	1.7548	14.1300
	(0.0000)	(0.0053)	(0.0000)	(0.0396)	(0.0000)

Modified inverse chi-squared test statistic (Pm).
P-values reported in parentheses.