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The economic cost of floods in Vietnam: a DMSP-OLS night-time imagery analysis

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ABSTRACT

This paper studies the economic cost of floods in Vietnam via nightlight data obtained by DMSP-OLS satellites. A panel dataset from 1992 to 2010 is constructed and analyzed for Vietnam's 56 provinces, making for a total of 1197 observations. The results obtained via the random effects model, which was found to be most applicable, showed a 0.12% decrease in nightlight emission due to a single flood, -799 in absolute terms. Similar results were obtained by a pooled ordinary least square regression and a fixed effects model. With a nightlight to gross domestic product elasticity between 0.27 and 0.3, a cost estimate per flood was calculated to be between 23 and 26 million US dollars (constant 2010 USD). Annually, with an average of 44 floods, corresponding to a reduction of 1.4 to 1.6 percent in real GDP, or 975 million to 1.1 billion USD in absolute terms. A prolonged effect was found as floods in the previous year affected the nightlight negatively, the second lag was found to have a positive correlation indicating a recuperation effect.

Keywords: nightlight, flood, DMSP-OLS, panel data

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1. Introduction

The wrath of natural disasters is indiscriminatory and ruthless. Conservative estimates state the global cost of natural hazards to be over 300 billion U.S. dollars between 1975 and 1998 (Mitchell, Thomas, 2001). Vietnam is no stranger to the consequences, in 2017 typhoon Damrey hit the popular resort town of Nha Trang in Khanh Hoa. This sole weather phenomenon was estimated to have caused 22 trillion Vietnamese dong in damages (nearly 1 billion US dollars), as well as taking the lives of 108 people. This natural disaster, being exceptional due to its magnitude, brought the human and material cost to the public foreground and emphasized the need for controlling measures as dikes. Across Asia, 8 million deaths resulted from floods alone. As the majority of Vietnam's population lives in flood prone areas, political relevance is high (Shaw, 2006). A relevance which is set to increase as climate change is expected to further increase the magnitude of natural disasters as well as the likelihood of occurrence (IPCC, 2014).

Due to Vietnam's notoriously bad data collection (further discussed in theoretical framework) estimating the cost of these disasters is difficult, as emphasized by the lack of literature. This paper attempts to stray away from officially reported figures, such as damage to properties or number of people killed, in order to quantify the damages. While official numbers might highlight the effect of direct consequences, the cost on non-market goods and on the informal economy is not accounted for. As to capture the entire economic effect of floods, including the informal sector, this paper investigates the effect of the natural disasters on nighttime light emission, which serves as a proxy for economic activity. A thorough search of relevant literature yielded no related papers estimating damages in economic activity due to natural disasters, specifically in Vietnam, by means of emitted light. Thereby providing the academic relevance and broadening the scope of satellite applications. Satellite imagery is however used to analyze flooding by the Early Damaged Area Estimation System (EDES), this application solely provides geographic information for immediate disaster relief activities. This paper will highlight the possibility of the DMSP-OLS satellites to obtain more accurate representations of the costs, allowing policy makers to compare the costs and benefits of controlling measures as dykes.

A balanced panel dataset ranging from 1992 to 2010 with provincial data concerning the emission of light and the number of floods is analyzed by means of three models, namely pooled ordinary least squares, fixed effects and a random effect. An F-test, Hausman test and Breusch and Pagan Lagrangian multiplier test were used as to find the most appropriate model to describe the relationship between floods and nightlight emission. A significant negative correlation of -799.47 is found between all floods and the difference in the sum of light in the random effects model, which is found to be the best fitting model. The coefficient corresponds to a 0.12% decrease in emitted light. Quantification of this deduction by means of elasticity results in a per flood cost between 23 and 26 million USD in constant 2010 dollars. On an annual basis, with an average of 42 floods per year, 1.4 to 1.6 percent of real GDP will be lost due to flooding. In absolute terms, 975 million to 1.1 billion USD. Floods have a significant impact on light emission for up to two years, significance of the first lag is however limited in the REM. A negative correlation can be found with the first lag, indicating a possible prolonged effect of floods in previous year on current light emission. A positive effect which can have resulted from a recovery effect can be seen from the second lag.

The following is the organization of this paper. After the introduction, chapter two discusses previous literature on both impacts of natural disasters and of the applications of nightlight and its relatedness to economic activity. Chapter three and four reflects on the data and methodology used. Following, chapter 5 presents the empirical results of the models and the translation to economic output. Finally, the conclusion, limitations and future research will be presented in chapter 6.

2. Theoretical framework

2.1 Economic cost of floods

The cost of disasters globally grew 15 times between the 1950's and 1990's, estimated at an annual cost of 66 billion U.S. dollars in 2012 prices (Benson, Clay, 2004). Climate change will increase both the likelihood and magnitudes of natural disasters (IPCC, 2014) rendering approximations to the economic costs of these disasters desirable. These economic costs of natural disasters are difficult to estimate. Datasets often exclude the costs or damages to non-market good, thereby underestimating the impact of these disasters (Mileti 1999; Toya, Skidmore 2007). Difficulties in data reporting arise from the complex nature of the high-magnitude events and the interrelatedness between them (Kron et all 2012). For example, a storm might cause a flood, rendering it difficult to analyze the impact of these events separately. A developing country, as Vietnam, has an incentive to overestimate the damages done. Doing so in order to gain additional international aid and help (Toya, Skidmore 2007). The developing countries often suffer from poor data collection, and low insurance penetration, in addition to much of the economic activity occurring in the informal sector (Tol leek 1999).

Floods and landslides have a significant cost to infrastructure (Barredo, 2009). They can occur because of both hydrological and geological characteristics, causing urban areas and areas along rivers to flood (Bates et al, 2008). Economic damages resulting from natural disasters tend to be higher in developed countries in absolute terms but are lower as a percentage of GDP (Guha-Sapir et al. 2012). Developing countries suffer relatively more from catastrophic events than developed nations (Kahn, 2005; Toya and Skidmore, 2007; Hansson et al., 2008; Raschky, 2008; Peduzzi et al., 2009; Jongman et al., 2015). Noy and Vu, in analyzing Vietnam, conclude that even at the sub-national level richer areas are better able to have economic growth after a natural disaster (2010).

Previous literature has focused on measuring the primary direct costs of disasters by the amount of lives lost, the number of people affected, and the damage done to infrastructure. The dataset which reports these figures, Emergency Events Database (EM-DAT) is used in serval papers (e.g. Anbarci et al., 2005; Toya and Skidmore, 2007). Further literature analyzes the secondary impacts of disasters as proxied by production, productivity, and output while differentiating between short, and long-run effects (e.g. Skidmore and Toya, 2002, Noy and Nualsri, 2007; Cuaresma et al, 2008; Cavallo et al., 2009). Finally, Noy and Nualsri estimate the fiscal cost, finding that fiscal behavior can be characterized as pro-cyclical in developing countries (counter-cyclical for developed countries). Thus, developing countries decrease spending and attempt to increase revenues following a disaster (2010). It must be noted that Vietnam was not included in their analysis. The pro-cyclical policy implemented after a disaster in developing countries leads to adverse macroeconomic outcomes. This paper therefore expects damages to influence both the immediate and non-immediate economic activity.

Literature concerning the immediate, or short-run impact of disasters is well established. Examples can be found in Bluedorn (2005), Hochrainer, (2009), Leiter et al. (2009), Loayza et al. (2009), Mechler (2009), Raddatz (2007) and Strobl (2008). The long-run effects are analyzed in Cuaresma et al. (2008), Hallegatte and Dumas (2009), Jaramillo (2009), Noy and Nualsri (2007), Raddatz (2009) and Skidmore and Toya (2002). It can be concluded that there is a significant short-run negative impact on development. We therefore expect a similar negative immediate effect of floods on GDP vis à vis nightlight.

The long-term consequences of disasters are highly controversial. Skidmore and Toya reach an apparent counterintuitive conclusion stating that “cross-country empirical analysis demonstrates that higher frequencies of climatic disasters are correlated with higher rates of human capital accumulation, increases in total factor productivity, and economic growth”

(2002). The conclusion that natural disasters led to positive economic outcomes is supported by Kim who found a positive correlation between the long-run economic growth and the number of disasters occurred. Kim's research does however find evidence for geologic disasters leading to loss in human capital (2010). Conversely to the aforementioned literature, Noy and Nualsri (2007) in addition to Jaramillo (2009) find evidence for negative long-run impacts resulting from natural disasters. Concluding that climate related disasters negatively correlate to the economic growth rate. Raddatz estimated the reduction in real GDP per capita to be a least 0.6 percent (2009). Due to the ambiguity in conclusions and data limitations, this paper abstains from analyzing the long-run impact of floods. Solely immediate and short-term (3 years) impacts will be analyzed.

2.2 Remote sensing data from space

A nation's economic well-being is typically measured in gross domestic product (GDP), the market value of all final goods and services produced in a given country in a given year. These GDP estimates are often incorrect or uncertain. This uncertainty is especially prevalent in developing countries, as a higher share of the total economic activity is conducted in the informal sphere. The informal economy is often excluded or solely estimated in formal statistics (Henderson et al. 2009, Ebener et al. 2005, Sutton et all 2007, Ghosh et al. 2009). Sub-national measures of economic activity are non-existent for most of the developing countries, including Vietnam, and even for some developed ones (Henderson et al. 2009). This lack in sufficient and accurate data collection, which is needed to assess the regional impacts of floods, is reflected in Vietnam's rating by the Penn World Tables (PWT).

The Penn World Tables (PWT) assign countries with a subjectively based grade on the quality of their reported data. It considers both the reliability of the reported data as well as baseline information concerning purchasing price parity (PPP). Grades range in decreasing ranking from level A to D. Chen and Nordhaus add a fifth class, E, as to symbolize the countries with essentially no statistical systems, or that are missing from the database (2011). Examples of countries in this fifth class are North-Korea and South-Sudan. Corresponding margins of error (root mean squared error) to the grades are 10 percent for A, 15 percent for B, 20 percent for C and 30 percent for D (Chen, Nordhaus, 2011). Vietnam is assigned the grade C. In comparison, almost all developed countries were given the grade A (Deaton et al. 2008). Dawson et all claim that the empirical link connecting output volatility and income growth in the PWT data is purely a result of measurement error in annual income (2001). A drawback of the PWT reporting is that it is unclear whether the rating is due to the standard of data collection or due to the PPP, as both are reflected. As a result, the international monetary fund (IMF) and the World bank consider solely the quality in the country's national account data in the constructing of their rankings. "High capability countries" are subscribed to the IMF's Special Data Dissemination Standard (SDDS) and therefore meet standards based on data quality requirements that is to be expected in international markets. Vietnam is placed under the category e-GDDS, which apart from the non-participating countries, is the lowest rating. The aforementioned reasons imply that official statistics of Vietnam concerning economic activity are either non-existent or not up to par with standards required in international markets. This paper will therefore abstain from using reported output figures directly.

Due to the shortcomings of GDP various economists used proxies to analyze economic activity. For example, Good used the number of letters mailed in the Habsburg Empire per region as a proxy (1994). Croft pointed out that nightlight images taken by satellites "sparkle with the bright light of man's creation" (1978). In building upon Croft's observation Elvidge et all estimated specific relationships, namely: population, GDP, and electricity usage in the lit areas (1997). A significant positive relationship between economic activities on ground-level and nighttime lights was found. A reduction in economic output by means of a flood, is therefore expected to result in a reduction of emitted light. Early research, as Elvidge's, used the amount of area lit, thereby equating for example a financial district with a more rural light-emitting area while economic output may differ. As to account for this light energy was later used by Sutton and Costana, allowing a differentiation in the amount of light emitted. The light energy is currently referred to as the sum of light intensity. Sutton's and Costana's research focused on estimating GDP more precisely at a global coverage of $1km^2$ resolution (2002).

Doll et all were the first to focus their research on sub-national estimations of economic output (2003). Night time radiance was analyzed alongside regional economic productivity. 11 European countries were used alongside the United States, this being because they accurately reported sub-national level data. As Vietnam does not have regional estimates, no similar analysis can be done. The results indicate a positive correlation between GDP and economic activity at the regional level, excluding cities of exceptionally high economic activity relative to night light. The gradient of gross regional product to sum of light intensity was found to be different per country (and region), ranging from 0.0499 in the United States to 0.2103 in West Germany including Berlin, excluding outliers. Henderson et all determined the elasticity on overall growth of GDP to nightlight to be 0.3. The optimal estimate of growth was concluded to be a composite of conventionally measured growth and growth as predicted by night lights, the weights on both being equal (2012). Thereby implying that if this paper were to obtain a more accurate representation of the cost of floods, that regional output data has to be weighted. As none is available, this paper will continue with estimates by night light. Keola et all found the elasticity to be 0.27, remarking that growth in nightlight is largely the result of expansion in the non-agricultural sector (2015). This paper will use a range of probable elasticities from 0.27 to 0.3. The sole use of reported GDP in this paper is to utilize it with respect to the elasticity, allowing for quantification of economic losses.

2.3 hypotheses

Several hypotheses will be used as to answer the research question:

How have floods impacted economic activity in Vietnam from 1992 to 2010 as proxied by nightlight?

Previously discussed literature in section 2.1 have found natural disasters to have an immediate negative impact on development. As economic growth can be analyzed by means of nightlight, previously discussed in section 2.2, the following first hypothesis results:

Hypothesis 1: There is a statistically significant negative relationship between the number of floods and the immediate GDP growth rate as proxied by nightlight.

In order to test the first hypothesis, the growth in provincial output will be measured in relationship to the number of annually occurred floods in the respective province. If no-significant relationship is found, or the relationship is non-negative, then the first hypothesis will be rejected.

The non-immediate impact of floods is unclear, long-term effects could be negative or positive, as discussed in section 2.1. This paper will therefore not hypothesize the sign of the relationship of previous floods on current economic growth as proxied by nightlight. The second hypothesis will therefore solely focus on the significance of the relationship.

Hypothesis 2: There is a statistically significant effect of floods in previous years on current economic growth.

To test the second hypothesis lagged terms will be included in the resulting model from hypothesis 1, taking into consideration differences between provinces. If the effect of the lagged values is non-significant, then the hypothesis will be rejected. The result will both indicate the effect of floods in previous years, as well as the economy's possible recovery time.

3. Data

3.1 Nightlight data

3.1.1 Overview

Nightlight satellite imagery was provided by the Defense Meteorological Satellite Program (DMSP), which is part of the United States Air Force (USAF). The group of satellites employed was designed to record and monitor the distribution of clouds as well as their top temperatures. During nighttime, most of the emitted electromagnetic energy observed by the satellites is a result of human light emitting activities (Keola 2015). Annually compiled images of visible pixels were processed and provided by the National Oceanic and Atmospheric Administration (NOAA), which this thesis uses to asses light intensity.

Observed electromagnetic energy can be highly influenced by solar activity, which can reach satellites by transmission, absorption, reflection, scattering, or emission (NASA, 2013). To account for this, the absolute measure of solar irradiance, W/m^2, was discarded in favor of a relative assignment of pixel values. Visible pixels are assigned a relative value based on increasing brightness ranging from 0 (no light) to 63. The seemingly arbitrary top value of 63 is due to a 6-bit quantization. Observations are adjusted to maintain constant cloud reference values under varying solar and lunar illuminations. In addition, a number of restrictions are put in place that exclude emissions from glare, auroras, fires, fishing boat activity, and other sources (Figure 1).

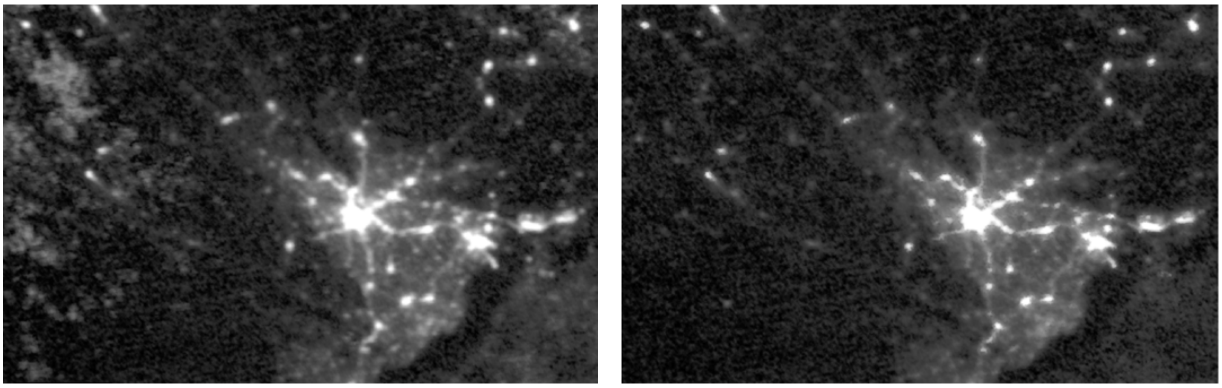

Figure 1: Composite OLS picture of Hà Nội and its surrounding area. The left picture is an average visible band imagery. The right picture is outlier removed. Note the presence of fires in the NW corner and the presence of fishing activity in the SE of the left picture.
Source: Baugh et al. 2009

Furthermore, due to the limited dynamic range of the DMPS Operational Linescan System (OLS) bright sources can saturate an area, thereby losing detail. To address the saturation problem, the "gain" setting of DMSP satellites are divided into 3 stages as to record the different intensities in brightness, with the highest gain being around 100 times more sensitive than the lowest. The image taken with the highest fixed-gain is taken as reference and the others are weighted according to it. Thereafter the composite image is combined with the rudimental image taken with a variable gain.

During the timespan of our data ranging from 1992 to 2010, 6 different satellites were used following a sun synchronous near polar orbit with a revisiting time of roughly 101 minutes at a height of 830 km (Keola 2015). At nighttime a photomultiplier tube (PMT) with a gallium arsenide opaque photocathode was used to collect visible, near infrared light (VNIR), at a wavelength range of 470 nm to 950 nm (miller et all, 2005). For years in which multiple images were provided, imagery was chosen as to minimize the number of satellites used. Pre-flight calibration is used to account for inter-satellite differences in sensitivity of the DMSP-OLS sensors.

The products are grids with a spatial resolution of 30 arc seconds spanning from -180° to 180° in longitude, and -65° to 75° latitude (the latitude being limited by the strong electromagnetic activity around the poles) (Figure 2). The satellites overpassed between 7 and 9 pm local time. The detectable lighting of the satellite sensor has radiances in the range of 10^{-9} W cm^{-2} sr^{-1} to 10^{-5} W cm^{-2} sr^{-1} (watt per square meter per steradian).

Figure 2: Merged stable lights and radiance-calibrated image of 2013

3.1.2 Satellite image processing

The best-fit linear translation between the product and a land scan population grid was established to match up the satellite image with "ground-truth" (Baugh et all 2009). A map outlining Vietnam's 58 provinces and 5 centrally-controlled cities was used to establish the amount of light intensity per region. The dataset therefore includes 19 years (1992 – 2010) of observations for 63 provinces, making a total of 1197 observations. The difference of the total sum of nightlight per province is taken as to obtain the growth rate.

3.1.3 descriptive statistics

Vietnam has an agricultural economy with rice as its biggest export. The agricultural share ranges from 18.38 percent in 2010 to 33.94 percent in 1992. As rice production and other agricultural economic activities require less light in production, it is unsurprising that Vietnam is mostly 'dark' with concentrated light emission from the concentrated areas as can be seen in table 1. On average 74.6 percent of the country is dark or under the detectable limit of the OLS sensor between 1992 and 2009. Hà Nội and Hồ Chí Minh were the sole cities to reach the top-coded value of 63 until 1999, when several other cities grew. Table 2 depicts the mean light emission per province alongside the standard deviation, minimum and maximum.

3.2 flood data

3.2.1 overview

The United Nations Office for Disaster Risk Reduction (UNDRR) provides data on every natural disaster that happened between 1989 and 2010 in Vietnam. Disasters being defined as "a set of adverse effects caused by social-natural and natural phenomena on human life, properties and infrastructure within a specific geographic unit during a given period of time". This paper focusses on events between 1992 and 2010 as to obtain a balanced panel dataset. As the scope of this paper is on quantifying the cost of floods more accurately solely flood-related disasters were considered. Therefore, regular floods and flash floods are combined into the variable "all floods".

3.2.2 descriptive statistics

Vietnam experienced 804 floods from 1992 until 2010, 101 flash floods and 703 regular floods. Making it the most regularly occurring disaster during the time period, 55 percent of all 1469 disasters were floods. On average there are 98.83 deaths per flood in Vietnam (Kahn, 2005).

3.3 Gross domestic product

Gross domestic product, as reported by the world bank is adjusted for inflation and taken in constant 2010 US dollar value, which is the last year in the panel dataset. The average GDP is 69,29 billion USD which is steadily increasing each year.

4. Methodology

This research paper will use three models to analyze the panel dataset, namely the Pooled Ordinary Least Square (OLS), the Fixed Effect Model (FEM) and the Random Effect Model (REM). The latter two models are uniquely suited to deal with panel data. The three models being in line with Wooldridge's explanation concerning the possible methods to analyze panel data (2014). All models will have robust standard errors as to account for possible heteroscedasticity. No control variables are used as there are no conceivable variables that influence both the sum of emitted light and the number of floods.

4.1 Pooled OLS model

The Pooled OLS method attempts to find the coefficient of interest by minimizing the sum of square vertical distances, also referred to as Pooled Cross Section (Wooldridge 2014). The method regards each individual observation as having no difference in effect regardless of the unit, or province, and the time. Thereby, not utilizing the possibility to analyze differences in observations. Province specific characteristics that potentially influence the amount of emitted light can be for example, the adaptation to natural disasters, geographic characteristics, etc. Due to this reason Wooldridge concluded that the sole reason to use a Pooled OLS regression when handling a panel dataset is as to create a larger sample size (2014). The resulting regression follows:

Formula 1: $\textit{difference of sum of lights}_{it} = \alpha + \beta \textit{ number of floods}_{it} + \varepsilon_{it}\ (u_i = 0)$

U_i represents the province or individual effect, with the subscript i denoting one of the 63 provinces. Subscript t depicts the time or years.

4.2 Panel data models

Two main approaches for analyzing panel data are put forward, namely fixed effects and random effects (Gujarati 2003; Judge et al. 1985; Hsiao (1986). Both techniques have advantages over the pooled OLS regression as they utilize the unique characteristics of panel data, as it both combines time series and cross-sections of units. Gujarati (2003) and Baltagi (2008) define six points of superiority of the panel data model over the OLS model. (i) Panel data models show individual heterogeneity, thereby accounting for bias which cannot be controlled for in a cross-section model nor in a time series model. (ii) Secondly, panel data models provide more information and variation, less collinearity among variables and more degrees of freedom. (iii) They are superior at expressing the dynamics of change within social phenomena, rather than having multiple cross-section estimations. (iv) The models measure the mixed and pure effects across year and entities. (v) They provide better representations of advanced models. (vi) Finally, by aggregating observations into broader classes, panel data models minimize bias.

4.2.1 Fixed effects model

The fixed entity effects model examines individual differences in intercepts, assuming that the slopes are identical and that there is constant variance across provinces. The model's estimator can be compared to a pooled OLS estimator which is established upon demeaned variables (Wooldridge 2014). Demeaned variables are the observed variables subtracted by the within-subject mean. Therefore, within each subject, the mean of the demeaned variables themselves will be zero, as differences cancel each other out. Time-invariant demeaned variables will have the value of 0 for every case, as the mean will be equal to each observed value. Therefore, the fixed effects model gets rid of all between-entity variability and allows for the analysis of solely within-subject variability.

There are two data requirements in order to use the model. Firstly, each province must have at least two measurements on the same dependent variable. Secondly, some or all units must have different values for the independent variable at two different times. The used panel data meets both criteria. Under strict exogeneity assumptions the model reports an unbiased estimated coefficient of the independent variable. As to meet the assumptions, the error term per province has to be uncorrelated with the independent variable, number of floods, for every year. Additionally, the error term has to be homoscedastic and serially uncorrelated. The possible heteroskedasticity is, as aforementioned, accounted for by robust standard errors. Formula 2 present the fixed entity effects regression.

$$\textit{Formula 2: difference of sum of lights}_{it} = (\alpha + u_i) + \beta \textit{ number of floods}_{it} + \varepsilon_{it}$$

The province or individual effect is represented by U_i. i denotes the different provinces and the years are depicted by subscript t.

4.2.2 Random effects model

As with the fixed effects model, the random effects model has different intercept terms for different entities, or provinces, being constant over time. The difference with fixed-effects model is that every province's intercept is affected by another intercept as the REM is estimated by means of partial pooling. In addition, there is a random variable that varies across entities but is constant throughout time. The REM's assumptions are identical to those of its fixed effects counterpart, apart from one additional assumption. This assumption being that the unobserved effect should be uncorrelated to the independent variable (Wooldridge, 2014). Therefore, characteristics which are not included in the model that influence light emission, e.g. the price of electricity, have to be uncorrelated with the number of floods that Vietnam experiences. The random effects model does not control for unmeasured provincial characteristics that stay stable over time. Thusly, if there is reason to believe that there is an unobserved effect which is correlated to the independent variable, a FEM should be used. Formula 3 depicts the REM:

$$\textit{Formula 3: difference of sum of lights}_{it} = \alpha + \beta \textit{ number of floods}_{it} + (u_i + \varepsilon_{it})$$

As the REM assumes that heterogeneity, the individual effect, is not correlated with the independent variable, U_i is a composite of the error term. Therefore, the random effect model is also referred to as the error component model. i depicts the provinces and t the years.

4.3 model selection

In order to answer the first hypothesis, the most appropriate of the three models has to be found. There are 3 tests available to compare the Pooled OLS, FEM and REM, namely a Hausman test, a F-test and a Breusch and Pagan Lagrangian multiplier test.

4.3.1 Hausman test

In order to decide between a fixed effect or random effect model a Hausman test is used, Hausman (1978). The decision depends on the correlation between the unit effects and the independent variable(s) (Bole & Rebec, 2013). The null hypothesis being that there is no correlation between the unique errors and the regressor(s), and that thusly the preferred model is random effects. The intercept and dummy variables are, and should be, excluded in the computation of the test statistic. In case of rejection of the null hypothesis, one may conclude that individual effects, u_i, are correlated with the independent variable, making the random effect model problematic. Clark and Linzer criticize the absolute weight that is put upon bias as the deciding factor in the Hausman test (2012). In addition, they state that “for the Hausman test to consistently reject the null hypothesis, it requires both a large amount of data and a moderately high correlation between x (the independent variable) and the unit effects; perhaps $\rho = 0.3$ or above.”. Concluding that no binary choice between models should be made based upon this test. This paper will therefore report both tests.

4.3.2 F-test

An F-test compares the FEM with the Pooled OLS model. The null hypothesis states that the observed and unobserved fixed effects u_i (not incorporated in the error term) are equal to zero. In other words, that the fixed effects are equal across all provinces. Rejection of the hypothesis means that the fixed effects model is preferred.

4.3.3 Breusch and Pagan Lagrangian multiplier test

The Breusch and Pagan Lagrangian multiplier test measures the conditional heteroskedasticity in a linear regression (Breusch, Pagan, 1979). The value of the independent variable's relationship on the estimated variance of the residuals is measured. The null hypothesis stating that all error variances are equal. The alternative implies that the error variances are a multiplicative function of at least one variable (Hassan, 2016). A rejection of the null hypothesis therefore suggests that an OLS model is not appropriate and that a random effects model has to be used.

4.4 Lagged effect

In order to observe the effect of floods in previous year on the current economic growth, as demanded by hypothesis two, lagged values of floods have to be included. These lagged values will be added to the most appropriate model resulting from hypothesis 1. The second, non-preferred model will be included in the appendix, alongside lagged values.

4.5 quantifying damages

The aforementioned models will depict the impact floods have on nightlight, but not on GDP. Previous literature placed the elasticity between nightlight and GDP to be between 0.27 and 0.3, section 2.2. Therefore, the following formula will be used as to estimate the cost of the average flood from 1992 to 2010, dependent on the reported average real GDP in constant 2010 US dollar.

$$elasticity = \frac{\frac{\Delta real\ GDP}{total\ average\ real\ GDP}}{\frac{\Delta nightlight}{total\ nightlight, average}}$$

Rearranging the formula allows for the change in the real GDP due to one flood to be obtained. The difference in nightlight due to a flood will be known from the best applicable model. The total nightlight average is the sum of all lights in Vietnam during the time period, divided by the number of years as to obtain the average. The total real GDP is calculated similarly, by summing the real GDP for every year and dividing it by the number of years. Therefore, the change in real GDP in constant 2010 US dollar will be the sole unknown variable.

5. Results

5.1 Pooled OLS

Table 3 presents the results of the pooled OLS regression between the number of floods and its correlation to the difference in the sum of emitted light. The coefficient of *All floods* is -799.47, which is significant at the 1% level. Meaning that a single flood, on average is correlated to a significant decrease of the sum of light of 799 or 0.12 percent of total nightlight. The R-squared which measures the goodness of fit, or the coefficient of determination, is 1%, which is relatively low. Meaning that *All floods* account or explain solely 1% of the variation in the difference in emitted light, which is to be expected as light emission is primarily driven by economic activity and not weather phenomena.

5.2 Fixed effects model

Next the fixed effects model, which considers differences between provinces. The output is presented in table 4. Similar to the Pooled OLS, the coefficient of the FEM is negative and significant at the 1% level. The magnitude of the coefficient is substantially different, a single flood now decreases the difference in light emission by 951 or 0.15 percent of total nightlight. The R-squared remains low as the independent variable solely explains 1% of the variation in the difference of total emitted light.

5.3 Random effects model

The final model, random effects, shows results similar to the Pooled OLS. Table 5 shows that a flood correlates to a reduction in the difference of sum of light of -799.47 (0.12 percent of total nightlight) at a 1% significance level. The number of floods similarly explains solely 1 percent of the variation in the difference of emitted light, as reported by the R-squared.

5.4 Model selection

5.4.1 Hausman test

With a significance level of 0.22 the null hypothesis cannot be rejected (table 6). The null hypothesis that random effects would be consistent and efficient is therefore not rejected. Implying that a random effects model is preferred to the Fixed effects model by the Hausman test. Both models do however carry different assumptions, benefits and shortcomings. The random effects model is estimated with partial pooling, while the fixed effects model is not. Partial pooling means that the province's effect estimate is based partially on the data of other provinces. This partial pooling makes the model statistically more efficient as for the same amount of data, coefficients are estimated more precisely. The random effects model does come with distributional assumptions, while the fixed effects model does not. Therefore, the fixed effects model will be more robust.

5.4.2 F-test

In comparing the Pooled OLS with the fixed-effects model, the F-test is used. The hypothesis that province effects are equal to zero is rejected at the 1% significance level. Hence the "poolability" of data is rejected and the fixed effects model will be preferred over the pooled OLS model.

5.4.3 The Breusch and Pagan Lagrangian multiplier test for random effects.

The null hypothesis of the Breusch and Pagan Lagrangian multiplier test states that the variances across entities are zero, meaning that no panel effects are present. This null hypothesis is rejected at the 1% level therefore a random effects model is preferred over a Pooled OLS model (table 7).

As the random effects model is preferred over the fixed effects model, and the random effects model is preferred over the Pooled OLS model, the REM will be considered the most appropriate model to explain the relationship between nightlight and the number of floods. Hypothesis one is confirmed as a significant and negative relationship is found between the two variables meaning that a flood corresponds to reduction in nightlight in the same year. The effect on GDP in US dollar terms will be shown in part 5.6, based on coefficient found in the random effects model.

5.5 lagged effect

Table 8 presents the random effects model with one to three lags. The coefficient of the non-lagged independent variable, all floods, has the same sign and magnitude as with the above presented REM model. The number of lags increases the impact of floods on emitted light. The lag of floods correlates to a decrease in sum of light of -405.51, which is non-significant at the 10% level. In model 2 and 3, the first lag does become significant. Implying that the effect of a flood impacts the economic activity negatively a year after its occurrence. The second lagged coefficient, presented in model 2 and 3, is positive and highly significant at the 1 percent level. The positive sign may indicate a recovery of economic growth two years after a flood. Finally, the third lag of floods in non-significant and positive. Hypothesis 2 states that there is a statistically significant effect of floods in previous years on current economic growth is not rejected for the first two lags, only the third lag falls short of significance. As mentioned in section 4.3.1, no binary choice between the fixed and random effects model can be made based upon the Hausman test. Therefore, the non-preferred fixed effects model will be included in the appendix with different numbers of lags (table 9). The reported fixed effects models with different numbers of lags have coefficients that are all significant (at least at the 10% level) and share the same sign as its random effects' counterpart.

5.6 quantifying damages

With the change in the nightlight difference being -799.47, an average annual nightlight of 648898.74 in Vietnam, an average real GDP of 69.28895 constant 2010 billion US dollar and an elasticity ranging from 0.27 to 0.3 results in the following change in real GDP. The average flood in Vietnam correlates to a reduction of 23 048 969 dollars to 25 609 889 dollars. With an average of 42.316 floods resulting in an average cost of 975,3 million to 1,084 billion dollars per year. Corresponding on average to 1.4 to 1.6 percent of real GDP. As Vietnam becomes more industrialized, and climate related events become larger in magnitude (section 2.1) this cost is expected to be larger in the more current years, and smaller in the earlier. Nguyen Xuan Cuong, head of the Central Steering Committee on Natural Disaster Prevention and Control, reports the cost of extreme weather events in 2016 to be 1.75 billion us dollars, and 858 million in 2018 (Guy, 2018; "natural disasters", 2017). The estimated cost is therefore of the same magnitude as the officially reported statistics.

6. Conclusion

This paper analyzes the impact of both floods and flash floods between 1992 and 2010 on nighttime light emission in Vietnam. In accordance with the first hypothesis; the immediate, intra-year effect per flood was a significant reduction in night light emission of 0.12% or 799.47 in absolute terms, as reported by the random effects model which was found to be the most appropriate. Similar results were found by a pooled OLS and a fixed effects model. This nightlight reduction corresponds to a deduction of GDP by 23 to 26 million US dollars (constant 2010 USD) on average over the time-period. With an average of 42 floods per year, the average annual costs is estimated at 975 million to 1.1 billion USD.

The delayed effect of floods on nightlight is negative for the first lagged value, based on the number of lags it ranges from -405.51 to -579.75 in the random effects model. The second lagged value has a positive sign, implying a possible recovery of the economic activity two years after the natural disaster. Therefore, the second hypothesis that there is a significant lagged effect of flooding is not rejected.

6.1 limitations and future research

A possible limitation in this paper is the quantification of the costs of floods. Keola et al. indicated that the elasticity of nightlight to GDP might not be an appropriate way to calculate economic growth in countries with an agricultural share between 20 and 40 percent, as agricultural activities take place in areas that emit no, or marginal nighttime light (2015). Unlike the average South-Asian elasticity, they obtain a negative elasticity for countries with this share in agriculture. Indicating that as a country experiences more economic growth, that they will emit less nighttime light. A conclusion which is not shared by other related literature. A second limitation on quantifying the costs comes from the dependency of reported outcome. The obtained cost estimate relies directly upon the reported GDP, which Vietnam has an incentive in overstating, as well as understating the damages on GDP due to floods (Toya, Skidmore, 2007). In addition, the elasticity between nightlight and GDP growth might be province-specific, as no regional output figures exist, the province-specific elasticity cannot be calculated.

A limitation of the interpretability of the lagged coefficients comes from the decreasing number of observations per additional lag. Rendering the external validity of lagged terms questionable.

For future research it can be recommended to differentiate between the different intensities of floods, as not solely the geographic characteristics play a role in the resulting damage but also the magnitude of the event. Additionally, future research can analyze the long-term effects by testing whether the sum of nightlight returns to a steady state growth level, increases as in a process of creative destruction, or decreases.

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8. Appendix

Table 1: nightlight data averages and descriptive statistics, 1992 -2009

	Vietnam
DN0	74.60%
DN1-2	0.00%
DN3-5	11.35%
DN6-10	9.10%
DN11-20	2.85%
DN21-62	2.02%
DN63	0.08%
Gini (DN)	0.848
Urban	29.15%

Source: Keola et al. 2015
Note: The presented percentages exclude 2010

Table 2: Descriptive statistics regarding emissions of nightlight

Provinces	Mean	Std. deviation	Min	Max
An Giang	10464.42	7480.769	1806	33918
Ba Ria-Vung Tau	18747.42	10907.65	2252	39560
Bac Giang	14873.05	6090.194	4497	26356
Bình Dương	22668.58	15945.51	3242	60721
Bình Phước	6581.474	7192.332	551	32017
Bình Thuận	20246.21	14600	1055	56076
Bình Định	8640.421	6257.845	481	25424
Bạc Liêu	4508.211	3867.907	317	16037
Bắc Kạn	802.5789	546.3591	18	1547
Bắc Ninh	10196.68	4048.949	5008	19762
Bến Tre	6440.158	4892.418	844	19603
Cao Bằng	932.4221	476.0126	306	2008
Cà Mau	5093.263	4540.911	459	19647
Cần Thơ	8471.737	5218.934	2010	23757
Gia Lai	8695.789	10616.05	546	48324
Hoà Bình	4203.105	2429.571	1011	10051
Hà Giang	1521	1068.73	213	3625
Hà Nam	6264.842	2390.036	1951	11559
Hà Nội	50308.37	16845.37	26675	93289
Hà Tĩnh	6301.895	4629.452	255	18038
Hưng Yên	8849.579	3483.266	4568	16755
Hải Dương	14725.16	5450.261	8322	27768
Hải Phòng	18197.58	6826.897	9254	32460
Hậu Giang	3966.579	3906.94	281	16120
Khánh Hoà	13789.63	8825.374	2916	40559
Kiên Giang	7332.105	6183.769	1113	28547
Kon Tum	4049.895	3339.069	241	14883

Lai Châu	869.2105	1299.098	0	4858
Lao Cai	3167.895	1948.96	790	8193
Long An	17358.95	12832.17	3121	56959
Lâm Đồng	13482.42	8775.462	1284	36076
Lạng Sơn	3657.421	1896.405	1081	7701
Nam Định	13557.42	4253.095	7386	22801
Nghệ An	15707.84	8771.713	2586	37409
Ninh Bình	7009.842	3398.7112423	2423	15445
Ninh Thuận	5806.579	3548.918	1136	15698
Phú Thọ	7879.895	3916.211	2990	16008
Phú Yên	6751.105	5897.163	480	23544
Quảng Bình	3891	2824.499	256	11721
Quảng Nam	6969.263	6128.373	133	25675
Quảng Ngãi	5823.474	5066.002	376	21041
Quảng Ninh	16463.68	8999.771	5764	37291
Quảng Trị	3618.947	2569.625	317	10305
Sóc Trăng	6803.421	6265.563	375	25318
Sơn La	3062.684	2515.345	359	9891
Thanh Hoá	20404.16	9627.389	4703	41762
Thành phố Hồ Chí Minh	50141.05	18542.31	18844	84717
Thái Bình	14096.11	3261.273	9208	21390
Thái Nguyên	9987	3975.89	4288	17089
Thừa Thiên-Huế	5702.053	3882.842	755	16910
Tiền Giang	12537.53	8894.462	2024	37304
Trà Vinh	3794.421	3918.175	173	16728
Tuyên Quang	3811.211	2434.211	834	8402
Tây Ninh	14690.74	10658.91	2251	43158
Vĩnh Long	7735.368	5510.262	928	21218
Vĩnh Phúc	8700.263	3883.655	3632	18249
Yên Bái	2782.211	1396.373	850	5297
Điện Biên	2110	1525.958	163	5796
Đà Nẵng	7351.684	4408.841	1410	19533
Đăk Lăk	9230.410	10838.6	1050	49160
Đăk Nông	2636.316	4452.8	101	19907
Đồng Nai	33405.16	19188.07	5939	79753
Đồng Tháp	11029.84	9108.096	1305	38858
Total	10299.98	11956.44	0	93289

Table 3: Pooled OLS regression

	(1)
	Difference sum
All Floods	-799.47***
	(204.6224)
Constant	1687.19***
	(199.1575)
Observations	1134
R-squared	0.01
Adjusted R-squared	0.01

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table 4: Fixed effects model

	(1)
	Difference sum
All Floods	-950.91***
	(242.9851)
Constant	1757.70***
	(113.1359)
Observations	1134
R-squared	0.01
Adjusted R-squared	0.01

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table 5: Random effects model

	(3) Difference sum
All Floods	-799.47***
	(163.5536)
Constant	1687.19***
	(176.9962)
Observations	1134
R-squared	0.01
Adjusted R-squared	0.01

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table 6: Hausman test

	Hausman Fixed Random
All Floods	
Fixed (b)	-950.91
Random(B)	-799.47
Difference (b-B)	-151.44
Sqrt(diag(V_b-V_B)) S.E.	122.20
Chi2(1).	1.54
Prob> chi2	0.22

Table 7: Breusch and Pagan Lagrangian multiplier test for random effects

Breusch and Pagan Lagrangian multiplier test for random effects	
Chibar2(01).	3935.31
Prob> chibar2	0.00

Table 8: Radom effects model including lags

	Model 1.	Model 2.	Model 3
	Difference sum of light		
All Floods	-686.75*** (207.12)	-894.87*** (211.16)	-930.45*** (234.97)
L.All Floods	-405.51 (287.38)	-579.75* (309.88)	-562.81* (308.11)
L2.All Floods		709.34*** (241.37)	726.73*** (243.71)
L3.All Floods			-269.82 (240.55)
Constant	1831.74***. (196.94)	1717.15*** (197.47)	1922.81*** (250.67)

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table 9: Fixed effects model including lags

	Model 1.	Model 2.	Model 3
	Difference sum of light		
All Floods	-911.71*** (254.48)	-998.74*** (256.26)	-1147.66*** (280.98)
L.All Floods	-667.00** (261.35)	-706.72** (266.76)	-775.45*** (284.00)
L2.All Floods		573.45** (256.95)	499.09* (261.14)
L3.All Floods			-539.88* (273.11)
Constant	2063.538***. (120.14)	1897.35*** (151.92)	2383.88*** (254.35)

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01