A G D I Working Paper

WP/21/094

Mitigating the Macroeconomic Impact of Severe Natural Disasters in Africa: Policy Synergies

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September 2021

Abstract

This study evaluates the economic impact of severe natural disasters in Africa using the generalized synthetic control method. In other words, it assesses how gross domestic product (GDP) would have been affected if severe natural disasters did not occur. Moreover, it explores the determinants of the destructiveness of the impact, focusing on the role played by capital. We find that severe natural disasters induce a significant and continuous reduction of GDP many years after the event. Indeed, economic losses caused by disasters depend on the level of capital (human capital, employment and capital stock) and aspects of governance quality (political stability and absence of violence). In other words, negative synergies are apparent because while capital stock, employment and human capital unconditionally reduce the macroeconomic impact of natural disasters, the corresponding conditional or interactive effects with political stability are also negative. Policy implications are discussed.

Keywords: natural disasters; economic growth; Africa

JEL Classification: Q54 ; O17; O55; P1

1. Introduction

The present study is motivated by two main trends in academia and policy circles, notably: (i) the effect of natural disasters on economic development and (ii) gaps in the literature. These trends are put in more perspective in the following paragraphs, respectively.

First, experiencing natural disasters, as well as its occurrence anywhere in the world can be troubling. The occurrence of natural disasters is both historical (for instance the 2011 earthquake of magnitude 9.0 which hit the Northeast of Japan; the 2010 earthquakes in Chile and in Haiti; the 2004 tsunami in the Indian Ocean, among others), and contemporary (Asongu, 2012, 2013). Recent evidence around the world can include: the 2021 earthquake in Haiti which has killed over 2000 people; the 2020 India floods which killed about 70 people (Reliefweb, 2020, 2021), *inter alia*. These disasters coupled with many others frequently engender human and property losses, which in the short and long runs cause economic and social challenges for the population. In Africa, some evidence can include the 2017 heavy rainfall and floods in Sierra Leone which led to about a thousand dead in the country (Kpaka, 2020). The 2011 drought which hit some Eastern African countries (e.g. Kenya; Ethiopia, Somalia, Eritrea and Djibouti) has been described as the worst drought experienced in these countries over the past 60 years (Adjei-Mantey & Adusah-Poku, 2019). Building on the above, the world is very interested by facts related to climate change and natural disasters. This can be explained by the fact climate change is influencing temperatures and provoking more natural catastrophes such as droughts, floods, storms, earthquake, *inter alia*. Moreover, human damages and natural disasters engender macroeconomic consequences both in the short and in the long run. Such consequences are often devastating and cause negative impacts on the affected people.

Second, there is an abundant literature on the relationship between the economy and natural disasters (Schumacher & Strobl, 2011; Loayza et al., 2012; Panwar & Sen, 2019; Noy, 2019; Klomp, 2015; Berlemann & Wenzal, 2016; Jaramillo, 2009, among others). Globally, their findings from the attendant literature could be summarized by the fact that there is a negative impact from natural disasters, mostly in poor countries. We can also note that these studies used classical models such as Ordinary Least Squares (OLS) estimation, Vector Auto Regression (VAR) or Logistic Regression and therefore suffer from many shortcomings especially in the issue of identification. In our study, we use the Generalized Synthetic Control (GSC) method to evaluate the impact. Consistent with contemporary literature on crisis, the GSC approach is more interpretable, efficient and transparent because of three main reasons (Diop et al., 2021), notably: (i) it generalizes the Synthetic Control (SC) method into many treated units and/or variable treatment periods; (ii) uncertainty estimates as well as confidence intervals are provided by the GSC and (iii) the risk of overfitting is mitigated by the GSC because the approach adjusts the number of factors using a cross-validating perspective.

Covallo et al. (2013) have already applied a counterfactual method to examine the short and long run average causal impact of catastrophic natural disasters on economic growth. In a different way, we bring a new extension of the synthetic control approach which allows us to deal with multiple treated countries and/or variable treatment periods. Furthermore, we extend the existing literature to analyse the role played by capital in the destructiveness of the impact caused by natural disasters. Finally, this study focuses only on severe natural disasters in Africa and we clearly select our pool donor, contrarily to Covallo et al. (2013). The positioning of this research is also based on an apparent shortcoming in the attendant literature, notably, the sparse contemporary empirical evidence of the macroeconomic impact of severe natural disasters in Africa.

Consistent with contemporary literature (Taghizadeh-Hesary et al., 2021), the impact of natural disaster is contingent on a plethora of factors, *inter alia*, the level of economic development, a justification that is consistent with some strands of the literature that, the consequences of negative signals such as terrorism are more apparent in poor countries which do not have the infrastructure and logical sophistication to hedge the corresponding negative effects (Asongu & Ssozi, 2017; Asongu & Kodila-Tedika, 2019). Khan et al. (2020) have assessed the Belt and Road Initiative and established a negative nexus between natural disasters and economic prosperity in terms of gross domestic product (GDP), and GDP per capita.

There are three perspectives to the debate on the nexus between natural disasters and economic growth. (i) While the effect of natural disasters is particularly unfavorable to poor households (Clarke & Grenham, 2013; Sawada & Takasaki, 2017), Panwar and Sen (2020) posit that such effects can last for long after the event. (ii) According to another strand of the literature, the nexus between natural disasters and poverty is not yet clearly established, not least, because the perspective that income levels mitigate the negative consequences of natural disasters is yet to withstand empirical scrutiny in a multitude of contexts (Sawada & Takasaki, 2017). (iii) A review of the attendant literature has led to the conclusion that while a negative relationship between risk indicators and income levels is apparent, the nexus is nonetheless non-linear in that, before risks eventually declined with income, these risks first increased with income levels (Kellenberg & Mobarak, 2008). For instance, Schumacher and Strobl (2011), in positing that the nexus between natural disasters and income levels is contingent on the level of exposure to natural distances, have found that losses are first experienced by countries confronted with low disaster levels, before such losses decrease with the development of attendant countries.

According to the neoclassical economic growth theory (Romer, 1986), a country affected by a disaster would experience a temporary drop in GDP caused by the destruction of productive capital. Thus, even if growth seems to recover over time, the GDP level could still be negatively affected many years after the date of the disaster. The recovery process depends on many country characteristics, including vulnerability and resilience of the economy and the state of infrastructures, human and physical capital, disaster prevention and responses, quality of institutions and governance, among others. In this study, we attempt to answer the following research questions: (i): how do severe natural disasters affect African countries? (ii) Can human and physical capital mitigate the destructiveness of the shock? More specifically, the objective of this paper is to evaluate the economic impact of severe natural disasters in Africa and to analyse the determinants of the destructiveness of the impact focusing on capital.

The remainder of the paper is structured as follows. Section 2 presents the methodology and the data. Section 3 discusses results obtained from the Generalized Synthetic Control method while Section 4 covers the role played by capital. Section 5 concludes with policy implications and future research directions.

2. Empirical methodology and presentation of data

This section first presents the Generalized Synthetic Control(GSC) method to evaluate the impact of natural disasters. It is followed with the presentation of data and identification of selected countries and their counterfactuals.

2.1. Methodology

The proposed empirical method will allow us to provide an answer to the following research question: how would have gross domestic product (GDP) been affected if severe natural disasters did not occur? To evaluate the macroeconomic impact, we use the GSC method developed by Xu (2017). This version presents several advantages compared to the synthetic control (SC) approach, including the possibility to work with multiple treated units and/or variable treatment periods. Before presenting the GSC method, it is worthwhile to describe the technical framework of the SC established by Abadie and Gardeazabal (2003) and extended by Abadie, Diamond and Hainmueller (2010).

We consider $J+1$ countries where only one is exposed to severe natural disaster events and we have J control units. Let Y_{jt}^{N} denote GDP for country j at time t in the absence of the disaster, with $j = 1, 2, \cdots, J+1$ and $t = 1, 2, \cdots, T$. Let T_0, represent the date when the event starts, with $1 \leq T_0 < T$. Let Y_{jt}^{I} denote the observed GDP for country j at time t which is exposed to the disaster from the period $T_o + 1$ to T. We assume that the disaster has no effect on GDP before the implementation period. Thus, for $t \in \{1, \cdots, T_0\}$ and for all $\in \{1, \cdots, N\}$, we have $Y_{jt}^{I} = Y_{jt}^{N}$.

With a GSC model, Xu (2017) defined the average treatment effect on the treated (ATT) at time t (when $t > T_0$) as:

$$ATT_{t,t>T_0} = \frac{1}{N_{tr}} \sum_{j \in \mathcal{T}} \left(Y_{jt}(1) - Y_{jt}(0) \right) = \frac{1}{N_{tr}} \sum_{j \in \mathcal{T}} \delta_{jt}$$

Where $Y_{jt}(1)$ and $Y_{jt}(0)$ are potential outcomes for unit j at time t. Thus, we can write:

$$Y_{jt}(0) = \beta X'_{jt} + \lambda'_j f_t + \varepsilon_{jt}$$

And

$$Y_{jt}(1) = \delta_{jt} D_{jt} + \beta X'_{jt} + \lambda'_j f_t + \varepsilon_{jt}$$

D_{jt} represents the treated indicator ($D_{jt} = 1$ when $j \in \mathcal{T}$ and $t > T_0$ and $D_{jt} = 0$ otherwise), δ_{jt} is the heterogeneous treatment effect on unit j at time t, X_{jt} is a $(K \times 1)$ vector of covariates, $\beta = (\beta_1, \cdots, \beta_K)'$ is a $(K \times 1)$ vector of unknown parameters, $f_t = (f_{1t}, \cdots, f_{rt})'$ is an $(r \times 1)$ vector of unobserved common factors, $\lambda_j = \left(\lambda_{j1}, \cdots, \lambda_{jr}\right)'$ is an $(r \times 1)$ vector of unknown factor loadings and ε_{jt} is the error term independent across countries and time, with 0 mean and $\mathcal{T}$ is the set of treated countries and N_{tr} their number.

To compare the model's fitness in order to make a selection, we use the Mean Square Prediction Error (MSPE) for a given factor r:

$$MSPE(r) = \sum_{s=1}^{T_0} \sum_{j \in \mathcal{T}} e_{js}^2 / T_0$$

With $e_{js} = Y_{js}(0) - \hat{Y}_{js}(0)$ for all $j \in \mathcal{T}$ and $s \in \{1, \cdots, T_0\}$

2.2. Presentation of data and selection of countries

On the one hand, we use a dataset of African countries over the period 1980-2020. The variables are presented in Table 1. The selection of the covariates is based on the neoclassical economic growth literature (Barro & Sala-i-Martin, 2003; Mankiw, Romer & Weil, 1992) and confirmed in several empirical applications of synthetic counter factual methods in the macro-economic literature (Abadie & Gardeazabal, 2003; Colonescu, 2017; Cavallo et al., 2013, among others).

On the other hand, data on natural disasters were obtained from the online Emergency Events Database (EM-DAT) dataset of the Centre for Research of the Epidemiology of Disasters (CRED). The EM-DAT contains essential core data of the events and their effects in the world since 1900. The natural disasters group includes: geographical (earthquakes, volcanic activity and mass movement), meteorological (storm, extreme temperature and fog), hydrological (flood, landslide, wave action), climatological (drought, glacial lake outburst and wildfire) and biological disasters (epidemics, insect infestation and animal accident). Table 2 presents the structure of the African dataset covering the period 1980-2020. It appears from the table that disasters are dominated by hydrological (48.22%) and followed by biological (31.28%) disasters. To have a panoramic view of natural disasters in Africa, we compute the average of the total events during the period 1980-2020. Figure 1 depicts the distribution of natural disaster intensity. It appears that large natural disasters occurred in the Southern, Eastern and Western Africa.

The dataset contains several measures of disaster impact including human impact (number of deaths, missing and affected people) and economic impact in US Dollars (total estimated damages, reconstruction costs and injured losses). Owing to data availability constraints, insights into linkages of macroeconomic effects and attendant natural disaster literature, we compute our disaster intensity based on the total number of affected people including deaths.

Affected people are those who require immediate assistance during the emergency situation following the EM-DAT guidelines, this indicator is widely used by different actors to convey the extent, impact and severity of a disaster. Since this indicator depends on the size of the country, we standardize it by dividing the total number of affected people by the lagged total population. In Table 3, we present the distribution of disaster intensity for all observations. Severe natural disasters equivalent to the 99th percentile correspond to disaster intensity of 0.353. Thus, in Africa during the period 1980-2020, severe natural disasters have affected 35.3% of the total population in the considered countries.

Since we have the disaster intensity continuous indicator, we can now create a dummy variable disaster that we need for the definition of the treated country and the treatment period. Let D_{it} be the natural disaster intensity for country i in period t. We define a dummy variable named *treatment*, for severe natural disasters as follows:

$$\text{treatment} = \begin{cases} 1 & \text{if} D_{it} > \gamma \\ 0 & \text{otherwise} \end{cases}$$

There are many strategies used in the literature to define the threshold γ. Panwar and Sen (2019) create a disaster intensity dummy with thresholds of 0.0001 and 0.01 for moderate and severe natural disasters, respectively. Other studies such as Cavallo et al. (2013) have employed the percentile cut-off point. Given that in this study we are interested in severe natural disasters, we then apply the 99th percentile of the distribution to define γ. The country i is treated if its natural disaster intensity at the period t is in the 99th percentile. This choice can be justified with two main reasons. First, several empirical research has found that the effects of natural disasters on economic prosperity are more significant in severe events (Cavallo et al., 2013; Panwar & Sen, 2019). Second, the employed methodology in this paper requires a sizeable number of countries as a control; hence,widening the threshold to 90th and 75th percentiles could strongly diminish the number of counterfactuals.

In the counterfactual method, we need pool donors that have characteristics closed to those with the treated countries before the treatment. This is why we have selected countries which have experienced severe natural disasters or other events of instability. For example, we have automatically excluded North African countries affected by the Arab Spring during the 2010-2012 period. Table 4 shows the descriptive statistics of the different covariates. We note that for all covariates, the average for the treated and the synthetic are very close. The counterfactual method also requires a long pre-treatment period range for better estimation. That is why we have considered 2000-2020 to be the range period of the natural disasters and

1980-2000 to be the pre-treatment period. Finally, Table 5 presents the treated countries and their counterfactuals. Figure 2 provides the different severe natural disasters and the date of their occurrences.

3. Presentation of results

This section presents empirical results from the GSC method. The estimated average treatment effect on treated is presented in Table 6. We use the MSPE of the logarithm of GDP to appreciate the overall pre-treatment fit and therefore make the choice for different estimated models. The ATT is negative and significant at 1% level, indicating that the economic losses from severe natural disasters are statistically significant at 1% level. Its value of -0.158 implies that in Africa, the GDP in logarithm is on average 15.8% lower in countries affected by severe natural disasters than in countries that are not affected.

Figure 3 displays the evolution of the ATT and its counterfactual. We note that the GDP level is permanently and negatively impacted by disasters. The comparison of the solid and the dashed lines before T_0 confirms that quality of the pre-treatment fit of the model. The vertical lines represent the date when the disasters occurred. In Figure 4, the treated (solid line) is compared to the counterfactual (dashed line). We note that the response of the economy to severe natural disasters is negative and instantaneous. The shock induces a significant and continuous decline of GDP during the entire period following the event. Thus, this result confirms that severe natural disasters cause significant losses in Africa. The second major finding reveals that both trends are continuously widening over time. The level of GDP is reduced in the long run and is stabilized at a lower level than the counterfactual. On average, growth seems to recover but the level of GDP is still negatively impacted many years after the shock.

4. Capital and the destructiveness of severe natural disasters

This section tends to evaluate the determinants of the destructiveness and the economic losses of severe natural disasters, focusing particularly on the role played by capital. Our endogenous variable is GDP losses provoked by the disaster. It is represented by the gap between the actual GDP and the counterfactual. We use variables such as human capital, employment and capital stock as proxies of the capital level on the one hand and, on the other, political stability and absence of violence to represent the governance level.

We expect a negative sign of these variables on the destructiveness of severe natural disasters. To capture the combined effect of capital and governance, we create interactive indicators. Likewise, we expect a negative effect of the interaction because the more the country is stable and has a high level of capital, the more the losses are small and vice versa. For diagnostics, we perform a Hausman specification test for the choice between fixed effects versus random effect models.

Table 7 presents the different estimations. All variables proxying for the capital level are negative and strongly significant (1% level). Hence, an increase of capital (both human and physical) tends to reduce the economic losses and therefore the destructiveness of the severe natural disasters. The effect is stronger when we consider human capital (-0.292). Political stability and absence of violence do not have a significant effect on the gap expected in Model 2. Regarding the interaction term, we note that even if political stability does not significantly affect losses, its interaction with human capital and capital stock is negative and significant. This result confirms that the negative effect of capital on the economic losses caused by the disaster increases strongly as the political stability increases.

Overall, our findings about the role played by capital in the recovery process support the perspective that economic losses caused by severe natural disasters depend on the capital level and some aspects of governance quality. In other words, negative synergies are apparent because while capital stock, employment and human capital unconditionally reduce the macroeconomic impact of natural disasters, the corresponding conditional or interactive effects with political stability are also negative. This notion of synergy effect is consistent with contemporary interactive regressions literature supporting the perspective that complementarities to influence macroeconomic outcomes can be both negative and positive (Asongu & Acha-Anyi, 2017; I. Ofori et al., 2021; P. Ofori et al., 2021).

5. Concluding implications and future research directions

This paper has assessed the macroeconomic impact of severe natural disasters in a dataset of African countries for the period 1980-2020. The Generalized Synthetic Control (GSC) method is applied to answer to the main research question: ‘what would happen (in economic growth) if the severe natural disasters did not occur?’ Moreover, economic losses represented by the gap between the actual GDP and its counterfactual have been used to explore the determinants of the destructiveness of the effects by focusing on the role played by capital dynamics to attenuate shocks. Results can be summarized as follows.

First, the economic losses from severe natural disasters are statistically significant at the 1% level. More precisely, in Africa, the GDP in logarithm is on average 15.8% lower in countries affected by severe natural disasters than in countries where such disasters are not apparent. Second, the GDP level is permanently and negatively impacted by disasters. Therefore, the response of the economy to the severe natural disasters is negative and instantaneous. The shock induces a significant and continuous decline of GDP during the entire period following the event. Thus, this result confirms that severe natural disasters cause significant losses in Africa. Additionally, we have found that both trends are continuously widening over time. The level of GDP is reduced in the long run and is stabilized at a lower level than the counterfactual. On average, the level of GDP is still negatively impacted many years after the shock. Finally, our findings about the role played by capital in the recovery process support the perspective that economic losses caused by severe natural disasters depend on the level of capital (human capital, employment and capital stock) and aspects of governance quality (political stability and absence of violence).

From the underlying findings, negative synergies are apparent because while capital stock, employment and human capital unconditionally reduce the macroeconomic impact of natural disasters, the corresponding conditional or interactive effects with political stability are also negative. The corresponding policy implication is that while the engaged capital dynamics are necessary conditions for the mitigation of the macroeconomic impact of natural disasters, the mitigating tendency is even more apparent when these capital conditions are considered simultaneously with policies designed to promote political stability and non-violence. Hence, policies designed to dampen the unfavourable macroeconomic consequences of natural disasters should be implemented such that the engaged capital dynamics are considered simultaneously with the maintenance of a non-violent and politically-stable macroeconomic environment. From a cross-country comparative standpoint, in order to hedge the unfavourable macroeconomic consequences of natural disasters, countries characterised by political stability and non-violence are more likely to benefit from policies designed to promote the capital dynamics, compared to their counterparts that are politically-unstable.

The study obviously leaves for future studies especially as it concerns employing the relevant estimation strategies to assess the consequences of natural disasters within country-specific frameworks. Moreover, given the global development agenda of sustainable development goals (SDGs), it is worthwhile for future studies to also assess the macroeconomic consequences of natural disasters on specific SDGs.

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Appendices

Table 1: Description of variables

Variables	Definitions	Sources
Gdp	Gross domestic product, current prices U.S. dollars Billions	WEO
Agriculture	Agriculture, forestry, and fishing, value added (% of GDP)	WDI
Oda	Net ODA received (% of GNI)	WDI
Mobile	Mobile cellular subscriptions (per 100 people)	WEO
Fdi	Foreign direct investment, net inflows (BoP, current US$)	WDI
Gcf	Gross capital formation (% of GDP)	WDI
Stability	"Political stability/no violence (estimate): measured as the perceptions of the likelihood that the government will be destabilized or overthrown by unconstitutional and violent means, including domestic violence and terrorism"	WGI
Natural	Total natural resources rents (% of GDP)	WDI
Employment	Number of persons engaged (in millions)	PWT100
Capital stock	Capital stock at current PPPs (in mil. 2017US$)	PWT100
Human Capital	Human capital index, based on years of schooling and returns to education.	PWT100

Source: Authors

Notes. GDP: Gross Domestic Product. WDI: World Development Indicators. WGI: World Governance Indicators. WEO: World Economic Outlook. PWT: Penn World Table.

Table 2: Structure of the natural disasters

Disaster subgroup	Frequency	Percentage	Cumulative
Biological	580	31.28%	31.28%
Climatological	166	8.95%	40.24%
Geophysical	31	1.67%	41.91%
Hydrological	894	48.22%	90.13%
Meteorological	183	9.87%	100.00%
Total	1854	100%	

Source: Authors' calculation on data from EM-DAT

Figure 1: Natural disaster intensity in Africa (average 1980-2020)

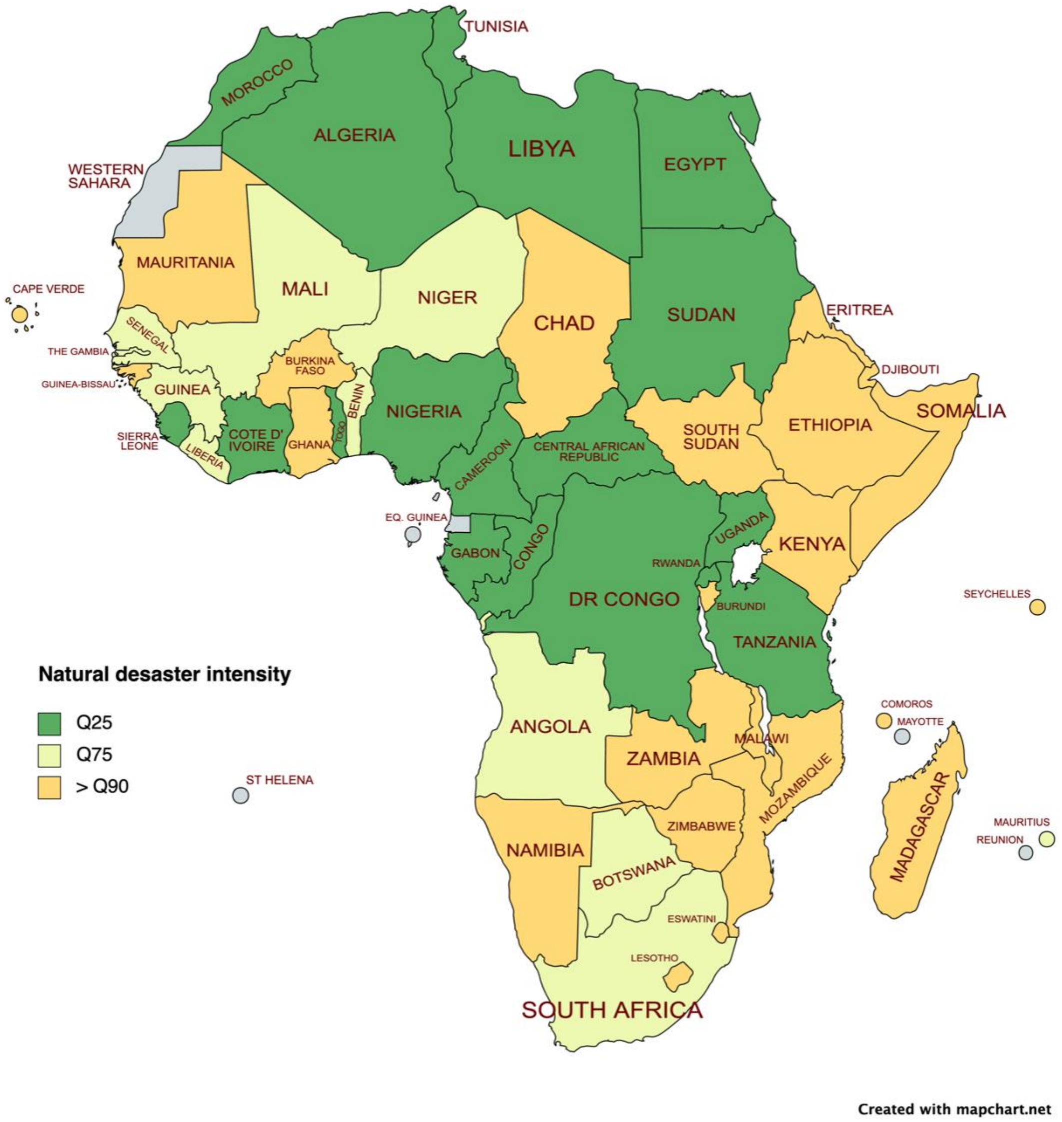

Table 3 : Distribution of disaster intensity in Africa (1980-2020)

	Obs	Mean	Std. Dev	P25	P75	P90	P99
Disaster Intensity	1849	0.015	0.064	0.000	0.002	0.021	0.353

Source: Authors' calculation on data from EM-DAT

Notes. Obs: observations. Std. Dev: Standard Deviation. P25: 25th percentile. P75: 75th percentile. P90 : 90th percentile. P99: 99th percentile

Table 4: Descriptive statistics of log(GDP) and covariates

	Mean	Std. Dev	Min	Max
Treated				
Log(gdp)	0.430	0.438	-0.538	1.340
Natural	5.352	4.496	0.000	40.129
Agriculture	18.086	11.987	1.148	45.652
Oda	9.934	7.966	0.000	41.379
Mobile	17.319	30.930	0.000	122.136
Human capital	1.745	0.385	1.020	1.713
Fdi	1.12e+8	2.00+8	-1.76e+8	1.07e+9
Synthetic				
Log(gdp)	0.805	0.654	-0.839	2.755
Natural	7.351	6.570	0.001	44.657
Agriculture	24.068	12.524	1.828	71.763
Oda	9.944	9.096	-0.251	58.363
Mobile	24.337	38.031	0.000	163.875
Human capial	1.654	0.451	1.014	2.939
Fdi	4.25e+8	1.05e+9	-7/39e+8	8.84e+9

Sources: Authors' calculation on data from EM-DAT, WDI, WEO, and PWT

Table 5 : Selected Countries

Treated Countries	Controls Countries
Djibouti-Eritrea- Lesotho- Malawi-Namibia-Niger-Swaziland-Zimbabwe-	Burkina Faso-Burundi-Kenya-Mozambique-Senegal-Togo-Benin-Botswana-Cabo Verde-Cameroon-Comoros-Ghana-Mauritius-Nigeria-Tanzania-Uganda-Zambia

Sources: Authors

Figure 2: Treatment status of the selected countries

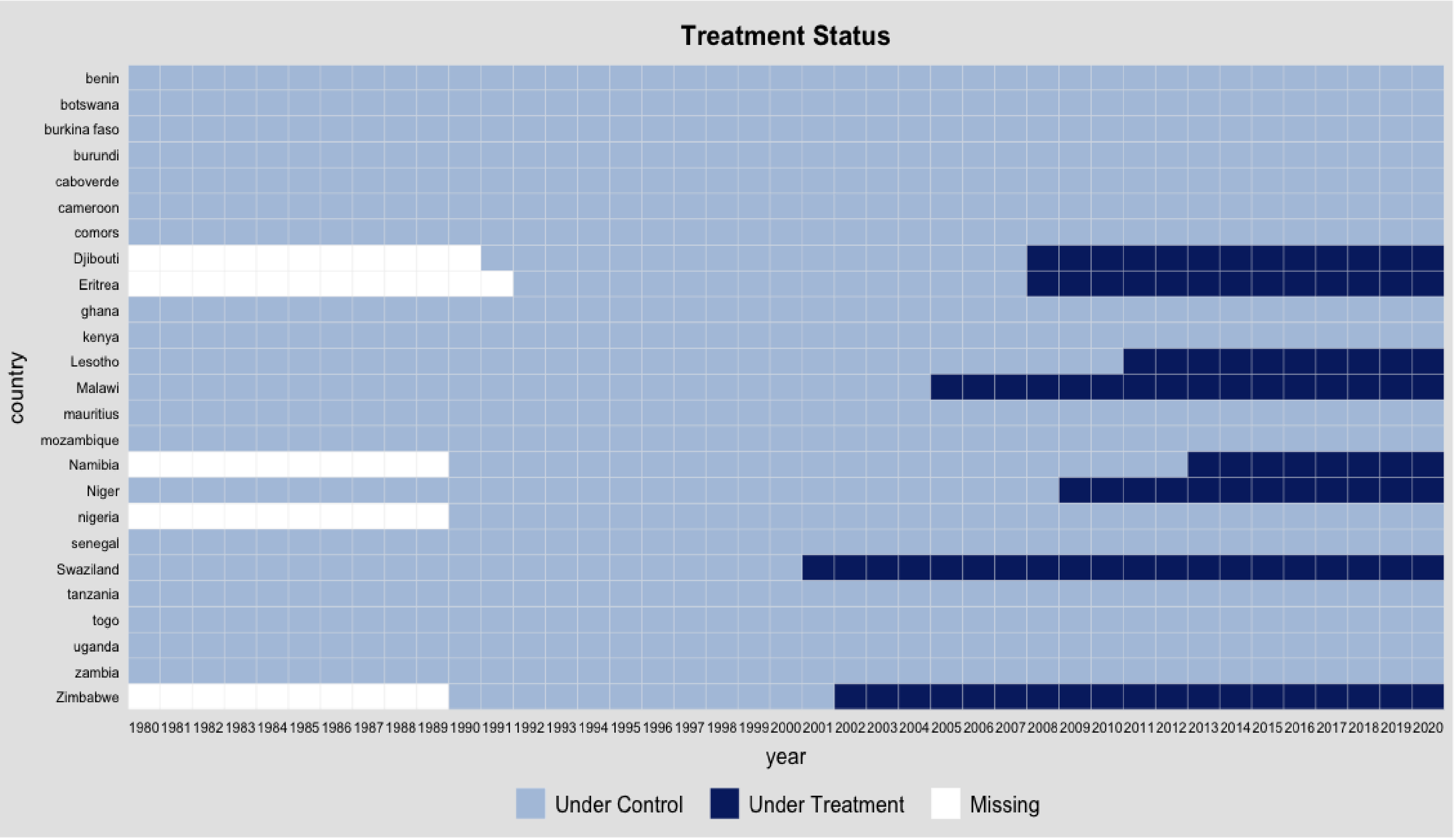

Table 6: Average Treatment effect on the treated (ATT)

	Coefficient	Standard Error	CI. Lower	CI. Upper	P. value
ATT. Average	-0.158***	0.060	-0.275	-0.040	0.008
Covariates					
Agriculture	0.005**	0.002	0.000	0.010	0.046
Oda	-0.005***	0.001	-0.000	-0.002	0.000
Human capital	0.214	0.162	-0.104	0.532	0.187
Fdi	-0.000	0.000	-0.000	0.000	0.143
Natural	-0.006***	0.002	-0.011	-0.002	0.006
Mobile	0.000	0.000	-0.001	0.002	0.763
MSPE=0.003					

Source: Authors' calculation on data from EM-DAT, WDI, WEO, and PWT. Notes: standard errors are based on parametric bootstraps of 1000 times. **, *** represent 5% and 1% level of significance respectively. For the model selection, we estimate few models with their covariates and choose the better from their MSPE.

Figure 3: ATT, treated country versus counterfactual evolution

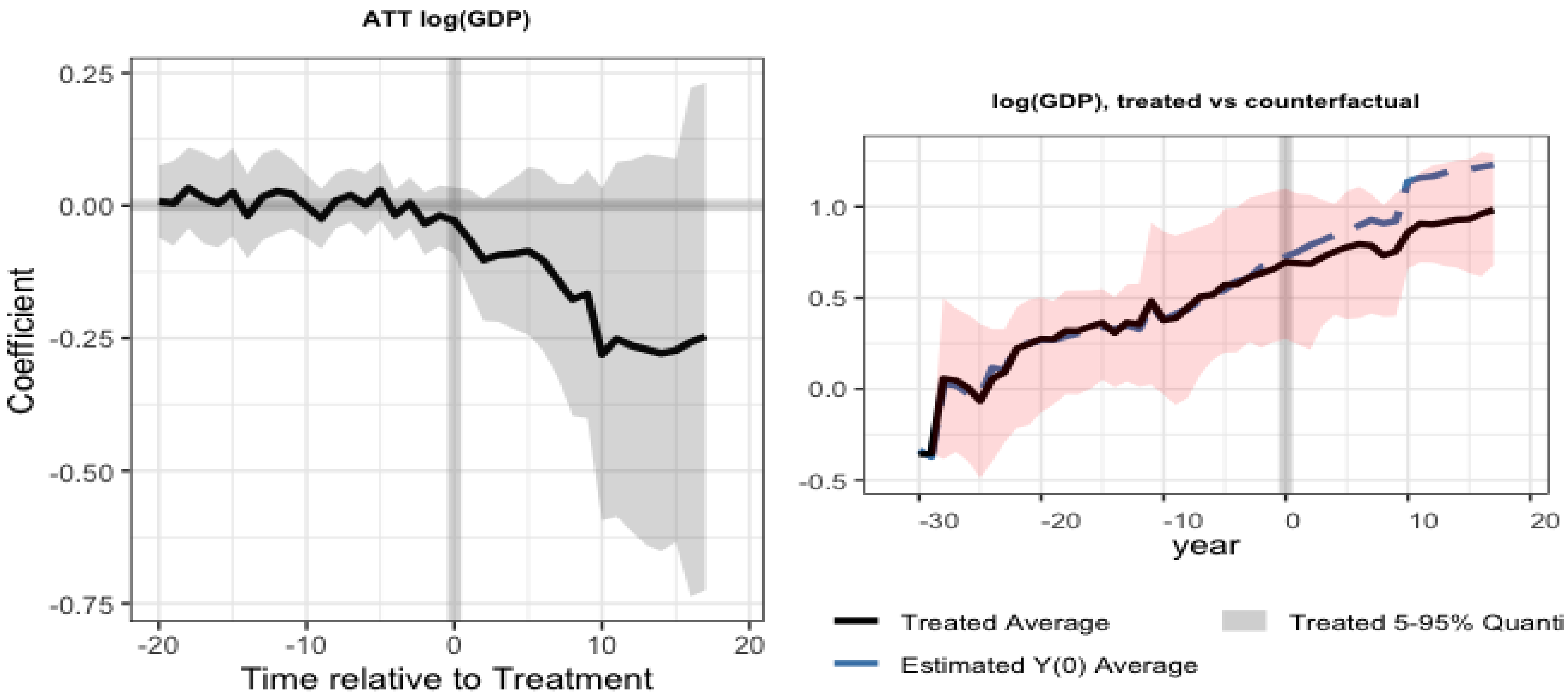

Table 7: Estimation results

	(1)	(2)	(3)	(4)	(5)	(5)
Stability	0.042 (0.101)	0.395*** (0.000)	-0.030 (0.147)	-0.019 (0.491)	-0.010 (0.456)	0.044 (0.163)
Human capital	-0.292*** (0.000)	-0.281*** (0.000)				
Human capital#Stability		-0.214*** (0.000)				
Employment			-0.093*** (0.000)	-0.097*** (0.000)		
Employment#stability				-0.004 (0.563)		
Capital stock					-0.000*** (0.002)	-0.000*** (0.000)
Capital stock#stability						-0.000* (0.061)
Constant	0.368*** (0.002)	0.347*** (0.002)	0.072** (0.026)	0.080** (0.024)	-0.148*** (0.000)	-0.137*** (0.000)
Haus (Prob>chi2)	0.000	0.001	0.000	0.000	0.450	0.158
Prob F	0.000	0.006	0.000	0.000	---	0.000
R^2	0.201	0.304	0.373	0.375	0.000	0.000
Observations	102	102	119	119	119	119

Source: Source: Authors' calculation on data from EM-DAT.
Notes: coefficients marked with *, **, *** are significant at 10%, 5% and 1% levels, respectively.
P-values are in brackets