Macroeconomic Impacts of the 2010 Earthquake in Haiti: A Replication and Sensitivity Analysis of Synthetic Control Results

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Abstract:
This thesis replicates the GDP and GDP per capita synthetic control results of Best and Burke's (2019) "Macroeconomic Impacts of the 2010 Earthquake in Haiti". It further tests the sensitivity of the synthetic control-based results to a change of the statistical software, the use of revised data, a modified sample, and an extended time frame. Best and Burke (2019) estimate a total loss of approximately 6 billion US dollars (constant 2010) until 2015, which equals an average annual loss of 12 percent. They further suggest an on-average 6 percent annual loss in GDP per capita. The macroeconomic loss may be permanent, according to the authors.

In accordance with Best and Burke (2019), this thesis' results suggest that the earthquake had a negative impact on Haiti's GDP and GDP per capita. The estimated total GDP loss ranges between 4.6 and 10.7 billion US dollars (constant 2010) from 2010 to 2015. These results equal a yearly loss between 9.0 and 19.4 percent in GDP. The mean annual loss in GDP per capita varies from 3.5 percent to 10.4 percent between 2010 and 2015. Hence, synthetic control-based results seem to be sensitive to software changes, data revision, and altered donor pools.
Replications estimating the earthquake's macroeconomic impact until 2018 do not suggest a decline in the yearly average difference between Haiti and its respective synthetic control measured in percentage points. The results for the GDP and the GDP per capita support Best and Burke's (2019) permanence assumption and, in fact, suggest an increase in the yearly average loss over time.

The missing statistical significance for all synthetic controls in this thesis is a noteworthy limitation. This, however, is in line with findings from previous literature analyzing the long-run effect of earthquakes (Loayza, et al., 2012) or large natural disasters in general (Cavallo, et al., 2013). The specific set of assumptions underlying the synthetic controls, Haiti's economic development, or data accuracy issues potentially cause the missing statistical significance and the differences among the estimated losses.

Keywords: Macroeconomic impact, Haiti, earthquake, synthetic control method, replication

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1 INTRODUCTION

The most devastating non-biological natural disaster in terms of human life losses in the 21st century is the earthquake on January 12, 2010, in Haiti. With 222,570 fatalities, this earthquake lists the second most fatal earthquakes ever recorded (EM-DAT, 2019). It affected 3.7 million people, accounting for 39 percent of Haiti's population recorded in 2009 (World Bank, 2020b). Like most natural disasters, it also affected or still affects the country's economic output through, for example, destroyed infrastructure, machinery, and crops, discontinued production and supply chains, and the impact on human lives. Experts value that the earthquake caused damages as high as 8 billion US dollars (EM-DAT, 2019).

In economic growth literature, such shocks to the economy and economic growth are studied with ambiguous outcomes. Depending on the type of natural disaster, its magnitude, its location, and the observed time frame, these shocks seem to have either a negative, a positive, or no effect on GDP growth (see Noy, 2009; Loayza, et al., 2012). The limitations to the economic growth studies might arise from the suddenness and unpredictability of natural disasters and their frequency in some and absence in other countries. However, methodological limitations in determining ex-post disaster impacts also play a crucial role in the field's indecisiveness. Different approaches and a broad range of study-specific assumptions may be sources of the contradictions.

However, the determination of ex-post economic losses of a natural disaster may appear meaningless anyway. Because of our inability to forecast or stop natural disasters, such analyses seem to have no future impact. However, the ex-post determination of macroeconomic losses has a purpose. Only when the economic outcome of natural disasters is clearly understood, evaluations on the best possible support for disaster-shaken economies can start. Given that climate science provides evidence that climate change supports the frequency or intensity of a variety of natural disasters, such as floods, droughts, and heatwaves (Anderson and Bausch, 2006), the ability to turn their impact into a favorable economic outcome will be even more crucial in the future. Therefore, research needs to understand natural disaster impacts on economies.

What makes the ex-post determination of disaster impacts complicated is the question, "what would have happened to the economy had this disaster not happened?". Naturally, no data exists for this unobserved case, and most econometric methods fail to derive an adequate solution. On the one hand, extrapolating the pre-disaster development denies other factors, such as global crises or global food prices. These factors influence aggregate units (such as cities, regions, or countries) overtime despite a disaster and have to be considered. On the other hand, aggregate units are one-of-a-kind. In spite of all simplification attempts in economics, applying the economic growth development of one aggregate unit to another, as in traditional comparative case studies, would be too simple. In Haiti's case, neither extrapolating its previous growth history nor adopting another country's economic growth development seems to be a suitable approach to understand earthquake-related economic losses.

Abadie, Diamond and Hainmueller's (2010) synthetic control method resolves these shortcomings. A synthetic counterfactual, based on a weighted average of an unaffected control group (a donor group), simulates the missing control unit. The weights assigned to each donor unit are calculated so that the unit of interest and its synthetic control resemble each other for various economic predictor variables and the outcome variable's pre-disaster values. If this resemblance is achieved, the synthetic control reflects the treated unit had the disaster not happened. A post-disaster difference between both the treated and the synthetic unit would consequently define the disaster effect.

Best and Burke (2019) use the synthetic control approach to find a numeric answer for Haiti's macroeconomic losses due to the 2010 earthquake. Their results display an average 12 percent GDP loss for all post-disaster years until 2015, next to a mean loss of 6 percent of GDP per capita for the same years. As their findings persist for several years, the authors classify the effects on Haiti's economy as potentially permanent. Best and Burke's (2019) findings are, however, dependent on their assumptions and choices made during the derivation of the synthetic controls. As for all econometric approaches simulating unobserved counterfactuals, debatable assumptions, such as the choice of the donor pool countries or the usage of a specific data set, are essential for the obtained results and their evaluation. Hence, synthetic control results may be sensitive to these choices.

This thesis replicates the study by Best and Burke (2019) and identifies the synthetic control outcome's sensitivity to changes in the statistical software, data set, sample, and time horizon. The replication focuses on GDP and GDP per capita results until 2015 and, in the time extended cases, until 2018. The synthetic control results for both outcome variables suggest essentially similar effects. The earthquake negatively affects the GDP and GDP per capita even after nine years. However, depending on the statistical software, data set, donor pool, and time horizon used to construct the synthetic control, the magnitude of the effect differs notably. The calculated total loss in GDP ranges from approximately 4.6 to 10.7 billion US dollars (constant 2010) over six post-earthquake years. These results equal a yearly loss of 9.0 to 19.4 percent in GDP. The annual loss in per capita GDP varies from 3.5 to 10.4 percent from 2010 to 2015. The missing statistical significance for all synthetic controls in this thesis is a noteworthy limitation. This, however, is in line with results from the previous literature analyzing the long-run effect of earthquakes (Loayza, et al., 2012) or incisive disasters in general (Cavallo, et al., 2013). The span between the estimated losses and the missing statistical significance might be attributed to the specific set of assumptions underlying the synthetic controls, Haiti's unique economic development, or data accuracy issues among low-income countries (Ley and Misch, 2014).

This thesis adds to the existing literature on the macroeconomic growth effects of natural disasters and the synthetic control method. It supports previous economic growth studies that miss statistical significance, although earthquake-related results to show permanent economic losses. It supplements the literature on the synthetic control method in multiple ways. First, studies using the synthetic control method are yet rarely replicated. That includes the test for the persistence of results to different changes in the synthetic control determination. Second, the sensitivity of synthetic control results appears to be a relatively new interest in the literature (see Firpo and Possebom, 2018; Abadie, 2020).

The remainder of this thesis is structured as follows: Section 2 (Replication in Economics) describes the importance of replications in economic research and their different types; Sections 3 (Natural Disasters in Economics) discusses previous theoretical and empirical literature which analyses the effects of natural disasters and specifically earthquakes on economic growth; Section 4 (Haiti Crisis) gives an overview on the pre-earthquake situation in Haiti and the earthquake on January 12, 2010; Section 5 (Empirical Approach) describes the synthetic control method and the replication steps conducted in this thesis; Section 6 (Data Sources and Descriptive Statistics) describes the two underlying data sets and the analysis-relevant samples; Section 7 (Results) presents the different synthetic control replications, interprets them and discusses these findings; Section 8 (Conclusion) concludes on the results.

2 REPLICATION IN ECONOMICS

This thesis builds its analysis on a data set and statistical software code published by Best and Burke (2019) as part of their study's online appendix. Public availability of data and traceable documentation of its processing is promoted since the *JMBC Data Storage and Evaluation Project* launched by the *Journal of Money, Credit and Banking* in 1982, as documented by Dewald, Thursby and Anderson (1986). They explain that researchers in social science appraised the replication of other authors' studies adversely. Replications implied distrust in published results and did not lead to recognition of a researcher's work. Due to the unavailability of hard- and software as well as data, researchers frequently struggled to replicate results. Selected replications based on the data collected in the *JMBC Data Storage and Evaluation Project* concluded that in empirical economics, errors seem to occur frequently (Dewald, Thursby and Anderson, 1986).

Replication, however, is not only a method to detect, point out, and correct errors in previous studies. Duvenback, Palmer-Jones and Reed (2017) sum up four types of behavior which are potentially either revealed by replication or prevented through the likelihood of replication: First, formulate a hypothesis only after empirical results are obtained; Second, manipulate data until statistical significance is attained; Third, act with fraud while conducting empirical research; Fourth, inappropriately often publish false-positive studies. While Duvenback, Palmer-Jones and Reed (2017) point to intentional and unintentional mistakes in the research process, replications offer the potential to unveil alternative outcomes and implications through minor changes in the analysis or to verify novel results. Therefore, replications should not be considered an enunciation of mistrust but a strategy to develop coherent knowledge of an economic field, model, or method.

Replications function as such because they are not limited to be exact repetitions of a previous study. The term refers to a practice where a researcher closely follows the idea of a particular already existing study. There are various attempts to cluster different forms of replication. Pesaran (2003) contrasts replications with a narrow and a wider sense. Replications with a narrow sense test consistency and accuracy using original data sets and identical or different computer packages. Replications with a wider sense test whether empirical results can be replicated using a data set that differs from the original data set to some extent. Hamermesh (2007) introduces three categories of replication: pure, statistical, and scientific. Pure replication refers to conducting the same analysis using the identical data, method, computer package, and etcetera. The definition of statistical replication refers to "[a] useful taxonomy [...] provided by the psychologist John Hunter (2001) who described *statistical replication*—different sample, but the identical model and underlying population" (Hamermesh, 2007, p. 716). Last, scientific replication uses a different sample from another population and another but a potentially similar model.

These categories already imply the different options available to conduct a replication that goes beyond pure replications. Data sets are usually restricted to specific points in time or periods, samples, numbers of observations, variables available, and sources. While these are common reasons for a limited validity of study results, adjustments to the data offer various options for study replications. Data revision, moreover, adds to these options and is often expected for governmental data. On the one hand, this impairs narrow replicability whenever the original data set is not available (Dewald, Thursby and Anderson, 1986). On the other hand, data revision implies a revision of empirical findings that have been obtained with the old possibly flawed data set. Varying the chosen model or method offer additional possibilities to replicate in a wider, respectively scientific sense. Unlike described by Dewald, Thursby and Anderson (1986), today, a variety of different software for economic data processing is available to most researchers worldwide. Their specific ways of execution offer further options to some replication works.

It seems as if the attitude towards replications in economics has changed since the 1980s. According to Müller-Langer, et al. (2019), more journals nowadays support replicability, for example, by introducing obligatory data disclosure policies. Published replication studies, however, remain rare (Müller-Langer, et al., 2019). Simultaneously, open access promotes replication work, for example, through dedicated journals (see International Journal for Re-Views in Empirical Economics) or collaborative online databases providing overviews of conducted replications (Höffler, 2017).

Replications are also a way to test, improve, and develop econometric methods, especially their software implementations. The sensitivity of results obtained by the synthetic control method is yet rarely studied in replications. One example, though, is Becker and Klößner (2017), who replicate Pinotti's study *(Economic Journal 2015*; 125, F203–F232, 2015) on the effect of Mafia activities on the GDP per capita of two South Italian regions. They replicate in a narrow sense and focus on the usage of different software packages. Results replicated with Matlab and the R package Synth are at bottom identical to those derived with Stata in the original study and suggest a GDP per capita drop of approximately 16 percent. Using the MSCMT package in R, Becker and Klößner (2017) estimate a slightly smaller GDP per capita reduction of approximately 13 percent. The authors argue that while the validity of Pinotti's conclusion remains unchanged, the latter statistical package presents the correct optimal solution. They argue they can obtain optimal solutions for the synthetic control donor weights and a smaller RMSPE (root mean square error) using this package.

3 NATURAL DISASTERS IN ECONOMICS

This section presents the theory and empirical results of economic growth studies, aiming to explain natural disasters' economic growth effects. The theoretical subsection includes endogenous and neoclassical growth theory. The empirical subsection divides into studies discussing the economic growth effects of all disaster types and studies focusing on earthquakes' economic growth effects.

3.1 Natural Disasters in Economic Growth Theory

Explaining economic growth and its premises has challenged economists ever since. Nevertheless, the field's attention to the specific impact of natural disasters on economic growth is marginal. There have, however, been attempts to implement the presumed mechanism of natural disasters as a generalized idea within endogenous and neoclassical growth theory.

Consider Crespo Cuaresma, Hlouskova and Obersteiner (2008) that natural disasters promote total factor productivity and, finally, GDP per capita. This builds on the idea that, after a disaster, outdated technology within the capital stock is replaced by newer technology. Therefore, outdated technology needs to be part of the destroyed capital stock. Advanced technology, furthermore, has to be able to recover the destruction of the capital stock more efficiently than the outdated technology. An example is advanced construction technology that builds houses faster (and most likely safer) than the previous standards. Crespo Cuaresma, Hlouskova and Obersteiner (2008) point out that this concept is often named after the Schumpeterian concept of "creative destruction". Schumpeter (1950) developed this term to describe that advanced technology's competitive advantage is an incentive for businesses to improve their technology. Therefore, the adaptation of this term in the context of natural disasters cannot directly be understood as a reference to Schumpeter (1950). It is a literate interpretation of the ex-post creation (technology promotion) due to preceding destruction (natural disasters) (Crespo Cuaresma, Hlouskova and Obersteiner, 2008)[1].

Models in the endogenous growth theory make more detailed use of this concept. In what Howitt (2007) names "A Simple Model of Endogenous Growth with Creative

[1] In their empirical analysis on the relation between knowledge transfer from developed to developing countries and catastrophic events Crespo Cuaresma, Hlouskova and Obersteiner (2008), however, cannot proof the above presumed relation. They find that the risk of natural disasters is negatively related to technology transfer (proxied by R&D stock embodied in imports). An effect tends only to be present for countries with relatively high levels of GDP per capita.

Destruction", he assigns this underlying idea a determining role for economic growth. In his theory, he focuses on savings and research (the incentive to perform R&D) and displays them in a diagram with the rate of economic growth on the y-axis and the stock of capital per efficiency-unit of labor on the x-axis. The downward-sloping savings rate curve and the upward-sloping R&D curve, hence, set the long-run growth rate. All institutional factors, for example, policies and property rights, are constant along the R&D curve. Given these factors, each firm sets its R&D level to maximize its profit. Whenever institutions, policies, or alike set an incentive for R&D, the curve shifts upwards. This upward shift implies higher economic growth regardless of the capital stock per effective labor unit. In contrast, consider a decrease in the steady-state stock of capital per efficient labor unit. This is synonymous with less capital per worker and a decrease in production per worker, which results in less income per worker. This situation limits the spending on new technologies and discourages firms from engaging in R&D. The curve moves downwards.

Howitt (2007) does not describe the impact of a natural disaster in this theoretical framework. However, implementing a natural disaster (for example, an earthquake) could lead to both outcomes: On the one hand, the destruction of old technology incentivizes investments in new technology. For instance, let the old technology be a traditional way to construct buildings, of which an earthquake destroyed a large part. The destruction would then incentivize the construction industry to invest in a construction method that prevents buildings from collapsing during future earthquakes. If such behavior, after a natural disaster, results in higher R&D levels, the curve shifts upwards, and consequently, the rate of economic growth increases.

On the other hand, the same destruction could decrease the capital stock per efficient labor unit. Disregarding the potential life loss, this is the case whenever parts of the destroyed buildings functioned as workplaces or contributed to the production otherwise. This scenario leads to less capital and, therefore, less production per worker. Workers, consequently, would earn less and cannot afford to rebuild or update their own houses with updated technology. It is, after all, more expensive than the traditional construction method. The market now experiences low demand for updated technology and firms are provided fewer incentives to invest in R&D. The R&D curve shifts downwards, and economic growth rates decrease. Finally, this theory is inconclusive on the potential outcome in a disaster scenario.

Neoclassical growth theory often describes a natural disaster as a one-time exogenous shock to the economy. Loayza et al. (2012), for example, explain the presumed effect of a natural disaster in a basic Solow model. This basic Solow model contains exogenous technological progress and savings. The authors differentiate between two cases: In the first case, the destruction of capital is severer than the reduction of effective labor. In the short run, the GDP consequently decreases. In the long run, "[d]isasters [...] increase the marginal return of physical capital and accelerate its accumulation, and thus economic growth (compared to its steady-state)" (Loayza, et al., 2012, p. 1319). In the second case, the disaster impacts the effective labor force more than capital destruction. Loayza et al. (2012) assume economic growth slows down in this scenario.

Okuyama (2003) highlights that this treatment of exogenous shocks in macroeconomic literature prohibits a careful analysis of the unique impact natural disasters have on the change and development of economic behavior. He builds on the short- and long-term theories by Dacy and Kunreuther (1969).

Their theoretical extensions are tailored to natural disasters and disaster response in the USA and other places, which usually experience significant capital loss but seldom experience loss in human capital following a natural disaster. Dacy and Kunreuther's (1969) short-term theories base on microeconomic theory, particularly decision-making theory and supply-demand theory. They, for example, argue that shortages are either counteracted by external aid or through decreased demand. Decreased demand refers to people's transitional solutions in which they provide for themselves out of their stocks and savings or live with more people to overcome the lack of housing. Their analysis of long-term recovery develops from a simple Solow-Swan growth model. They divide the capital stock divides into the sectors public, commercial, and residential. Resources should always be allocated to the sector that contributes best to overall productivity. Dacy and Kunreuther (1969) claim that marginal productivity is highest for the public sector, which through public utility infrastructure, provides essential goods for the survival and recovery of the two other sectors as well. Later simultaneous reconstruction in all three sectors is seen as favorable. The authors further note that aid and the type of aid (reimbursable or not) play a decisive role in how and how fast the pre-disaster situation is rebuilt. For developing countries, they notice that a constricted capital flow slows the recovery process because the rebuilding activities have to compete with other investment projects. Dacy and Kunreuther (1969) also mention that new technologies might replace outdated precursors and potentially speed the recovery process.

Okuyama (2003) explains this in more detail. He restructures a basic Solow-Swan model that reflects the recovery process of an economy after a disaster. The economy departs from its steady-state due to the disaster, and the per capita capital growth rate changes from zero to positive. Reconstruction activities lead to a higher savings rate, which gradually declines to its previous level as the reconstruction continues. Hence, the capital re-accumulation or recovery speed accelerates whenever more resources are invested in the recovery process. The recovery activities in the disaster-shaken economy, which replace outdated structures with newer technology, increase the rate of technological progress. That, however, does not imply that the recovery boosts the level of technology. Okuyama (2003) also explains that the rate of technological progress is limited in time. After integrating the technology replacement into his model, the author concludes a faster growth of effective labor and a slower growth recovery rate of capital accumulation than for a case without technological replacement. Technological progress, consequently, is considered a driving force of economic growth in the long run.

In summary, economic growth theory lays out opportunities to support a negative, neutral, or positive growth impact of natural disasters. To understand and possibly predict the disaster specific growth effects, it is essential to factor in the damage caused to the different production factors, the direction of post-disaster investments, and the handling and potential of new technologies.

3.2 Natural Disasters in Empirical Economics

Results from empirical research are not much clearer. As described in the previous section, natural disasters affect economies differently in terms of labor and capital. Regarding quantitative results, negative and positive effects net to either positive, negative, or zero impact on economic growth. This is because most disasters affect both production factors. Loayza, et al. (2012) design a hypothetical situation of moderate earthquakes and storms in developing economies: Economic growth potentially speeds up in their aftermath due to the capital stock reduction, which is the sudden physical damage. It leads to "[…] larger marginal returns to remaining capital and larger average returns of replacement capital […]" (Loayza, et al., 2012, p. 1325). The damage calls for extensive reconstructions. Reconstructions support growth within the industrial sector through infrastructural, manufactural, and housing-related demands. Whenever growth within these industries is large enough, it potentially countervails negative overall growth consequences. Finally, negative, positive, or zero growth can be achieved in this hypothetical scenario.

Moreover, disasters are unique events. As for most other sudden events affecting economic growth, that leads to many different options to study the topic. Researchers can choose the measure for disaster impact, the time frame investigated, and the type of natural disasters analyzed (Mochizuki, et al., 2014). Hence the actual comparability of the individual studies within this empirical research area is limited. However, inspecting this diversity enables informative deductions on the topic.

The remainder of this section is split into two. The first subsection presents empirical research on more than one disaster. There, however, is a focus on work that reveals results for developing countries and earthquake scenarios. The second subsection concentrates on studies on the economic growth impact of single earthquake events. It finally presents the study which this thesis aims to replicate.

3.2.1 Growth Effects of Multiple Disasters

The studies displayed in this section show the results of aggregated disaster data. That means that different disaster types are analyzed regardless of their type or location. Although the studied disaster may have happened in the same country or potentially be of the same type, researchers might also categorize the findings ex-post by country type or disaster magnitude. This approach has a variety of advantages and disadvantages compared to single disaster effect analyses. However, following the theoretical literature's assumptions that all natural disasters represent a shock to the economy due to the destruction of labor and capital, one might want to suppose that at least the trend of the impact is similar for all disaster types.

Noy (2009) examines the short-run macroeconomic costs of natural disasters using panel data. He conducts a study using the Hausman-Taylor three-step estimation method in a multi-country and multi-event framework. Noy (2009) estimates that a natural disaster's monetary amount of property damages correlates negatively with GDP growth. In developing countries, an increment in direct property damages by one standard deviation results in an approximate nine percent decline in GDP growth. There, however, is a small positive effect found for developed countries. In general, developed countries experience a smaller macroeconomic effect than developing countries following a natural disaster of the same relative magnitude. Compared to smaller nations, larger nations are less vulnerable to disasters of the same size.

Loayza, et al. (2012) support findings on a higher sensitivity to natural disasters by developing countries. The authors analyze the underlying mechanism and suggest that higher sensitivity is consistent with the greater importance of agriculture and a stronger inter-sectoral linkage in developing nations. Their cross-country panel study includes 94 countries over a five-year time horizon and applied a dynamic generalized method of moments panel estimation. Loayza, et al. (2012) suggest disaggregating the impact of disasters by disaster type, sectors, and severeness to understand the ambiguity of results within the literature. In particular, they find that earthquakes and storms both positively impact industrial growth in developing economies. At the same time, storms are also found to influence agricultural growth in these countries negatively. The authors, however, find no significant growth effect for earthquakes over ten post-disaster years. After investigating the capital investment as a driver of growth, Loayza et al. (2012) suppose that capital accumulation conciliates the effect of earthquakes. The results further suggest that no severe disaster has positive growth effects, whereas this can be the case for moderate disasters.

Among the first ones that extended the question on growth impacts of natural disasters to the long-term were Skidmore and Toya (2002). In their attempt to understand the relationship between disaster risk, investment decisions, total factor productivity, and the long-term economy, they use the number of catastrophic events between 1960 and 1990 to measure disaster risk.[2] Skidmore and Toya (2002) use an OLS regression on 89 countries to find that geophysical disasters[3] are negatively and, at times, significantly correlated with economic growth. They assume that natural disasters affect economic growth through total factor productivity and capital accumulation and test these channels. Geophysical disasters feature negative non-significant coefficients for total factor productivity. Skidmore and Toya (2002), in general, claim that more disaster-prone countries grow faster economically.

Kim (2010) replicates this study. He responds to the research question using the identical method and a data set from a different source, including disasters between 1990 and 2004. The positive relationship between disaster frequency and economic growth rates are less significant in the more recent period. Kim's (2010) results suggest stronger evidence of human capital destruction caused by geologic disasters than the original study.

[2] The more disasters occure the greater the risk of another one to take place. This is one hypothesis on how people perceive disaster risk and an important assumption here. It allows experience to have an impact on investment decisions and technological adaptations.
[3] A geophysical disaster is"[a] hazard originating from solid earth [...]"(EM-DAT, 2019) like an earthquake, dry mass movement or vulcanic eruption.

As of late, a more regularly used analysis method for long-run growth consequences is the synthetic control method. This method computes a synthetic counterfactual that simulates a treated unit in case the treatment had never happened. The treatment in the following examples is a natural disaster. A weighted average of untreated units, referred to as the donor pool, forms the synthetic counterfactual. The individual weights are chosen so that the synthetic counterfactual fits the actual unit best in the pre-treatment period and for several predictor variables. The latter are variables with predictive power concerning the outcome variable. The synthetic control method is popular in analyses on the macroeconomic effects of a single disaster. Hence, the estimated outcome variables are not limited to the GDP or the GDP per capita. The method is used with socio-economic variables (Coffman and Noy, 2012; duPont IV et al., 2015; Lynham, 2017) as well.

An example of a multi-disaster study that uses the synthetic control method in a long-term analysis is conducted by Cavallo et al. (2013). With data from 196 countries, they analyze the impact of large natural disasters on per capita GDP from 1970 to 2008. Their data includes earthquakes (including tsunamis), storms, and floods. The authors define a disaster as large by people killed as a population share. They proceed with disasters within the 75th, 90th, and 99th percentile largest disasters. The authors find no effects for the 75th and 90th percentile. For the highest percentile group of disasters, they discover that the GDP per capita is, on average, ten percent smaller a decade after the disaster compared to its pre-disaster value. Compared to the counterfactual, which measures the GDP per capita if the disaster had never occurred, the actual per capita GDP loss is 18 percent. After a close examination of the four catastrophes that are among these very largest disasters, it is clarified "[...] that only very large natural disasters followed by radical political revolution show long-lasting negative economic effects on economic growth" (Cavallo, et al., 2013, p. 1559). The authors further use their average long-term outcomes to speculate that "[...] by 2020, [Haiti] would have an income per capita of $1,060, while it could have had a per capita income of about $1,410 had the earthquake not occurred (all figures in PPP 2008 international dollars)" (Cavallo, et al., 2013, p. 1558). It remains to be said that the largest natural disaster studied by Cavallo et al. (2013) killed five times fewer people per one million inhabitants than the earthquake in Haiti.

In summary, studies estimating the growth effects of disasters, in general, suggest higher sensitivity for developing (and smaller) countries in the short-run. However, whether such effects are positive, negative, or null depends on the individual study framework. It further seems as if disasters have, if at all, a negative growth effect in the long-run.

3.2.2 Growth Effects of Earthquakes

This subsection introduces studies that deal with the economic (growth) impacts of earthquakes, excluding tsunamis.[4] In this subsection, synthetic control studies often utilize a country's unaffected regions to construct an affected region's synthetic control. This approach is suitable if the country has enough regions, if regional data is available, and if the donor pool regions are genuinely unaffected by the earthquake.

A study on the Kobe 1995 earthquake by duPont IV and Noy (2015) examines its long-term economic impact on the Hyogo prefecture. The authors use panel data with information on 53 variables from 1,719 economic units (cities, towns, and wards) between 1980 and 2010. They estimate the Hyogo prefecture's GDP per capita in 2003 to be nine percent lower than its counterfactuals. Immediately after the earthquake, it, nonetheless, rose above the counterfactuals GDP per capita. In 2008 it was twelve percent lower than the counterfactual. The authors, hence, presume this to be a persistent effect that sums up to a total loss of approximately 172 billion US dollars in GDP per capita during the 13 post-disaster years. That is despite large fiscal expenditures into the region. The earthquake immediately led to high migration out of the Hyogo prefecture, according to duPont IV and Noy (2015). In the medium-term, the economic downturn did not influence migration. In the long term, however, the migration into the prefecture seems to decline due to the overall economic situation.

Barone and Mocetti (2014) conduct an inner country synthetic control study on two Italian earthquakes in 1976 and 1980. They construct two regional synthetics control analyses for the GDP per capita using time series data at the regional level. The authors suggest that in the short-run financial aid countervails otherwise observable negative effects. As the two analyses show converse results (23 percent higher GDP per capita after 20 years versus 12 percent lower GDP per capita after 20 years), they assume that the economic and social environment existing before the earthquake is essential. Barone

[4] While tsunamis are generally classified as a disaster sub-type among the disaster type earthquake (EM-DAT, 2019), their perception differs drastically. Tsunamis potentially have a range of other destructive impacts on the economy. While, Loayza et al. (2012) do not find any impact of earthquakes on the agricultural sector, it is easy to assume a influence which a tsunami wave could have on crops. It is, after all, not the geologic formation of a natural disaster that determines its impact on an economy but rather its force of destruction. Essential here is the way disasters affect economies not their geologic root.

and Mocetti's (2014) findings adumbrate that the earthquake intensifies the predominant situation of institutional quality before the earthquake.

In summary, these analyses in high-income countries suggest a negative impact on the GDP per capita development over a short post-earthquake period. The impact seems ambiguous in the long run; however, both studies suggest that the impact is persistent and intensifies over time. The yet presented studies discuss the effects on GDP per capita for earthquakes, which rank 27th, 32^{ond}, and 61st among the deadliest earthquakes recorded since 1970. On the same list, the 2010 earthquake in Haiti ranks second and is the earthquake causing the most fatalities since 1977 (EM-DAT, 2019). The remainder of this subsection presents studies on this earthquake. The latter is the study by Best and Burke (2019), which is replicated in this thesis.

Using OLS regression Cavallo, Powell and Becerra (2010) evaluate the direct economic damage by the 2010 earthquake in Haiti. They employ historical data on natural disasters and the corresponding estimations of damage. The underlying data set included around 2,000 disasters from 1971 to 2008, of which Cavallo, Powell and Becerra (2010) excluded 250 minimal events. Under the assumption that 250,000 fatalities are recorded due to the earthquake, they estimate damage worth 8.1 billion US dollars (2009, all data converted via US CPI). However, the 90 percent confidence interval reaches from 4.6 to 13.9 billion to US dollars, which is why the authors suspect 8.1 billion US dollars to be a lower-bound estimate.

The IMF (2015) estimates an output gap of 5.3 percent in 2010 for the real GDP (level, 2004 = 100). By extrapolating time series data on the previous GDP growth rate of approximately 2 percent, the IMF (2015) documents a return to the counterfactual's real GDP in 2014.

Best and Burke (2019) analyze the macroeconomic consequences of the 2010 earthquake in Haiti using the synthetic control method. They, more precisely, ask for the quantifiable losses Haiti suffered from this event. Therefore, they use panel data to create a unique synthetic control from a preselected donor pool for each outcome variable.

Best and Burke (2019) find an annual average loss in GDP of 12 percent for six post-disaster years using WDI data. The total loss in GDP over that period sums to approximately 6 billion US dollars (constant 2010). The donating countries are Togo (73%), Cameroon (19.9%), Moldova (5.5%) and Liberia (1.6%). The UN data analysis supports the general result as it shows an average loss of 10 percent for the five post-disaster years. The GDP per capita analysis from WDI data suggests a 7 percent deficit in 2010 and, on average, a 6 percent deficit for six-post disaster years. When accounting for population loss due to the earthquake, this result matches the previously mentioned GDP results. Countries donating to the counterfactual in the GDP per capita analysis are Burundi (45.1%), Cameroon (27.7%), Senegal (16.8%), Liberia (4.9%), Nicaragua (3.7%), and Nepal (1.9%). In total, the authors construct synthetic control analyses for 23 different variables. They also check the robustness of the GDP per capita results. A longer pre-disaster period starting in 1998 with an adjusted donor pool results in an 8 percent loss in GDP per capita in 2010 and, on average, 9 percent for each consecutive year until 2015. The authors perform another test with UN data and a donor pool underlying more restrictions to represent Haiti in further dimensions. The five countries left in the donor pool (Benin, Comoros, Lesotho, Nepal, and Togo) already contributed above-average to synthetic controls in the study's previous analyses. This calculation shows a 9 percent loss in 2010 and, on average, a 7 percent loss in GDP per capita until 2014.

Best and Burke (2019) assume that their results indicate a permanent effect on Haiti’s GDP, although it is mentioned that it is too early to draw a clear conclusion. They indicate that “[p]ermanent impacts of natural disasters, such as the earthquake in Haiti, can contribute to explanations of lower levels of economic development in more disaster-prone countries” (Best and Burke, 2019, p. 1670).

The authors, naturally, have to base their analyses on a particular set of assumptions (for example, which countries to exclude from their donor pool or how many pre-disaster years are appropriately included). These choices are essential to create the unobserved counterfactual and compare it to the outcome variable's actual values. However, such assumptions remain debatable. This thesis aims to understand how sensitive Best and Burke’s (2019) main results are towards changes within this set of assumptions. The original study, therefore, is presented in more detail throughout the following chapters.

4 HAITI CRISIS

Empirical analyses, for example, by Barone and Mocetti (2014), have shown that the economic consequences of disasters are inseparable from the economy in which a disaster occurs. Different, measurable and immeasurable factors determine how an economy reacts and recovers from a disaster. History, culture, and societal behavior are among the hardly measurable factors influencing the economy's recovery and post-disaster growth performance. A nation's pre-disaster economy, income level, political system, and institutional quality are among the factors that are quantifiable and have received detailed attention in economic literature. Kahn (2005), for example, finds that democratic nations and nations with high institutional quality suffer fewer fatalities following a natural disaster. Noy (2009) furthermore concludes that "[…] countries with higher literacy rates, better institutions, higher per capita incomes, larger governments and [a] higher degree of openness to trade appear to be better able to withstand the initial disaster shock […]" (p.229). The study also finds fewer spillovers to GDP growth rates for nations with less-open capital accounts, higher foreign exchange reserves, and a higher domestic credit level.

Every country is unique within these categorize and Haiti is no exclusion. Therefore, this section briefly expresses the existing institutional environment before the earthquake, touches on Haiti's disaster history, and describes the earthquake's destructive power.

4.1 Institutional Environment

Located on the northeast Caribbean island of Hispanola, the Republic of Haiti shares a land border with the Dominican Republic. In 2009 Haiti's population counted nearly 9.8 million people (World Bank, 2020b). Approximately 3 million people live in Haiti's capital, Port-au-Prince, or the metropolitan area surrounding it (DesRoches, et al., 2011). Figure 1 displays the development of the total population from 1995 to 2018. It shows continuous population growth. In 2009 the population was 126.5 percent the size it was in 1995. The annual population growth declined from approximately 1.8 percent in 1996 to approximately 1.5 percent in 2009 (World Bank, 2020b).

As the first Caribbean state and black nation worldwide, Haiti became independent in 1804 (CountryWatch, Inc., 2019). Once among the wealthiest French colonies, Haiti underwent many political and economic setbacks, such as dictatorial regimes and high indebtedness. After the end of Haiti's latest despotism in 2004, an UN-mandated

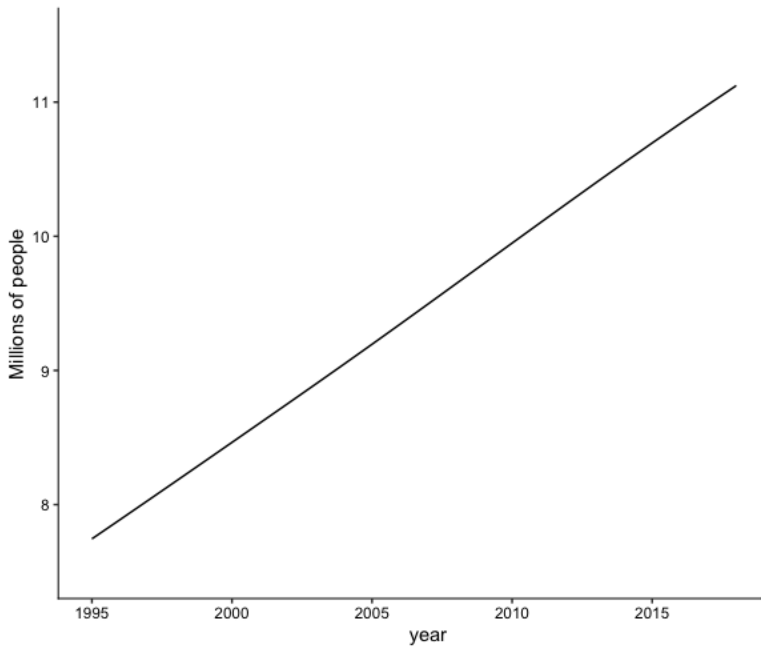

Figure 1 Haiti's total population in millions
Total population from 1995 to 2018 in millions (World Bank, 2020b).

mission supported the nation's functioning, which led to some improvement in Haiti's stability (CountryWatch, Inc., 2019).

Haiti also experienced an economic recession in 2004, but according to the IMF (2008), it started recovering already in 2005. Estimations by the IMF (2008) further suggested that in 2007 real GDP growth approximated to 4 percent, and the fiscal deficit was about as large as the GDP. The gross foreign exchange reserves grew substantially (by 2,100 percent) from 2004 to 2007. The economic recovery included a decline in the inflation rate. It decreased from 28.7 percent in 2003 (previously estimated as 38.3 percent (World Bank, 2016)) to 6.7 percent in 2007 and 0.4 percent in 2009 (World Bank, 2020b). These numbers are snapshots of an overall volatile inflation rate, indicating a lack of prize stability in Haiti. Foreign trade is another crucial factor for economic growth. Simoes and Hildalgo (2011) report that in 2009 textiles accounted for 90 percent of the 642 million US dollar exports. 87 percent of Haiti's overall exports went to the United States. According to Simoes and Hildalgo (2011), the 2.97 billion US dollars imports were mainly spent on textiles, vegetable products, machines, and food (all with more than ten percent share of the overall sum). The Dominican Republic (29 %) and the United States (26 %) were the main countries of origin for imports in 2009. On the third rank was China, with 7 percent (Simoes and Hildalgo, 2011).

The UNDP (2010) identifies Haiti as one of the poorest countries in the world. Among the countries of Latin America and the Caribbean, it, with 57 percent, had the highest share of people affected by multidimensional poverty in 2009. One year later, Haiti ranked 145th in the HDI (Human Development Index) ranking. In the same year, 83 percent of its inhabitants did not have access to improved sanitation services. Further, only 39.2 percent of the population had access to electricity in 2008 (UNDP, 2010). Access to health care was overall limited, and nutritional needs were hardly met. Moreover, in 2003 nearly 40 percent of the population ten years or older were illiterate (IMF, 2008).

4.2 Earthquake on January 12, 2010

The earthquake hit Haiti with magnitude 7 on the Richter scale on January 12, 2010 (at 4:53 pm local time). The epicenter was located approximately 25 km south-west of Port-au-Prince and severely devasted the metropolitan area. The country was not prepared for the quake because it lacked modern seismic tools (DesRoches, et al., 2011). As described in Table 1, 222,570 people lost their lives, total damage worth 8 billion US dollars is estimated, and approximately 3.7 million people were affected. Among the dead people were 17 percent of the central government and 100 UN members (Haitian Evaluation Task Force, 2010). According to DesRoches, et al. (2011), the earthquake forced approximately 1.3 million people to live in temporary shelters in the metropolitan area. More than half a million people left the area. Further, more than 50 health and 1,3000 educational institution buildings were damaged so that they remain unsuitable for use. This also applied to the country's main port and various governmental buildings (180 government buildings and 13 of the 15 government offices) (DesRoches, et al., 2011). Approximately 70 percent of the quantifiable monetary losses are attributed to the private sector, while the remainder belongs to the public sector (Government of the Republic of Haiti, 2010).

During the evaluation of a particular disaster's treatment effect, it is crucial to keep in mind that other disasters that a country experienced simultaneously could distort the effect attributed to the disaster of interest. Only one other major disaster is listed for the years 2009 and 2010 in Table 1. It is the nationwide cholera epidemic that spread in the latter half of 2010 and killed nearly 10,000 people until the last infection was recorded in 2019 (UN News, 2020). There are, however, two arguments why the earthquake and the epidemic should not be considered independent events. First, studies found that the cholera epidemic's pathogen in Haiti was similar to that of a cholera outbreak happening

Table 1 Severest disasters in Haiti between 1990 and 2019
Severest disasters in Haiti by number of people affected, number of fatalities and economic damage. (Adapted from EM-DAT, 2019)

Type	Date	Total affected	Totals deaths	Total damage ('000 US$)
Drought	April 1992	1,000,000	NA	NA
Storm	5. November 1994	1,587,000	1,122	50,000
Storm	20. September 1998	12,029	190	180,000
Flood	20. December 2003	150,000	38	NA
Flood	23. May 2004	31,283	2,665	NA
Storm	17. September 2004	315,594	2,754	50,000
Storm	7. July 2005	15,036	40	50,000
Storm	28. October 2007	108,763	90	NA
Storm	2. September 2008	48,000	529	NA
Earthquake	12. January 2010	3,700,000	222,570	8,000,000
Epidemic	22. October 2010	513,997	6,908	NA
Storm	24. October 2012	201,850	75	254,000
Drought	January 2014	1,000,000	NA	2,000
Epidemic	2015	20,000	170	NA
Drought	January 2016	3,600,000	NA	84,000
Flood	28. February 2016	48,280	5	2,000
Storm	28. September 2016	2,100,439	546	2,000,000

at the same time in Nepal (Orata, Keim and Boucher, 2014). It is acknowledged that UN peacekeepers imported the bacterium from Nepal during their relief efforts in Haiti after the earthquake (UN, 2016). Second, the earthquake is considered a reason for an even less appropriate hygiene situation in Haiti at that time (Sidder, 2016). Low hygiene standards abetted the spread of cholera and promoted life loss in Haiti. Hence, this epidemic might be seen as part of the earthquake's aftermath and does not distort the disaster effect.

In the long-term other disasters might also cause such distortion. However, all other disasters are less devastating in all three dimensions in Table 1. Table 2 adds further information on Haiti’s disaster history and helps understanding the earthquakes dimensions for Haiti. It illustrates the frequency for each disaster type in Haiti from 1900 to 2019. From both Table 1 and Table 2, it is evident that Haiti has a long disaster history of mostly floods and storms. Nevertheless, earthquakes have caused the highest fatality numbers and monetary damage, followed by tropical cyclones and droughts. Table 1 clarifies that nearly all of the damage caused by earthquakes results from the earthquake in 2010. The potential distortion of the earthquake's effect through other disasters consequently can be considered as minor.

Table 2 Disaster frequency in Haiti by disaster type from 1900 to 2019
(EM-DAT, 2019)

Disaster type	Disaster subtype	Events count	Total deaths	Total affected	Total damage ('000 US$)
Drought	Drought	9	NA	6,905,217	87,000
Earthquake	Ground movement	3	222,593	3,739,336	8,020,000
Epidemic	Bacterial disease	5	7,128	545,910	NA
Epidemic	Parasitic disease	1	NA	2,724	NA
Epidemic	Viral disease	2	40	39,543	NA
Flood	--	27	879	277,327	959
Flood	Coastal flood	1	NA	4,690	NA
Flood	Flash flood	6	82	100,717	1,000
Flood	Riverine flood	26	3,093	547,910	2,000
Landslide	Landslide	2	262	1,060	NA
Storm	--	3	66	270	NA
Storm	Convective storm	1	6	73,122	NA
Storm	Tropical cyclone	40	15,814	7,120,120	3,286,906

5 EMPIRICAL APPROACH

This thesis aims to replicate Best and Burke's (2019) findings and to identify how sensitive the synthetic control method-based results are to changes in the statistical software, data revision, sample choice, and time period. This section, therefore, starts with a presentation of the synthetic control method. Finally, it discusses the replication steps performed.

5.1 Synthetic Control Method

The synthetic control method is an approach among the difference-in-difference estimations and first introduced by Abadie and Gardeazabal (2003). The method, hence, bases foremost on the assumptions underlying all difference-in-difference approaches. Based on these, the synthetic control method suggests an approach to estimate a counterfactual for large aggregate units.

5.1.1 Background

Difference-in-difference approaches typically answer research questions with a, to some extent, time-critical treatment effect. They identify "[...] the difference of the mean outcomes of treated and controls after the treatment and subtract the outcome difference that had been there already before the treatment had any effect (conditional on a given value of further observable variables)" (Lechner, 2010, p. 176). Hence, the non-treated group serves as a control to estimate the treated group's potential outcome if the treatment had never happened.

Six identifying assumptions underly difference-in-difference approaches which should not be violated to obtain reliable results. The observation rule (or Stable Unit Treatment Value Assumption (SUTVA, Robin (1977) as cited in Lechner (2010), p.176)) and the assumption of exogeneity apply to all standard econometric causality estimation approaches. The first assumption refers to the impact a treatment outcome has on the untreated group and is violated whenever spillover effects or treatment externalities exist. In other words, the treatment may never influence the untreated control in any way. The second assumption presumes that the treatment does not influence other observable variables. It can be relaxed to the condition of there being no potential outcome effects for any influence the treatment has on these variables. The third assumption is, according to Lechner (2010), difference-in-difference specific. It premises that the treatment does not affect the pre-treatment population before the treatment. Hence, it also forbids that the treated group, given the presumption of a forthcoming treatment, changes its behavior in a way that it affects the group-specific pre-treatment outcome. Lechner (2010) next explains the common trend assumption. It assumes that if neither the treated nor the control group had been exposed to the treatment, their outcome would have followed the same trend, conditional on other observable variables. This assumption makes it possible to associated any difference in the outcome between the treated and control group once the treatment occurred to the treatment. Consequently, if any treatment effect different from zero occurs before the treatment, the estimator is biased. In this case, the fifth assumption, the constant bias assumption, is essential. It indicates that if (and only if) the observed bias is constant over time, it serves as a corrector for the treatment effect estimate after the treatment. Finally, the common support assumption requires that all subgroups, whether treated or not, have sufficient overlap in their characteristics (Lechner, 2010).

Compared to other difference-in-difference estimation methods, the synthetic control method is incredibly valuable in studies which "[...] aim to estimate the effects of aggregate interventions, that is, interventions that are implemented at an aggregate level affecting a small number of large units (such as [...] cities, regions, or countries), on some aggregate outcome of interest" (Abadie, 2020, p. 3). This suitability prevails because, in the synthetic control approach, the combination of more than one control unit is used. Whenever no adequate control for the difference-in-difference treatment estimation exists, this method computes one. A synthetic control unit is calculated as the weighted average of a set of controls. The weighted average might improve the estimation results because a combination of several potential control units' outcome variables typically reflects the treated unit's outcome variable better than the outcome variable of a single control unit (Abadie, Diamond and Hainmueller, 2010).

A systematic and data-driven approach to derive this weighted average, as suggested in the synthetic control method, eliminates a series of doubts generally associated with comparative case studies. Abadie (2020) asserts that comparative case studies, in general, compare a treated unit to an untreated unit, which shows similarities to the treated unit. Furthermore, common factors drive the outcome variables of both treated and untreated. Abadie, Diamond and Hainmueller (2010) explain that in non-data-driven comparative case studies, the chosen control group and its ability to replicate the unobservable state in which the treatment would not have happened to the treated unit is questioned due to highly subjective selection criteria. Using observed quantifiable characteristics enables researchers to reason their choice of control units and their ability to reproduce data mathematically. When applied with a minimum distance approach restricting the weights to be non-negative and sum up to one[5], the synthetic control method protects the findings from extrapolation issues (Abadie, Diamond and Hainmueller, 2010, 2015).

Abadie, Diamond and Hainmueller (2015) also highlight that unlike regression analysis approaches, the synthetic control method concedes quantitative and qualitative comparisons of the treated unit and its counterfactual. They further claim that it might be advantageous for comparisons to distinguish which untreated unit contributes to the counterfactual.

This subsection's remainder illustrates the underlying model, computational implementation, and inference testing approach of the synthetic control method. This presentation is such that it resembles the approach used by Best and Burke (2019). The methods specification will remain unchanged throughout the replication analysis. Therefore, more recent recommendations to adjust the method, such as bias corrections or regression-based methods (see Abadie, 2020), are not considered. Thanks to the availability of the full data set and code from Best and Burke (2019), a (pure) technical replication of the synthetic controls using Stata, the statistical software applied in the original study, works well. If not indicated otherwise, the remainder of this section follows Abadie, Diamond and Hainmueller (2010, pp. 5-13) closely in their theoretical display of the synthetic control method.

5.1.2 Model

The following model motivates using the synthetic control method in comparative case study research, as described by Abadie, Diamond and Hainmueller (2010). Haiti is the treated country within this thesis. Abadie, Diamond and Hainmueller's (2010) model aims to construct an untreated counterpart, a synthetic Haiti, to estimate the treatment effect. The synthetic control is a weighted average of untreated countries, the so-called donor pool. On these grounds, suppose there are $J + 1$ countries observed. Further, suppose that only the first country is exposed to the treatment, and J countries do not experience treatment. They remain as the donor countries. Assume that the first country (the treated country) is uninterruptedly exposed to the treatment after some initial

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[5] Abadie, Diamond and Hainmueller (2010) use these requierements to derive the weights for the control units. The restrictions are 'non-negativity', 'adding-up' and 'no-intercept'. This is chosen so that there is a unique solution for the set of weights with a decent number of outcomes compared to control units available (Doudchenko and Imbens, 2016).

treatment period. The initial treatment, in this scenario, is the earthquake. When a country is exposed to a natural disaster, uninterrupted exposure to the treatment includes the natural disaster and its aftermath. This assumption indicates that the treatment effect in this specific case is allowed to vary over time.

To begin with, T_0 refers to the number of pre-disaster periods, with $1 \leq T_0 < T$. $T_1 = T - T_0$ represents the number of post-disaster periods. Y_{it}^N is the outcome that would be observed for country i at time t in the absence of the natural disaster, for countries $i = 1, \ldots, J + 1$, and time periods $t = 1, \ldots, T$. In this case Y_{1t}^N refers to the GDP, respectively, the GDP per capita observed for Haiti at time t if the earthquake in 2010 would never have happened. Y_{it}^I is the observed outcome for country i at time t if country i is exposed to the disaster in periods $T_0 + 1$ to T. In this case Y_{1t}^I refers to the outcome variable observed for Haiti in 2010 and later. The natural disaster does not affect the outcome before the treatment period, so for $t \in \{1, \ldots, T_0\}$ and all $i \in \{1, \ldots, N\}$, $Y_{it}^I = Y_{it}^N$.

Let $\alpha_{it} = Y_{it}^I - Y_{it}^N$ be the treatment effect of the disaster for country i at time t, in case country i experiences treatment in $T_0 + 1, T_0 + 2, \ldots, T$. It is the purpose of this method to estimate the parameters $\left(\alpha_{1T_0+1}, \ldots, \alpha_{1T}\right)$ which represent the causal effect of a natural disaster. For all $t > T_0$ these parameters are estimated by $\alpha_{1t} = Y_{1t}^I - Y_{1t}^N$. Y_{1t}^I is observed. Consequently, Y_{1t}^N needs to be estimated to calculate α_{1t}. Y_{it}^N is described by a linear factor model: (1)

$$Y_{it}^N = \delta_t + \theta_t Z_i + \lambda_t \mu_i + \varepsilon_{it}.$$

Abadie, Diamond and Hainmueller (2010) define δ_t as an unknown common factor with constant factor loading across countries, θ_t as a $(r \times 1)$ vector of unknown parameters, and Z_i as a $(r \times 1)$ vector of observed but treatment unaffected predictor variables. Further, λ_t is an unknown common factor with varying factor loadings, μ_i is a vector of unobserved predictors, and ε_{it} represents the zero mean and unobserved transitory shocks for all i. The model allows for dependency between Z_i, μ_i, and ε_{it}. Moreover, it permits time variation for the measured determinants of the outcome variable.

Let D_{it} be a disaster indicator. It becomes one if country i is exposed to the disaster at time t, and zero if not. Since only country "one" is exposed to the disaster and only after period T_0, it holds that:

$$D_{it} \begin{cases} 1 & \text{if } i = 1 \text{ and } t > T_0 \\ 0 & \text{otherwise.} \end{cases}$$

It follows that the observed outcome for country i at time t is $Y_{it}^I = Y_{it}^N + \alpha_{it} D_{it}$.

Now consider a $(J \times 1)$ vector of weights $W = (w_2, \ldots, w_{J+1} + 1)'$ with $w_j \geq 0$ for $j = 2, \ldots, J+1$ and $w_2 + \cdots + w_{J+1} = 1$. Each value in vector W represents a particular weighted average of control countries.

In $\bar{Y}_i^K = \sum_{s=1}^{T_0} k_s Y_{is}$ the $(T_0 \times 1)$ vector $K = (k_1, \ldots, k_{T_0})'$ characterizes a linear combination of pre-disaster outcomes. After simplification, $\bar{Y}_i^K = T_0^{-1} - \sum_{s=1}^{T_0} Y_{is}$ represents the pre-treatment simple average of the outcome variable. Suppose now there is a combination of $(w_2^*, \ldots, w_{J+1}^*)'$ for which: (2)

$$\sum_{j=2}^{J+1} w_j^* \bar{Y}_j^K = \bar{Y}_1^K, \text{and} \sum_{j=2}^{J+1} w_j^* Z_j = Z_1$$

holds. The model can be extended in several directions, with one of them being essential for this thesis. It is the inclusion of multiple unobserved factors. Suppose there are M linear combinations of pre-disaster outcomes. $\bar{Y}_i^{K_1}, \ldots, \bar{Y}_i^{K_M}$ then are used for the selection of the synthetic control country. The first part of equation (2) consequently becomes, $\sum_{j=2}^{J+1} w_j^* \bar{Y}_j^{K_1} = \bar{Y}_1^{K_1} \ldots \sum_{j=2}^{J+1} w_j^* \bar{Y}_j^{K_M} = \bar{Y}_1^{K_M}$.

Abadie, Diamond and Hainmueller (2010) solve equation (2) further and suggest using: (3)

$$\hat{\alpha}_{it} = Y_{1t} - \sum_{j=2}^{J+1} w_j^* Y_{jt}$$

for all post-disaster periods $t \in \{T_0 + 1, \ldots, T\}$ as an estimator of α_{1t}.

They mention that in practice, often, no set of weights exists such that equation (2) holds precisely in the data. The selection of synthetic control is then made so that it holds by approximation.

5.1.3 Implementation

This subsection explains how the vector of weights $W = (w_2, \ldots, w_{J+1} + 1)'$ is computed so that it is contributed to the true outcome of equation (3) under the restrictions of equation (2). The outcome variable of interest, here either the GDP or the GDP per capita, is monitored for T periods $(t = 1, \dots, T)$ for the treated country Y_{1t} and the untreated countries $Y_{jt}, (j = 2, \dots, J + 1$. Any weighted average of untreated countries is considered as a potential (synthetic) control. Y_1 is a $(T_1 \times 1)$ vector of post-disaster outcomes for the first country, and Y_0 is a $(T_1 \times J)$ matrix of post-disaster outcomes for the potential donor countries. As defined previously, W is a $(J \times 1)$ vector of positive weights that sum to one. Each particular value of W constitutes a synthetic control as it is the weighted average of the available donor countries.

$X_1 = \left(Z_1', \bar{Y}_1^{K_1}, \dots, \bar{Y}_1^{K_M}\right)'$ is a $(k \times 1)$ vector of pre-disaster characteristics. In other words, a vector of untreated output linear combinations and predictor variables, for the treated country (with $k = r + M$). Similarly, $X_0 = \left(Z_j', \bar{Y}_j^{K_1}, \dots, \bar{Y}_j^{K_M}\right)'$ is a $(k \times J)$ matrix that contains the same types of variables for the untreated countries. The values of vector W^* are chosen so that the distance, $\|X_1 - X_0W\|$, between X_1 and X_0W, is minimized w.r.t. $w_2 \geq 0, \dots w_{J+1} \geq 0$ and $w_2 + \dots + w_{J+1} = 1$. Note that this is mathematically expressed by $\|X_1 - X_0W\|_V = \sqrt{(X_1 - X_0W)'V(X_1 - X_0W)}$. V, further, is a $(k \times k)$ symmetric and positive semidefinite matrix. When optimally chosen, V assigns weights to the linear combination of the variables in X_0 and X_1 and hence minimizes the mean square error of the synthetic control estimator. The choice of V, as in Abadie and Gardeazabal (2003) suggested, can be data-driven. Following the previously named studies, V can be chosen so that the pre-disaster outcome variable of the actual and the synthetic control country match approximately.

5.1.4 Inference

Abadie, Diamond and Hainmueller (2015) explain the difficulties of inference testing for comparative case studies. These difficulties are the absence of randomization and probabilistic sampling for sample unit selection as well as small-sample data. Traditional approaches to statistical test inference fail under such conditions. Due to the systematic approach underlying the synthetic control method, it is, however, possible to provide confidence that the synthetic control fails to reflect the treatment's effect correctly. This is true if untreated placebo cases show an effect of similar or greater magnitudes than the treated case. The authors categorize such placebos cases as either "in-time placebos" or "in-space placebos". The first option assigns the placebo treatment to another point in time for the treated unit. The second option assigns the placebo treatment to another unit (a unit from the donor pool) at the same point in time.

This thesis follows Best and Burke (2019), who choose an "in-space placebo" approach for inference testing. They proceed as Abadie, Diamond and Hainmueller (2010) suggest in the remainder of this paragraph. They determine the difference in the post- to pre-treatment mean square prediction error (MSPE) for the treated unit. Next, they apply the synthetic control method to every potential donor country from the donor pool. In a third step, post- to pre-treatment MSPE ratios are determined for all donor pool synthetic controls. That is to understand if the estimated result for the treated country is relatively large compared to all effects computed for any donor country $i \in \{2, \dots, J+1\}$.

Computing the ratio between both MSPE values normalizes the results. This alternative testing for statistical significance controls the pre-treatment fit of the actual outcome variable and its synthetic control. This fit is assumed to be good (in other words, the actual outcome variable and its synthetic control are close) if the pre-treatment MSPE is small. Controlling for the pre-treatment fit is crucial due to the specific nature of the inferential tests of synthetic control estimates. "The MSPE inferential test is based on the uncertainty that the synthetic control is adequate, rather than uncertainty that a sample is an adequate reflection of an aggregate population" (Best and Burke, 2019, p. 1653). This adequacy can only be assumed with a good pre-treatment fit. Abadie (2020) documents the MSPE as

$$MSPE_i(t_1, t_2) = \frac{1}{t_2 - t_1 + 1} \sum_{t=t_1}^{t_2} (Y_{it} - \hat{Y}_{it}^N)^2,$$

for $0 \leq t_1 \leq t_2 \leq T$ and $i = \{1, \dots, J+1\}$. The size (small or large) of the post-treatment MSPE indicates the size of the treatment's impact on the outcome variable. Hence, controlling for pre-treatment fits verifies that the treatment drives the post-treatment outcomes. Abadie's (2020) post- to pre-treatment MSPE ratio for all individual i equals

$$r_i = \frac{MSPE_i(T_0 + 1, T)}{MSPE_i(1, T_0)}.$$

A high r_i indicates a large treatment effect for any synthetic control, which is close to the actual outcome variable before the treatment. Whenever this ratio remains relatively high compared to all unaffected donor pool countries, which have not been influenced by the treatment, it can be assumed that the treatment causes the divergence of the actual and the synthetic control outcome variable. This is only true under the circumstances that the pre-treatment fit is also good for all donor pool countries (Abadie, 2020).

This procedure can be compared to a permutation test and is a frequently used alternative to standard statistical significance tests in conjunction with the synthetic control method. It assures that inference is constructed exactly although the number of potential control units and the number of available time periods might be small (Abadie, Diamond and Hainmueller, 2010).

Furthermore, this approach does not fall short in providing a *p*-value. It is given as "[...] the fraction of such effects greater than or equal to the effect estimated for the treated unit" (Abadie, Diamond and Hainmueller, 2015, p. 500).

5.2 Replication Steps

Given the aim of this thesis, changes in the assumptions of the synthetic controls are applied to analyze the sensitivity of the analyses results by Best and Burke (2019). The previously presented method and its implications on the predictor variable choices, however, remain unchanged. Adjustments are conducted successively. Subject to changes are the statistical software, the data set (original or revised), the sample (original or new donor pool), and the time period (six or nine post-disaster years)[6].

Pure replication – The (pure) technical replication uses the original data set, the original STATA code, the original donor pool, and the time period from 2004 to 2015. The first modification is a change in the statistical software. The replication is now conducted with the R package Synth. No further changes are made, and the R code copies that of Best and Burke (2019) as precisely as possible under the conditions of a statistical software change. Following Becker and Klößner (2017), one assumes essentially identical results after introducing this modification. All analyses computed hereafter are conducted with R/Synth. Given the results in Becker and Klößner (2017), the predictor weights and, consequently, the donor weights w^* are not optimally chosen in STATA or R/Synth, this choice needs explanation. The main argument for the R package choice is the comparability of the underlying software settings and analysis tools. Abadie, Diamond and Hainmueller (2011) introduced the R/Synth package as the equivalent to the STATA function used by Best and Burke (2019). For their R/MSCMT package, Becker and Klößner (2018) introduce different algorithms to estimate faster and potentially more

[6] Six (or nine) post-disaster years can be examined with data spanning until 2015 (or 2018) because the earthquake happened in early January 2010. It is supposed that all data from 2009 is not affected by the treatment (since the earthquake yet has not happened) while all data from 2010 can be considered as affected by the treatment (only eleven days within the whole year are not affected by the treatment).

reliable outcomes. While the development of (supposedly) better software tools is advantageous, this replication focuses on introducing several smaller adjustments to the original analysis assumptions.

Replication with a revised data set - Keeping the new statistical software, the sample, and the analysis time frame from 2004 to 2015 unchanged, the synthetic control method is applied with a revised data set. Adjustments made during the revision of data potentially lead to changes in findings obtained with the preliminary data set. In this particular case, the revision of data for Haiti and the donor pool countries could change the synthetic controls ability to display a Haiti if the earthquake had not happened. Low data accuracy and a greater vulnerability to shocks suggest that these data revisions are more extensive for low-income countries. "The mean absolute error is more than twice as high as in OECD countries, over-optimism in preliminary growth figures is more severe than in other countries, and extreme revisions occur much more frequently" (Ley and Misch, 2014, p. 3). Economic factors are the main drivers for these revisions, while higher national statistical services' capacity and organizational supervision diminish revisions (Ley and Misch, 2014). Therefore, differences in synthetic control results or their fit are expected after introducing a revised data set. Note that two countries are removed from the original donor pool due to missing data in the revised data set.[7]

Replication with a longer time horizon - Using the revised data set has another advantage in responding to Best and Burke's (2019) presumption on the permanence of the earthquake's macroeconomic impacts. This advantage lies within the longer post-earthquake period. The replication is extended by data from 2001 to 2018, together with the revised data set and the original donor pool for an analysis in R/Synth. The post-treatment period covers nine years (from 2010to 2018). Because Best and Burke (2019) incorporate data from as many pre-treatment years as post-treatment years available to them, this replication expands the pre-treatment period to nine years as well. Consequently, the time frame over which the analysis optimizes lasts from 2001 to 2009. Best and Burke (2019) already introduce a longer pre-treatment time frame as a robustness test to their GDP per capita analysis. It suggests a loss of 8 percent in 2010 and an average loss of 9 percent from 2011 to 2015.

Another reason for including a longer pre-treatment time horizon is that a small number of pre-treatment periods might result in an overfitting bias. Abadie (2020) describes the

[7] A more detailed explanations follows in 6.3.2 Revised Data Set.

source of this type of overfitting and the potentially arising bias. If $X_1 = X_0W^*$ holds, the ratio between the number of pre-treatment periods and the scale of the individual transitory shocks controls the bias of $\hat{\alpha}_{it}$ following the linear factor model from equation (1). Under the same condition, the synthetic control is matched on the observed predictor values in Z_1. Since μ_i is unobserved in this case, matching is not possible. Hence, a synthetic control might be unable to reproduce the values of μ_i correctly. Abadie (2020) explains that in such a case, the synthetic control might still produce close pre-treatment outcomes when the pre-treatment period is short, and the variation of the individual transitory shocks between the synthetic control and the treated unit is large enough. That is because this variation compensates for the variation in unobserved factor loading. Abadie (2020) consequently claims that a sufficiently long pre-treatment period, T_0, and small scale of transitory shocks, ε_{it}, counteract this source of overfitting. He, however, notes that if the approximate fit of $X_1 = X_0W^*$ is bad a long pre-treatment period, T_0 cannot reduce the bias.

Replication with a new donor pool - Another source of bias is a large J, in other words, a donor pool consisting of many potential donor countries. This, first of all, simplifies the pre-treatment outcome fitting. That is true, as explained by Abadie (2020), even if the donor pool's unobserved predictors μ_i and the treated unit's unobserved predictors μ_1 diverge greatly. According to the author, substantial discrepancies between the treated unit's and the control's factor loading do not prevent overfitting. Such an outcome is unfavorable, and the treated country's outcome, if the treatment would not have happened, could be falsely reflected by the synthetic control. Furthermore, "[if] the process that determines Y_{it}^N is non-linear in the attributes of the units, even a close fit by a synthetic control, which is a weighted average, could potentially result in large interpolation biases" (Abadie, 2020, p. 15). Consequently, a donor pool limited to countries considered suitable might prevent overfitting and interpolation bias (Abadie, 2020).

Best and Burke (2019), hence, limit their donor pool with a threshold. It restricts the donor pool to only those countries whose GDP per capita was less than 4,000 intl. dollars PPP (2011 constant) in 2009. The revised data set offers a new donor pool calculated with an identical threshold of less than 4,000 intl. dollars PPP (2011 constant). That means another set of countries fits into this threshold and hence suggests a *replication with a new donor pool*. This idea follows the previously highlighted finding by Ley and Misch (2014) that revisions of low-income countries' national account data are likely.

With a donor pool by definition containing low-income countries, data revision potentially leads to changes in the donor pool data. The introduction of this new donor pool to the synthetic control analysis equals an alteration of the used sample. The replication utilizes the revised data set and the original time frame (2004 to 2015) to observe this alteration's impact best possible.

Replication with the new donor pool and a longer time horizon - Finally, the latterly described replication is extended by a longer time period. This replication, consequently, builds a synthetic control for Haiti using the revised data set, a new sample (the new donor pool), and a longer time period (2001 to 2018) in another statistical software (R/Synth). All modifications which are subject to this thesis are included at the same time.

6 DATA SOURCES AND DESCRIPTIVE STATISTICS

The choice of data sources and variables in this replication follows Best and Burke (2019). This section, therefore, also aims to either present the adopted choices or to highlight modifications. It starts with the data source, defines the variables, and then presents the descriptive statistics.

6.1 Data Source

Two data sets, both panel data, form the data basis of this replication. Both contain economic data and are collected initially from the World Bank. Although the same variables are used from both data sets, the data sets differ due to their source and initial purpose. While the first data set is already used in the original study by Best and Burke (2019), the second data set is collected for this thesis.

The first is collected through Best and Burke (2019) and comprises a time period from 1996 to 2015. It is referred to as the original data set throughout this thesis and one of four data sets the authors made available in the online appendix. All four data sets are pre-arranged and comprehend data from various sources. For their, in total 23 different synthetic control analyses, Best and Burke (2019) use data from the WDI, the UN, the IEA, and the IMF. This multi-data source usage creates a deliberately doubling of variables. Thereby, the authors aim to reduce the impact of measurement errors caused by potential shortcomings of low-income countries' data quality. A list of all data collected and its source can be found in Table 7 in Appendix 1. This replication solely aims to replicate the GDP and GDP per capita analyses. Although Best and Burke (2019) integrate the UN data to reassure their GDP analysis' result, this replication is constrained to the analysis using the world development indicator data. The data set relevant for this is named "section 1" in the online appendix. It comprehends 4,574 observations in 28 variables for in total of 275 countries and country groups. That are more variables available than needed for the replication. This WDI data set was accessed on 26 September 2016. (The data set is retrieved from World Bank, 2016, as cited in Best and Burke, 2019).

The second data set, accessed on 19 April 2020, contains world development indicators and includes a period from 1995 to 2019 (World Bank, 2020b). It is referred to as the revised data set throughout this thesis. It comprehends 2,381 observations in 9 variables for 267 countries and country groups. After eliminating entries of grouped countries and double entries, both data sets are left with 217 countries.

6.2 Variable Definition

The variable choice is identical to that made by Best and Burke (2019). All variables are collected as annual observations. The gross domestic product (GDP), the first outcome variable, is given in billions of constant 2010 US dollars. The gross domestic product per capita (GDP per capita), the second outcome variable, is given in 2011 international dollars converted using purchasing power parity (PPP). Seven predictor variables are part of the analysis. Consumption refers to the final consumption expenditures as a percentage of GDP. Exports and imports are the exports respectively imports of goods and services as percentages of GDP. Investments refer to gross capital formation as a percentage of GDP. Inflation is measured by the consumer price index. It is given as an annual percentage change. The land area is measured in square kilometers and the population is given as the total number.

The X_i $(r \times 1)$ vectors of predictor variables and pre-treatment outcome values for the synthetic control of the GDP and the GDP per capita are consequently constructed in the same manner as those by Best and Burke (2019). X_i for the synthetic control of the GDP include consumption, exports, imports, investments, inflation, land area, population, GDP per capita, and the GDP from 2005, 2007, and 2009. X_i for the synthetic control of the GDP per capita are consumption, exports, imports, investments, inflation, land area, population, and GDP per capita from 2005, 2007, and 2009. Abadie (2020) notes that the way pre-treatment outcome variables are included in the vectors depends on the researcher's choice, given that the pre-treatment fit is good. Considering the linear factor model (1) their inclusion is essential to reproduce unobserved factor loadings in μ_J.

6.3 Descriptive Statistics

This section introduces an overview of the values for the outcome and predictor variables. 2009 marks the last year before the earthquake potentially influences the national accounts data. Therefore, 2009 is a suitable year to compare Haiti's specific values to a donor pool countries' average and the world average in an overview. The original data set from 2016 is introduced first and followed by the revised data set from 2020.

6.3.1 Original Data Set

Best and Burke (2019) introduce a preselected donor pool within the original data set, hereafter referred to as the original donor pool. They "[...] restrict the donor pool to countries with GDP per capita PPP (in constant 2011 international dollars) of less than

$4000 in 2009" (Best and Burke, 2019, p. 1652). The preselection of a donor pool from a data set like this can be understood as a sample selection.

The comparison of Haiti's data and the world average helps to understand the case-specific necessity of restricting the donor pool. Figure 2 displays Haiti's GDP and the world's average GDP from 2004 to 2015. Figure 3 presents the same, respectively, for the GDP per capita. Both figures illustrate that the world's average is considerably higher for both outcome variables than Haiti's values. In both figures, the gap between Haiti and the world average is distinct so that all fluctuations in Haiti's GDP or GDP per capita vanish due to the large y-axis scale needed to display the world values. A more detailed impression of the movement of Haiti's values is later on presented in Figures 4 and 5. Figure 2 and 3, however, also present the mean average values of the outcome variable of the donor pool, which was constructed by Best and Burke (2019). Although the gap between Haiti and the donor pool grows over time, the donor pool average is closer to Haiti than the world average. This is intuitive for Figure 3 since the donor pool threshold is essentially set so that no country has a GDP per capita higher than 3999.99 intl. dollars PPP (constant 2011).

Columns 1 to 3 in Table 3 display the descriptive statistics of the original data set. The table splits into Haiti, a donor pool average, and a world average (including Haiti and the

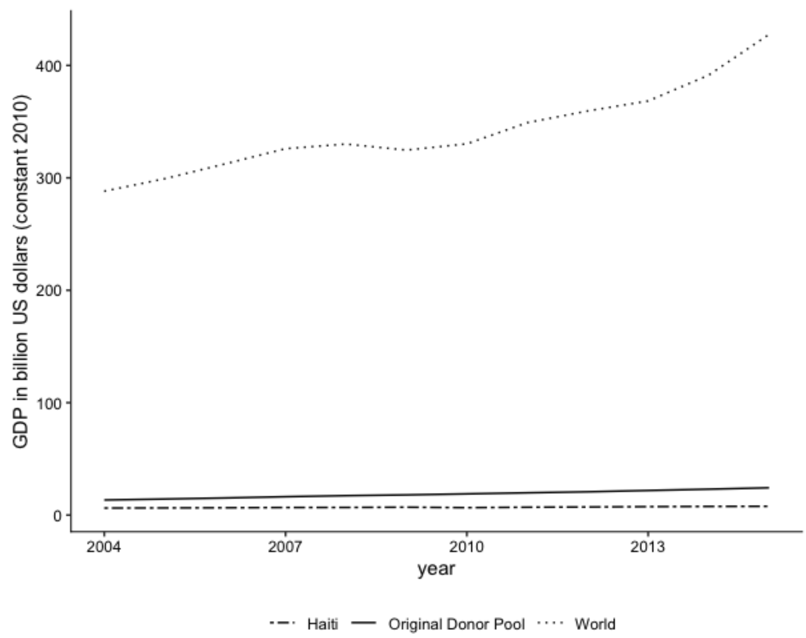

Figure 2 GDP comparison from 2004 to 2015
GDP values from Haiti and mean GDP values for the original donor pool and the world average taken from the original data set (World Bank, 2016). The world average values include Haiti and the original donor pool. All values in billion US dollars (constant 2010).

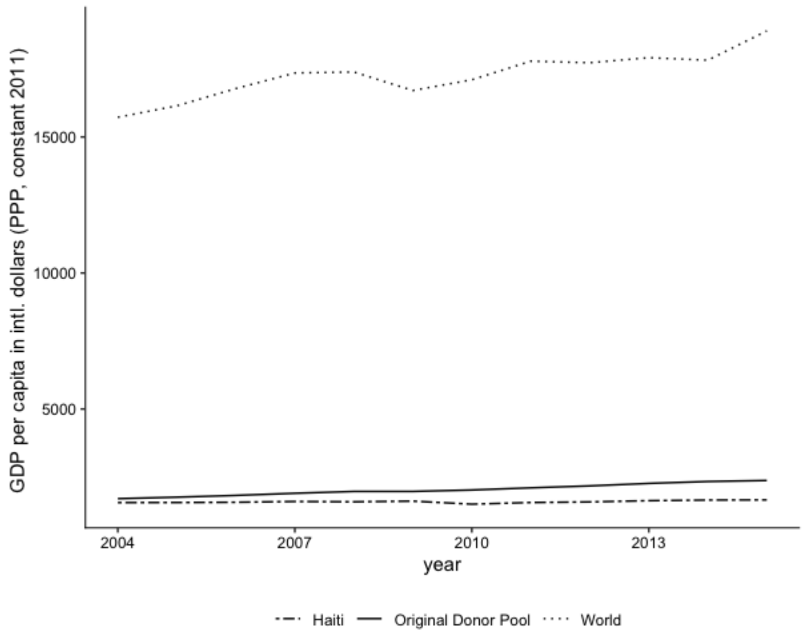

Figure 3 GDP per capita comparison from 2004 to 2015
GDP per capita values from Haiti and mean GDP per capita values for the original donor pool and the world average taken from the original data set (World Bank, 2016). The world average values include Haiti and the original donor pool. All values PPP in intl. dollars (constant 2011).

donor pool countries). All values refer to the year 2009. Comparing the predictor values of the world average and Haiti intensifies the impression that the world data does not constitute an adequate donor pool for Haiti, as required by Abadie (2020). In 2009 Haiti consumed 99.4 percent of its GDP. The world's average consumption to GDP ratio is 82.9 percent. Haiti exports less than the world's average, yet, the value still lies within the standard deviation. Imports and investments, both as a percentage of GDP, are values for which Haiti performs relatively close to the World's average. Haiti's annual inflation, however, appears to be slightly negative in 2009, while the world experienced an annual inflation average of 4.22 percent with a high standard deviation. As mentioned before, Haiti's inflation rate is volatile, and 2009 marks an extraordinary low. The annual inflation rate is displayed in Figure 6 and further discussed in the following subsection. The non-economic predictor variables, land area, and population display Haiti as a comparably small country in size and population.

This shows that in a rather extreme case, such as Haiti, a preselected donor pool is helpful. The synthetic control method suggests that donating countries are chosen depending on their ability to contribute to the pre-treatment synthetic outcome variable to match the actual outcome variable best. The weighted contribution of each country is also determined by the fit of the predictor variables. Geographic variables, such as the land area, are not directly linked to a country's GDP. While landmass contributes to a

Table 3 Descriptive statistics of the original data set and the revised data set
Descriptive statistics comparing Haiti, the donor pool(s) and the world from both data sets (World Bank, 2016; World Bank, 2020b). All values display the year 2009.

	Original Data Set			Revised Data Set			
	Haiti (N=1)	**Original Donor Pool (N=22)**	**World (N=217)**	**Haiti (N=1)**	**Original Donor Pool (N=20)**	**New Donor Pool (N=39)**	**World (N=217)**
GDP billion (constant 2010 US$)							
Mean (SD)	7.01	18.0 (24.9)	325 (1250)	6.86	16.6 (23.8)	13.4 (19.1)	311 (1230)
Min, Max		1.22, 109	0.0327, 14600		1.88, 109	0.638, 109	0.0327, 14600
GDP per capita, PPP (constant 2011 intl.$)							
Mean (SD)	1613	1970 (898)	16700 (19000)	1582	2090 (934)	2150 (940)	17700 (19600)
Min, Max		681, 3950	575, 118000		721, 4420	637, 3950	637, 113000
Consumption (%)							
Mean (SD)	99.4	96.8 (21.5)	82.9 (20.4)	99.4	94.5 (18.1)	95.4 (17.5)	81.6 (19.0)
Exports (%)							
Mean (SD)	15.7	24.1 (12.8)	40.0 (26.9)	15.7	22.8 (12.6)	24.0 (12.9)	40.7 (31.4)
Imports (%)							
Mean (SD)	42.6	43.7 (27.9)	47.0 (25.5)	42.6	41.2 (20.3)	42.3 (21.0)	47.7 (29.0)
Investment (%)							
Mean (SD)	27.5	22.7 (5.29)	23.6 (9.12)	27.5	23.4 (6.10)	23.0 (7.84)	23.8 (8.45)

	Original Data Set			Revised Data Set			
	Haiti (N=1)	**Original Donor Pool (N=22)**	**World (N=217)**	**Haiti (N=1)**	**Original Donor Pool (N=20)**	**New Donor Pool (N=39)**	**World (N=217)**
Land Area (sq.km)							
Mean (SD)	27560	397000 (546000)	600000 (1760000)	27560	279000 (317000)	369000 (482000)	592000 (1760000)
Min, Max		24700, 2380000	2.00, 16400000		24700, 1220000	1860, 2270000	2.00, 16400000
Population (thousand)							
Mean (SD)	9852	23000 (30800)	31400 (127000)	9798	22100 (31400)	17000 (25600)	31400 (127000)
Min, Max		3570, 150000	9.8, 1330000		2860, 146000	230, 146000	9.9, 1330000
Inflation (annual %)							
Mean (SD)	-.02	6.07 (4.55)	4.22 (5.12)	0.39	5.99 (4.67)	5.70 (4.44)	4.21 (5.07)

country's production, some small countries are high-income countries, while some are low-income countries (World Bank, 2016). Belgium, for example, with its 30,280 sq.km and roughly 10.7 million inhabitants in 2009, is just slightly bigger than Haiti in terms of size and population. Belgium, however, had a GDP per capita of 39,993 intl. dollars (PPP, constant 2011) in the same year. When computing synthetic Haiti, a solely data-driven approach with the world as a donor pool would potentially choose Belgium to contribute as a donating country, although this contribution is likely to distort the pre-treatment fit. Therefore, a restriction to low-income countries, as Best and Burke (2019) perform, improves the fit. More precisely, this is why they established the threshold of less than 4,000 intl. dollars PPP (2011 constant). While their approach in the first step is not data-driven, the restrictions are suggested by data. In addition, all countries whose GDP per capita is more than 15 percentage points different from Haiti in either the pre- or post-disaster period are removed from the original donor pool by Best and Burke (2019). Another step of restriction is that if a nation's State Fragility Index[8] rises more than four points per year, the country is removed from the donor pool.

Best and Burke's (2019) restrictions result in a donor pool sample consisting of 22 countries: Bangladesh, Benin, Burkina Faso, Burundi, Cambodia, Cameroon, Kenya, Kyrgyz Republic, Liberia, Madagascar, Mali, Moldova, Mozambique, Nepal, Nicaragua, Rwanda, Senegal, Sierra Leone, Sudan, Tanzania, Togo, and Uganda. The authors get to this list after also excluding those countries that would create an unbalanced panel. This is in line with the assumption of a balanced panel, as suggested by Abadie, Diamond and Hainmueller (2015). Best and Burke (2019) further assume no earthquake spillover effects to any country in the donor pool, neither by trade relations nor for geographical reasons. They, however, cannot control if there was another shock to Haiti or the donor pool countries after the earthquake that potentially distorts the results.

Table 3 shows that the donor pool's average values for consumption, exports, and imports are relatively close to Haiti's. Haiti's investment percentage of GDP is higher than that of the average donor pool country. However, it still lies within the standard deviation. This is not the case for the annual inflation rate. The donor pool countries seem to have an on average 6.05 percentage points higher inflation rate than Haiti. The absolute numbers of land area and population suggest that Haiti is among the smallest

[8] The State Fragility Index in use is from Marshall and Cole (2014).

low-income countries. It is approximately 2,800 sq. km larger than the smallest country in the donor pool and has a population of less than half the donor pool's average.

6.3.2 Revised Data Set

The second data set referred to as the revised data set, contains the same outcome and predictor variables, however, it was accessed roughly three and a half years later. This, on the one hand, gives access to a longer post-treatment period. On the other hand, the previously available data might have been revised. This is the consequence of a tradeoff between prompt publications of relevant economic aggregates and information availability. While their availability is necessary for the fiscal and monetary decision-making processes, traditionally, not all relevant components of national account data, such as the GDP, are available in time. Once more and better information is available, the previously published values are revised.

Data accuracy, hence, is a limitation to both data sets. To better comprehend statistics' qualities worldwide, the World Bank (2020a) provides a statistical capacity score for 150 countries. Haiti ranked 140 in 2016 and 130 in 2019. The Kyrgyz Republic, a donor pool country, in contrast, ranked first in 2019.

Figure 4 suggests that Haiti's GDP data indeed has been revised between 2016 and 2020. Graphically it stands out that the GDP values from the pre-earthquake period, here from 1998 to 2009, are revised. The differences of both data sets' values range from 0.154 to 0.172 billion US dollars (constant 2010) in 2004, respectively 2009. The revision of the post-earthquake values is comparably small.

The comparison of the GDP per capita and revised GDP per capita data presents a similar picture. Figure 5 indicates that the GDP per capita was overestimated in the World Bank (2016) data set from 1998 to 2009 and slightly underestimated from 2010 to 2014. Revision suggested a deduction of 30.7 intl. dollars (PPP, constant 2011) for 2009, which is roughly 2 percent of the previously assumed GDP per capita for the same year.

Another variable that displays changes in the revised data set is the inflation rate. Haiti's inflation rate is, as previously described, a volatile economic indicator. Compared to the outcome variables' revisions, the inflation rate revision is less stable. In other words, the gaps between the annual inflation rate reported in the original data set and the revised data set are changing yearly, as Figure 6 shows. This stands out compared to the revisions of the GDP and GDP per capita, for whom the difference due to revision appears unchanged over longer periods.

Since especially low-income countries experience extreme data revision (Ley and Misch, 2014), the donor pool data has to be revisited. The synthetic control method demands a

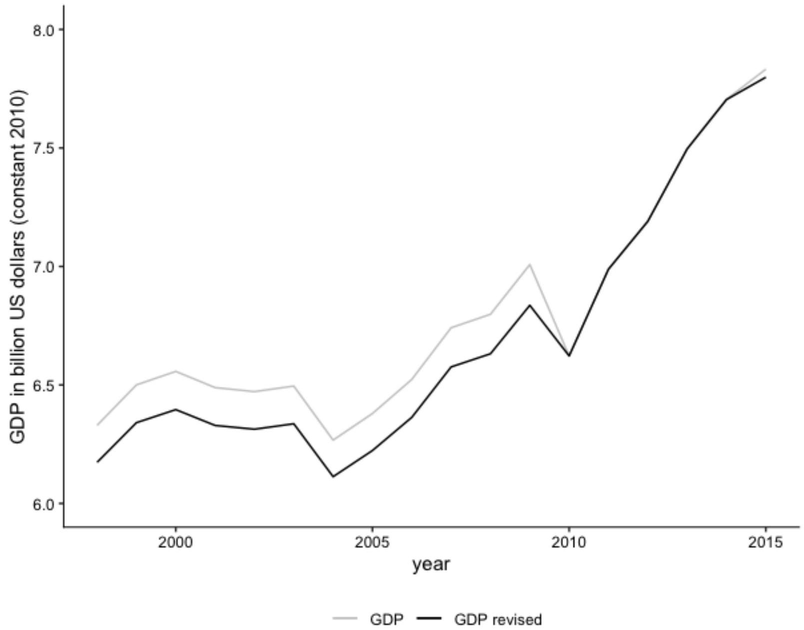

Figure 4 Haiti's GDP in the original data set and the revised data set
The GDP values from 1998 to 2015 as published by the World Bank (2016). The revised GDP values from 1998 to 2015 as published by the World Bank (2020b). All values in billion US dollars (constant 2010).

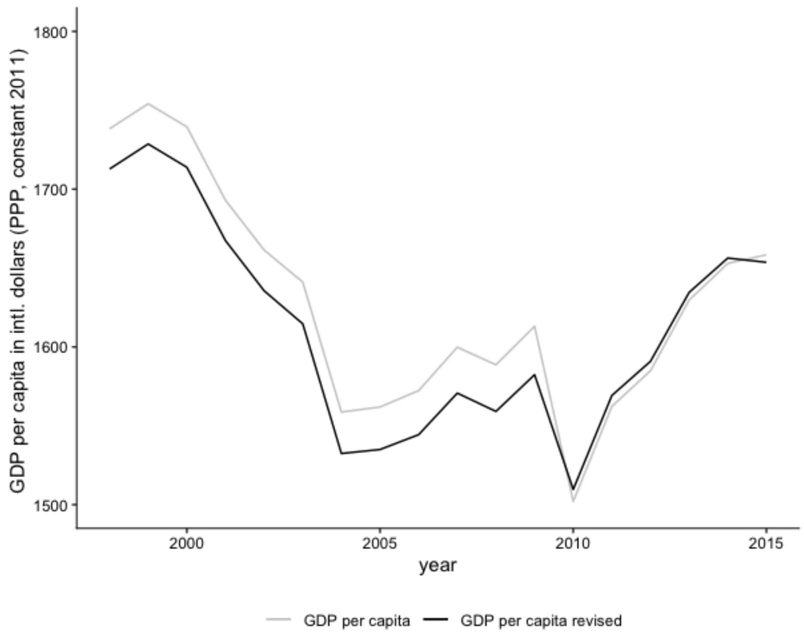

Figure 5 Haiti's GDP per capita in the original data set and the revised data set
The GDP per capita values from 1998 to 2015 as published by the World Bank (2016). The revised GDP per capita from 1998 to 2015 as published by the World Bank (2020b). All values PPP in international dollars (constant 2011).

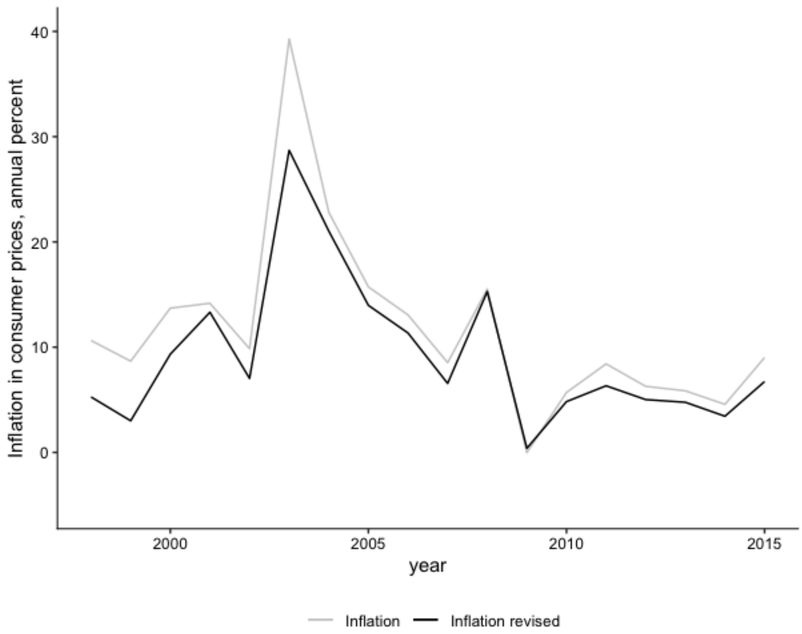

Figure 6 Haiti's inflation in the original data set and the revised data set
The annual inflation percentages from 1998 to 2015 as published by the World Bank (2016). The revised inflation data from 1998 to 2015 as published by the World Bank (2020b). Measure by consumer price index in annual percentage change.

balanced panel with at least one pre-treatment observation for each prediction variable per donor country. This restriction results in eliminating Mozambique and Sudan from the original donor pool in the revised data set.

Furthermore, the data revision suggests a reassessment of the countries that fall beneath the GDP per capita threshold (<4,000 intl. dollar, PPP constant 2011). This could be either because previously missing values are now available or because the GDP per capita of a country previously calculated higher than the threshold is revised downwards. After adjusting for the restriction for missing data, the new donor pool consists of 39 countries: Bangladesh, Benin, Burkina Faso, Burundi, Cameroon, the Central African Republic, Chad, Comoros, the Democratic Republic of the Congo, Cote d'Ivoire, the Gambia, Ghana, Guinea, Guinea-Bissau, Honduras, Kenya, the Kyrgyz Republic, the Lao People's Democratic Republic, Lesotho, Liberia, Madagascar, Malawi, Mali, Mauritania, Myanmar, Nepal, Nicaragua, Niger, Papua New Guinea, Rwanda, Senegal, Sierra Leone, Solomon Islands, Tajikistan, Tanzania, Togo, Uganda, Vanuatu, and West Bank and Gaza.[9] Unlike the original donor pool, this list is not corrected by the countries' GDP per capita difference to Haiti or their individual fragility index.

[9] 12 Countries removed from the new donor pool due to missing data. They are Afghanistan, Cambodia, Eritrea, Ethiopia, Kiribati, the Marshall Islands, the Federated States of Micronesia, Mozambique, Sao Tome and Principe, South Sudan, Sudan Tuvalu, Zambia, and Zimbabwe.

Note that only one country from the original donor pool, excluding Mozambique and Sudan, is not included. The revised GDP per capita suggests that Moldova exceeds the threshold. In the original data set, Moldova had a GDP per capita of 3,661 intl. dollars (PPP constant 2011) in 2009. The revised data set displays 4,416 intl. dollars (PPP constant 2011) in the same year. A revision of this size seems surprising because Moldova scored high on the World Bank's (2020a) statistical capacity indicator in 2016 and 2019. In the latter year, the Central African Republic, the Democratic Republic of the Congo, and Guinea, all part of the new donor pool, scored lower than Haiti in the same ranking (World Bank, 2020a). Both examples indicate that measurement errors for the macroeconomic aggregates are likely for Haiti and at least some of the donor pool countries. Henderson, Storeygard, and Well (2012) estimate these measurement errors for WDI data to be up to 3.2 percent for the annual real GDP growth for low- and middle-income countries with poor data quality.

Given the recommendations for a restrictively chosen donor pool (Abadie, 2020), the choice of a larger donor pool as the new donor pool might be questioned. Abadie (2020), however, also suggests a change of countries in the donor pool as a sufficient method to check the analysis' robustness with regards to the study design. Figures 7 and 8 display the (mean) GDP, respectively, the (mean) GDP per capita of Haiti, the new donor pool, and the original donor pool from 2001 to 2018. Figure 7 suggests that the new donor

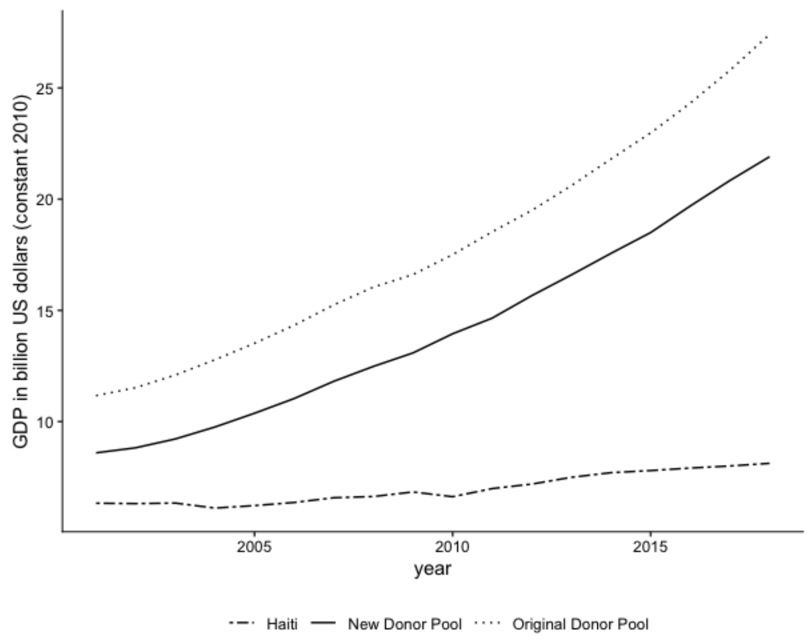

Figure 7 Haiti's and donor pools' GDP from 2001 to 2018
The GDP values from 2001 to 2018 from the revised data set (World Bank, 2020b). The GDP for the new donor pool and the original donor are averages. All values in billion US dollars (constant 2010).

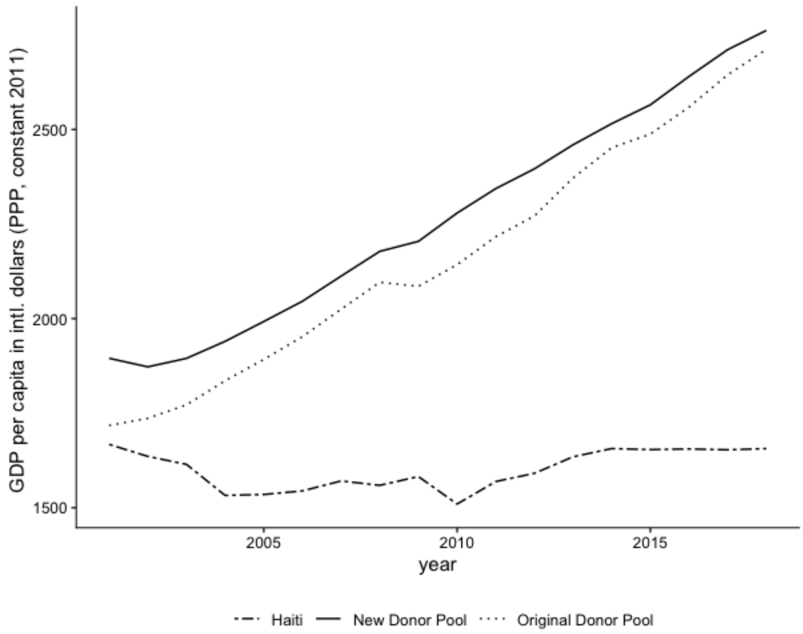

Figure 8 Haiti's and donor pools' GDP per capita from 2001 to 2018
The GDP per capita values from 2001 to 2018 from the revised data set (World Bank, 2020b). The GDP per capita for the new donor pool and the original donor are averages. All values PPP in international dollars (constant 2011).

pool's average GDP is closer to Haiti than the original donor pool. Though, both donor pool time series diverge notably from Haiti's overtime and illustrate a different trend. On the contrary, Figure 8 shows that the original donor pool has an, on average, closer GDP per capita to Haiti. Both average time series grow nearly steadily and reach an approximately 60 percent higher value in 2018 compared to their departure value in 2001. Haiti's GDP per capita experienced a downward trend for approximately 9 nine years before it grew back close to its original state in 2001. Recent values suggest that Haiti's GDP per capita remained stable for around four years until 2018.

Columns 4 to 7 in Table 3 display the descriptive statistics of the 2009 values from the revised data set. They are split into Haiti, the original donor pool, the new donor pool, and the world (including Haiti and all donor pool countries). The averages of both donor pools are similar when contrasted to the world's average or Haiti. This is unsurprising because the new donor pool shares nearly 50 percent of the countries with the original donor pool. It further stands out how well the average land area of the original donor pool, after the removal of Mozambique and Sudan, resembles Haiti's land area. The comparison of columns 1 and 4 Table 3 in shows that, despite the GDP, the GDP per capita, and the inflation rate, only Haiti's population data is revised for the year 2009.

7 RESULTS

Based on the original study, the replication steps from subsection 5.2 are implemented to obtain replication results. The results section splits into four subsections: First, the presentation of the replication results for the GDP synthetic control, second the presentation of the replication results for the GDP per capita synthetic control, third a comparing summary of both, and last, a discussion of these results.

Before introducing the different replication steps in R/Synth, it needs to be highlighted that the (pure) technical replication of Best and Burke's (2019) synthetic control with the original Stata code works well for both outcome variables. In other words, it is possible to achieve identical results under identical circumstances. In their analysis, Best and Burke (2019) neither prove nor claim statistical significance for their synthetic control analysis with World Bank (2016) data. An attempt to test inference for both synthetic controls, based on the inference test the authors perform for other synthetic controls, which they show in their code, fails. A necessary condition for the inference test is the availability of dummy synthetic controls for each donor pool country. Due to data issues, the code is unable to calculate synthetic controls for each donor pool country. Hence, a test for statistical significance cannot be performed.

7.1 GDP

The results from the *pure replication* of the synthetic control for the GDP in R/Synth suggest a loss of approximately 7.0 billion US dollars (constant 2010) in total over the first six post-disaster years. Figure 9 shows an average yearly loss of approximately 13.7 percent over the same time and a 13.0 percent loss in 2010. These findings, at bottom, correspond to those estimated by Best and Burke (2019). They found an overall loss of 6 billion US dollars (constant 2010) and an annual average loss of 12 percent. These dissimilarities in results can be explained by the software specific differences in the synthetic control computation. Columns 1 and 2 in Table 4 indicate that the two software programs find different weight combinations for the 23 potential donor countries to construct a synthetic control for Haiti's GDP. Only one country, Moldova, contributes to both weighted average synthetic controls. The comparison of both columns further indicates that the original synthetic control is, with a weight of 73 percent (Togo), more dependent on a single country. The *pure replication*, at the same time, apportions the weights more equally on the donating countries. Inferential testing for the replication, however, suggests little adequacy of the replication's synthetic control. The probability for a country to have a post- to pre- MSPE ratio in the top 5 of the 22 donor countries and Haiti is 5/23. As visualized in Figure 10, Haiti does not rank higher than this. This probability is not considered statistically significant at a common level.

The *replication with the revised data set* estimates a total GDP loss of approximately 5.4 billion US dollars (constant 2010) from 2010 to 2015. This corresponds to an average yearly loss of 10.9 percent. Hence, the *replication with the revised data set* generates

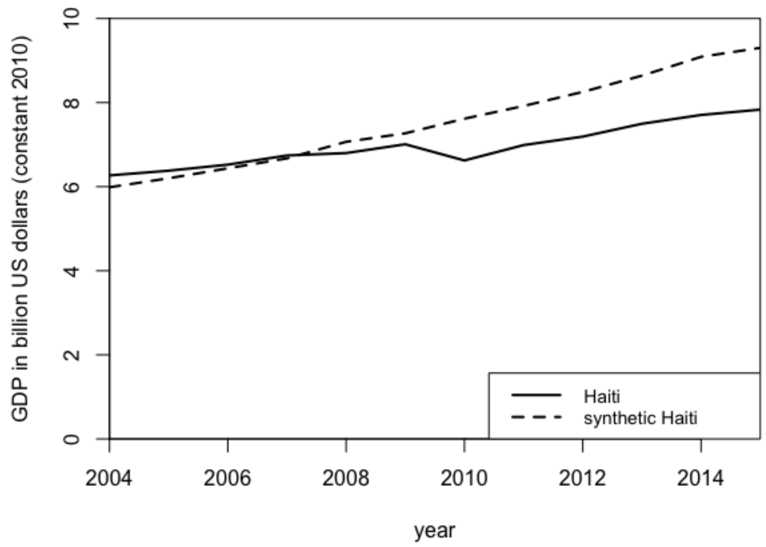

Figure 9 Pure Replication: GDP
The GDP values from 2004 to 2015 from the original data set (World Bank, 2016). All values in billion US dollars (constant 2010).

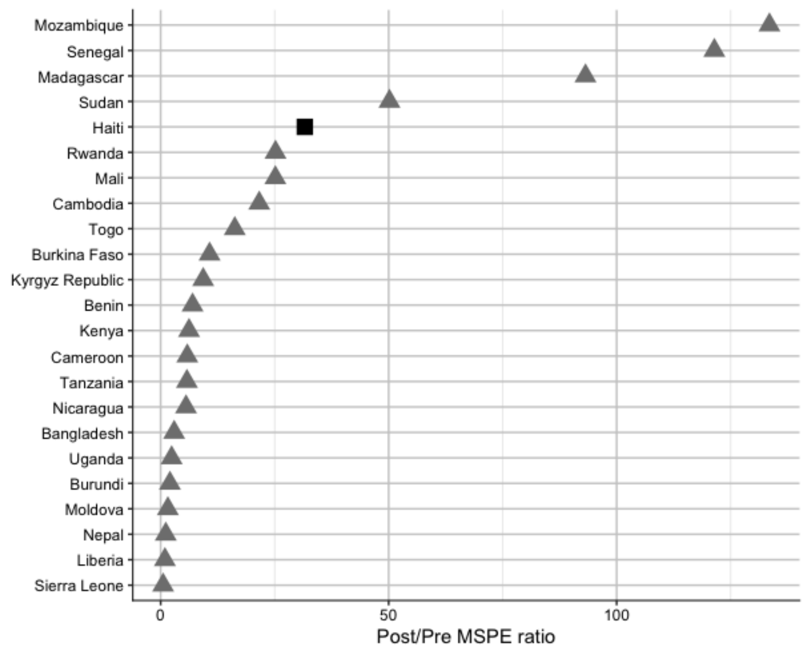

Figure 10 Pure Replication: GDP - Ratio of post- to pre-treatment MSPE
Comparison of all 22 donor countries and Haiti.

Table 4 Weights of donor pool countries for replications using the original donor pool
* Mozambique and Sudan are excluded from the original donor pool for all replications using the revised data set due to missing data as explained in subsection 6.3.2.

	GDP				GDP per capita			
	Original (Best and Burke, 2019)	Pure Replication	Rep. Revised Data Set	Rep. Longer Time Horizon	Original (Best and Burke, 2019)	Pure Replication	Rep. Revised Data Set	Rep. Longer Time Horizon
Bangladesh	0	0	0	0	0	0	0.002	0
Benin	0	0	0.001	0	0	0	0	0
Burkina Faso	0	0	0	0	0	0	0.003	0
Burundi	0	0.483	0.661	0	0.451	0.595	0.390	0.070
Cambodia	0	0	0.001	0	0	0	0.001	0
Cameroon	0.199	0	0.169	0	0.277	0	0.001	0
Kenya	0	0	0	0.141	0	0.265	0.003	0.393
Kyrgyz Republic	0	0	0.002	0	0	0	0.001	0
Liberia	0.16	0	0.001	0.789	0.049	0	0.032	0.379
Madagascar	0	0	0.004	0.70	0	0	0.034	0.158
Mali	0	0	0.001	0	0	0	0.001	0
Moldova	0.055	0.121	0.003	0	0	0	0.001	0
Mozambique	0	0	*	*	0	0	*	*
Nepal	0	0.341	0.006	0	0.019	0	0.003	0
Nicaragua	0	0.055	0.146	0	0.037	0.139	0.014	0
Rwanda	0	0	0	0	0	0	0.002	0

	GDP				GDP per capita			
	Original (Best and Burke, 2019)	**Pure Replication**	**Rep. Revised Data Set**	**Rep. Longer Time Horizon**	**Original (Best and Burke, 2019)**	**Pure Replication**	**Rep. Revised Data Set**	**Rep. Longer Time Horizon**
Senegal	0	0	0	0	0.168	0	0.328	0
Sierra Leone	0	0	0.001	0	0	0	0	0
Sudan	0	0	*	*	0	0	*	*
Tanzania	0	0	0	0	0	0	0.002	0
Togo	0.730	0	0.002	0	0	0	0.180	0
Uganda	0	0	0	0	0	0	0.003	0

results indicating a slightly smaller GDP loss than Best and Burke's (2019) analysis and the pure replication. The loss in 2010 was 8.9 percent or 0.7 billion US dollars (constant 2010). Column 3 in Table 4 reveals that the donor pool weighting changed again due to introducing the revised data set. Note that 13 out of 20 donor pool countries are assigned weights, 10 of them with a contribution of less than 0.7 percent. Figure 11 shows the development of Haiti's GDP and that of its synthetic control for the *replication with the revised data set*. Again, the direction of the synthetic control movement is similar to that found by Best and Burke (2019) and the *pure replication*. The inference test, however, does not suggest an adequate synthetic control. Haiti's synthetic control ranks 8th out of 21 countries (donor pool, including Haiti).

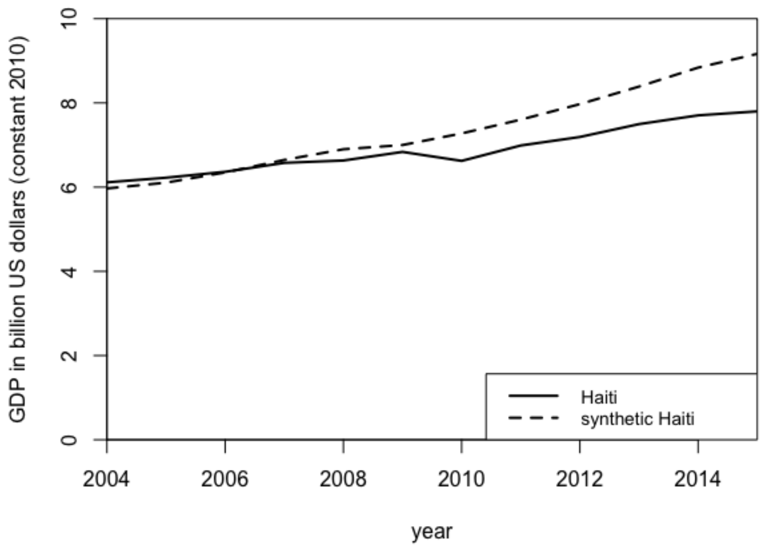

Figure 11 Replication with the revised data set: GDP
The GDP values from 2004 to 2015 from the revised data set (World Bank, 2020b). All values in billion US dollars (constant 2010).

The *replication with a longer time horizon* (from 2001 to 2018) suggests an average yearly GDP loss of 19.4 percent between 2010 and 2015 and 22.2 percent until 2018. This sums up to a loss of approximately 20.0 billion US dollars (constant 2010) over the nine post-earthquake years. The sum is nearly 2.5 times higher than Haiti's GDP in 2018. Figure 12 shows Haiti's versus its synthetic control's GDP. (For comparison, Figure 25 in Appendix 2 presents the identical graphs on a y-axis scale equivalent to the previous figures. If not mentioned otherwise, all figures are shown with the y-axis scale used in the original study to make a visual comparison possible.) Only three countries, Liberia (78.9%), Kenya (14.1%), and Madagascar (7%) contribute to the synthetic control (see column 4 in Table 4). This is the least number of included countries among all GDP synthetic controls for Haiti in this thesis. Among the post- to pre-treatment MSPE's, Haiti's synthetic control ranks 6th out of 21 and is not considered an adequate synthetic control.

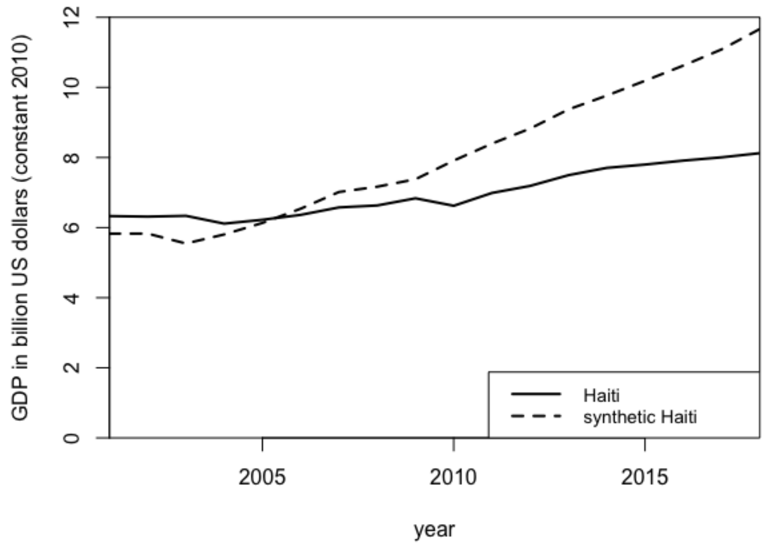

Figure 12 Replication with a longer time horizon: GDP
The GDP values from 2001 to 2018 from the revised data set (World Bank, 2020b). All values in billion US dollars (constant 2010).

The *replication with the new donor pool* from 2004 to 2015 estimates a 9.2 percent average yearly loss for all 6 post-earthquake years. It sums up to approximately 4.7 billion US dollars (constant 2010) in total. Table 5 suggests that eleven out of 39 potentially donating countries are weighted zero. Remember that this donor pool is constructed using Best and Burke's (2019) threshold for the revised data set. Burundi (58.5%), Cote d'Ivoire (18.3%), Comoros (17.2%), and Kenya (1.6%) contribute most to the synthetic control, which indicates that the majority of donor countries make up for less than 1.6 percent of the weighted average. However, if many minor contributions of donor pool countries are considered potential evidence for overfitting (Abadie, 2020), then the implementation of the new donor pool creates less bias than the introduction of the revised data set. Two features of the graphs in Figure 13, which display Haiti's GDP and its synthetic control for this replication step, are remarkable. First, the supposedly good pre-treatment fit. Second, the development immediately after the earthquake. The 2010 gap between the actual and synthetic Haiti is large, while both GDP values are comparably close in 2011 (a gap of 0.11 billion US dollars (constant 2010)). This observation might support the theory that immediately after a disaster, quick recovery (and foreign aid) lead to high economic growth as the destroyed infrastructure is rebuilt. This marks one potential outcome described in theory by Howitt (2017). The inference test attests the synthetic control a post- to pre-earthquake fit, suggesting that the observed differences can be attributed to the earthquake.

Table 5 Weights of donor pool countries for replications using the new donor pool

	GDP		GDP per capita	
	Rep. New Donor Pool	Rep. New Donor Pool and Longer Time Horizon	Rep. New Donor Pool	Rep. New Donor Pool and Longer Time Horizon
Bangladesh	0	0	0	0
Benin	0.001	0.001	0	0.293
Burkina Faso	0.001	0	0	0.010
Burundi	0.585	0.574	0.331	0.292
Cameroon	0.012	0.001	0	0
Central African Republic	0.001	0	0	0
Chad	0	0	0	0
Comoros	0.172	0.070	0.181	0.246
Congo, Dem. Rep.	0.001	0	0	0
Cote d'Ivoire	0.183	0.165	0	0
Gambia, The	0.001	0	0	0
Ghana	0	0.001	0	0
Guinea	0.002	0	0	0.001
Guinea-Bissau	0.001	0	0	0
Honduras	0.001	0.002	0	0
Kenya	0.016	0.001	0	0
Kyrgyz Republic	0	0	0	0

	GDP		GDP per capita	
	Rep. New Donor Pool	**Rep. New Donor Pool and Longer Time Horizon**	**Rep. New Donor Pool**	**Rep. New Donor Pool and Longer Time Horizon**
Lao PDR	0.001	0	0	0
Lesotho	0	0.001	0.001	0
Liberia	0	0	0.024	0.087
Madagascar	0.002	0	0	0.056
Malawi	0.001	0.001	0.001	0
Mali	0.001	0	0	0
Mauritania	0.001	0	0	0
Myanmar	0	0	0	0
Nepal	0.001	0.002	0	0.001
Nicaragua	0.007	0.167	0.122	0.013
Niger	0.001	0	0	0
Papua New Guinea	0.001	0	0	0
Rwanda	0.001	0.001	0.001	0
Senegal	0.002	0.002	0	0
Sierra Leone	0.001	0	0	0
Solomon Islands	0.001	0.001	0	0
Tajikistan	0	0	0	0
Tanzania	0.001	0	0	0

	GDP		**GDP per capita**	
	Rep. New Donor Pool	**Rep. New Donor Pool and Longer Time Horizon**	**Rep. New Donor Pool**	**Rep. New Donor Pool and Longer Time Horizon**
Togo	0	0.001	0.333	0
Uganda	0	0	0	0
Vanuatu	0	0.001	0.001	0
West Bank and Gaza	0.001	0.005	0	0

The *replication with the new donor pool and a longer time horizon* (2001 to 2018) approximates an overall loss in GDP of 4.6 billion US dollars (constant 2010) until 2014 and of 11.9 billion US dollars (constant 2010) until 2018. Figure 14 illustrates this replication result. The difference between both sums after only three more years, on the one hand, suggests that the effect of the earthquake is persistent. On the other hand, a more than 2.5 times higher loss in this comparably short period leads to the presumption that the earthquake-attributed GDP loss intensifies over time. These results align with the previous findings by Barone and Mocetti (2014) and duPont IV and Noy (2015). The

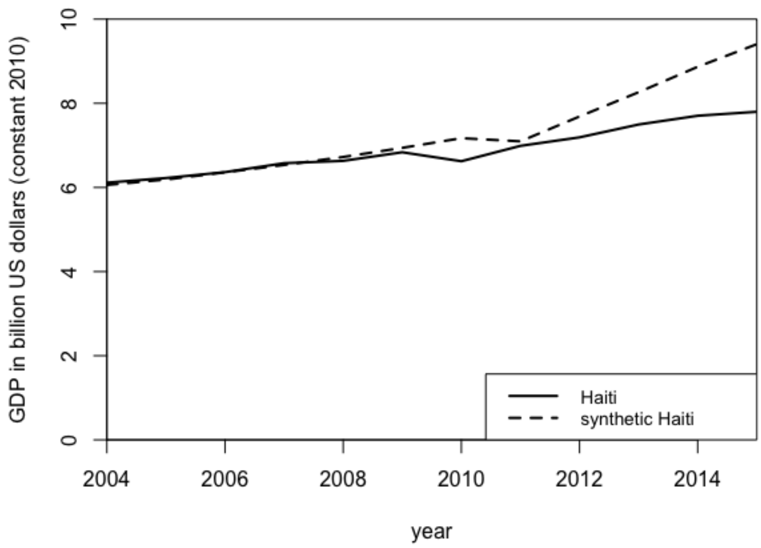

Figure 13 Replication with the new donor pool: GDP
The GDP values from 2004 to 2015 from the revised data set (World Bank, 2020b). The synthetic control is based on the new donor pool. All values in billion US dollars (constant 2010).

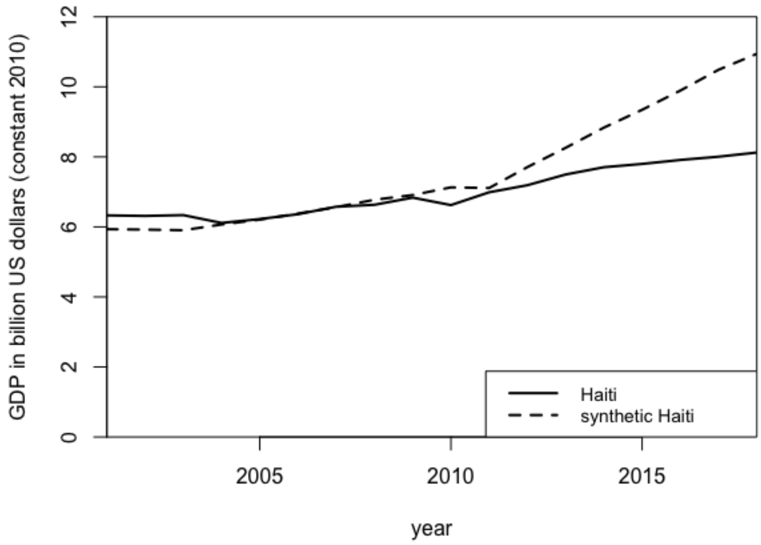

Figure 14 Replication with the new donor pool and a longer time horizon: GDP
The GDP values from 2001 to 2018 from the revised data set (World Bank, 2020b). The synthetic control is based on the new donor pool. All values in billion US dollars (constant 2010).

loss in 2018 alone is estimated to sum to 2.8 billion US dollars (constant 2010), which equals 35 percent of Haiti's GDP in 2018. The percentage losses over time are, on average, 9.0 percent until 2015 and 13.7 percent until 2018. Figure 14, like Figure 13, reflects Haiti's GDP in 2011 might have been close to its GDP if the earthquake had not happened. (Figure 26 in Appendix 2 displays the identical graph on a different y-axis for better overall comparison.) Column 2 in Table 5 also hints that the major weight, with more than 50 percent, remains with Burundi even after the time frame extension. The rank of the post- to pre-treatment MSPE ratio is the lowest of all synthetic control replications for Haiti's GDP.

7.2 GDP per capita

A *pure replication* of Best and Burke's (2019) synthetic control analysis in R/Synth estimates an average yearly GDP per capita loss of 9.6 percent until 2015 and a 9.3 percent immediate loss in 2010. The loss sums up to 1020.5 intl. dollars PPP (constant 2011) in GDP per capita until 2015. According to the original data set, this sum equals approximately 61 percent of Haiti's GDP per capita in 2015. Figure 15 visualizes the GDP per capita development of the replicated synthetic control and Haiti. The result shows a noteworthy difference from the original study. The *pure replication* estimates a 2.3 percentage point higher GDP per capita loss in 2010 than the original study. Likewise, the average annual GDP per capita percentage point loss from 2010 to 2015 is 3.6 percentage points higher for the *pure replication* than for the original study. Column 6 in Table 4 presents three donating countries for this pure replication. Like Best and

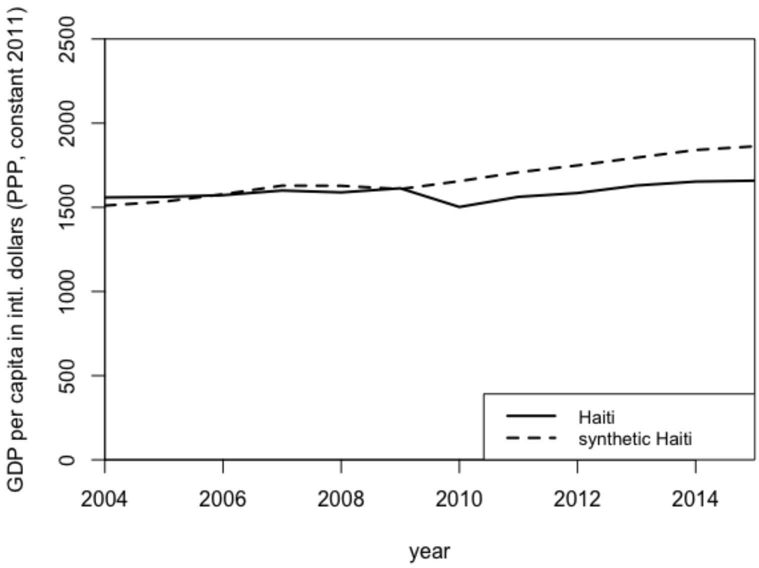

Figure 15 Pure Replication: GDP per capita
The GDP per capita values from 2004 to 2015 from the original data set (World Bank, 2016). All values PPP in international dollars (constant 2011).

Burke's (2019) synthetic control, column 5, Burundi is the main contributor to the synthetic control (59.5% in the replication and 45.1% in the original study). Nicaragua (13.9% and 3.7%) is another donating country both synthetic controls have in common. The inference test for this replicated synthetic control suggests no statistical significance at a standard level (see Figure 16). The synthetic control ranks in the post- to pre-treatment MSPE comparison similar to the pure replication of the GDP synthetic control in subsection 7.1. Further comparison to Figure 10 also highlights that the post- to pre-treatment MSPE ratio of both synthetic controls is smaller than that of Madagascar and Senegal.

Figure 17 illustrates another visual way to understand the idea of determining the adequacy of the synthetic control with the help of dummy synthetic controls. It presents the difference between the (dummy) synthetic control GDP per capita and the actual GDP per capita for all 22 donor pool countries and Haiti. Intuitively, this difference, or gap, should be minimal before the treatment because a good pre-treatment fit suggests a synthetic control that adequately represents the unit in the absence of the treatment. Only a good pre-treatment fit makes it possible to associate the post-treatment gap with the treatment. In other words, if the graph in the pre-treatment phase in Figure 17 follows the baseline, all differences from the baseline in the subsequent period are caused by the treatment. This difference then equals the treatment effect α_{1t}. Alternatively, a constant deviation from the baseline in the pre-treatment period can be offset against the

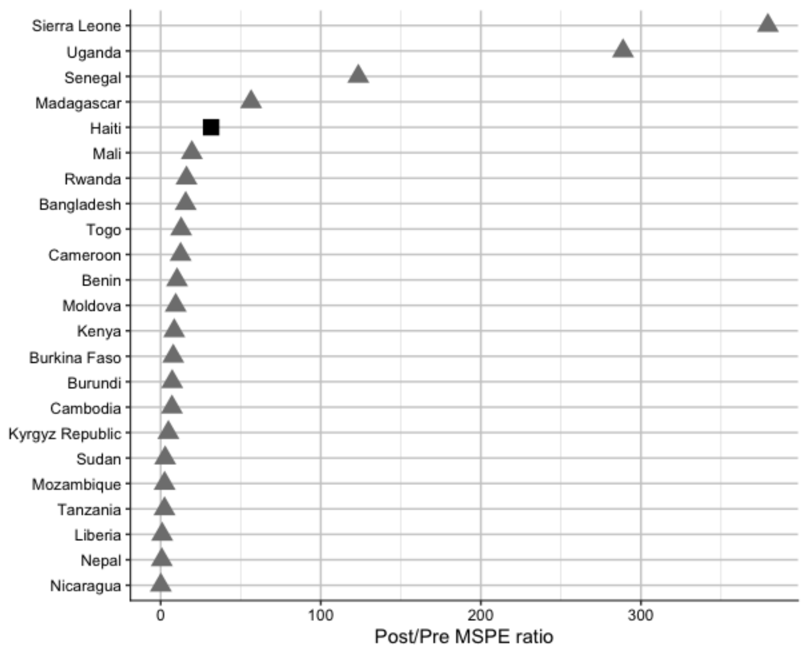

Figure 16 Pure Replication: GDP per capita - Ratio of post- to pre-treatment MSPE
Comparison of all 22 donor countries and Haiti.

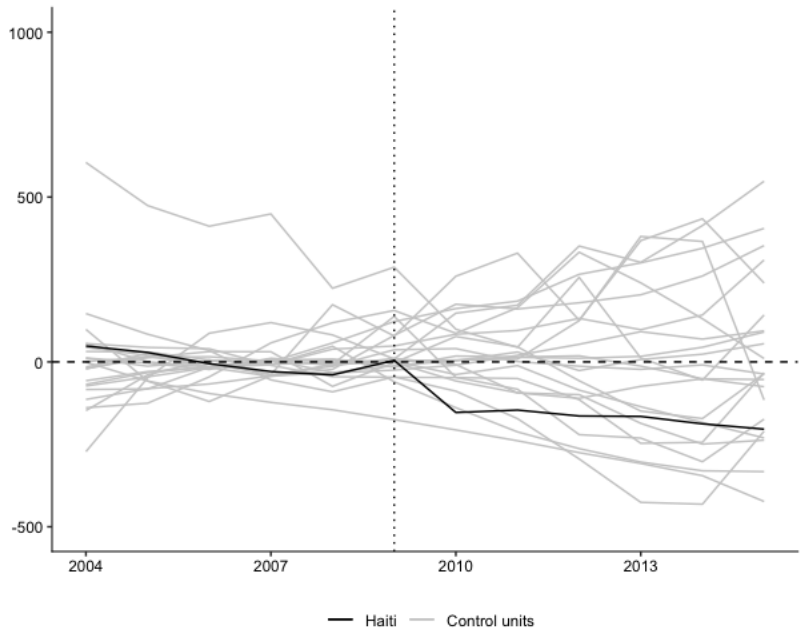

Figure 17 Pure Replication: GDP per capita – pre- and post- treatment difference
A single line displays the difference between the (dummy) synthetic control GDP per capita and the actual GDP per capita. This presents all 22 donor countries and Haiti over time.

treatment effect. Hence, Figure 17 is another presentation of the idea and results underlying Figure 16. Figure 17, however, can display the pre- and post-treatment differences over time. It shows that Haiti's difference graph performs comparably decent in the pre-treatment period. However, the fluctuation prefigures a non-optimal MSPE. In the post-treatment period, Haiti seems to have a perpetual difference from zero. However, compared to the differences observed for countries from the donor pool, Haiti's difference from zero is inconspicuous. Given that none of the donor pool countries experienced an individual shock comparable to the earthquake at the same time, it seems as if the earthquake did not have a significant impact on Haiti's GPD per capita.

The GDP per capita synthetic control *replication with the revised data set* estimates an annual loss of approximately 4.1 percent for the six post-earthquake years and an initial loss of 6.4 percent in 2010. The GDP per capita loss adds up to 411.8 intl. dollars PPP (constant 2011), which is less than half the amount estimated in the *pure replication* over the same six years. These numbers imply a small gap between Haiti's GDP per capita and its' synthetic control, as visualized in Figure 18. With 39.6 intl. dollars PPP (constant 2011), the difference between both is the lowest in 2013 in the post-earthquake period. This replication suggests a loss in GDP per capita, approximately 1.9 percentage points lower than the original study. The distribution of weights assigned to the individual donor pool countries, as in column 7 in Table 4, is again manifold. 18 out of 20 potentially donating countries are assigned nonzero weights. However, only Burundi (39%), Senegal

(32.8%), and Togo (18%) contribute to the synthetic control with more than 10 percent. The inference test suggests no statistical significance for this synthetic control, implying that it is not an adequate reflection of Haiti's GDP per capita had the earthquake not happened.

Extending the latter *replication with the longer time horizon* (Figure 19) leads to an estimated total loss of 1115.2 intl. dollars PPP (constant 2011) after six years and 1915.2 intl. dollars PPP (constant 2011) after nine years. That is identical to 67.3 percent, respectively, 115.6 percent of Haiti's GDP per capita measured for 2018. In other words,

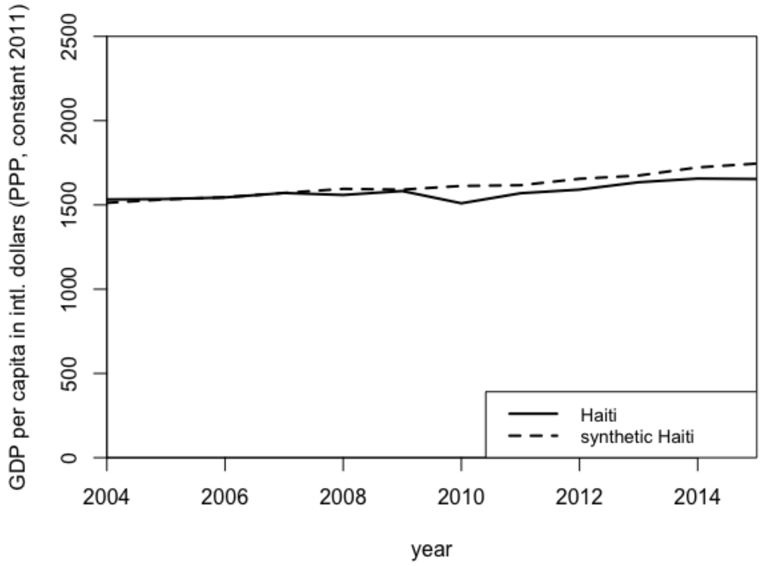

Figure 18 Replication with the revised data set: GDP per capita
The GDP per capita values from 2004 to 2015 from the revised data set (World Bank, 2020b). All values PPP in international dollars (constant 2011).

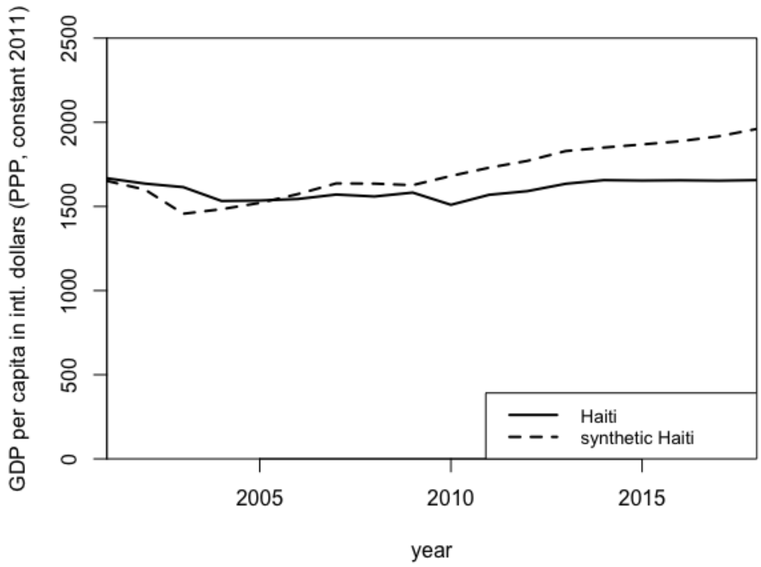

Figure 19 Replication with a longer time horizon: GDP per capita
The GDP per capita values from 2001 to 2018 from the revised data set (World Bank, 2020b). All values PPP in international dollars (constant 2011).

if this synthetic control was an adequate counterfactual for Haiti had the earthquake not happened, it would display that Haiti lost approximately one year in GDP per capita by 2018. The inference test, however, suggests that it is not an adequate synthetic counterfactual.

Figure 20 presents the *replication with the new donor pool,* which assesses a 7.8 percent loss in GDP per capita from 2010 to 2015 and an initial loss of 7.2 percent in 2010. That corresponds to an initial loss of 116.7 intl. dollars PPP (constant 2011) in 2010 and a total loss of 819.6 intl. dollars PPP (constant 2011) until 2015. Compared to all other replications for the GDP per capita synthetic control, this replication creates loss values closest to the original study. They differ by circa 1.8 percentage point. From column 3 in Table 5 Weights of donor pool countries for replications using the new donor pool, it becomes clear that 9 out of 40 donor pool countries are assigned nonzero weights. The synthetic control consists of 33.3 percent of Togo, 33.1 percent of Burundi, 18.1 percent of the Democratic Republic Congo, 12.2 percent of Nicaragua, and five more, all with less than ten percent contribution. The inference test, again, implies that this synthetic control is not statistically significant.

Finally, the *replication with the new donor pool and a longer time horizon* presents a synthetic control for Haiti's GDP per capita. It displays an on-average 3.5 percent higher GDP per capita than Haiti's actual GDP per capita from 2010 to 2015 and an on-average 3.6 percent higher GDP per capita from 2010 to 2018. The initial loss in 2010 is 5.8

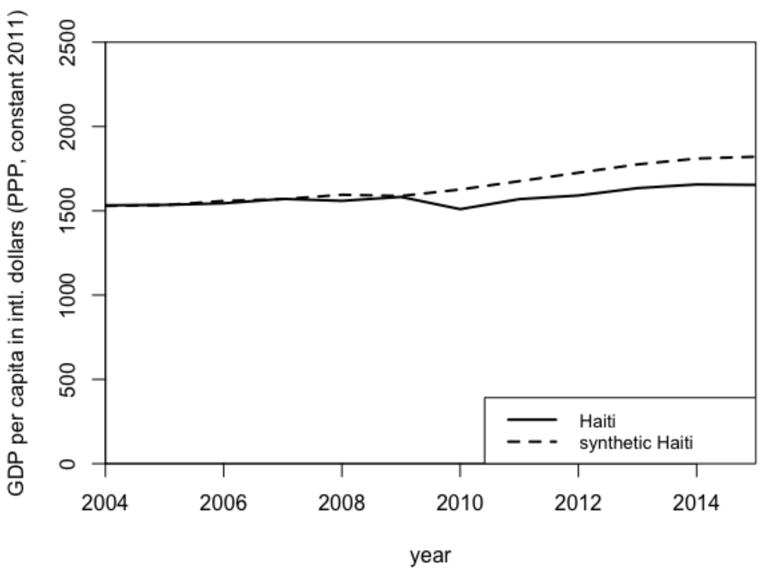

Figure 20 Replication with the new donor pool: GDP per capita
The GDP per capita values from 2004 to 2015 from the revised data set (World Bank, 2020b). The synthetic control is based on the new donor pool. All values PPP in international dollars (constant 2011).

percent or 92.5 intl. dollars PPP (constant 2011). The total estimated GDP per capita loss sums up to 352.1 intl. dollars PPP (constant 2011) until 2015 and 540.1 intl. dollars PPP (constant 2011) until 2018. This synthetic control, consequently, suggests the smallest loss in GDP per capita for all replications. It estimates a loss in GDP per capita of 2.5 percentage points smaller than the loss estimated by Best and Burke (2019). Figure 21 illustrates the comparison between Haiti and this particular control. However, the displayed synthetic Haiti is not considered an adequate control as its post- to pre-treatment MSPE ratio is the sixth lowest among all potential donor countries and Haiti. Again, nine countries are donating to the weighted average synthetic control, as shown in column 4 in Table 5.

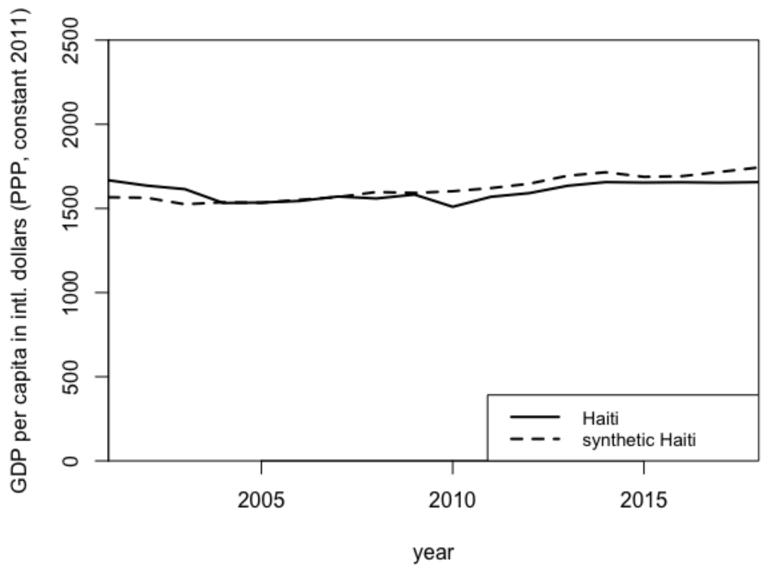

Figure 21 Replication with the new donor pool and a longer time horizon: GDP per capita
The GDP per capita values from 2001 to 2018 from the revised data set (World Bank, 2020b). The synthetic control is based on the new donor pool. All values PPP in international dollars (constant 2011).

7.3 Summary

Table 6 summarizes all replication results from the previous two subsections. Column 1 refers to the gap between synthetic Haiti's and Haiti's GDP in billion US dollars (constant 2010). Column 2 shows it in terms of percentages. Columns 3 and 4 respectively display the same for the GDP per capita. The total loss is estimated in intl. dollars PPP (constant 2011). The overall pattern of differences between the GDP and GDP per capita replication results are noticeable. It appears that the GDP losses are generally extremer than those of the GDP per capita. Extreme here refers to the percentage difference, or, more precisely, the percentage loss between the synthetic's and Haiti's real outcome variable. This peculiarity, on the one hand, depends on the different choices and composition of the donor pool countries (compare within Table 4 and Table 5). On the other hand, it might also be explained by the population growth (see Figure 1), which could absorb the

Table 6 Summary of results

	GDP		GDP per capita	
	Total Loss in billion US dollars (constant 2010)	**Average Yearly Loss**	**Total Loss in intl. dollars PPP (constant 2011)**	**Average Yearly Loss**
Original (Best and Burke, 2019)	6	12 %	-	6 %
Pure Replication	7.0	13.7 %	1020.5	9.6 %
Rep. Revised Data Set	5.4	10.9 %	411.8	4.1 %
Rep. Longer Time Horizon				
2010 to 2015	10.7	19.4 %	1115.2	10.4 %
2010 to 2018	20.0	22.2 %	1915.2	11.5 %
Rep. New Donor Pool	4.7	9.2 %	819.6	7.8 %
Rep. New Donor Pool and Longer Time Horizon				
2010 to 2015	4.6	9.0 %	352.1	3.5 %
2010 to 2018	11.9	13.7 %	540.1	3.6 %

loss by distributing it among a growing number of inhabitants. That is because, even if the loss in GDP would remain equal for all post-earthquake years, a growing population results in a diminishing yearly GDP per capita loss.

Figure 22 displays a visual summary of all five synthetic control replications of the GDP constructed with R/Synth against Haiti's actual GDP. It illustrates the range between the smallest and highest GDP value of all synthetic controls created in this analysis per year (between 2004 and 2015). Compared to Haiti's GDP after the earthquake, the synthetic control range presents a different direction the GDP would have taken if the earthquake never happened. According to the estimated results, it would have grown faster, especially after 2011. The synthetic controls, further, suggest a GDP between approximately 9.2 and 10.2 billion US dollars (constant 2010) in 2015. One may claim a difference of 1.0 billion US dollars (constant 2010) six years after the treatment is a decent range. For Haiti, however, 1.0 billion US dollars (constant 2010) in GDP is a noteworthy difference. Haiti's GDP grew by 1.0 billion US dollars (constant 2010) from

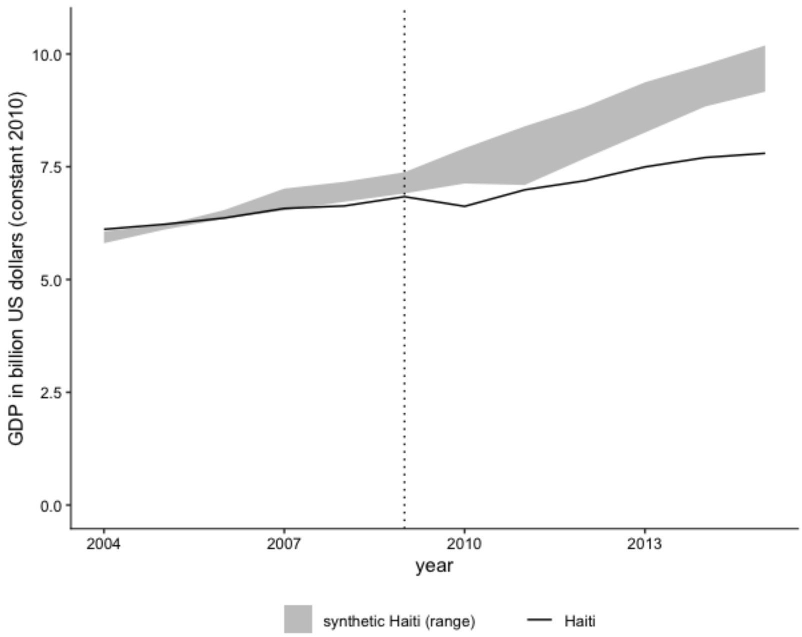

Figure 22 Replication summary: GDP
Haiti's actual GDP values from 2004 to 2015 from the revised data set (World Bank, 2020b). The synthetic control range displays the area within which all synthetic control replications lie. All values in billion US dollars (constant 2010).

1995 to 2008 or from 2009 to 2015 each. Considering that Haiti had a GDP of around 7.8 billion US dollars (constant 2010) in 2015, the difference to both synthetic control presumptions, 9.2 and 10.2 billion US dollars (constant 2010), is sizable. In total, the GDP loss accumulates to range between approximately 4.6 and 10.7 billion US dollars (constant 2010) over six post-earthquake years. The latter value equals 137 percent of Haiti's GDP in 2015. Best and Burke's (2019) estimation of approximately 6 billion US dollars (constant 2010) lies within the lower-bound.

In addition, Figure 22 highlights a crucial pattern of the synthetic controls. All synthetic controls appear to have a 2004 GDP value, which is lower than Haiti's real GDP but a GDP value for all pre-treatment years following 2006, which is higher than Haiti's real GDP. The pre-treatment synthetic controls' movement seems not to follow the pattern of Haiti's real pre-treatment GDP. Comparing this movement to Figure 7 shows that the synthetic Haiti range instead follows the donor pools' overall movement. This is not surprising given that the synthetic Haiti is a particular weighted average of the donor pool countries. However, these movements reveal that the pre-treatment development of Haiti's GDP is not a typical development among low-income countries.

All in all, the *pure replication* and the *replication with the revised data set* estimate a total GDP loss close to Best and Burke's (2019) estimation (compare Table 6). The first, however, suggests a higher total loss, while the latter suggests a slightly smaller total loss.

They differ by up to 1.0 billion US dollars (constant 2010) or 1.7 percentage points from the original analysis. Both *replications using the new donor pool* produce estimations showing GDP losses 1.3 to 1.4 billion US dollars (constant 2010), smaller than the original study. The *replication with the new donor pool and a longer time horizon* suggests the least GDP loss after six post-earthquake years among all replications and the original study. The extension to nine post-earthquake years, however, suggests intensified losses in GDP attributed to the earthquake. The only replication whose loss estimations differ noteworthy from the original study is the *replication with a longer time horizon*. The summed GDP loss over six post-earthquake years is 4.7 billion US dollars (constant 2010) higher than the values the original study suggested. It yields to the highest suggested loss in GDP.

Figure 23 summarizes the different synthetic control replication results for the GDP per capita. It suggests that in 2015 Haiti's per capita GDP would have been at least 2.1 percent and at most 13.0 percent higher had the earthquake not happened. This span alone prefigures the sensitivity of the synthetic control outcome to changes in the computation process. Figure 24 provides a more detailed look at the same graphs. It shows that the GDP per capita synthetic controls may be interpreted differently for the earthquake's mid-term economic growth effects. The upper-bound of the synthetic control range suggests that the difference between the actual and the synthetic GDP per capita grows

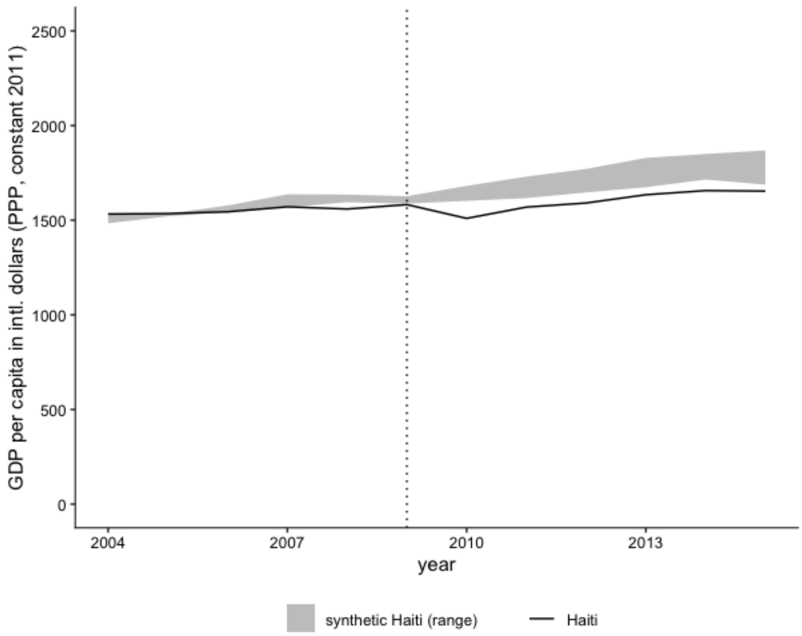

Figure 23 Replication summary: GDP per capita
Haiti's actual GDP per capita values from 2004 to 2015 from the revised data set (World Bank, 2020b). The synthetic control range displays the area within which all synthetic control replications lie. All values PPP in international dollars (constant 2011).

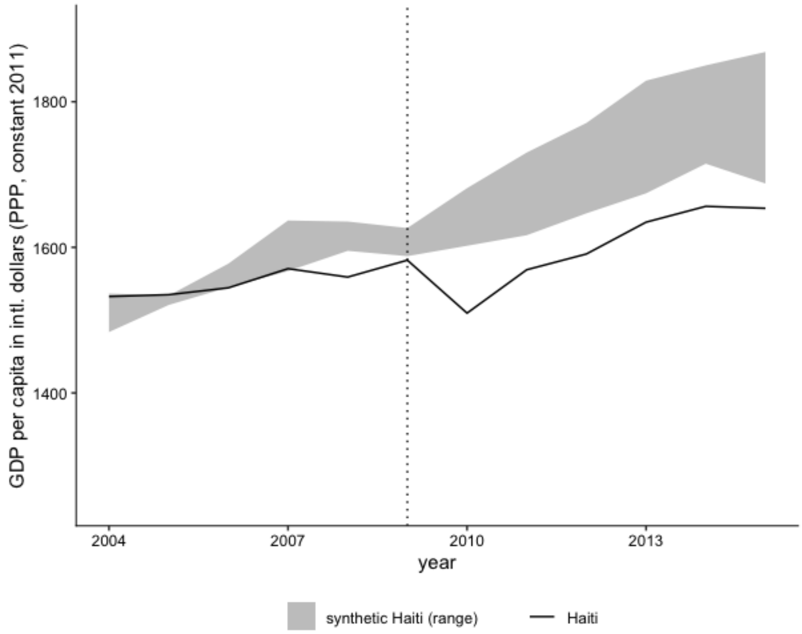

Figure 24 Replication summary: GDP per capita (detailed)
Haiti's actual GDP per capita values from 2004 to 2015 from the revised data set (World Bank, 2020b). The synthetic control range displays the area within which all synthetic control replications lie. All values PPP in international dollars (constant 2011).

annually even six years after the disaster. On the contrary, the lower-bound shows that Haiti and its synthetic control might converge over time. This lower-bound corresponds to the synthetic control displayed in Figure 21 (*replication with the new donor pool and a longer time horizon*). Figure 21 suggests a mid-term convergence between the synthetic control and the actual GDP per capita. The gap between both, however, diverges again in 2016 and the following years. Hence, the mid-term macroeconomic effects measured in GDP per capita are equivocal. Nevertheless, the results over an extended time period support Best and Burke's (2019) assumption of a permanent effect of the earthquake on macroeconomic growth.

The mid-term presumption is different for the GDP analysis (as presented in Figure 22). By definition, the only difference between both measures is the population. Its development is displayed in Figure 1. The steady but declining population growth explains why the growth visible for the synthetic and Haiti's GDP in Figure 22 does not fully translate to Figure 23. Otherwise, the synthetic controls of both measures display similar patterns of sensitivity to changes in the replication. This is surprising because the synthetic controls are dependent on the respective outcome variable of the potential donor pool countries. The donor pool countries' composition yet, is different for all replications (compare Table 4 and Table 5). Consequently, population growth influences the donor country weighting for the synthetic GDP per capita directly as a predictor variable and indirectly through the outcome variable. That means one reason why the software finds other donor pool combinations for the GDP per capita than for the GDP is the population, which alters Haiti's GDP per capita and all potential donor pool countries.

The synthetic control replications for the GDP per capita, in general, show a more considerable difference in percentage points from the original study's results than those of the GDP (compare Table 6). Both synthetic controls, however, display similar responses to the different replication steps. Although this thesis cannot motivate these responses, they need to be outlined. Therefore, three commonalities of the outcomes variables' synthetic controls are briefly presented in the remainder of this paragraph. The extension of the time horizon, executed for the original and the new donor pool, leads both cases to changes of the synthetic control. The changes for the new donor pool are less drastic than for the original donor pool. These changes are always compared to the outcome under the same setting within the original time frame. (In Table 6 compare row 4 to row 3 respectively row 7 to row 6.) Another similarity of both outcome variables is that the revised data set's introduction leads to a notably broader distribution of weights among the available donor countries (compare Table 4). Besides, all but three analyses show the least difference between the actual outcome variable and their synthetic counterpart in 2011. This is in line with the assumptions in the endogenous growth theory. It is intuitive to assume that after the immediate drop in 2010, reconstruction efforts supported the GDP values in 2011. Such efforts, however, decline over time, and the potentially permanent impact of the disaster is revealed.

All in all, the synthetic control analysis results for both outcome variables essentially suggest similar effects. The earthquake seemed to negatively affect the GDP and GDP per capita even nine years after the earthquake. However, depending on the statistic software, data set, donor pool, or time horizon used to construct the synthetic control, the effect's magnitude differs significantly. The calculated loss ranges from approximately 4.6 to 10.7 billion US dollars (constant 2010) over six years in GDP. The annual loss in per capita GDP varies from 3.5 percent to 10.4 percent from 2010 to 2015.

The greatest limitation to all synthetic controls in this thesis is their missing statistical significance. The potential reasons for this lack and the sizeable effect of the replication steps are discussed in the next subsection. Before, it must be mentioned that the missing statistical significance is in line with the previous literature. Loayza, et al. (2012) cannot demonstrate significant growth effects for earthquakes over ten years. Cavallo, et al.

(2013) highlight that larger long-lasting and statistically significant effects on the GDP per capita are only existent whenever a political revolution follows a disaster. Although Haiti's political situation is unstable and unemployment, corruption, and electoral fraud led to street protests (BBC, 2019), Haiti is not reported to experience a political revolution.

7.4 Discussion

This thesis's main results are: All replications suggest a negative effect of the earthquake on the GDP and the GDP per capita; Depending on the replication, the magnitude of this effect differs substantially; All replication results lack statistical significance. The latter two findings may be attributed to various causes. On the one hand, a specific set of debatable underlying assumptions plays a crucial role in determining unobserved counterfactuals. On the other hand, the findings can be associated with data immanent issues or irregularities or Haiti itself. Both types of causes are subject to the discussion below.

There exists doubt in the optimal variable fitting by the used Stata function and R package, which suspects that both software might cause the absence of statistically significant results. As previously mentioned, Becker and Klößner (2017) suggest that neither Stata nor R/Synth find the solutions with the lowest possible pre-treatment (R)MSPE. If this is true, none of the above presented synthetic controls accurately reflects Haiti had the earthquake not happened. Though, this claim also implies that two official synthetic control calculation tools are immaculate. Hence, this doubt has to be reviewed by the software tools' original authors. Concerning this thesis, it, however, encourages rereplication with a more suitable software tool and suggests the possibility for more adequate replications.

Another explanation of the findings and limitations to the replications is indicated by Abadie (2020). He highlights the importance of including the pre-treatment outcome variable to X_1 and X_0 and stresses that the way of inclusion is selectable by the analyst. Abadie (2020) proposes to utilize the average of a particular period, which not necessarily contains all available pre-treatment years. Best and Burke (2019) chose the inclusion of three single points in time. These are 2005, 2007, and 2009. While this could be a choice to improve the pre-treatment fit for a particular analysis, it might be less appropriate whenever this analysis is modified. Hence, especially for the replications with a longer time horizon, it might have been reasonable to adjust the inclusion of the pre-treatment outcome variable. This approach could be interpreted as another replication step and maybe one reason to explain the missing statistical significance.

Additionally, Abadie (2020) illustrates the importance of the donor pool among the synthetic control assumptions. An advisedly chosen donor pool is indispensable for a well fitted synthetic control. Hence, the new donor pool, including more countries, has to be critiqued. After comparing the obtained results in Table 6 (rows 6, 7, and 8 to the those above), the assumption that a larger donor pool produces smaller differences between the actual and the synthetic outcome variable suggests itself. Supposing that a larger donor pool falsifies the estimates, the implication would be that the larger donor pool underestimated the true treatment effect of this particular earthquake. This thesis, however, does not prove this implication.

The question on the donor pool size, furthermore, contributes to a higher-order issue. The choice of the potentially donating countries is as important as difficult. While the synthetic control method needs a substantial number of donating countries to produce a reliable synthetic counterfactual, a too-large donor pool might lead to overfitting (Abadie, 2020). Simultaneously, the definition of large is subjective and dependent on the number of units available to contribute to the synthetic control. There, further, exists no standard method to reduce the number of donor pool countries. Abadie (2020) suggests that "[...] the units in the donor pool have to be chosen judiciously to provide a reasonable control for the treated unit" (p. 15). Concurrently, a specific advantage of the synthetic control method is its prevention of cherry-picking. Compared to other comparative case study methods, the results generated with the synthetic control method are data-driven. The countries eventually contributing to the control are, hence, justifiable. Therefore, choosing a data-driven approach to reduce the number of donor pool countries, as performed by Best and Burke (2019), seems reasonable. This discussion, nonetheless, highlights a need for further research in the construction of donor pools and its effect on the counterfactual.

The example of Haiti also illustrates that further donor pool restrictions should be discussed. Best and Burke's (2019) original donor pool and the new donor pool created in this thesis includes Nepal, a country that tragically connects to the earthquake's aftermath. The transmission of Nepal's cholera pathogen to Haiti affected human lives, Haiti's recovery, and, eventually, its productivity. While this is not considered a spillover of the treatment to a potential donor country, a suitable paraphrase is "a reverse spillover effect". This paraphrase, here, defines the case of an unrelated event in a donor pool country spilling over to the treated unit during the treatment period and being considered to have a sizeable influence on the treatment effect. To the best of my knowledge, this particular case is yet to be discussed in the synthetic control method literature. Although it does not violate any of the underlying difference-in-difference assumptions, it might, at least in the case of Haiti, be reasonable to reconsider the exclusion of Nepal from the donor pool. After all, it has nonzero weights for Best and Burke's (2019) GDP per capita synthetic control and 6 out of 10 replications in this thesis (see Table 4 and Table 5).

The relocation of the UN peacekeepers who brought cholera to Haiti (UN, 2016) was an act of support by the UN. Aid and external help, in general, play a crucial role in the recovery process after a natural disaster (Dacy and Kunreuther, 1969). However, this thesis does not address the role of aid and its influence on the GDP or GDP per capita values. Although Best and Burke (2019) perform a synthetic control analysis for official development assistance and official aid received, they do not account for it when constructing the synthetic controls for the GDP or GDP per capita. The presumption that the received aid potentially reduced the earthquake's negative effect is intuitive. Consequently, the pure effect of the earthquake might be underestimated.

The number of pre-earthquake years included is another debatable assumption made for any synthetic control. It seems to be not only useful to include a sufficiently long pre-treatment time frame (Abadie, 2020) but to consider the outcome variables' development and the reasons for this development. In this example, it is the inclusion of the year 2004 in the original analysis, respectively the years 2001 to 2004 in the replications with a longer time horizon, which should be questioned. As mentioned earlier, Haiti was ruled by despotism until 2004 and experienced a recession in the same year. Hence, 2004 marks an outstanding year in Haiti's history, and the time prior might be characterized by very different political and economic goals. Therefore, 2004 might not correctly reflect Haiti's potential and unobserved economic development for future years.

Hait's history and economic development shape up as potential limitations to a comparable case study. Consider, once more, the differences between the mean donor pool countries and Haiti in Figures 7 and 8. While the mean does not indicate that each included low-income country follows the illustrated graph's movement, it shows the direction for some of them. It differs considerably from Haiti's movement. As displays well in Figure 22 and Figure 23, the higher growth rate of the respective donor pool in the pre-treatment period remains visible even among most synthetic controls. Therefore, it is questionable if, given the unique overall pre-treatment development of Haiti's outcome variables, any set of low-income countries can reflect Haiti. It would, however, be too easy to attribute the shortcomings of this thesis to Haiti's uniqueness. After all, it is essentially the aim of the synthetic control method to provide suitable control for the unique, large, and aggregate unit.

However, a suitable counterfactual depends on the data available to create it. Unlike other single-earthquake synthetic control analyses (for example Barone and Mocetti, 2014; duPont IV and Noy, 2015), this thesis cannot draw on regional data. That is because, on the one hand, sufficient data might not be available, and, on the other hand, the earthquake affected the whole country to some extent. Spillover effects seem to be certain in this case.

Haiti's history further points to another reason for the missing adequacy of the synthetic control replications. Contrary to some previous results, such as those suggested by the IMF (2015), the earthquake could lack a sizable macroeconomic effect or, instead, not be the main reason for the economic development. Consider the possibility that the previous political events or the prevailing instability maybe exert stronger influences on the economic development, and the earthquake solely acts as an endogenous intensifier. Then the assigned treatment in all analyses is wrong, and the calculated differences between the actual and the synthetic outcome variables cannot be attributed to the earthquake but should be attributed to the political and economic upheaval. That would, again inversely, point to the results by Cavallo et al. (2013), who find that statistically significant and permanent effects of natural disasters only exist when political revolutions follow them. To my knowledge, the question of whether this holds for a vice versa situation is unstudied. It presumably will remain unstudied due to the missing link of cause and the arbitrariness of occurrence because natural disasters are endogenous and unpredictable.

Best and Burke's (2019) synthetic control for Haiti's GDP based on UN data, however, is statistically significant at a 10 percent level. Consequently and against some of the previously discussed ideas, it suggests that an adequate reflection of the pre-treatment Haiti is achievable. The calculated average annual 10 percent GDP loss from 2010 to 2014 can be attributed to the earthquake. This result points out two other potential causes for the variation in results and the missing statistical significance within this thesis. First, the questionable accuracy of data and the occasionally extensive revisions have, as previously discussed, a noteworthy influence on the results. The use of the revised data set leads to a loss reduction of 2.8 percentage points for the GDP and 5.5. percentage points for the GDP per capita. Nevertheless, the revised data set usage does not free the synthetic control from missing data accuracy. Missing data remains an issue that contributes to doubts concerning the quality of the results. Second, the earthquake could only have a statistically significant effect on Haiti's GDP until 2014. This presumption would support the idea that the earthquake effect only persists for up to five post-earthquake years. The IMF's (2015) analysis suggests that Haiti's real GDP returned to its untreated counterfactual level in 2014 by extrapolating the previous growth rate. For Best and Burke's (2019) UN data analysis, the gap between Haiti's and the synthetic control's GDP, however, does not close in 2014.

In summary, the results' sensitivity to the different replication steps may result from an insufficient pre-treatment outcome variable inclusion, an overfitting bias due to a large donor pool, a misleading inclusion of pre-treatment years, and extensive data revisions. Non-optimal software results, falsely in- or excluded potential donor pool countries, Haiti's history, and data accuracy and availability may cause missing statistical significance. The results suggest the possibility that the earthquake did not affect Haiti's macroeconomic growth significantly from a statistical perspective. The results still show that reliable software tools, more research on the choice of donor pool countries and the pre-treatment periods, and steady improvement of low-income countries' data are indispensable for accurate and robust synthetic control method results.

8 CONCLUSION

This thesis replicates the GDP and GDP per capita synthetic control results of Best and Burke's (2019) "Macroeconomic Impacts of the 2010 Earthquake in Haiti". A synthetic control is an unobserved counterfactual that displays the outcome variable had the earthquake not happened. This control is based on a certain but debatable set of assumptions that can change the analysis outcome. Hence, this thesis tests the sensitivity of synthetic control-based results to a change of the statistical software, the use of revised data, a modified sample, and an extended time frame.

The overall findings suggest a loss in GDP and GDP per capita following the earthquake. The estimated GDP loss ranges between 4.6 and 10.7 billion US dollars (constant 2010) over six post-earthquake years. Best and Burke (2019) estimate a total loss of approximately 6 billion US dollars (constant 2010) until 2015. Their results, hence, fit the lower bound of the range estimated in this thesis. Considering that Haiti's mean GDP between 2004 and 2015 values 6.9 billion US dollars (constant 2010) per year, this deficit approximates a year lost in GDP. The results are similar for the GDP per capita. According to the replications, the annual loss in per capita GDP varies from 3.5 percent to 10.4 percent from 2010 to 2015. Best and Burke's (2019) estimate of 6 percent, hence, infixes well. Best and Burke (2019) presume that the earthquake-associated loss is permanent. After an extension of the time frame by three years, the replications for both outcome variables do not suggest a decline in the yearly difference between Haiti and its respective synthetic control. Therefore, the findings in this thesis support their assumption.

The explanatory power of the presented results, however, is limited. While the statistical significance cannot be tested for Best and Burke's (2019) findings, all replications display statistically non-significant results. Limitations in the analysis design, such as the chosen pre-treatment time frame or donor poll, offer explanations for the sizable range between the estimated loss and the missing statistical significance. Data accuracy issues and Haiti's economic history potentially contribute to these limitations. The sensitivity of the here displayed results stresses the importance of a well-founded choice of the analysis assumptions.

Fortunately, recent literature, such as Abadie (2020) and Firpo and Possebom (2018), who propose an approach to analyze the sensitivity of a p-value test result to deviations from the equal weights benchmark for the synthetic control method, discuss and enhance the practicalities for the synthetic control method. The importance of further improving a method that can determine ex-post effects created by a natural disaster is self-evident. The increasing risk of climatic natural disasters due to the progressing climate change (Anderson and Bausch, 2006) supports the need for reliable and accurate estimation methods in this field.

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Appendix 1 Summary of variables from Best and Burke (2019)

Table 7 Summary of all variables used by Best and Burke (2019) and their source

Variable	Source
GDP (constant 2010 US $)	World Bank (2016)
GDP per capita, PPP (constant 2011 international $)	World Bank (2016)
Final consumption expenditure, etc. (% of GDP)	World Bank (2016)
Final consumption expenditure, etc. (constant 2010 US $)	World Bank (2016)
Gross capital formation (% of GDP)	World Bank (2016)
Gross capital formation (constant 2010 US $)	World Bank (2016)
Imports of goods and services (% of GDP)	World Bank (2016)
Imports of goods and services (constant 2010 US $)	World Bank (2016)
Exports of goods and services (% of GDP)	World Bank (2016)
Exports of goods and services (constant 2010 US $)	World Bank (2016)
External balance on goods and services (current US $)	World Bank (2016)
Land area, square kilometers	World Bank (2016)
Personal remittances received (current US $)	World Bank (2016)
Population in largest city	World Bank (2016)
Population	World Bank (2016)
Net official development assistance and official aid received (constant 2013 US$)	World Bank (2016)
Inflation, consumer prices (annual %)	World Bank (2016)
GDP (constant 2005 US$)	UN (National accounts main aggregates database as in 2016)
Final consumption expenditure (constant 2005 US$)	UN (National accounts main aggregates database as in 2016)
Gross capital formation (constant 2005 US$)	UN (National accounts main aggregates database as in 2016)
Imports of goods and services (constant 2005 US$)	UN (National accounts main aggregates database as in 2016)
Exports of goods and services (constant 2005 US$)	UN (National accounts main aggregates database as in 2016)
Agriculture, hunting, forestry, fishing output (constant 2005 US$)	UN (National accounts main aggregates database as in 2016)
Manufacturing output (constant 2005 US$)	UN (National accounts main aggregates database as in 2016)

Wholesale, retail trade, restaurants, and hotels output (constant 2005 US$)	UN (National accounts main aggregates database as in 2016)
Dataset: World Energy balances: Total: Road: thousand tonnes of oil equivalent (ktoe)	IEA (2004–2014 IEA world energy statistics and balances as in 2016)
Dataset: World energy statistics: Electricity (GWh) Production	IEA (2004–2014 IEA world energy statistics and balances as in 2016)
Dataset: World Energy balances: Total: Total primary energy supply (ktoe)	IEA (2004–2014 IEA world energy statistics and balances as in 2016)
General government revenue, % of GDP	IMF (World economic outlook database Oct 2016, 2004–2014)
General government total expenditure, % of GDP	IMF (World economic outlook database Oct 2016, 2004–2014)

Appendix 2 Figures displayed with comparable y-axis scale

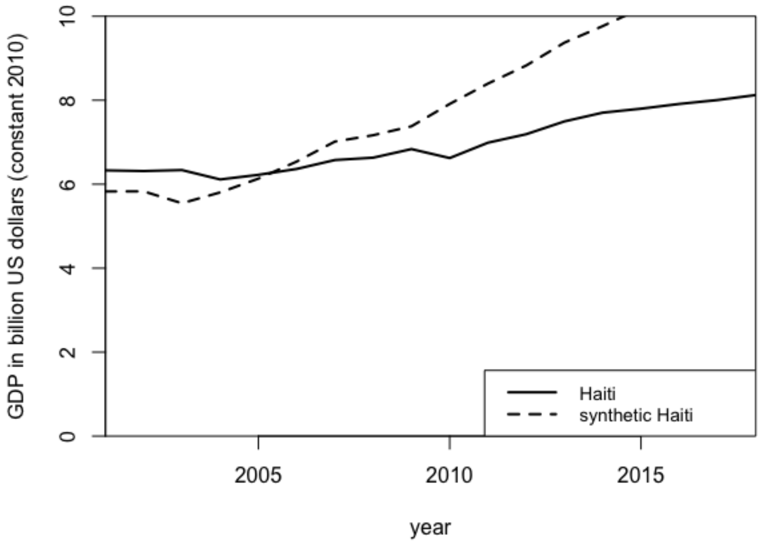

Figure 25 Replication with a longer time horizon: GDP
The GDP values from 2001 to 2018 from the revised data set (World Bank, 2020b). All values in billion US dollars (constant 2010).

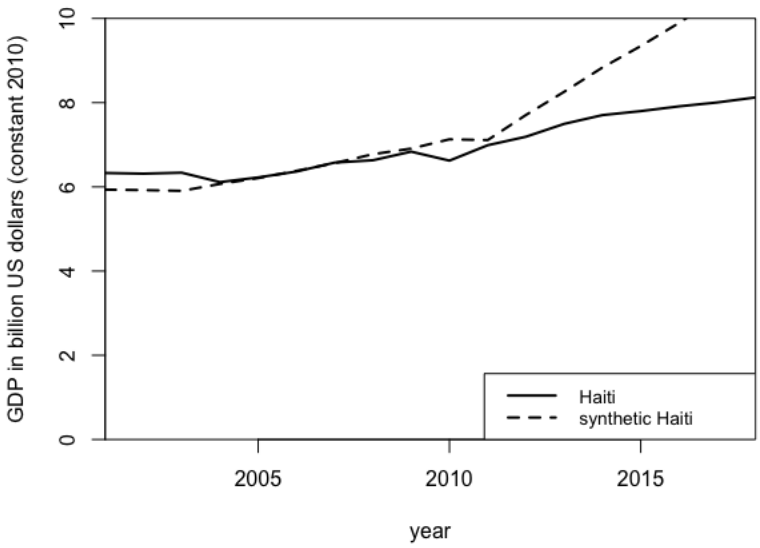

Figure 26 Replication with the new donor pool and a longer time horizon: GDP
The GDP values from 2001 to 2018 from the revised data set (World Bank, 2020b). The synthetic control is based on the new donor pool. All values in billion US dollars (constant 2010).