Analyzing Effects of Large and Rare Events with an Augmented Synthetic Control Method

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Chapter 1

Disasters and institutions: recovering from large-scale events the right way

Abstract

Countries affected by large and rare shocks experience different effects on their economies over time, even if they are relatively similar regarding factors such as GDP per capita, unemployment, or other macroeconomic variables. While rare, these disasters have a significant impact on long-run growth. The synthetic control model is used to find the effects of these disasters for countries that have experienced somewhat comparable disasters. The results show that the degree of democratization is insignificant, but the regulatory quality is vital in determining post-disaster recovery. On average, countries with poorer regulatory authorities experience a 10% decrease in GDP 5 years after a disaster, while countries in the top 30% of regulatory power experience an 8% increase in GDP over its predicted value over the same period.

1.1 Introduction

Disasters are low-frequency large-scale events that affect a country or a region and result in significant destruction of capital or loss of life. These could be any number of events such as natural (earthquakes, floods, hurricanes), political (revolutions, instability, war), or financial. The effect of these events on the economy has garnered much attention over the years. Traditionally, the approach to understanding the impact of rare destructive events has focused on the damage and loss of physical and human capital, usually up to three years after their occurrence. Focusing on the short term is a myopic view of the impact of disasters as countries tend to overspend to counteract the disaster's negative impact leading to contradicting results amongst researchers. For example, Jaramillo (2009) finds that for specific countries, the impact of natural disasters lasts beyond the first five years in which recovery happens, with some disasters impacting GDP up to 10 years after their occurrence.

Historically, a negative correlation between disasters and economic growth has been established. Researchers have identified various channels through which disasters can limit growth. This includes lowering interest rates and returns on assets (Barro, 2001), (Ikefuji and Horii, 2012), human capital destruction (Baez, Fuente, and Santos, 2010), or simply permanently contracting GDP through significant loss of capital in smaller countries (Heger, Julca, and Paddison, 2008). When looking at regions that have experienced (or are more at risk of experiencing) such rare, devastating events, researchers have observed lower long-run growth rates than their less risky counterparts across and within countries. Disasters lead to loss of labor, whether direct (death) or indirect (relocation), and with less labor, an influx of capital may not be very effective. It is better to look at various disasters rather than ones that only impact capital.

Some evidence also shows that disasters do not affect long-term growth, as any change is only temporary (Skidmore and Toya, 2002). These conflicting results are often due to model specifications, data selection, or modeling techniques. For example, post-disaster recovery usually implies that capital stock could increase due to over-investment, even more than before the disaster. Five years later, that might not be the case. While GDP is temporarily boosted, the scope of the analysis could lead to contradicting results. This variation in experiences is partially attributed to the quality of political institutions across countries. Old and antiquated capital is replaced by newer and more efficient capital, the 'creative destruction ' of capital (Ikefuji and Horii, 2012). The channels through which these disasters affect growth are many, and in this chapter, the focus is on several institutional quality indices as accelerators or dampeners to post-disaster recovery. These include but are not limited to the degree of democratization, corruption levels, and ease of doing business.

The first motivation for tackling this topic is the increased frequency of disasters, even when controlling for the increased reporting of disasters and their expanding impact over the years. As societies interact more and as we start exploiting more of the limited amount of land we have, large-scale events will have a bigger and more significant impact, something all the more evident with the recent COVID-19 pandemic. Accelerating climate change means that certain disasters will become more frequent and severe, and it is crucial to focus on them moving forward. Growing inequality also leads to turbulent political upheavals, which leads to a spiraling sequence of even more inequality. The other motivation behind this chapter is reconciling and explaining the differences found in the literature.

Using the synthetic control method for a panel of selected countries and GDP data from 1975 to 2018, I model counterfactuals to the occurrence of a disaster and identify the impact of 96 significant and sizeable events. The percentage deviation difference between the counterfactual model and the real data is calculated and used to assess the impact of such events. Results indicate that disasters played a statistically significant role in altering GDP per capita for the countries in the data set. This chapter identifies the impact that a disaster has on GDP, and it finds that on average, in countries where recovery was slower than predicted due to the disaster, GDP was 10% lower than expected up to ten years after the disaster, while in countries where recovery was faster, GDP was on average 8% higher ten years after the occurrence of the disaster. I then look at those deviations and find that specific institutional quality indices explain the size and movement of those deviations. Data limitations do not allow a proper analysis of the trade-off between investing in infrastructure before a disaster and the recovery post-disaster.

While the degree of democratization was insignificant in determining the recovery from a disaster, regulatory power and corruption perception are the most significant factors in the recovery phase, contributing to around 20% of the recovery size. Looking at disasters as events with long-term repercussions, where the impact can be positive or negative, depending on specific co-factors, can help provide policy recommendations for post-disaster relief. This chapter finds that the size of the disaster, identified by the value of capital lost as a percentage of GDP calculated by the Center for Research on the Epidemiology of Disasters (EMDAT, 2020), does not affect the direction of the change in GDP. Large disasters do not necessarily imply negative GDP growth rates. The results support the fundamental theory that a country with more solid political institutions such as an independent judiciary, will see a boost in its long-run growth after a disaster, despite experiencing a significant loss of capital. The path to achieving these strong institutions is not discussed in this chapter.

This chapter contributes to the literature by quantifying the impact of the quality of institutions on post-disaster recovery and identifying critical institutional quality elements through which the channels impacted by disasters affect growth. This empirical analysis explains the different results in the literature around the impact of disasters through institutional quality. The rest of the paper is organized as follows: in section 1.2, I present an up-to-date review of the literature surrounding disasters. Section 1.3 presents the model used in the analysis, while section 1.4 provides a primary historical empirical analysis of disasters and an explanation of the synthetic regression model, section 1.6 highlights the results from the regressions, and finally concluding remarks are presented in section 1.7.

1.2 Literature review

Authors have found that when controlling for reporting, large-scale events are increasing year-on-year (Ruiter et al., 2020). They find that this increase is in both frequency and scale of disasters over time. Table 1.1 highlights this fact for Canada and shows the largest disasters in terms of economic size for Canada over the last 90 years. Data older than this time period is unreliable due to lack of reporting or record keeping in terms of the occurrence of disasters, and their impact on the economy. Economic data prior to 1920 for a large portion of countries is often unavailable, and does not allow for comparison across countries. These data points are therefore excluded from this analysis. Two of the top three disasters that occured in Canada happened in the last 10 years, something not unique to just Canada, but seen all over the world. The heat wave that impacted eastern Canada in July 2020, as well as record temperatures hitting Western Canada in July 2021, are additional examples that extreme events are getting more frequent and more devastating.

Type	Date	Total damage ('000 US$)
Flood	2013	5,700,000
Wildfire	1989	4,200,000
Wildfire	2016	4,000,000
Drought	1977	3,000,000
Extreme temperature	1992	2,000,000

Table 1.1: Estimated disaster damage (top 5 in Canada)

There is much research concerning the short-term impact of disasters on macroeconomic variables, where the focus is usually on the immediate destruction of physical capital (Kajitani and Tatano, 2018), (Benson and Clay, 2000). This view is slowly changing. The impact on long-run growth has been emphasized more in recent years, and this subsection summarizes some of the significant work done in this field. Many mechanisms dictate how disasters affect GDP, and political institutions are crucial in increasing the efficiency of those mechanisms (Drury and Olson, 1998).

One of the main channels through which GDP can be affected post-disaster is the interest rate. Research from Barro (2006) and Barro (2009) tries to explain the equity premium puzzle through disaster risk. He concludes that the allowance of low-probability disasters explains several puzzles about asset returns, specifically the equity-premium and low real rate of return on government bills, or why the expected real interest rates were low in the U.S. during major wars. Gourio (2012) extends his model by adding variable disaster risk. This extension implies that changing disaster risk induces business cycles, mainly through precautionary savings, highlighting how disasters can impact long-run growth by affecting interest rates for a long period. These models expand the definition of disasters to include man-made disasters, such as financial or technological crises.

Additionally, some work has tried to understand the impact disasters have on human capital, such as Baez, Fuente, and Santos (2010), especially since the importance of human capital to long-run growth has been highlighted often (Barro, 2001) (Erosa, Koreshkova, and Restuccia, 2010). Loss of human capital through a disaster can then drive a country to a lower balanced growth path, increasing the gap in income between rich and developing countries.

The type of disaster is also an essential factor in the recovery process. While considering large-scale events without filtering for types, Raddatz (2007) found that natural disasters lowered real GDP by 2 to 4% for a panel of low-income countries. This is not the case when focusing on specific types of disasters. Hsiang and Jina (2014) find that cyclones have small but significant negative implications on long-term growth, leading to a GDP loss of about 6% for a panel of U.S. states. Barone and Mocetti (2014) find that earthquakes in Italy reduced GDP by about 10% for specific regions compared to what they should have been. Using a two-sector endogenous growth model, Ikefuji and Horii (2012) argue that theoretically, the negative effects of disasters could be mitigated, and economic growth could be improved if a per unit tax on polluting inputs is imposed. Institutional quality is crucial in ensuring tax policy is implemented properly and applied, as the revenue from these taxes should be invested in replenishing capital lost from the disaster. This also proves important before a disaster occurs, as tax revenue can be used to insure against disasters.

The negative impact of disasters is not always consistent, and there has been more evidence that disasters can lead to higher GDP in the long run. 'Creative destruction' of capital is the most prominent theory supporting positive effects from disasters. Several authors have researched this theory and put forth the idea that while the short-term effects of disasters are adverse, there are observable positive spillovers on long-run growth rates (Ikefuji and Horii, 2012) and (Skidmore and Toya, 2002). When such an event occurs, inefficient capital is destroyed, and an increase in precautionary savings with investment directed towards newer, more productive capital is observed. The replacement of capital would not have occurred at such a pace had the country not been affected by a disaster. This could be due to many reasons such as corruption, bureaucracy, or insufficient funding (Matta, Bleaney, and Appleton, 2022). Disasters can then act as catalysts for change and provide opportunities to grow faster in the long run. Jaramillo (2009) shows that these events have permanent adverse effects for a few geographically small countries typically affected by consistently large disasters. In contrast, larger countries typically experience better recovery rates since they can replace capital better. They attribute this to the relative size of the country shielding certain areas from the disaster and the ability to reallocate more resources (physical and human) towards recovery.

More recently, Akao and Sakamoto (2018) attempted to reconcile this contradiction in the disaster literature. They used an endogenous growth model with both aggregate and idiosyncratic shocks to find that if resources are allocated efficiently, disasters will not hurt long-run growth. A caveat of their research is that they do not mention the source of these inefficiencies. A potential reason those other authors put forth is political institutions. Barone and Mocetti (2014) found that the same disaster had a different impact on growth for different regions in Italy. They focused on the quality of the political institutions of these regions and found that the region with the better quality of political institutions experienced higher than expected growth rates.

Cavallo et al. (2013) argued that disasters have no long-run effects except under particular circumstances, where a disaster is followed by significant political change, highlighting the importance of political institutions in post-disaster recovery. This idea had been supported in other papers. Drury and Olson (1998) find that increased development and regime responsiveness dampen or increase post-disaster political unrest. These varying channels could also explain why we observe different impacts of disasters across different countries. Existing conditions such as corruption levels, capital availability, and institutional quality might play significant roles in determining post-disaster outcomes. Jong-A-Pin (2009) analyzes how some political instability measures affect growth. He finds that instability of the political regime hurts growth, while instability within the political regime works the other way around. This body of work is crucial in identifying the variables used for the model, while the focus remains on political institutions as critical drivers of growth post disasters.

The initial section of this work follows that of Cavallo et al. (2013) and Barone and Mocetti (2014). The former conducted a cross-country study on the impact of disasters on GDP growth rates, while the latter researched the impact of the same disaster on two regions in Italy. Both works use the synthetic control method to understand a disaster's impact on GDP, which is a well-suited tool for studying such events. Differences between both papers include model specification (such as co-factor selection) and inference methods. Cavallo et al. (2013) find that for a disaster to impact long-run GDP, it needs to be followed by drastic political change. Barone and Mocetti (2014) find that the Italian region with better institutions recovered faster and stronger, and GDP was even higher than predicted had they not been exposed to the disaster.

There is excellent support for the idea that institutions play an essential role in the process of recovery post-disasters. Attention needs to be paid to these variables (Matta, Bleaney, and Appleton, 2022). While Cavallo et al. (2013) focus on post-disaster political turmoil, this chapter expands the scope of their research. In this chapter, the period and disasters considered are more considerable. Variables related to political institutions and institutional quality are selected to provide a more accurate analysis of the recovery, and the model is improved to be more accurate. The Synthetic Control Method allows then for both in-sample and out-of-sample forecast.To the best of my knowledge, the model presented in this chapter is unique in its approach to the joint analysis of disasters, growth, and institutions.

1.3 Synthetic Control Method

This section introduces the synthetic control method (SCM) initially proposed by Abadie, Diamond, and Hainmueller (2010b). This model allows the user to generate counterfactual data series and compare them to the actual development of that series. This chapter tackles a given disaster's impact on GDP growth rates per capita. A disaster is defined as a treatment in the context of the Synthetic Control Method. The accuracy of this methodology is improved for data sets where the variance of the treated variable is significant. This is done by grouping the regions selected into different tiers depending on where they are in the initial distribution of the treated object. For this chapter, this treated object is GDP per capita. This is expanded on in the following subsections.

1.3.1 Why Synthetic Control Method

There are several benefits of using the Synthetic Control Method in analyzing regional treatments compared to the more typical regression methods used in the literature, such as Difference-in-Difference regressions. The most important of those is circumventing the problem of credible untreated observations by allowing the use of weighted averages of other units. The only requirement when conducting the analysis is that an appropriate amount of pre-treatment observations exists. For the Synthetic Control Method, this number is relatively small and could be as low as ten to fifteen observations per treated unit (region or country). This advantage is evident when studying yearly GDP observations as long-time series data on GDP for many countries is not always available. Synthetic Control Method also allows country-by-country analysis compared to more general regression methods. Including appropriate covariate variables eliminates biases that control units could potentially have. For example, if certain control units experienced a regional disaster similar to the one experienced by the main region being studied, or if there is a global event (such as a pandemic) that affects many regions, at the same time, the selection of donors can be adjusted to suit the needs of the researcher. The synthetic control method is extremely well suited for regional policy analysis (Barone and Mocetti, 2014).

1.3.2 Synthetic Control Method model

A brief overview of the mathematical implications of the mode is presented, and the improvements proposed in this chapter are discussed. A partial mathematical intuition behind the optimization sequence is discussed in the appendix. I start with a set $I = \{1, \ldots, N\}$ of so-called "regions" (these can be countries, states, counties). One of the regions is exposed to the "treatment", such as a disaster, where $N - 1$ regions are not treated and a region $i = tr$ is the region exposed. The model includes an outcome variable (GDP) referred to as the treated outcome y_i, and a set of predictors. I assume $y_{i,t}$ is the outcome (or treated) of region i at time t, is the GDP per capita of region i. The outcome variable is observed over T periods. At a point $t = T_0 < T$, the treatment occurs (disaster happens), but only for the affected region $i = tr$, leaving $T - T_0$ of treated periods moving forward, meaning the treatment is uninterrupted. In our case here, the treatment only occurs at $t = T_0$, but Synthetic Control Method also works for treatments that occur after that period as explained by (Abadie, Diamond, and Hainmueller, 2010b). We assume that:

$$y_{i,t} = \hat{y}_{i,t} + \alpha_{i,t} D_{i,t}$$

where

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

where $y_{i,t}$ is the observed value and $\hat{y}_{i,t}$ is the predicted variable. In other words $y_{i,t} = \hat{y}_{i,t}$ for $t < T_0$ and after the treatment

$$\alpha_{i.t} = y_{i,t} - \hat{y}_{i,t} \qquad \text{and} \quad t > T_0.$$

Our goal is then to estimate $\hat{y}_{i,t}$ to be able to estimate $\alpha_{i,t}$. (Abadie, Diamond, and Hainmueller, 2010b) make the assumption that $\hat{y}_{i,t}$ can be estimated through the following factor model

$$\hat{y}_{i,t} = \beta_0 + \theta_i \boldsymbol{z}_{i,t} + \lambda_i \boldsymbol{x}_{i,t} + \epsilon_{i,t}$$

where $\boldsymbol{z}_i$ is a vector of observed covariates (not affected by the intervention), $\boldsymbol{x}_i$ is a vector of unknown factor loadings, with θ_i unknown parameters, and λ_i a vector of unobserved common factors. To solve this model, we build a set of positive weights w_n where $n = 1, \ldots, N-1$ and $i \neq tr$, such that $\sum_{i=1}^{N} w_i = 1$. There are ideal weights w_i^* such that

$$\sum_{i=1}^{N-1} w_i^* y_{i,t} = y_{tr,t} \quad \forall t \ \in T \qquad \text{and} \qquad \sum_{i=1}^{N-1} w_i^* z_i = z_{tr} \quad \forall t \ \in T$$

$y_{i,t}$ is defined as any linear combination of the outcome variable at time t for region i using the outcome variable of the other regions. We can then use

$$\hat{\alpha_{i,t}} = y_{i,t} - \sum_{i=1}^{N-1} w_i^* y_{i,t}$$

as a way to estimate $\alpha_{i,t}$ where $t \in [T_0 + 1, \ldots, T]$.

The vector $\boldsymbol{z}_i$ for region i is built such that

$$\boldsymbol{z}_i = (\boldsymbol{x}_i; \boldsymbol{y}_i^L)$$

where $\boldsymbol{y}_i^L$ is a vector of pre-treatment outcomes for the treated region. Y_i^L could include any combination of $\boldsymbol{y}_i$ up until the treatment, in other words $\boldsymbol{y}_i^L = \{y_i^0, \ldots, y_i^{tr}\}$. In building the vector $\boldsymbol{z}_i$, Cavallo et al. (2013) and Abadie (2021) use the first half of the pre-treatment period outcome observations, and reserve the other half for out-of-sample validation or

$$\boldsymbol{z}_i = (\boldsymbol{x}_i, y_i^0, \ldots, y_i^{tr/2})$$

This is the most common out-of-sample validation method, and has been used in literature from Bouttell et al. (2018), Donohue, Aneja, and Weber (2019), Mills and Rüttenauer (2022), Alfano, Ercolano, and Cicatiello (2021), and Li and Shankar (2020a). The training periods chosen for this thesis are not always chosen as the first half of the pre-treatment observations. The training set is determined depending on the amount of available pre-treatment observations and the value of the Mean Square Predicted Error. Clearly there is a trade-off between the two as a short training period is more likely to result in a higher Mean Square Predicted Error, and the lowest Mean Square Predicted Error is obtained by using the full pre-treatment period for training. In his paper Abadie (2021) does not recommend a specific way to set the training data period.

Taking all of this into consideration, the training data points are chosen randomly between 1/4 at the least and 3/4 at most of the pre-treatment observations, as long as at least 8 observations are possible for training. For example, if the number of data points available for the pre-treatment observations (y) is less than 15, in other words, the treatment starts in 1985, the minimum training period can be is half of the length of the values pre-treatment, guaranteeing at least 8 out of 15 observations will be used in training, otherwise Mean Square Predicted Error is large. The training period with the lowest mean-square predicted error for pre-treatment training values is chosen, and then out of sample-validation is conducted on the rest of the pre-treatment data.

If the distance between 0 and tr is odd, I round up for more accuracy. X_i is the set of predictor variables, as described earlier, with the explanation already provided for their use. The vector Z_i is then defined as the vector of covariates. To get around the lack of data for certain disasters, especially since a lot of the data is missing with regards to the corruption perception index (starts from 1995), certain covariates are included only if data is available. The vector V is key in finding the optimal weights, and improvements to the selection of this vector is explained in the following subsection.

1.3.3 Improvements to selection of vector of relative importance

The weights for the donor pool are chosen in such as a way as to minimize a penalty function

$$\underset{W^*}{argmin} ||\boldsymbol{z}_1 - W\boldsymbol{z}_0|| = \sqrt{(\boldsymbol{z}_1 - \boldsymbol{z}_0 W)' V (\boldsymbol{z}_1 - \boldsymbol{z}_0 W)}$$

where $\boldsymbol{z}_1$ is a vector of pre-treatment variables relevant for the treated region and $\boldsymbol{z}_0$ is the same vector of variables for the non-treated regions, and V is a positive semi-definite matrix that highlights the relative importance of every co-factor variable in determining the treatment variable. The choice of V is done in such a way as to replicate the path of the outcome variable of the treated "region", by minimizing the distance between the variables of concern, which means it cannot be arbitrary.

A general case for the initial guess for V is for it to be data driven, based on the treated region, i.e. including the data values as a guess for V. The values in this vector are all positive, with the first element of the vector always having a value of 1, and the remaining values reflect the relative importance of the other variables in determining my outcome observations. For this chapter, this includes the pre-treatment outcome variable or the GDP per capita prior to the occurrence of the disaster, as well as the covariates selected for this regression. The selection of the non-treated variables is also crucial in ensuring that the values of the weights sums up to 1. The values obtained from the matrix V reflect how important each variable in $\boldsymbol{z}$ is in determining the synthetic treated variable. These V values we obtain help us define the relative importance of the covariates. Once V^* is obtained, I then find the vector of weights W^* that minimizes the following distance:

$$\underset{W^*}{argmin}(\boldsymbol{y}_1 - \boldsymbol{y}_0 W^*(V^*))'(\boldsymbol{y}_1 - \boldsymbol{y}_0 W^*(V^*)).$$

An improper selection of V may lead to an improper solution to the minimizing problem and a choice of V that does not minimize the mean squared prediction error (Mean Square Predicted Errors) of the outcome variable. I augment the standard Synthetic Control Method technique of selecting V^* by using a two-step selection method. Countries are first grouped by the similarity of their dependent variable, in this case, GDP per capita PPP, prior to the treatment. For the selection of countries available three groups are created low income ($< \$5000$), middle income($< \$15000$ and $> \$5000$), and high income($> \$15000$). This selection is made because the importance of covariates is likely to vary between these groups. For example, the importance of government expenditure or secondary school enrolment in determining GDP could vary significantly between a low-income and a high-income country. Once countries have been sorted into these groups and for a given treated period, I run a synthetic regression for all these countries given the specified treated period and for an initial guess of V being data-driven. The average Mean Square Predicted Errors (Mean square predictive error) of the pre-treated periods is then calculated for every country in every group prior to the treatment period T_0. The optimal V^* of the country with the lowest Mean Square Predicted Errors in their respective region is then chosen, and this vector is used as a guess for any future regressions for that particular group. When conducting an Synthetic Control Method regression for the desired period and country, the guess is then selected from a pool of already calculated vectors. This thesis provides a new way of obtaining the optimal vector of relative importance, and highlights the benefits of using this two-step procedure. This method leads to faster and more accurate convergence to an optimal V^* than the data-driven guess when running multiple regressions and placebos while either lowering or not changing Mean Square Predicted Errors for pre-treatment outcome variables. This comes at the cost of increasing the time needed to conduct successful regressions for smaller data sets. As the number of regressions conducted increases, the time required to conduct the regressions decreases as the initial guess of the vector V is more accurate.

1.3.4 Inference

In terms of statistical significance, the synthetic control method does not rely on traditional inference tests but rather on "placebo" tests. As per Abadie, Diamond, and Hainmueller (2010b) and Cavallo et al. (2013), the p-value of the level of significance of a disaster is obtained using the following:

$$p\text{-value} = \frac{\sum_{np=1}^{N_{pl}} I(\bar{\alpha}_l^{pl(np)} < \bar{\alpha}_i)}{N_{pl}}$$

where N_{pl} is the number of placebo tests conducted. In the context of synthetic regression, placebo refers to the counterfactuals obtained from running an Synthetic Control Method regression on a region that was not treated for the selected treatment period. The goal of such a process is to see whether the deviation of the synthetic country's GDP from the actual country's GDP is larger than that of a potential placebo region. In other words, in a random country not affected by this disaster. To conduct this inference Cavallo et al., 2013 propose the following method:

1. For every disaster, compute the place effect using the available controls for the corresponding disaster

2. At every point in time following the occurrence of the disaster (called leads) compute all the placebos, and then take the average across all placebos

3. The actual lead average is ranked in the distribution of placebo averages

4. The lead specific p value is given by the following formula

$$p\text{-value} = \frac{\sum_{np=1}^{N_{pl}} I(\bar{\alpha}_l^{pl(np)} < \bar{\alpha}_i)}{N_{pl}}$$

where α_l is the effect of the disaster on the country in question and α_i is the placebo effect

There are caveats to using this particular method. First, the full data set cannot be considered as potential placebos. Some regions in the pool of donors could have also experienced disasters or significant events that impacted their GDP during the same period as the treated region. These countries need to be excluded from the list of placebos since a significant event in two regions needs to be compared to insignificant events. Second, the placebo test cannot include countries that are considered outliers as the model cannot find enough donors to build the counterfactual of the treated variable (GDP per capita PPP) accurately, given the constraint of $0 \leqslant w_i \leqslant 1$, since it would be impossible to build a counterfactual for an outlier such that $\sum_{i=2}^{N} w_i y_{i,t} = y_{tr,t}$ This constraint can be relaxed and placebos can be formed using those outlying regions, and Li and Shankar (2020b) show that this does not alter the results. The only noticeable drawback of relaxing this assumption is significantly higher computational times. Given the large enough data set, and the small amount of outliers, inference can be successfully conducted without having to include the outlying regions.

From the possible set of countries used in most inferences tests done in this chapter, the following countries are excluded: Burundi, Qatar, Luxembourg, Sierra Leone, Botswana, and Switzerland. These countries display the most extreme outcome variable values for a large portion of the time series considered. This means that it is almost impossible for the model to build an exact synthetic counterpart for each one without a noticeable increase in computational time. Adding to this, any country that experienced a significant disaster (as mentioned previously) three years prior to the treatment period (not just those that experienced an event during the same year) is excluded from being in the placebo pool. The reasoning is simple since a placebo is supposed not to have experienced treatment at T_0. Given the nature of disasters and their prolonged effect, it is expected that if a country experienced a disaster, this effect might still be noticeable several years after its occurrence, impacting the accuracy of the placebo.

Finally, a limit to the inference period is imposed and is one of two criteria: 10 years post-disaster or the closest significant disaster, depending on the shortest period. For example, Mexico experienced massive earthquakes in 1985 and 1995, and the closest selected disaster to the 1995 earthquake was in 2010. Therefore, the inference period for the 1985 earthquake is nine years, the inference period for the 1995 earthquake is ten years, and the inference period for the 2010 disaster is eight years as it is data-limited. This is done for every inference test. A treatment is considered significant at p-values less than 0.1 or 90% significance. Changing this 0.05 results in the loss of only three significant events.

To sum up, the contribution to the existing literature is two-fold. In terms of the model, the selection of the V-vector improves accuracy of the simulations but increases computational time. This vector reflects the relative importance of every co-factor in the model, so an accurate selection of this vector results in more accurate regressions. Several propositions have been made to estimate this vector, such as out-of-sample validation (Abadie, Diamond, and Hainmueller, 2015). This is improved by grouping all the units (regions) depending on the values of their treated observations at a specified point in time (the occurrence of the treatment). The number of these groups is chosen to be three because it allows for he best trade-off between accuracy and speed, meaning the lowest 1/3 of the outcome observations in terms of values are put in one group, the second 1/3 in another, and the final 1/3 in another. A representative vector for each group is found, which would then be the initial guess for each simulation for a member of that group. This technique is robust to out-of-sample validation, as all the simulations conducted in this chapter relied on an out-of-sample selection for the vector V with no loss of accuracy in predicting the pre-treatment outcome variable.

1.4 Empirics and data

1.4.1 Data sources

To conduct this analysis, data were obtained from several sources. The GDP data selected is available from 1975 to 2018. Co-factor variables are selected if they are statistically significant in determining GDP per capita. The literature on their importance is well established, so this subsection only summarizes the variables and their sources. The list is as follows:

- *Share of value-added (Agriculture and Industry)*: I use the World Bank Database for a panel series dataset from 1970 to 2018, that describes the share of two different sectors in the economy in the value added.

- *Secondary enrolment rate:* I use the World Bank Database for a panel series dataset from 1980 to 2018.

- *PolityIV*:[1] I use the Polity5 project that codes the degree of democratization of a country. The values range from -10 (full autocracy) to +10 (full democracy), and data is available from 1960 to 2013.

- *Capital stock at current PPP:* I use the capital stock data obtained from FRED that uses the perpetual inventory method of calculation.

- *Corruption Perception Index:* I use the corruption perception index values calculated by Transparency international.[2] This data set is based on several sources that have to qualify to certain criteria. I also use this data set in my regression. This is an additional control variable in the synthetic regression model.

- *Population, Labor Force, Enrolment rates, and Trade openness:* I use the World Bank Database to obtain these data series from 1975 to 2018. Not all countries have sufficient data points.

- *Disaster Data:* I use the EM-DAT database from the Catholic University of Louvain in Belgium. The data covers disasters from 1970 until 2018. This data is not used in the synthetic regression calculations, but is used to generate the disaster list, which includes the country and the time of the disaster of interest.

Both *polity* and corruption perception (cpi) are used as proxy measures of institutional quality in the regression analysis done in section 1.5.2. Several other variables are added to the analysis of the results that are not included in the Synthetic Control Method, as there is not enough data for the entire sample of countries. Despite having data for 98 countries, and those countries being the pool of donors, this chapter only focuses on the impact of disasters on a list of 30 countries. This list is separated into two regions, South East Asia (SEA) and South and Central America (SCA). Initial work had been done on the full set of 98 countries prior to narrowing down the list. Simulations were inaccurate for pre-treatment periods for some countries that either lacked sufficient covariate data or were on the edge of the convex set of countries concerning their

[1] https://www.systemicpeace.org/polityproject.html
[2] https://www.transparency.org/en

GDP. Not enough suitable donor countries were found to build counterfactuals due to the extreme values of the dependent variable of these countries. The final countries selected do not exhibit such qualities, making the estimations much more reliable. Countries in one of the regions mentioned before tend to have similar economies, especially regarding GDP per capita in 2017 international U.S. dollars using purchasing power parity rates.

Regressions on richer countries found no impact of disasters on GDP or insignificant results. The final list of countries and the relevant and significant disasters can be found in Appendix A. These regions were chosen for two reasons. First, the disasters affecting each region are very similar in size and nature, mainly due to their proximity. Second, the quality of institutions between these regions is significantly different, with outliers in each region. So while SA countries are on the lower end of the institutional quality spectrum, except Peru, Ecuador, and Chile, most of the SEA countries chosen are on the higher end. Other minor reasons for selecting these regions are the availability of complementary data (GDP per capita, consumption per capita, trade immigration/migration data, accuracy of the data reported, and the frequency/impact of large-scale disasters). Improvements in this chapter could include more regions for robustness.

1.4.2 Disasters

In this subsection, the selection process of disasters is described in detail. As mentioned previously, the impact of disasters is more than just on physical capital, which is why in this chapter, the criteria for disaster are expanded to consider the impact on human capital by considering the number of affected individuals and capital destroyed. Data for disasters is obtained from the Emergency Database (EM-DAT), collected by the Catholic University of Louvain, which defines a disaster as an event that satisfies at least one of the following criteria:

- 10 or more people are reported killed.
- 100 people are reported affected (displaced); a state of emergency is declared.
- A call for international assistance is issued.

This is a broad definition of disasters and is biased towards smaller countries. The two main criteria I care about are affected individuals and economic impact. The latter refers to the direct value of the destruction caused by the disaster and does not consider any long-term effects, as it is hard to track economic loss months or years after the disaster. The database records direct estimated damage in terms of losses to GDP. The database includes various types of disasters. For this research, I include natural disasters as a general classification group, which includes geophysical disasters such as earthquakes, hydrological such as floods or landslides, biological such as an epidemic, climatological such as droughts and wildfires, and meteorological such as storms. I exclude technological or financial disasters from this list.

It does not make sense to single out unique disasters for two reasons. First, disasters tend to be followed by an influx of financial aid, meaning losses in potential GDP may not be adequately measured. Second, richer countries have been historically more prepared over time for disasters (and become even more prepared the more disasters to happen), which contributes to the decreasing impact of these disasters on GDP over time. This could be due to over-investing in disaster-prone areas, another trade-off that countries must consider. Richer countries will be able to provide this level of investment and often do not rely on external aid to alleviate the impact of the disaster. This means that policy implications are different between rich and developing countries. There is a sizeable gap in the maturity of the insurance markets between the rich and developing countries. This chapter also analyzes areas where these markets are underdeveloped to discuss alternative policy implications for these countries. I argue that the well-preparedness of these richer countries, which includes more mature financial and insurance markets, has contributed to the income gap between them over time, despite significant moral hazard problems. This preparedness is partly due to higher institutional quality that takes advantage of the increase in spending after a disaster and the influx of new, more advanced capital.

In this chapter, disasters are selected depending on the percentage impact on population or GDP. A sample selection criteria for a disaster is the event with the largest impact as a percentage of GDP, without considering the impact on the population. The selection process is similar to that designed in Cavallo et al. (2013) to select a minimum of three disasters in the pool of countries for each country. Using the EM-DAT database, a list of all the disasters for the 98 countries occurring between 1975 and 2018 is obtained. I select disasters specific to the countries in one of the two regions mentioned in this list. The economic and human impact of every disaster recorded is calculated as a percentage of the country's nominal GDP during the disaster and percentage of the total population, respectively. All the disasters for the 98 countries in the pool are obtained to ensure that when conducting inference, no country is also experiencing an event in the same time frame as the treated country. For every country, two lists are made, the economic list, which ranks the disasters from highest to lowest depending on their impact on GDP, and the human list, which ranks the disasters from highest to lowest similarly. The top three disasters from each list are then selected. This means that three to six disasters are selected per country, depending on whether the economic disaster list selection overlaps with the human disaster one. The disasters obtained are from 1975 to 2018, and for the 98 countries, the result is a total of 457 disasters selected. For the specific regions, the total is 106 disasters or an average of 3.5 disasters per country. For the panel of countries considered and out of the 96 disasters considered, 72 caused significant deviations from GDP (positive or negative) up to 10 years after the occurrence of the disaster.

A key addition presented by this chapter and that has been overlooked by Cavallo et al. (2013) and Barone and Mocetti (2014) is that countries have had to deal with a series of disasters with no predictable interval for their occurrence. Therefore, any analysis of the impact on long-term growth needs to take that into account, which means that any subsequent disasters limit the scope of the impact of a particular disaster. By ranking these events in terms of their effect on GDP and population and choosing the top disasters such that there is a minimum of five years between each disaster considered for the Synthetic Control Method, I guarantee that the events chosen are infrequent and significant enough to be classified as "disasters", but also providing an adequate time frame to analyze the long term effect of these events.

It is important to note that disaster impact is biased towards smaller or poorer countries, meaning the sample of disasters studied disproportionately includes poorer countries. Richer countries with better institutions have likely been able to mitigate the effect of these disasters over time through proper planning. This bias is tackled by not including minimum thresholds for disasters to be considered. In other words, in previous research, a disaster needed to have a certain minimum level of impact on GDP to be included in the sample selection. Given that the sample of countries in the two regions selected includes richer countries, not setting a minimum threshold allows for a broader sample. The results from the Synthetic Control Method indicate that their inclusion is significant, even if the impact is not as pronounced compared to poorer countries.

While in this chapter only natural disasters are included, a possible extension would be the addition of financial, technological, or political disasters. This would also expand the possible sample of countries studied. However, it would require a change to the covariates and the model.

1.4.3 Region selection

Two sets of countries were chosen for analysis in this chapter. The properties set for this selection were done in such a way to ensure that events were significant and comparable. The first group is South and Central America (SCA), and the second is South East Asia (SEA). The choice of groups was decided by the similarity of events that affected each country in this group and the high variance in institutional quality and GDP per capita. When comparing institutional quality, a wide range is observed both between and within groups. Most SCA countries are significantly lower ranked than their SEA counterparts in terms of corruption, regulatory power, and stability rankings. This, however, does not translate similarly to GDP per capita values. Even within each group, countries exhibit radically different institutional quality values. These values are also not static and varied over time.

Country	*Polity*	*Corruption Perception Index*	*year*
Mexico	8	3.5	2005
Argentina	-8	n/a	1988
Chile	10	7.2	2010
Peru	9	3.5	2007
Ecuador	-9	n/a	1992

Table 1.2: Polity and corruption index for select SCA countries

Country	*Polity*	*Corruption Perception Index*	*year*
Indonesia	-7	n/a	1994
Philippines	-8	3.6	2013
Australia	10	8.8	1996
Malaysia	4	n/a	1985
Singapore	-2	9.1	2000

Table 1.3: Polity and CPI index for SEA countries

1.5 Results

The limitations of the data used and the selection criteria for the disaster list allow the analysis of no more than ten years of post-disaster impact across all disasters. This is because the interval of the occurrence of a disaster for some countries is sometimes less than ten years. However, in the selection process of the disasters, a minimum of five years between disasters was imposed. The post-disaster average deviation for all countries is calculated for a maximum of 10 years. The final selection is the three-year and five-year averages. The three-year average is considered by the literature as usually the long-run effect, and the five-year is where most disasters end up peaking in terms of their effect, as seen in figure 1.2. This subsection presents the results of both the simulations from the Synthetic Control Method and the regressions on the deviations (or α) from the Synthetic Control Method. The first subsection discusses the average impact of a disaster on GDP, while in the second subsection, and using an OLS regression; different institutional quality variables are regressed on these deviations to quantify their impact and importance.

1.5.1 Results from changes to V-selection

This subsection highlights the impact of the changes to the vector of relative importance through stylized examples. The goal is to understand how these changes affect the Mean Square Predicted Errors (MSPE) for pre-treatment outcome variables. A smaller value of this number leads to more robust conclusions about the impact of the treatment. The selection of regions and treatment periods impacts the results of this robustness test, however, the conclusion is that Mean Square Predicted Errors are on either reduced or the same as the base Synthetic Control

Model. Computational time depends on the number of regressions conducted. All regressions were conducted and recorded using a 2021 Apple Macbook Pro (M1 Max chip), with 32 GBs of RAM, running Python 3.

Three tests were conducted to compare the Mean Square Predicted Errors from the base Synthetic Control Method to the augmented version of the model (grouped version). The tests were done using $N = \{20, 30, 40\}$ regions as donor pools. For each pool, three groups were selected for the tests. To stay consistent with the method proposed in this chapter, the groups were chosen based on the ranking of the outcome variable for each country, where the first group included the highest one-third values, the second, the middle one-third, and the third group was composed of the bottom one-third values. This grouping can be altered to include more or fewer groups or by changing the grouping criteria. This grouping is ex-post because obtaining the data used in obtaining the optimal weights for the Synthetic Control Simulations is only up to the treatment i.e. T_0. Using ex-ante data (or post-treatment) data may lead to higher Mean Square Predicted Errors and bad fits. The dataset of regions and treatment periods was selected randomly from the available data used in this chapter.

Tests were conducted twice on a sample of three, five, seven, and ten random countries from these pools, with the rest of the countries used in the simulation of the Synthetic Control Model. Significance does not matter in this case since the purpose of the test is to simply find the Mean Square Predicted Errors pre-treatment. Since the number of pre-treatment periods impacts the convergence of the Synthetic Control Method, the results displayed in Table 1.4 capture the average Mean Square Predicted Errors difference between the grouped version of the Synthetic Control Method and the base model. A negative value indicates that the base Synthetic Control Method has a higher Mean Square Predicted Errors than the grouped version.

Pool size \ Sample Size	3	5	7	10
$N = 30$	-10.2**	-23.4***	-1.5**	-4.3**
$N = 40$	0.8	-30.2***	-20.3**	-0.05
$N = 50$	0.01	-5.8**	-3.4**	-0.85*
Note:	*p<0.1; **p<0.05; ***p<0.01			

Table 1.4: Mean Square Predicted Errors differences

In every case, the augmented Synthetic Control Method resulted in lower or similar pre-treatment Mean Square Predicted Errors for the pre-treatment variables. This implies that the weights calculated are a better fit for the model and would provide more accurate results for forecasted variable. This adds confidence to the validity of the results from the Synthetic Control Simulation, leading to more robust conclusions. The trade-off, in this case, comes at the cost of higher computational time. The average computational time to complete regression is highlighted in Figure 1.1. The augmented model is significantly slower, but the average time per regression decreases as the number of regressions increases. This augmented version is therefore helpful for large data sets.

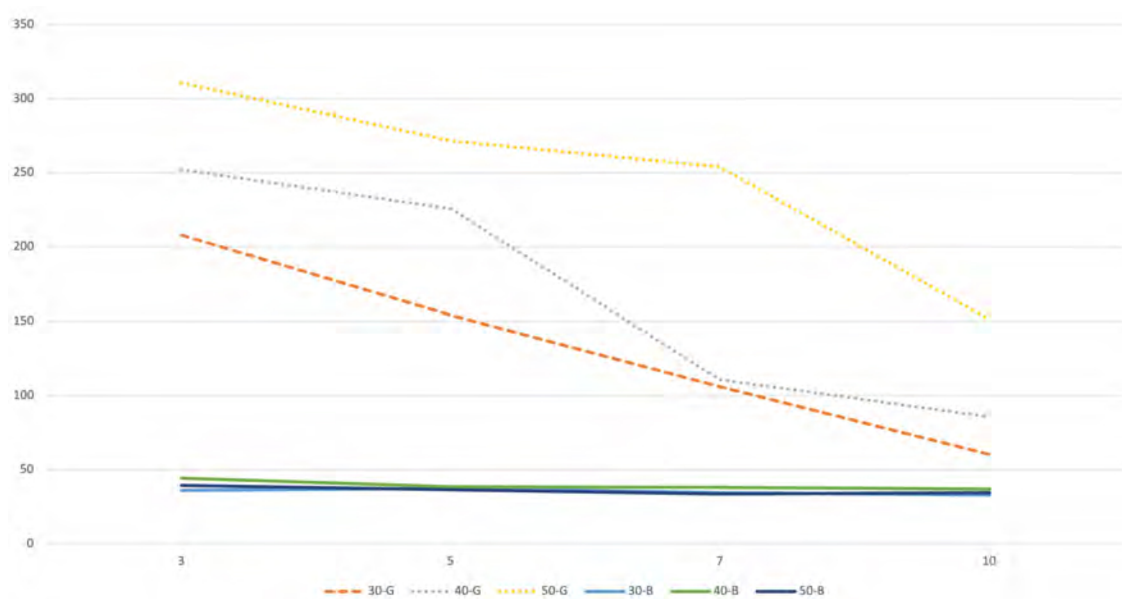
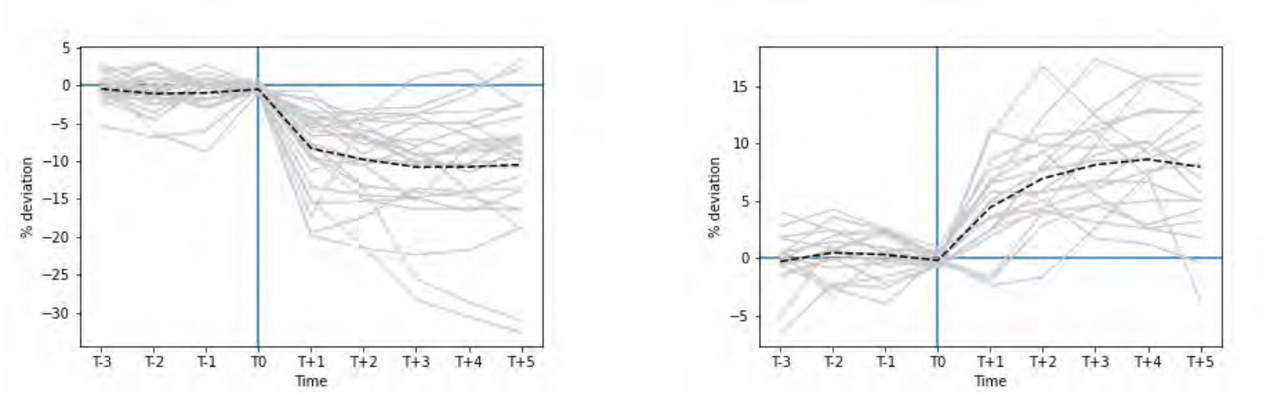


Figure 1.1: Average time per regression (in seconds)



(a) Disasters with negative recovery (b) Disasters with positive recovery

Figure 1.2: Percentage deviations for significant events

1.5.2 Impact on GDP from Synthetic Control Method

Running the synthetic simulations described above for all possible countries provides 45 statistically significant disasters from the set of 106 disasters chosen. The deviations of the synthetic model from the actual data are saved for all periods after the occurrence of a significant event. Out of the 45 observed events, 26 resulted in negative post-recovery differences (three-year and five-year average), indicating that the synthetic regression predicted a higher value of GDP per capita than its data counterpart. The split in the results matches the differences in results in previous research (Ikefuji and Horii, 2012) (Akao and Sakamoto, 2018), and the results include disasters that had both a positive and a negative impact. Figures 1.2b and 1.2a show the various percentage deviation between the predicted minus the treated variable five years after the occurrence of an event. Each grey line represents one statistically significant event, and the dotted line represents the average of all events. This dotted line is also presented in table 1.5. While this difference becomes minimal for certain countries after five years, the majority show the long-term implication of these events. These values are essentially the dotted line in figures 1.2a and 1.2b.

Several conclusions can be made from these results. First, while the most significant positive recovery was around 15% higher than the actual GDP, this amount was more than half the negative recovery values. It is a result that is to be expected, as it is harder to rebuild. While rebuilding can be more beneficial than staying on the post-disaster path under certain conditions, disasters will often just exacerbate an already underperforming system, heavily stifle growth, and impact

GDP for extended periods.

To understand what these conditions are and what are the underlying factors behind this split, several OLS regressions are done on the data obtained from the Synthetic Control Method using both three and five-year average differences. These regressions include various proxies of institutional quality. Table 1.5 shows the average disaster value for the data set, for both the negative and positive values.

	Negative		Positive	
Time period	Mean	SD	Mean	SD
$T-3$	-0.46	1.69	-0.29	2.36
$T-2$	-1.09	2.57	0.47	2.02
$T-1$	-0.97	2.38	0.30	1.84
T_0	-0.52	0.42	-0.19	0.508
$T+1$	-8.32	5.46	3.41	1.78
$T+2$	-9.79	5.27	6.95	2.90
$T+3$	-10.79	5.96	8.13	3.96
$T+4$	-10.76	5.76	7.79	2.44
$T+5$	-9.96	4.47	6.25	5.35

Table 1.5: Average impact of disasters

1.5.3 Importance of political institutions

In analyzing the impact of political institutions on recovery, simple OLS regressions are conducted, once for the three-year post-disaster GDP averages and another for the five-year average. The goal is to understand the impact of *polity*, corruption perception index, and other institutional quality variables on this deviation. The model is as follows :

$$D_{i,t} = \alpha + \beta_i X_i + \gamma_i Z_i + e_i$$

where D_i is the average deviation from actual GDP for the countries in the sample for the inferred post-treatment dates for country i and periods t, depending on the model, this can be the three year average or five year average. X is a matrix of dependent variables and Z is a matrix of controls. I include the following variables in X:

- **Regulatory power:** I use data calculated by (Kaufmann, Kraay, and Mastruzzi, 2010), to estimate the regulator power in a country. It captures perceptions of the ability of the government to formulate and implement policies and regulations that develop the private sector. The data is normally distributed, and ranges between -2.5 to 2.5.

- **Government effectiveness:** I use data calculated by Kaufmann, Kraay, and Mastruzzi (2010). The data captures perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures. It is normally distributed, and ranges between -2.5 to 2.5.

- **Violence:** I use data calculated by Kaufmann, Kraay, and Mastruzzi (2010). The data captures frequency of acts of violence and civil disobedience. It is normally distributed, and ranges between -2.5 to 2.5.

- **CPI and Polity:** Data for the Corruption perception index is limited, and only extends to 1994. If a disaster happened during a time where there is no corruption perception index data, the average of total CPI is used as a proxy. Dropping this and lowering the sample does not lead to any change in significance in the model. *polity* is an index that refers to the degree of democratization of a country. It is between -10 and 10, where 10 indicates a full democracy, and -10 refers to a full authoritarian regime.

- Z **is a vector of controls:** This vector includes population, labor force, land size, and interest rates, as explained in earlier section, as they are significant variables when determining GDP.

The motivation behind including *polity* in addition to the other institutional quality is to highlight the importance of democratization in disaster recovery. *Polity* measures patterns of authority, and is essentially an index of the level of authority in a country. A score of 10 indicates full democracy, but is not fully reflective of the quality of institutions, so while Denmark and Cyprus have the same polity score, the quality of the regulatory institutions are not the same. The results of the regression can be seen in tables 1.6 and 1.7. The conclusions that can be drawn from these table is that political government regulatory power and corruption play a significant role in determining how well a country recovers from a disaster.

This is an opposite conclusion to that of Cavallo et al. (2013) who finds that large enough disasters induce political revolutions, linking the impact of disasters on GDP to these revolutions. The results in this chapter challenge this idea to a certain extent. The *polity* index for the affected countries seems insignificant, and regime changes are not necessarily the direct reason why disasters impact GDP, but rather the deterioration of political-institutional quality. This is based on the fact that a revolution leads to a significant decrease in the polity index of a country.

Insurance markets play a crucial role in hedging against disasters for both households. There is a lack of comparable insurance data for the countries selected in this chapter, which does not allow for a direct comparison of the insurance markets between countries. Historical values for variables such as regulatory power, government effectiveness, and the corruption perception index serve as valuable proxies for the ability of a government to direct capital to where it is needed most and the confidence of citizens as well as foreign governments in funneling aid to governmental agencies. This analysis does not extend, however, to the trade-off between preparing for a disaster prior to its occurrence and the impact of the disaster.

The results from the regressions shown in Tables 1.6 and 1.7 provide evidence that, while controlling for various factors, cpi and regulatory power are the only statistically significant variables in determining post-disaster recovery, with regulatory power being the strongest of the two and the more significant. A one standard deviation off the distribution, in other words, being in the top 30% of countries regarding regulatory power, leads to a 13% increase in recovery rate. This can be observed in the row titled *reg* in the regression tables. A country is expected on average to recover 13% above their path prior to the disaster, five years after the disaster occurs if they are in the top 30% of countries in regulatory power. Similarly, being on the opposite end will lead to lagged recovery and a lower GDP 5 years after the disaster than had the disaster not occurred.

For example, Panama experienced two disasters of relatively similar impact. One was in 1989 and the other in 2013. Rocked by political turmoil prior to the first disaster, Panama's recovery for the following five years proved to be difficult, almost 16% less than the synthetic model. Without

	Reg. 1	Reg. 2	Reg. 3	Reg. 4	Reg. 5
cpi	1.358*	1.311*	1.281*	1.295*	1.271*
	(0.774)	(0.816)	(0.774)	(0.831)	(0.824)
pol	0.2281	0.2240	0.2281	0.2273	0.2191
	(0.3147)	(0.3320)	(0.4157)	(0.3523)	(0.3451)
gov	-7.8913	-7.9961	-7.8521	-7.1261	-8.1961
	(5.4229)	(5.7210)	(5.3216)	(5.4253)	(6.3147)
reg	13.0713**	13.3504**	13.2310**	13.4154**	13.2152**
	(6.2258)	(6.5680)	(6.4312)	(6.3156)	(6.1283)
vio	3.7847	4.0835	4.52261*	4.0835	4.1422*
	(2.8122)	(2.9668)	(2.0431)	(2.512)	(2.1318)
labor force			1.2041	1.4512	1.041
			(1.4511)	(1.410)	(1.325)
land size				0.002351*	0.002281*
				(0.001161)	(0.001025)
interest rate					0.5281***
					(0.01147)
R-squared	0.2305	0.2220	0.2013	0.2512	0.4211
R-squared Adj.	0.1343	0.1248	0.1281	0.1247	0.2255
N	45	45	45	45	45
Note:			*p<0.1; **p<0.05; ***p<0.01		

Table 1.6: OLS results for three-year averages

	Reg. 1	Reg. 2	Reg. 3	Reg. 4	Reg. 5
cpi	1.632	1.512	1.415	1.421	1.364
	(0.912)	(0.879)	(0.945)	(0.913)	(0.925)
pol	0.142	0.135	0.131	0.131	0.148
	(0.121)	(0.113)	(0.107)	(0.101)	(0.098)
gov	-7.315*	-7.321	-7.451	-7.422	-7.962
	(4.381)	(4.765)	(4.915)	(4.453)	(4.221)
reg	10.522**	10.415**	10.387*	11.327**	13.2152**
	(4.314)	(4.217)	(4.597)	(4.512)	(5.323)
vio	6.821	6.587	6.891	6.098	6.922*
	(5.210)	(6.124)	(5.997)	(6.014)	(5,326)
labor force			0.665	0.621	0.258
			(1.331)	(1.521)	(1.425)
land size				0.0032**	0.0025**
				(0.0041)	(0.0056)
interest rate					0.4219**
					(0.1427)
R-squared	0.2014	0.2025	0.2142	0.2314	0.4211
R-squared Adj.	0.1285	0.1275	0.1264	0.1235	0.3187
N	45	45	45	45	45
Note:			*p<0.1; **p<0.05; ***p<0.01		

Table 1.7: OLS results for five-year averages

going into the political details of the disaster, the drop in politicization, regulatory power, and governmental effectiveness prior to the 1989 disaster contributed to the slow recovery. The period from 1990 to the mid-2000s marked an increase in government effectiveness and a reduction in corruption as the country became more democratic. Compared to 1989, Panama's recovery from the disaster in 2013 is better than expected, averaging 12% over its synthetic counterpart over the following five years.

1.5.4 Robustness check

In order to test the validity of the results, several robustness checks are conducted. First, the data is split into two different groups. The first group includes the countries where the post-disaster recovery leads to a positive difference, i.e., the predicted GDP is higher than the actual GDP path, and the other group is the inverse. In addition, the Quality of Government variable obtained from the quality of government project run by the Department of Political Science at Gteborg University is added to the regression. It is a variable that considers the core features that determine the QoG such as impartiality, bureaucratic quality, and corruption, as well as measures that are broader such as the rule of law and transparency. This is done to account for omitted variable bias. The results in the appendix show that splitting the data or adding variables do not add to the significance of the model or affect the significance of the previously mentioned variables. Regulatory quality and cpi are still the only statistically significant values. The tables can be found in Appendix B.

Reverse causality of the quality of institutions and democratization is another important factor to consider here. Several authors, such as Jong-A-Pin (2009) found evidence of reverse causality between political instability and growth. To test for this, a two-stage regression with instrumental variables is applied. In the first stage, the endogenous explanatory variables are treated as functions of their instruments. The instruments considered are: education levels (primary and secondary), distance to equator (Hall and Jones, 1999), and mortality rates (Acemoglu, Johnson, and Robinson, 2001). The predicted value is used as an explanatory variable in the second stage in the equation. In this case, the original function's endogenous variable is the regressor. In testing for endogeneity, a few instrumental variables are selected to control for the endogeneity between the exogenous variables and endogenous variables.

	polity
cpi	-0.24
polity	1.0
gov	-0.18
reg	-0.25
vio	-0.03

Table 1.8: Correlation matrix for polity and other explanatory variables

Another potential issue is the link between any explanatory variables and *polity*. I test for multicollinearity and show the correlation matrix for *polity* and the other variables. No significant evidence of collinearity exists in this case. To test for endogeneity a simple Hausman test is conducted and for both models listed above the p-valeues are respectively $p_3 = 0.24$ and $p_5 = 0.31$. The null cannot be rejected and no evidence of endogeneity is found for the quality of institutions and growth rates. While things like *polity* and interest rates are crucial in GDP determination, the variables selected in the model do not display any statistically significant sign of endogeneity. While the literature does mention political instability, *polity* itself is not necessarily a measure of instability, but rather democratization, which explains the lack of endogeneity in the model.

1.6 Simulations from Synthetic Control Method

This section presents the results of the Synthetic Control Method regressions conducted on both regions. A sample of these results is provided in figures 1.3 and 1.4, and the rest are shown in the appendix. The dotted lines show the predicted GDP per capita values, while the solid red lines show the actual values of the treated variable. Some notable observations for each region. are also provided.

1.6.1 South and Central America

In the SCA region, the biggest disaster impacting the following countries are considered: Argentina, Brazil, Bolivia, Mexico, Chile, Ecuador, Dominican Republic, Honduras, Colombia, Paraguay, Panama, Uruguay, and Peru. Table 1.2 presents an exciting range of the *polity* and corruption levels of these countries during highlighted periods. For example, in the case of Mexico, three major natural disasters are chosen. These occurred in 1985 (earthquake), in 2005 (earthquake), and finally in 2010 (flood), but only two of these were statistically significant. The earthquake in 1985 led to an increase in public scrutiny and increased expenditure on infrastructure. However, prior to this, the quality of institutions was relatively poor, which is why the predicted values for Mexico are higher than the actual values, meaning this disaster had adverse effects, even ten years after its occurrence. There was also a severe restructuring of public safety codes, infrastructure investment, and improvements in relief and response efforts which would be necessary in dealing with upcoming disasters (UNDRR, 2017). Despite a worldwide financial crisis in 2008, the disaster that hit Mexico City, one of Mexico's biggest cities in 2010, seemed not to have as big of an impact on the GDP per capita in Mexico. However, Mexico's infrastructure investment, regulatory power, and cpi index prior to this disaster were relatively poor, even with higher *polity* values (in 1985, polity was -3, in 2007, it was 9). The recovery is statistically significantly lower than expected, similar to what happened in 1985.

For the countries in this group, the disasters that seem to have the most significant impact are earthquakes, which is a benefit for comparing across countries and regions. In contrast, the most devastating type of disasters in SEA are hurricanes and floods.[3] When conducting the OLS regression on the deviations and controlling for the various types of disasters, there is no statistically significant difference between institutional quality and the impact of the disaster on average.

Figure 1.3 shows the synthetic analysis for a selection of countries from this subset. As mentioned in section 1.3, only the first half of the pre-treatment outcome variable was used to estimate the weights, thereby testing the model's validity over the second half of that period as an added

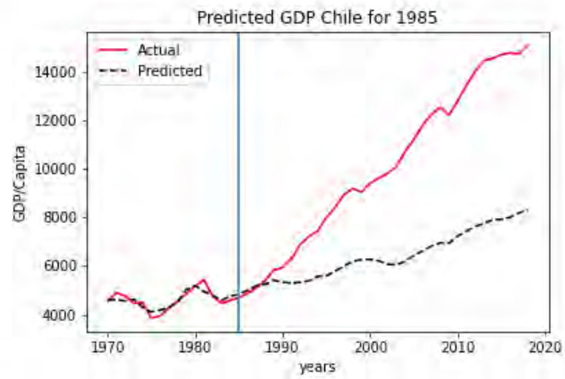
[3] I cannot state whether the type of disasters can make a difference in the recovery process, but this is work that can be developed in future research.

measure to check the accuracy of the simulation. When looking at figure 1.3, the results of the Synthetic Control Method display a fairly good pre-treatment fit to the data. This lends even more credibility and robustness to the inference results. Except for Argentina, most regressions were good with very low pre-treatment Mean Square Predicted Errors values. Inference tests are conducted for every treated period regardless of pre-treatment Mean Square Predicted Errors values, and the p-values for the forecasted periods are obtained for each simulation. These are displayed below the graphs for the events chosen. Since the objective is to calculate the impact of these disasters, the percentage deviation of GDP for a given period post-treatment is calculated depending on the maximum post-treatment periods possible. The results of these deviations are shown in Table 1.5, which provides the average impact of disasters up to five periods after one has happened.

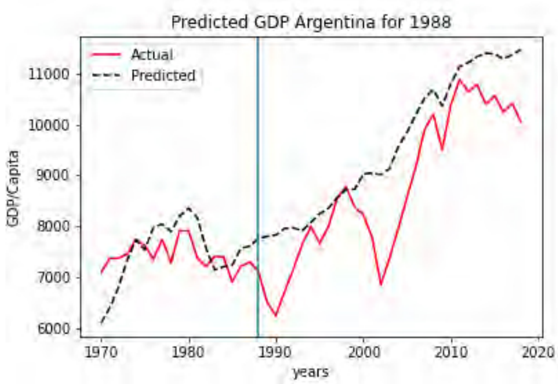
In terms of politics, the SCA countries display many fluctuations in different institutional quality variables, as seen when looking at *polity.* For example, Ecuador, one of the poorer countries in Latin America, was subjected to a financial crisis in 1998 which led to a political crisis soon after, where the president was ousted and replaced by his vice president a year later. The result was a drop in polity over the years that improved over time. However, the quality of the political institutions was rather low, which meant that Ecuador performed relatively poorly in recovering from three disasters in 1982, 1987, and 1993.

While Mexico and Chile were affected by devastating earthquakes in 1985, Chile's post-disaster recovery is better than Mexico's. At the same time, Mexico underperformed relative to its synthetic counterpart, and Chile over-performed. As seen in table 1.2, Chile's polity index is -1. A few years later, Chile's polity index jumped from -6 to 8. In context, Chile's military regime was ousted in 1989. The 1985 earthquake caused more than 1 Billion dollars worth of damages and killed 177 people. Due to the military's inability to deal with this earthquake, the Finance minister at the time implemented reforms in the form of privatization of the construction sector, loosening the military's grip on a crucial sector of the economy (Vogler, 2010). In 2010 Chile experienced another devastating earthquake, and the predicted GDP 8 years after was 6% lower than the actual GDP, potentially owing to these reforms that occurred almost two decades before.

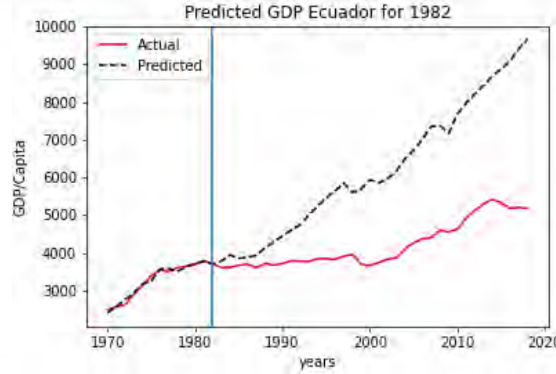
(a) Mexico 1985, p-value = 0.08



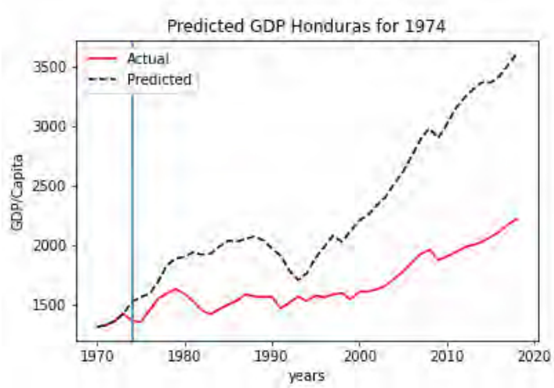
(b) Chile 1985, p-value = 0.04



(c) Argentina 1988, p-value = 0.45



(d) Ecuador 1982 , p-value = 0.07



(e) Honduras 1974, p-value = 0.21

Figure 1.3: Synthetic Control regressions (SCA)

1.6.2 South and South-East Asia

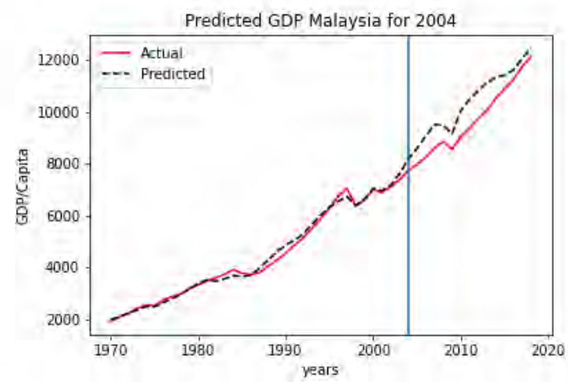
In the SEA region, similar to the SCA region, a mixture of countries is chosen on the spectrum of the *polity* and corruption indices. These are Australia, Philippines, Malaysia, Thailand, Taiwan, Indonesia, and Singapore. Table 1.3 shows the different *polity* levels at the time of their most significant disasters and their corruption perception index for those periods. These values show the disparity within these countries and highlight an important fact. A higher polity value does not correlate with a higher CPI. This can be seen when looking at Singapore and Australia. Singapore has a higher CPI value but a lower *polity* score than Australia. A -2 score indicates an authoritarian regime that is also perceived to be less corrupt than the full democracy of Australia. This will be crucial in understanding how each of these countries will be impacted by disasters.

The following graphs are selected results of conducting synthetic regressions on the aforementioned countries. Australia and Singapore also present a contrasting image to the majority of the other countries discussed so far in this chapter. They are the only countries in the SEA region where the synthetic control country under-performs the actual country in all disasters selected. These two countries rank lowest in terms of corruption but vary differently when it comes to *polity*, their degree of democratization. For SEA countries, the majority of disasters are hurricanes or typhoons. The result of the inference tests are available in the appendix, showing the distribution and type of significant disasters.

1.7 Concluding remarks

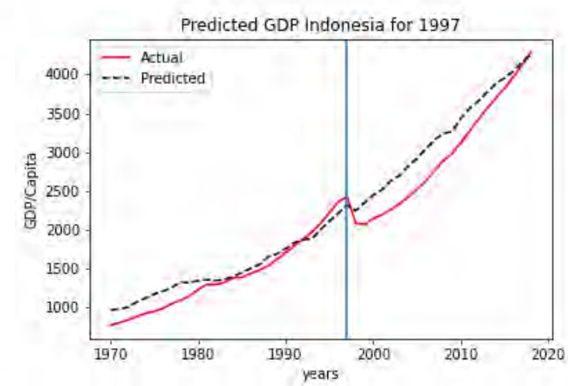
In this chapter, I find that institutional quality plays a significant role in the recovery of GDP per capita after the occurrence of a disaster for countries where GDP per capita is less than $35,000. The two most important measures of institutional quality are regulatory power and level of corruption. These two variables, combined contribute to around 20% to the recovery from disasters. The scope of the analysis is limited to 5 years for most of the countries chosen. Therefore, a claim cannot be made about the optimal post-disaster recovery path with confidence, especially since there is no criteria discussed about the optimal path for growth in this analysis.

(a) Australia 1996, p-value = 0.04

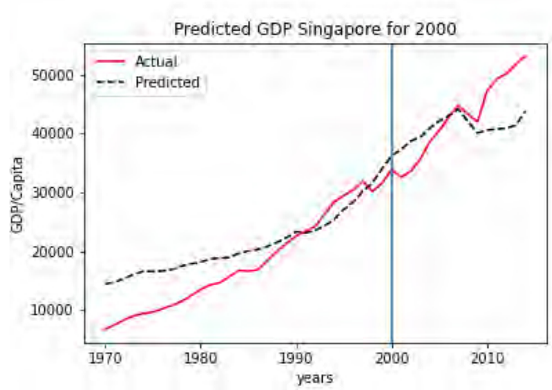


(b) Malaysia 2004, p-value = 0.08

(c) Philippines 1990, p-value = 0.03



(d) Indonesia 1997, p-value = 0.07



(e) Singapore 2000, p-value = 0.33

Figure 1.4: Synthetic Control regressions (SEA)

While the importance of political institutions prior to the occurrence of the disaster is highlighted in this research, there is no claim made about the cost required to establish these institutions and the impact on GDP prior to the disaster. Further research could be directed towards answering this question.

This chapter attempts to tackle an issue raised by various studies conducted on the long-term impact of disasters. Since there is no clear consensus on the long-run effect of disasters on GDP, this chapter contributes to the literature by studying the impact of disasters on a large panel of countries using the Synthetic Control Method and quantifying the significance of various factors on this impact. The findings in this chapter suggest that politicization levels are insignificant in affecting GDP during the recovery phase. There is no evidence that democracies perform better than autocracies recovering from a disaster. Even when considering institutional quality variables, this research finds that only regulatory power seems to be the most significant factor. Regulatory power and corruption are vital components in achieving a positive recovery from disasters and even outgrowing its pre-disaster outcome. In practical terms, countries in the top 30% of the distribution of regulatory authority will recover from a disaster in such a way that they will overtake the path of their pre disaster GDP.

On average, and over five years after their occurrence, disasters will have a more significant negative impact than positive impact, with an absolute difference of around 3% between the average positive and negative values. While the negative impact can be pretty significant, there is a smaller limit regarding how much more a country can recover after a disaster. The results from the Synthetic Control Method regressions on richer countries show that disasters do not affect long-run GDP. For countries where GDP per capita is greater than 35,000$ U.S. per year, the effect of the disaster is negligible one year after its occurrence. Finally, I extended the methodology used in performing regressions from the Synthetic Control Method. Grouping regions according to their outcome variable leads to an efficient selection of the vector V, the vector of relative importance. This results in faster and more accurate regressions for research that includes many events and regions.

Future work can extend the model by looking at the consecutive impact of disasters or adding different types of disasters. In terms of the former, ignoring the accumulated effect of disasters over time and their interaction with institutional quality seems unwise. Repeated disasters could lead to a significant overhaul in institutional quality. The framework presented by this chapter only studies the impact of a particular disaster until another occurs. In practical terms, this means that the impact of some disasters can only be studied for less than five years. Adding multiple steps to the synthetic control regression will provide a deeper insight into the true impact of these disasters.

Appendix A

Table 1.9 summarizes the list of countries and dates selected for the final regressions.

Country	Date	Country	Date
Bolivia	1992	Indonesia	2004
Bolivia	1997	Honduras	1974
Brazil	1984	Honduras	1993
Colombia	1985	Mexico	1985
Colombia	1999	Mexico	1995
Colombia	2011	Mexico	2005
Costa Rica	1988	Malaysia	2004
Costa Rica	1996	Malaysia	2007
Chile	1985	Panama	1988
Chile	2010	Panama	2013
Dominican Republic	1979	Paraguay	1983
Dominican Republic	1998	Paraguay	1998
Ecuador	1982	Paraguay	2007
Ecuador	1987	Philippines	1990
Ecuador	1993	Philippines	1995
Indonesia	1997	Philippines	2013
Thailand	2011	Thailand	2013
Thailand	1984	Singapore	2000
Singapore	2003	Uruguay	1999
Singapore	2007	Uruguay	2002

Table 1.9: List of countries and dates selected where a disaster was significant

Appendix B

Tables 1.10 and 1.11 are summaries of the regressions conducted on the data that was split between positive and negative values using the five-year averages

VARIABLES	Reg 1	Reg 2	Reg 3	Reg 4	Reg 5
corruption perception index	1.314*	1.221	1.314*	1.289	1.264*
	(0.665)	(0.542)	(0.684)	(0.712)	(0.613)
polity	0.458	0.551	0.528	0.671	0.591
	(0.853)	(0.546)	(0.485)	(0.543)	(0.613)
government authority	-6.241	-7.112	-6.895	-7.1261	-8.1961
	(4.223)	(4.387)	(4.335)	(5.425)	(6.314)
regulatory power	12.891***	13.251**	13.449**	13.124**	13.667**
	(4.321)	(6.531)	(6.351)	(5.951)	(6.220)
violence		4.025	4.985	4.835	4.231
		(4.221)	(4.877)	(4.996)	(4.212)
labor force			1.315	1.312	1.381
			(1.332)	(1.322)	(1.455)
land size				0.0021*	0.0019*
				(0.0011)	(0.0011)
interest rate					0.455***
					(0.032)
R-squared	0.182	0.195	0.201	0.205	0.253
R-squared Adj.	0.180	0.173	0.169	0.168	0.155
N	26	26	26	26	26
Note:			*p<0.1; **p<0.05; ***p<0.01		

Table 1.10: OLS results for five-year averages for negative events

VARIABLES	R 1	R 2	R 3	R 4	R 5
corruption perception index	1.271	1.277	1.753*	1.741	1.887
	(0.852)	(0.899)	(0.923)	(1.132)	(1.453)
polity	0.422	0.452	0.531	0.557	0.581
	(1.214)	(1.227)	(1.315)	(1.087)	(1.023)
government authority	-4.321	-5.221	-5.432	-5.257	-7.885
	(3.891)	(4.047)	(3.987)	(3.996)	(7.243)
regulatory power	13.921***	13.857***	13.449***	12.985***	12.775***
	(2.483)	(2.335)	(2.875)	(2.645)	(2.578)
violence		2.520	2.557	2.894	3.024
		(3.8511)	(3.781)	(3.857)	(4.002)
labor force			1.224	1.386	1.251
			(1.459)	(1.231)	(1.557)
land size				0.0020**	0.0021***
				(0.0012)	(0.0009)
interest rate					0.583***
					(0.0342)
R-squared	0.210	0.235	0.241	0.252	0.267
R-squared Adj.	0.208	0.204	0.203	0.198	0.205
N	19	19	19	19	19
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 1.11: OLS results for five-year averages for positive events

Tables 1.12 shows the results of the regression with the added QoG value.

	R 1	R 2	R 3	R 4	R 5
corruption perception index	1.632	1.512*	1.415*	1.421*	1.271*
	(0.774)	(0.712)	(0.7740)	(0.8165)	(0.8165)
polity	0.2281	0.2240	0.2281	0.2273	0.2191
	(0.3147)	(0.3320)	(0.4157)	(0.3523)	(0.3451)
government authority	-7.8913	-7.9961	-7.8521	-7.1261	-8.1961
	(5.4229)	(5.7210)	(5.3216)	(5.4253)	(6.3147)
regulatory power	13.0713**	13.3504**	13.2310**	13.4154**	13.2152**
	(6.2258)	(6.5680)	(6.4312)	(6.3156)	(6.1283)
violence	3.7847	4.0835	4.52261*	4.0835	4.1422*
	(2.8122)	(2.9668)	(2.0431)	(2.512)	(2.1318)
labor force			1.2041	1.4512	1.041
			(1.4511)	(1.410)	(1.325)
land size				0.002351*	0.002281*
				(0.001161)	(0.001025)
interest rate					0.5281***
					(0.01147)
R-squared	0.2305	0.2220	0.2013	0.2512	0.4211
R-squared Adj.	0.1343	0.1248	0.1281	0.1247	0.2255
N	19	19	19	19	19
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 1.12: OLS results for five-year averages for all events with added variables

Appendix C

The Synthetic Control Method works by minimizing a loss function defined as $f(V)$ using quadratic optimization with equality constraints defined as follows

$$\frac{1}{2}V'PV + q'V$$

subject to

$$GV \leqslant h$$

$$AV = b$$

where $P \in R_{n\times n}$ is a symmetric matrix. D is defined as the diagonal of the V vector. We then have

$$P = X_0' D X_0.$$

and

$$q = X_1' D X_0.$$

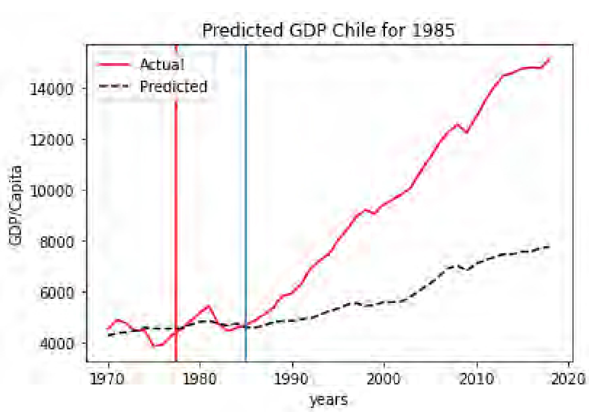
with l being the column size of Z_0. In this case $h = 1$ and so G is bounded by 0 and 1. A is a matrix of ones with a size $1 \times l$. The Lagrange function of this problem is

$$L(V, u) = \frac{1}{2} V' P V + q' V + v'(GV - h) + \mu'(AV - b).$$

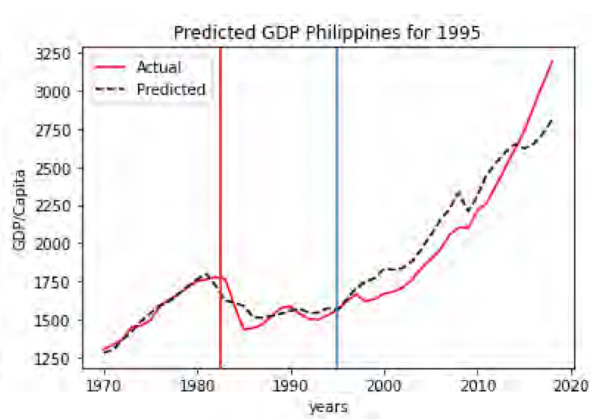
In order to minimize this loss function an initial guess of V is assumed called V_{guess}. The closer the guess is to the actual optimizing value of V the faster and more accurate the convergence is. This function is minimized using a Sequential Least Squares Programming method. This iterative process requires that both the objective function and constraints are twice continuously differentiable. Fu, Liu, and Guo (2019) provide more details on the SLSQP method and its application.

Appendix D

The results from selected different training periods



(a) 2/3 training period



(b) 1/3 training period