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The Economic Consequences of a Triple Disaster:
A Comparative Case Study of the Great East Japan Earthquake

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Abstract. This thesis examines the economic effects of natural disasters by studying the particular case of Tohoku earthquake and tsunami 2011 in Japan. Specifically, the statistical methodology of synthetic controls is used to estimate the change in GDP per capita caused by this incident. In order to determine the causal effect, a synthetic Japan that produces counterfactual outcomes is created with macroeconomic data covering the period 1999-2018. It is found that, contrary to popular belief, the natural disaster did not have a statistically significant negative impact on the Japanese economy. Instead, this paper finds a positive, albeit insignificant influence on GDP per capita. Several channels of influence are discussed and it is suggested that Japan's approach to "build back better" has contributed to its industries' resilience and overall recovery. However, the external validity and applicability of this result is open to question since Japan's disaster management capabilities are highly interlinked with country specific institutions, culture and norms.

Keywords: Natural Disaster, Synthetic control method, Economic impact, Japan, Tohoku

JEL: O1, Q53, Q54, R11

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Contents

Introduction

Natural disasters can be seen as a natural experiment and opportunity to examine how unanticipated shocks impact the economic growth of a country. Even though it is to everyone's knowledge that climatic and geologic catastrophes bring death and destruction, less is known about the longer-term or lagged economic effects of such incident. As general public's attention to these events often decreases after the first few weeks of emergency and chaos, there is more to be understood about the recovery process of a country and the underlying factors that contribute to this process. Economists have tried to fill this void of knowledge through empirical research, but up until this day there is little consensus on the matter. It seems like the true impacts of natural disasters are more complex than just accounting for the initial costs and damage. The question of whether long-run equilibrium will be lower or unchanged compared to before is a topic of controversy, and the fact that a proportion of studies even find higher equilibrium and positive outcomes only adds to the inconclusiveness of existing literature.

Limitations to study design and comparative data have also caused existing research to produce less well grounded results. For instance, some conduct cross-country analyses which is not considered an ideal methodology to use in the context of natural disasters. This is because the occurrence of natural disasters is highly linked to, and concentrated around, specific geographic locations and topographies. Thus, by construction the outcome will be subject to attenuation bias as countries that are not directly exposed to such shocks are also included in the data set. To add on, conclusions drawn from these cross-country evaluations are based on disasters that differ in their characteristics and economic impacts. And the fact that the level of economic development also differs across countries causes the data to not be immediately comparable, since the recovery process is greatly affected by the financial aid received, the quality of institutions, level of corruption, and so on (Cavallo et al., 2013; Barone and Mocetti, 2014).

Some alternative ways to study the economic effects of natural disasters include the fixed effects model, difference in difference model, and comparative case studies. The complications and shortcomings here typically involve time dependent unobservable confounders as well as the difficulty in finding an appropriate comparison unit. To deal with the aforementioned incompleteness of existing research I will in this thesis examine the economic consequences of the Tohoku earthquake that occurred in Japan 2011, by using the synthetic control method (SCM) proposed by Abadie and Gardeazabal (2003) and Abadie (2021). This method is not novel in disaster studies, however it is less frequently used and has, at least to my knowledge, not yet been implemented to analyze the case of the Great East Japan Earthquake. The greatest advantage SCM has over other comparable methods lies in its systematical way of constructing a comparison unit. Instead of manually trying to find a single comparative unit that is as similar to Japan as possible the synthetic control creates a synthetic 'doppelganger' Japan from an optimal combination of donor pool countries. This method employs a rigorous mathematical approach to construct a proper counterfactual which allows it to produce more accurate, realistic and statistically reliable results compared to other established methodologies.

In order to study the economic effects of the chosen disaster incident, I analyze the GDP per capita trend for Japan over the period 1999-2008, with the treatment year being 2011. I also investigate the same trend for synthetic Japan that depicts the trajectory for a hypothetical scenario where the earthquake did not happen. The treatment effect is consequently the difference in post-treatment values of GDP per capita. I find that even with the extreme magnitude of Tohoku earthquake the economic impact remains insignificant. However, even though the effect size is not sufficiently large to be statistically notable, the direction of influence suggests that the disaster had a positive impact on GDP per capita. I discuss some possible explanations and factors that could have caused this result. I also relate my findings to literature on disaster management in developing and industrialized countries respectively, to see if perhaps Japan's level of income and economic development plays a contributing factor to this indifferent outcome.

The economic effects of natural disasters is a research question of growing political, economic and humanitarian importance. Data from the Emergency Events Database (EM-DAT) points to the alarming fact that the frequency of natural catastrophes have been steadily increasing over the years, from over 1300 in 1975-1984 to over 3900 in 2005-2014. This is a three-fold increase during a span of 40 years (EM-DAT, 2021; Thomas and López, 2015). Prevailing division in the literature speaks for a greater pressure and need to find concrete and tangible results that governments and disaster relief organizations can rely on. Indeed, scientific findings that constitute the basis for policy recommendations not only influence the distribution of public transfers and financial aid, but they are also crucial for the recovery of affected communities and the development of future disaster resilient societies. My thesis contributes to this cause by utilizing the synthetic control method in a disaster context. This method, with its ability to systematically generate counterfactuals, is very suitable to analyze large scale macroeconomic shocks such as the Tohoku earthquake. It also has distinct methodological advantages over previous studies which I exploit, as well as greater empirical precision. This paper is also of value since I am focusing on Japan, a country that has managed to thrive economically, in spite of its long history of being exposed to frequent natural disasters of various kind.

The rest of the paper is organized as follows. In section 2 I present the triple disaster of Tohoku, including the earthquake, tsunami and subsequent meltdown of nuclear plants. Section 3 illustrates an overview of relevant theoretical and empirical literature in disaster and growth economics. Section 4 introduces the synthetic control method as an empirical methodology, with model specifications and explanations on how to conduct inferential analysis, since it differs from conventional regressions. Section 5 deals with the data, its sources and requirements. Section 6 reveals the statistical output as well as robustness checks and sensitivity analyses. Section 7 includes a detailed empirical discussion of my findings, as well as a macroeconomic debate regarding underlying and mediating factors. Section 8 concludes.

Background

2.1 Tohoku earthquake and tsunami 2011

On March 11 2011, at 14.46 JST, Japan was hit by the greatest natural disaster the country has ever recorded in history. Thousands of casualities were reported alongside hundred billions of dollars worth of economic damage. The Tohoku earthquake, also referred to as the Great East Japan Earthquake, is not your typical tremor. Its extreme magnitude of 9.0 measured on the Richter scale generated a tsunami that ultimately became the main source of immediate destruction to ports and cities of coastal communities. Even though protective sea walls were in place to keep the flood out, they were not strong enough to withstand the sheer force and size of the incoming crashing waves that could reach up to 40 meters high. This sudden catastrophe truly took Japan by surprise, and in spite of persistent efforts of disaster preparations and prevention, the eventual fallout was nothing but desolation and regional crisis (NOAA, 2021; Norio et al., 2011; Mori et al., 2011).

To understand the immensity of this quake, it was reported that over 20 countries on both sides of the Pacific Ocean issued tsunami warnings, and energy equivalent to 600 million times the Hiroshima atom bomb in 1945 was effectively released (Norio et al., 2011). The earth axis was estimated to have shifted by 10 to 15 centimeters, causing daytime to be shortened by 1.8 microseconds (WHO, 2012; BBC, 2021).

Although the undersea earthquake was the origin of the disaster, it was mainly the tsunami that caused local casualties and damages. It is estimated that 20 000 people either lost their lives or went missing, most likely from drowning. Another misfortunate consequence was the meltdown of 10 nuclear reactors and 3 nuclear plants in Fukushima and Onagawa (WHO, 2012). The disastrous event not only compromised national levels of energy and electricity supply but the spreading of nuclear pollution and radioactive waste also imperiled the natural environment as well as jeopardized public health. It was later determined that the accident would be labeled as a level 7 nuclear event, which is the most severe grade on the International Nuclear and Radiological Event Scale (INES) (Norio et al., 2011;IAEA, 2021).

2.1.1 Economic overview of affected regions

The Tohoku region is located on the northeastern part of Honshu, the largest island of Japan. Six prefectures constitute this geographical area (Nussbaum, 2002), out of which Miyagi, Iwate and Fukushima were most heavily affected by the earthquake and tsunami. Together, these three regions account for 6-7% of Japan's GDP and stand for 20% of Japan's total fisheries production (Kajitani, Chang, and Tatanoc, 2013). The region is also known for its agricultural production and has also a considerable number of industrial facilities. These industries' economic activity are highly dependent on physical assets such as ports, plants and farming land, which is why these sectors were hit the hardest by the tsunami. In fact, many re-known automakers had to temporarily stop their production, consequently affecting businesses all over the country, as well as overseas (Nanto et al., 2011).

Indeed, Japan plays an important role as a supplier and producer in the global production chain of electronic and automated goods. Therefore, local disruptions in the supply chain caused domestic firms to fail in providing components to international customers, creating havoc down entire product lines (Tokui, Kawasaki, and Miyagawa, 2017). This crisis was largely unforeseen and it highlighted the need for globally linked supply networks to become more resilient in the future. Tokui, Kawasaki, and Miyagawa (2017) examine the economic impact of these supply chain disruptions on Japan's economy and concluded a production loss worth 0.35% of the country's GDP. Likewise, the shortage of intermediary goods led to a 15.5% decrease in the Industrial Production Index in March 2011, where the largest decline was felt in the automobile and electronic industries. But even though the sector was subject to many economic hardships, it was also fast to recover as manufacturing rebounded with a growth of 6.2 and 3.6 percentage in May and June the same year, respectively

(Ranghieri and Ishiwatari, 2014; Kajitani, Chang, and Tatanoc, 2013).

Still, the economic damage of the disaster was substantial. Governments, private firms and international organizations estimated costs up to $300 billion (Saito, Acosta, and Moriarty, 2021), out of which $210 billion were judged to be direct economic costs by the Japan's Cabinet Office (Ranghieri and Ishiwatari, 2014). This makes the Tohoku Earthquake the most expensive natural disaster in history (NOAA, 2021; B. Zhang, 2011; Waldenberger and Eilker, 2011; Economist, 2011). About 90% of total costs were covered by the central government for infrastructure damage, and supplementary budgets for expenditures, emergency, relief and reconstruction were primarily founded by increases in tax and government bonds (Kajitani, Chang, and Tatanoc, 2013). Japan's economy dropped by 2.1% in real GDP by the second quarter from previous year, and experienced a 7% and 8% drop respectively in industrial production and export (Ranghieri and Ishiwatari, 2014). The latter was exacerbated both by the shortfall in supply but also the fact that the earthquake caused the value of yen to appreciate against the U.S dollar which harmed the export dependent Japan even more (Norio et al., 2011). The reason why the currency strengthened in an earthquake-ravaged economy is mainly because of two things. The first is the repatriation of foreign assets to bring back cash from abroad in order to cover the costs of capital and reconstruction projects. This raises the demand for yen and lowers the demand for other currencies. The second reason is that the unstable market caused anxious investors to bring their overseas investments back to Japan, strengthening the currency in the process. The appreciation of the Japanese yen became so severe that the exchange rate reached ¥76.25 to $1, the strongest it has ever been since the Second World War. Indeed, for the first time in 31 years Japan was confirmed to suffer from a negative balance of trade. The currency crisis even forced the G7 countries to jointly intervene in the currency market for the first time since 2000 (Ranghieri and Ishiwatari, 2014; Stewart, 2011; Hawkes, 2011; BBC, 2011b; BBC, 2011a).

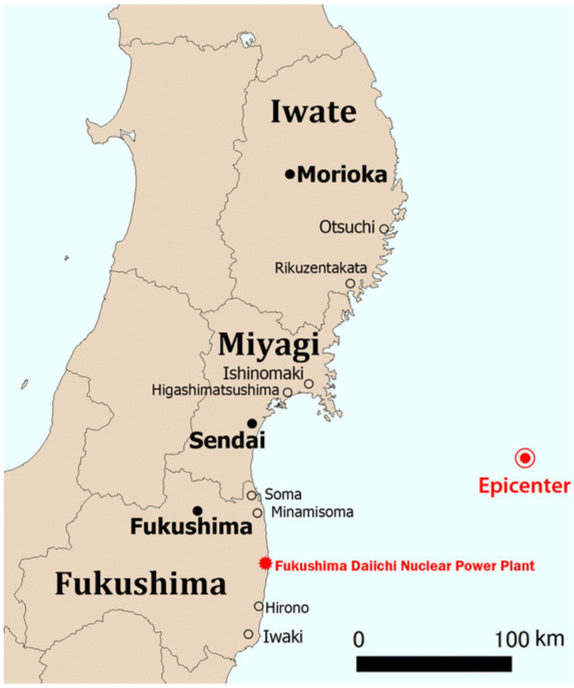


Figure 1: Affected prefectures of Tohoku. Source: Harada et al., 2015.

2.2 The aftermath of a triple catastrophe

Today, the affected regions are still recouping from the catastrophe that happened 10 years ago (Takemoto, Shibuya, and Sakoda, 2021). Already before the shock, the coastal districts of Tohoku was experiencing slow economic growth due to emigration, population decline and employment challenges. The immense complexities that followed the triple disaster (earthquake, tsunami, nuclear meltdown) showcase how the road to recovery is a bumpy journey, even for a country that pioneers in disaster management, like Japan. Many challenges involved the planning of reconstruction programs as time compression and urgency to rebuild was compromised by quality requirements and the necessity for careful and effective use of limited resources (Iuchi, L. A. Johnson, and Olshansky, 2013).

What particularly sets the Tohoku earthquake apart from other disasters is the subsequent shut down of several nuclear power plants in the region. Not only did this heavily affect the national supply of electricity, but the radioactive waste also had a large influence on the progression of post-disaster recovery. While many studies examine the Fukushima nuclear accident, they typically revolve around the effects of radiation rather than the indirect economic and social consequences. Compared to regions in Tohoku that were only subject to the earthquake and tsunami, the areas with additional radioactive pollution faced supplementary challenges and obstacles to recovery. For not only were the costs higher due to extra decontamination efforts, but the speed and degree of recuperation were also compromised by delays in reconstruction projects (Sato and Lyamzina, 2018).

Even though the Japanese Nuclear Emergency Response Headquarters (NERHQ) and scientific papers eventually deemed the contamination levels to be within safe limits (WHO, 2014; Government, 2016) there has not been any surge in repatriation (Sato and Lyamzina, 2018). There are three major factors that impede the rehabilitation of affected regions, and these are highly linked to macro-level issues such as long-term displacements, change in immigration patterns as well as local demography. First, social stigma, subjective perception of health risks and the unknown long-term effects of living in areas with low radioactivity deters former citizens from returning home. As these concerns are more prevalent in the younger population there has been a disproportionate emigration where the elderly stay behind, making the community more vulnerable to future disasters (Adams et al., 2011). Second, psychological traumas, anxiety and public distrust of governmental institutions have contributed to the emigration of working-age residents. This problem stems both from a rooted fear of radiation and ambiguous scientific information provided by official government bodies (Tateno and Yokoyama, 2013). And lastly, weak economic outlooks with the absence of a leading industry makes the region less attractive overall (Matanle, 2014).

These three factors have together induced an outflow of labor following the nuclear accident, resulting in a regional mismatch between job-vacancies and applicants (Higuchi et al., 2012). This serious shortage of labor is evident in all aspects of recovery. For instance, the slow decontamination progress, limited business hours in the service sector and industry production remaining below full capacity. As a contributing influence, a decline in consumption and demand for regional products curtailed economic activity and prosperity, causing investors to deem the area as less appealing. Finally the lack of permanent jobs is also a discouraging factor for immigration. The jobs that are both highest in demand and in terms of availability are project based manufacturing jobs, aimed to rebuild the region. Since these positions will most likely be terminated in the end, few are willing to take them, hence the gap in the labor force remain substantial (H. Zhang et al., 2014).

Similarly, the nuclear incident caused additional societal disruptions in terms of energy and electricity supply in the Tohoku and Tokyo regions. The accident caused an immediate shut down and loss of 17.3% Japan's total electricity supply and a gradual loss of 49 GW over the course of 14 months of installed nuclear power (Hayashi and Hughes, 2013). The capacity was dramatically reduced, leading to blackouts, cut cell phone and internet services and disabled transportation. To address this sudden shortfall, the Japanese government inaugurated a novel energy saving strategy, resulting in a reduced power demand by 15% in Eastern Japan and about 10% in Central Western Japan (Kajitani, Chang, and Tatanoc, 2013). To meet this new demand reduction targets households, industries and the commercial sectors executed various plans of actions. A roughly 40% of electricity savings in Tokyo was achieved by households adjusting their use of air conditioning. Similarly, the commercial sector limited their use of air condition also, and dimmed their lighting, alternatively used energy saving lamps. This transition proved to be effortless with little discomfort compared to the industrial sector. Here, firms had no choice but to set up in-house power generators, effectively reducing the demand by 25%, and another 30% was accomplished by shifting working hours of operation to off-peak periods which were proven to be both burdensome and costly. However, it was noted that this sudden reduction of consumption and demand was achieved without increasing the prices, which was probably attained thanks to high public awareness and strong normative behavior (Kimura and K.-i. Nishio, 2013; Kimuera and K. I. Nishio, 2016; Fujimi and Chang, 2014).

Ultimately, Tohoku Earthquake is a reminder that even Japan, a country that pioneers in disaster management, cannot leave unscathed from an incident of this scale. Still, it is believed that the existing structural precautions by the government as well as local prefectures to counteract natural disasters is what saved Japan from experiencing a greater suffering and destruction (Ranghieri and Ishiwatari, 2014). It is also because of these legislations and plans of actions that enabled the economy to recover rather quickly. For instance, the construction industry saw 25.5% more orders compared to the same period in the previous year, inducing production levels to rise back quickly. Airports, transportation and telecommunications were restored in a short amount of time and the majority of affected companies were estimated to return to full production at the end of 2011 (Waldenberger and Eilker, 2011). Companies that were hurt by the earthquake bounced back quickly with the use of networking, holistic inter-firm behavior and social capital to mobilize resources and speed up the recovery and restoration of industry production (Olcott and Oliver, 2014).

From what was seen from the Great East Japan Earthquake, even though the disaster caused devastating consequences to human lives and properties, it remains unclear whether the real impacts truly are as detrimental to the economy as one may have first assumed. News of earthquakes and tsunamis typically generate negative associations that can lead to cursory assessments and biased examinations. It is natural to believe that the demolition of physical and human capital hampers future investment incentives and curtails growth, leading to a slower development. What may then appear as a revelation to many readers is the fact that it is very commonly found in the literature, as well as predicted by economic models, that natural disasters do not have a significant negative impact on the economy where output decreases and GDP falls. In fact, more often than not no significant effect is found and at times, even positive ones are observed. These ambiguous results are found both in the short run as well in the long run.

Literature Review

3.1 Natural Disasters and Theory of Economic Growth

Economic growth is a well debated topic with many school of thoughts, some of which embody applicable frameworks to explain the potential influence natural disasters may have on society at large. The two theories most often discussed in the literature is the neoclassical growth model and the endogenous growth model. These two contentions postulate two distinct hypothesis and there is no way to conclude which one poses a higher degree of correctness, since even empirical studies cannot conform to a unified voice on the true impacts of natural disasters. Nonetheless, I shall in the following sections introduce the main arguments for both philosophies as well as display the adverse and conflicting findings presented in empirical studies that either corroborate, and hence falsify, one hypothesis at the expense of the other.

3.1.1 Neoclassical Theory of Growth

In the theory of neoclassical growth a natural disaster is to be viewed as a one time exogenous shock to the economy. A sudden destruction of capital stock and durable goods forces the country on a lower growth path away from steady state. That is, it results in an inward shift of the production possibility frontier causing lower output levels. In real life this is reflected as a drop in GDP per capita directly after the event.

Even so, the model predicts there to be no particular influence on the rate of technological progress, and if there had to be a certain impact it would be a short term positive one. This is due to the concavity of the frontier increasing its marginal return, denoting that even if the level of output is lower the growth rate will be temporarily higher than before. In other words, short term growth prospects will be enhanced as the economy tries to rebound to its normal growth path (Okuyama, 2003; Shabnam, 2014; Loayza et al., 2012; Strulik and Trimborn, 2019; Cavallo et al., 2013).

3.1.2 Theory of Endogenous Growth

In contrast to the neoclassical model, the endogenous growth model does not have a clear cut indication on how the output dynamics might be influenced by an external shock such as a natural disaster. Economic theories based on Schumpeter's creative destruction (Schumpeter, 1942) explain how the reduction of physical assets leads to higher positive long term economic growth. Because, as societies strive to rebuild their communities a considerable amount of resources are spent on upgrading existing capital. This kind of response to catastrophes creates opportunities to stimulate development, improve productivity and encourage reinvestment (Panwar and Sen, 2019; Shabnam, 2014; Caballero and Hammour, 1994). Similarly, the endogenous framework models individuals to invest in both physical and human capital. A natural disaster that reduces the stock of physical capital will simultaneously create positive externalities to human capital accumulation in the form of higher relative return. This may consequently have positive effects on economic growth through greater emphasis on human capital investments (Skidmore and Toya, 2002).

Nevertheless, academic disciplines in growth theory promote a wide spectrum of standpoints that contrast both in methodologies and conclusions. For instance, in the AK endogenous growth model, which assumes a constant return to capital, negative shocks to the capital stock is predicted to have no impact on growth rates (Cavallo et al., 2013). On the other hand, endogenous growth models in which technology exhibits an increasing returns to scale projects that destroying either physical or human capital will permanently push the economy to a lower growth trajectory than before (Romer, 1990; Cavallo et al., 2013). Hence, according to the last-mentioned model natural disasters are expected to be very costly and destructive which is a contradiction to other endogenous frameworks.

3.2 Findings in Empirical Economics

It is only in recent years that development and growth economics have really started to analyze the macro effects of natural disasters empirically. Until now, it was a rather neglected topic, but seeing how the frequency of such disasters has been steadily increasing over the years (IEP, 2020) this field of research is sadly becoming more relevant also. And as societies evolve with the rate of technological progress, these events are becoming more threatening to the economy than what they are to human lives (WMO, 2021). It is therefore interesting to gain an understanding of the economic impacts natural disasters have by using real data from real incidents. However, the empirical community cannot seem to come to an agreement as studies arrive at conclusions that either advocate adverse, positive or no effect.

Lima and Barbosa (2017) studied the flash flood in Brazil 2008 and its potential spill-over effects on bordering municipalities. They highlighted how the existing literature typically lays out four competing perspectives on how the growth trajectory may proceed after a natural disaster shock. The first one is referred to as the "No recovery" possibility, which argues that the damage caused by disasters is too great for societies to rebound from. Output levels will be lower than before due to poor business expectations as people are scared to invest in the future. The second outlook is "Rebound to trend". This hypothesis is very similar to the neoclassical growth model, as it predicts there to be a negative shock in the short run but that levels should converge back to the pre-disaster trajectory in the long run. This is because the marginal return will be greater in disaster-struck regions, attracting businesses and labor from other parts of the country. A third hypothesis is "Build back better". In contrast to the previous perspective, build back better believes that disasters may generate positive incentives to re-build stronger infrastructure and capital stock than the ones destroyed. In the long run, natural disasters may therefore have a net positive effect as societies learn from experience and becomes more resilient. The last possibility is "Creative destruction" as mentioned in the endogenous growth model. It reasons that financial aid and new government loans will raise short run income and create demand for goods and services. Old assets will be replaced by new capital and as new technologies are adopted the total factor of productivity will also increase.

An issue that has been brought to light in the community is how a sizeable amount of papers all use the same data source to build their statistical analyses. This source is EM-DAT, a leading international database in disaster studies, supported by WHO and the Belgian government (EM-DAT, 2021). Felbermayr and Gröschl (2014) argued that even though EM-DAT has proven to be very useful for estimating direct human and monetary damages, it is considered lacking if one wishes to assess economic growth. This is because the database is for the most part built from insurance data rather than geophysical or meteorological data, and there is a high likelihood that disaster intensity measurements are correlated with GDP per capita, which risks endogeneity problems. Hence, the authors created an alternative database that is primarily built on geophysical and meteorological data. They found that disasters have a significant and substantial negative impact on growth and that poor countries are more vulnerable to geophysical disasters whilst richer countries are more affected by meteorological ones.

Likewise, Nakamura et al. (2013) used a new panel data set that covers 24 countries and stretches more than 100 years and found natural disasters to have a negative impact on consumption. The average disaster effect culminates after 6 years and consumption can experience a drop as large as 30%. Estimations reveal that about half is recovered in subsequent years of recovery.

Compared to empirical studies that investigate short term effects, long term consequences of macro shocks are less commonly analyzed. Skidmore and Toya (2002) are some of the first researchers that took on the challenge to determine the long term relationship between disasters, capital accumulation, total factor productivity and economic growth, with a cross-country data set of 89 countries over the time period 1960-1990. Their statistical findings are very interesting because they are very much in line with the idea of Schumpeter's creative destruction. It appears that climatic disasters have a significant and positive relationship with the growth of a country's TFP, indicating that the cycle of destruction and creation of capital stock supports and encourages implementations of new technology, leading to an increasing GDP. The authors also found a particular substitution effect where a decrease in physical assets caused more investments in human capital formation.

Albala-Bertrand (1993) examined the question of natural disasters' effect on economic output through a quantitative application of a macroeconomic model. His empirical findings supported this model and thus he concluded that it was unlikely for capital loss to have a significant impact on growth. His deductions implied that only a small expenditure was sufficient for post-reconstruction efforts, even if the disaster per se was large in size (large loss-to-out ratio), and that these expenditures could be spread over a time span consisting a couple of years without having a considerable negative effect on GDP. Similarly, Cavallo et al. (2013) conducted a cross-country comparative case study using synthetic controls. Their initial results indicated that large disasters, in terms of economic damage, had a significant impact on GDP growth. More precisely, they estimated that 10 years after the incident, affected countries would on average experience a 28 percentage points difference in GDP per capita compared to their counterfactual outcomes had the disaster not happened. However, once they controlled for political events this notable effect disappeared. It seemed to be the case that only very costly disasters followed by unruly political reforms (such as the Islamic Iranian Revolution 1979 and the Sandinista Nicaraguan Revolution 1979) had an effect on a country's economic development, since the results for countries that were subject to large disasters but not followed by a disruptive political event were insignificant.

As a vast proportion of the literature display contradicting results, the economic effects of natural disasters remain unclear and ambiguous. In order to estimate the heterogeneous nature of this question Fomby, Ikeda, and Loayza (2013) and Loayza et al. (2012) decided to conduct their analyses by examining distinct economic sectors separately as well as the type of disaster (droughts, floods, earthquakes and storms). They found that the economic effects differed depending on the type of disaster and industry sector affected. For instance, floods tend increase GDP whilst earthquakes are found to have a smaller effect size and weaker significance levels. Moderate disasters may bring positive growth whilst severe disaster either have no or negative effect. Also, developing countries are found to be more sensitive generally, which is partly due to a larger dependency on agricultural production. These results were confirmed by Panwar and Sen (2019) who studied disaster impacts across economic sectors for 102 countries between 1981-2015.

Strulik and Trimborn (2019) used an extension of the neoclassical model of growth to try and unravel the inconclusiveness of previous empirical research. They do so by adding a labor supply variable as well as distinguish between durable consumption goods and productive capital. They discovered that destruction of capital stock impacts GDP negatively and the revers is true for durable goods. In fact, an exogenous shock to the latter may drive GDP above its pre-disaster levels. Higher employment and output levels is also predicted to increase in the reconstruction phase if the shock mainly affects the supply of durable goods. This is because households wish to quickly rebuild their consumption good stock and counteract the negative shock to wealth by supplying more labor. This conclusion is very insightful since it helps to explain why some papers end up with insignificant results and why others find either positive or negative impacts on GDP. This revelation can also elucidate why droughts have a negative effects on GDP (since they mainly ruin productive capital) and why floods sometimes display positive impacts (since mainly durable goods are destroyed), therefore supporting the research by Fomby, Ikeda, and Loayza (2013) and Loayza et al. (2012).

3.2.1 Natural disasters in rich and poor countries

Many studies (e.g. Songwathana, 2018 and Toya and Skidmore, 2007) find that a country's resilience to external shocks increases with income, education and better financial systems. This is why developing countries are seemingly more vulnerable to natural disasters than developed countries. Credit, fiscal stimulus and insurance programs are proven to play important roles in the road to recovery, but since poor countries are less able to access resources and effectively adopt policies, they are even more exposed to the aftermaths of severe exogenous shocks (duPont-IV and Noy, 2015).

Indeed, McDermott, Barry, and S.J. Tol (2011) showed that rich countries are likely to remain unaffected by extreme weather events. And even if output were to decrease temporarily, given accessibility to credit post-disaster, investments will recompense losses allowing the economy to return to its previous growth path in the long run. This is however not true for developing countries for which the authors modeled to be credit constrained and characterized by low levels of financial development. They estimated that a negative shock would make up to 3 years of economic development forfeit with effects still being significant 10 years after the incident.

Analogous findings by Peter, Dahlen, and Saxena (2012) point to the insurance market's role in the context of natural disasters. Similar to some previously mentioned studies, the authors find natural catastrophes to have a negative impact on economic activity. It also appears that insurance is a vital risk transferring mechanism that is important for mitigating economic costs associated with disasters, as these are mainly driven by uninsured losses.

Short term limitations to economic recovery are detrimental to long-term economic growth if the ability to fund and execute reconstruction plans do not meet a threshold value in relation to the severity and frequency of the disaster (Hallegatte and Dumas, 2009). Hallegatte and Dumas (2009) deem this as a potential source to poverty traps, as the losses can reach extremely high values, thus impeding development. For rich countries, that are economically insulated from being victims of disaster induced poverty traps, the productivity effect (creative destruction) is essential for canceling out the long run costs caused by a negative shock. [1]. Even if growth rates temporarily increases the authors found that the long-term growth rate is unlikely to stay elevated. This is because economic advancement is by definition created by technological innovation rather than the occurrence of natural disasters.

Still, it is widely known that developing countries' economy is highly volatile with historical data showing great fluctuations. Specifically, Raddatz (2007) state that "During 1965 to 1997, the standard deviation of output growth and the frequency of drops in real GDP larger than 3% were respectively two and five times larger in low-income countries than in high-income countries.". His scepticism towards the reasoning that volatile trends are caused by exogenous shocks induced him to

[1] In comparison, previously mentioned studies sees the productivity effect as a source of continuous development rather than simply offsetting the negative impacts of natural disasters.

empirically investigate this question. Similar to the findings by Ahmed (2000) and Acemoglu et al. (2003), Raddatz argue that external shocks only account for a small portion of GDP's total fluctuation, and that it is instead internal turmoils such as political conflicts, poor institutions, corruption and economic mismanagement that are the main sources of instability. Poorer countries have also economic systems that are to a greater extent based on primary commodities (with higher price volatility compared to industrial goods), a higher exposure to natural disasters and a dependency on financial aid (Raddatz, 2007). The empirical results from Raddatz study validate his previous discussion. He finds that external shocks have a significant impact in relation to countries' historical economic performance, but that this effect remains small in absolute terms. Specifically, climatic and humanitarian disasters reduce GDP per capita by 2% respectively 4% whilst geological disasters do not have a significant economic impact. In fact, external shocks do not explain more than 11% of total GDP volatility, out of which changes in commodity prices are proven to be the driving force behind external fluctuations. Hence, this paper gives an interesting perspective regarding observed dissimilarities in post-disaster recovery responses between rich and poor countries.

Empirical Methodology

4.1 Synthetic Control Method

The statistical method of synthetic control (SCM) was originally proposed by Abadie and Gardeazabal (2003) and Abadie, Diamond, and Heinmueller (2010) as a way to conduct comparative case studies in a more transparent, simple and intuitive way. In recent years, the empirical tool has increasingly gained popularity and been applied to various research fields such as political economy (Born et al., 2019), immigration and labor markets (Peri and Yasenov, 2019), recessions and suicide (Chen et al., 2010), health policies (Kreif et al., 2016), crime interventions (Robbins, Saunders, and Kilmer, 2017) and tax reforms (Adhikari and Alm, 2016) to name a few.

SCM is an empirical method for causal inference, motivated by the belief that the impact of certain interventions may only be empirically estimated through a comparison with the counterfactual outcome. It is an appropriate method to use when the intervention of interest takes place on an comprehensive level, and the studied objects are larger aggregate entities such as regions, states or countries. This is because it is hard to find an appropriate comparison unit to a body that is distinct and unique in its constitutions, characteristics and history (Lijphart, 1971). The general idea is to follow the trend of a chosen outcome variable of the affected unit and compare it with a synthetic version of itself, made up of a linear combination of several other *unaffected* units. Through a data-driven procedure a common evolution is constructed for the two entities pre-treatment. It later allows them to diverge post-treatment with the affected unit changing its course after being exposed to the intervention. Then, the impact is measured post-treatment by taking the difference between the actual and counterfactual outcome (Abadie, 2021). For instance, Abadie, Diamond, and Heinmueller (2010) investigate the effect of the California tobacco control 1988 and compares it with a counterfactual California constituting of other unexposed American states, and Born et al. (2019) study UK's economic costs associated with Brexit by creating a doppelganger UK with OECD countries. In my case, I examine how the natural disaster that hit Japan in 2011 affected their GDP per capita, by creating a synthetic Japan with other similar high-income countries. More detail on the data and how I create my donor pool can be found in section 5.

4.1.1 Advantages and Limitations

If employed under the right conditions and circumstances, the synthetic control can be a powerful and informative tool. Depending on the quality of the research question, SCM may be more suitable than other conventional methods such as time-series, comparative case studies, fixed effects and regular regressions. Athey and Imbens (2017) even deem SCM as "arguably the most important innovation in the policy evaluation literature in the last 15 years".

To start, the credibility of the synthetic control lies in the doppelganger's ability to closely track an extended pre-intervention trajectory of the affected unit. This is the most crucial part to get right in comparison studies, and it is also the hardest to bring about (Abadie, Diamond, and Heinmueller, 2010; Hashem Pesaran and Smith, 2016). Because, we are essentially creating a trend of something that has never happened, and thus cannot be observed. Due to the lack of standard procedures, comparative case studies in social sciences typically use informal means to select a comparison unit. This poses a great threat to internal and external validity since the ambiguity of subjective choices generates uncertainty as to how well the trend of the counterfactual is reproduced (Abadie, Diamond, and Heinmueller, 2010). The synthetic control method deals with this issue in several ways.

First, the comparison unit is made up of a *combination* of *several* entities, chosen from a donor pool of potential candidates, rather than simply picking a single best-fit comparison unit. These candidates, along with relevant explanatory variables, are given specific weights in order to closely reflect and match the pre-intervention trajectory of the treated unit. The weights are distributed according to each entity's and variable's relative importance and pertinence in predicting the outcome of interest. This procedure makes SCM very transparent, as the reader can clearly see how well the hypothetical counterfactual replicates the original integer. This also allows for an uncomplicated and straightforward analysis of potential sources and direction of biases (McClelland and Gault, 2017).

The given weights range between [0,1] and sum to 1, which differs from linear regressions where negative weights may also be assigned to predictors. By limiting weights to be non-negative SCM avoids extrapolating the results, which generates outcomes that cannot be supported by the available data and may induce bias (Abadie, Diamond, and Heinmueller, 2014; King and Zeng, 2006).

Another advantages is that the synthetic control does not require any sharp or strict assumption, such as the parallel trend assumption in difference-in-difference models. However, there are some general conditions that must be fulfilled if SCM is to produce reliable results and I present them in the next subsection.

Additional strengths that make SCM attractive is the fact that the essence of creating a duplicate comparison unit makes the synthetic control more robust to omitted variable biases, which is a common problem in both cross-sectional studies as well as panel models, such as fixed effects and D-i-D, that only deal with time-invariant unobservables (Adhikari, A Duval, et al., 2016; Billmeier and Nannicini, 2013). Abadie, Diamond, and Heinmueller (2010) and Abadie (2021) illustrate how a well matched synthetic control can reduce the endogeneity problem, by proving that the size of the bias caused by unobserved time-varying confounders approaches zero as the number of pre-treatment periods goes to infinity. The intuition behind this argument is that a synthetic control can only produce a well matched trajectory for the pre-intervention outcome if, and only if, it successfully replicates both observed and unobserved predictors alike.

Furthermore, SCM deals with serially correlated errors by using placebo tests as its main inference method. Since no parametric assumptions about the distribution of errors is required, there will be no over-rejection bias of the standard t-test (Adhikari, A Duval, et al., 2016). Moreover, these falsification tests, as they are also called, deal with another weakness of the synthetic control method. Frankly, the small nature of the data, absence of randomization and the lack of probabilistic sampling when selecting candidates for the donor pool (Abadie, Diamond, and Heinmueller, 2014). I talk more about placebo tests as an alternative form of causal deduction in section 4.3.

Other limitations to keep in mind when conducting SCM analyses is that this method does not deal with reverse causality.[2] Neither does it break down the underlying mechanisms that might drive a result, and even though we have ruled out extrapolation by only distributing positive weights, there is still risk for interpolation biases. This might happen if the the outcome variable cannot be approximated by a linear function for the entire set of units, or if the matching process averages out large discrepancies between the characteristics of the real and comparison unit, for the sake of creating a good fit (Abadie, Diamond, and Heinmueller, 2010; Abadie, 2021; Adhikari, A Duval, et al., 2016).

4.1.2 Contextual Requirements and Assumptions

As I have previously mentioned, the synthetic control does not require any particular strict assumption that is of similar fashion to parallel trends. However, Abadie (2021) do state some general contextual requirements needed for SCM to become an adequate tool for policy assessment.[3] I do a short briefing of these conditions accordingly.

1. *Effect size and volatility.* Small effects and volatile outcomes cannot be clearly distinguished from other shocks to the treatment variable and affected unit. In order to correctly estimate the impact, the magnitude of the results must be large enough to be detected and singled out. Also, if there is too much noise in the outcome variable (from volatility caused by idiosyncratic shocks) there is a risk of over-fitting the trajectory.

2. *Availability of a comparison group.* Due to the fact that comparison studies heavily depend on the development of the counterfactual, inference will be rendered defective in case there is no appropriate donor pool. This is because SCM takes advantage of common macro-movements and similarities in characteristics between the treated body and the entities constituting the comparison unit.

3. *No anticipation.* If the policy intervention or its components are suspected to be anticipated by forward-looking agents who start to react and respond in the pre-treatment period, then the results may be biased.

4. *No interference.* The stable unit treatment value assumption (SUTVA) by Rubin (1974) states that for causal deductions, any particular event assigned

[2]Since I am studying natural disasters reverse causality is not much of a concern in my thesis.
[3]The author also mentions a few ways these conditions may be accounted for, if they, for some reason, do not hold.

to the treated unit should not be felt by, or affect other units in the study; there should be no spillover effects.

5. *Time horizon.* It is important to extend the analysis to include sufficiently many pre-treatment as well as post-treatment periods. The former is essential for projecting a good comparison trend. The latter is central because some effects may lag in time, hence the full magnitude of the impact will only be known later on.

6. *Convex hull condition.* The SCM estimate is only able to closely replicate the affected entity if the donor pool units share similar pre-treatment characteristics. That is, the predictor values should fall close to the convex hull.[4] However, it is not a big problem if a certain value is extreme as long as the synthetic control can closely approximate the real trajectory.[5]

4.2 Model Specification

The original application of this model was for a case study on terrorism in the Basque country (Abadie and Gardeazabal, 2003). Later on, the method was further developed and comprehensively summarized by Abadie, Diamond, and Heinmueller (2010), Abadie, Diamond, and Heinmueller (2014) and Abadie (2021). Since I will only be giving an overview of the formal and mathematical aspects of the SCM here, I highly recommend reading the aforementioned papers in order to gain a deeper understanding of this statistical tool.[6][7]

4.2.1 Mathematical aspects of SCM

Suppose we observe $J+1$ units for $1, 2, 3, ..., T$ periods, where $j = 1$ is the unit of interest. The donor pool then consists of $j = 2, 3, 4, ..., J+1$ controls that are unaffected by the intervention which happens at time T_0. Y_{jt} is the outcome of interest and is observed for each unit across all time periods. The hypothetical outcome in absence of treatment is defined as Y_{jt}^N and the observed outcome for the treated unit in the post-intervention period $t > T_0$ is defined as Y_{1t}^I. The effect of treatment can then be estimated by the following difference:

[4] I talk more about the convex hull and interpolation bias in section 4.2.2.

[5] See for instance the inflation level in the study conducted by Abadie, Diamond, and Heinmueller (2014).

[6] Section 4.2-4.3 are heavily based on Abadie (2021).

[7] An alternative read that is shorter and simplified can be found in Scott Cunningham's Mixtape: https://mixtape.scunning.com/synthetic-control.html?panelset=stata-code&panelset2=stata-code3.

$$\tau_{1t} = Y_{1t}^I - Y_{1t}^N. \tag{1}$$

This equation highlights two things. First, since Y_{1t}^I is the true post-treatment outcome that is observed, the main challenge will be to estimate the unobserved counterfactual outcome Y_{jt}^N. Second, a great feature of this model is that it allows the outcome of interest to change over time, which is a very plausible and realistic set up since some effects may accumulate or dissipate over time.

In order to determine Y_{jt}^N, we observe for each unit k predictor variables with respective outcome being defined as $X_{1j}, ..., X_{kj}$. It is important to keep in mind that pre-treatment outcomes of the dependent variable are suggested to be included in the vector of covariates as they will not only improve the fit but also account for unobserved time-varying factors.

Formally, a synthetic control is characterized as a weighted average of the donor pool units. By giving the comparison group a set of weights $\mathbf{W} = (w_2, w_3, ..., w_{J+1})'$ the synthetic control estimates for Y_{jt}^N and τ_{1t} can be written as

$$\hat{Y}_{1t}^N = \sum_{j=1}^{J+1} w_j Y_{jt} \tag{2}$$

and

$$\hat{\tau}_{1t} = Y_{1t}^I - \hat{Y}_{1t}^N \tag{3}$$

respectively. As I previously mentioned, the weights are strictly positive and sum to 1. When conducting the SCM, the weights are typically sparsely allocated, meaning only a few donor units out of the entire pool will be given a weight greater than zero and actually contribute to the counterfactual. The weights are chosen in a way so that the final synthetic control is equivalent to the pre-intervention values for the treated unit's predictor variables.

In mathematical terms, let $\mathbf{V} = v_1, ..., v_k$ be a set of non-negative constants that reflect the relative importance and predictive power of variable X on the outcome variable. It is suggested that the weight $\mathbf{W(V)} = (w_2(\mathbf{V}), ..., w_{J+1}(\mathbf{V}))'$ given to each donor unit is chosen to minimize

$$||\mathbf{X_1} - \mathbf{X_0 W}|| = \left(\sum_{h=1}^{k} v_h \left(X_{h1} - w2X_{h2} - ... - w_j X_{hJ+1} \right)^2 \right)^{1/2}. \tag{4}$$

In similar fashion, the treatment effect materializes as

$$\hat{\tau}_{1t} = Y_{1t}^{I} - \sum_{j=2}^{J+1} w_j^* Y_{jt}. \tag{5}$$

The non-negative constants $\mathbf{V} = v_1, ..., v_k$ are chosen to minimize the mean square prediction error (MSPE) of the synthetic control

$$\sum_{t=1}^{T_0} (Y_{1t} - \sum_{j=2}^{J+1} w_j^*(V) Y_{jt})^2. \tag{6}$$

The choice of these variable weights is important since, together with the donor weights, they are supposed to recreate the behavior of the affected unit's outcome variable in absence of treatment. And since we cannot observe the relative importance of a variable x on outcome Y_{1t}^N post-treatment, pre-intervention data is used for this step. One practical way to execute this is to use cross-validation. The main idea is to divide the pre-treatment period into two sub-periods, where one is assigned as a "training period" and the other as "validation period". Donor pool weights are then calculated in the former and MSPE is minimized in the latter (Becker, Klößner, and Pfeifer, 2018). This approach deals with a potential source of bias that is cherry picking, which I further discuss in section 4.2.2.

4.2.2 Sources of potential bias

I shall proceed the model specification by considering Y_{jt}^N to be following a linear factor model. For an in depth analysis in the case where Y_{jt}^N is generated by an auto regressive model, I suggest reading Abadie, Diamond, and Heinmueller (2010).

The linear factor model can be seen as a generalization of the difference-in-difference/fixed effects model, where, instead of time invariant unobservables, the outcome variable is dependent on unobserved components that are allowed to change with time. This distinction implies that the linear factor model is not subject to the parallel trends assumption. Empirically, it is written as

$$Y_{jt}^N = \delta_t + \theta_t \mathbf{Z}_j + \lambda_t \boldsymbol{\mu}_j + \varepsilon_{jt}. \tag{7}$$

Here, δ_t is a common factor that changes with time, with constant loading across all units. $\mathbf{Z}_j$ and $\boldsymbol{\mu}_j$ are vectors of observed and unobserved covariates of Y_{jt}^N, with their respective coefficients being θ_t and λ_t. The last term, ε_{jt}, represents zero mean individual transitory shocks.

A well matched synthetic control is distinguished by well reproduced values of $\mathbf{Z}_j$ and $\boldsymbol{\mu}_j$. If the observed variables are well replicated, we get $\mathbf{X}_1 = \mathbf{X}_0\mathbf{W}^*$. Still, problems persist if the model fails to estimate $\boldsymbol{\mu}_j$, which is a realistic concern as unobservables are not included in the data. This leads to the potential threat of *over-fitting bias* where large transitory shocks balance out the otherwise incongruity between the synthetic control and the treated unit. This may happen if the pre-treatment period, T_0, is small or if the magnitude of ε_{jt} is large.[8] This is why it is crucial to include pre-intervention values of the outcome variable Y_{jt}^N in $\mathbf{Z}_j$. Because by doing so, we can capture and account for a large portion of unobserved predictor variables that would otherwise be a potential source of bias.

The over-fitting bias may also come about if the donor pool includes too many units. As the size of the pool increases, the easier it is to successfully match the trajectory, even in the presence of large deviations in predictors' factor loadings. The bias is then again exacerbated if T_0 is small and if the mismatch originates from $\boldsymbol{\mu}_j$.

To close off this section, I shall mention again the possibility of *interpolation bias* if the outcome variable cannot be predicted with a linear approximation by the properties of the other units. In this case, bias will be prevalent even in there is a good fit. Another source of interpolation bias is when the treated unit's predictor values fall outside the convex hull of the donor pool's values. This is especially the case if the disparity is relative a unit that has been given a positive weight and consequently actively contributes to the construction of the synthetic control.

4.3 Inference

Inference analysis in the synthetic control framework differs from RCTs. Due to the absence of randomization permutation methods are used instead, which is done by iteratively assigning the intervention to each unit in the data set and deriving so called "placebo effects". The treated unit will be included in the donor pool for each placebo run. Afterwards, a permutation distribution is obtained and significant results will be acquired if the treated unit's effect is extreme relative to the distribution. This inference method is often referred to as in-space-placebo test.

One caveat with this method is the risk of badly fitted pre-intervention values for units in the donor pool. To circumvent this, a test statistic is calculated. It is a measure of the ratio between pre- and post-treatment fit for time periods $0 \geq t_1 \geq t_2 \geq T$ and for all units $j = \{1, ..., J+1\}$. The fit is measured by the root mean square prediction error (RMSPE) and is defined as

[8] Even though T_0 has an inverse relationship with the bias, Abadie, Diamond, and Heinmueller (2010) explains that if the fit is bad then it does not matter if $T_0 \to \infty$, a sizeable bias will exists nonetheless.

$$R_j(t_1, t_2) = \left(\frac{1}{t_2 - t_1 + 1} \sum_{t=t_1}^{t_2} \left(Y_{jt} - \hat{Y}_{jt}^N \right)^2 \right)^{1/2}. \tag{8}$$

By stating the relevant time periods, we obtain the test statistic for which we will use to create the permutation distribution.

$$r_j = \frac{R_j\left(T_0 + 1, T\right)}{R_j\left(1, T_0\right)}. \tag{9}$$

Pseudo p-values in the synthetic control framework is based on the distribution of r_j, and even though there is a lack of randomization, the interpretation remains the same. That is, the probability of obtaining a synthetic estimate as extreme as the one we did for the treatment unit, in case we re-assign the intervention to another random unit in the dataset. Formally, it is given by

$$p = \frac{1}{J+1} \sum_{j=1}^{J+1} I_+\left(r_j - r_1\right), \tag{10}$$

where I_+ represents an indicator function that takes on the value one if the argument is nonnegative and zero otherwise. An informal way to define the p-value is to simply take the ranking of the unit of interest, given the extremeness of its test statistic, and divide it by the total number of units in the data.

An alternative method to account for poor pre-treatment fit is to simply discard them in the analysis and conduct placebo runs on the entities that do not have considerably larger $R_j(1, T_0)$ than the unit of interest.

Data

5.1 Data requirements

The selection of relevant and appropriate data is a fundamental process in any kind of statistical research. In the case of SCM, the choice of donor pool units, variables and time period is especially important. Similar to the previous contextual requirements, Abadie (2021) also state a few points regarding data requirements, all of which I will be presenting here.

1. *Aggregate data on predictors and outcomes.* The synthetic control method is dependent on aggregate time series data on both the outcome variable and its predictor variables for all units in the data set. Typically, these type of

data are widely available and can be obtained from either government websites, international organizations, private corporations as well as NGOs. If aggregate data is for some reason not available, it is accepted to use aggregated micro-level data.

2. *Sufficient pre-intervention information.* By now, it should be clear that a well matched synthetic control is contingent on its ability to replicate the treated unit's pre-intervention trajectory. And with the further assumption that it follows a linear factor model, it is established that potential bias has an inverse relationship with T_0, making it crucial to include a large pre-treatment time window. Because, with insufficient pre-intervention information and a small time window, a good, if not perfect, fit may be falsely attained which induces unreliable results and estimates. This problem may be diminished by including solid predictors in $\mathbf{X}_j$, other than pre-intervention values of Y_{1t}^N. By doing so, residual variance and the risk of over-fitting will be substantially reduced.

3. *Sufficient post-intervention information.* It is not guaranteed that the intervention effect will be noticeable immediately after treatment. Some results increase and accumulate with time while others diminish and eventually dissipate. No matter the nature of the effects, by having sufficient post-intervention information and time periods, one will obtain a more cohesive and complete understanding of the incident of interest.

4. *Selection of variables.* Abadie (2021) states in his paper that "The credibility of a synthetic control estimator depends on its ability to track the trajectory of the outcome variable for the treated unit for an extended pre-intervention period. Provided that a good fit for pre-intervention outcomes is attained, the researcher has some flexibility in the way pre-intervention outcomes are incorporated in $\mathbf{X}_1$ and $\mathbf{X}_0$". However, this particular freedom given to the researcher comes with the additional danger of cherry picking the variables through an endogenous selection process with the aim of trying to "hack" the system in order to create a convincing synthetic control estimate. This is an issue highlighted in a study by Ferman, Pinto, and Possebom (2018) that addresses several problems regarding the lack of guidance regarding the procedure of variable selection. On the other hand, most often the greatest weights are given to the pre-intervention values of the outcome variable rather than external independent predictors, and these alone are enough to create a decent synthetic control. However, the importance of other covariates with

predictive power should not be overlooked, since by excluding them from $\mathbf{Z}_j$ means that they are automatically absorbed by μ_j which increases the risk of bias. It is possible to create a perfect synthetic unit by including all lagged variables of the outcome variable, but this would render all other predictors irrelevant, consequently threatening the accuracy of the SCM by introducing further bias (Kaul et al., 2015). Luckily, there is a data driven procedure for variable selection that helps to assess the predictive power of independent variables and thus circumvents all of the issues above. As briefly mentioned at the end of section 4.2.1, this process involves dividing the pre-treatment periods into two parts, an initial period of training and a subsequent period of validation. Data in the former period is used to generate the optimal variables and their respective weights while the latter is used for evaluating the predictive power of the generated synthetic control. Finally, it is worth mentioning that data from the post-intervention period is not used for calculating variable weights.

5. *Selection of donor pool units.* Similar to choosing variables, the researcher is also free to choose what unit to include in the donor pool. But as the SCM relies on the exploitation in co-movement of predictors to create the synthetic unit, it is only logical to select units that share similar characteristics. Depending on the research question, this could mean close proximity in economic features, history, geography and culture. Including entities that are too different from the unit of interest will lead to a bad fit and interpolation bias. One should also exclude units from the donor pool if they are subject to similar intervention during the period of study or is afflicted by other idiosyncratic shocks to the outcome variable.

5.2 Donor pool

Japan is considered one of the largest economies in the world (Park, Ryu, and Lee, 2019; FDI, 2021; G20, 2021), and as a highly industrialized Asian country it was only natural for me to include other highly developed nations in my donor pool. I tried to choose countries that share similar trends in GDP per capita as Japan, and that are not too different in the levels of economic welfare. I ended up with an initial pool that covered several continental regions, however, due to the course of world history and economic development, the majority of the countries included are of western heritage. I found the lack of Asian representation in my data set less than ideal, yet acceptable in my case, since I am investigating the economic impact of the Tohoku earthquake, rather than a cultural phenomenon.

Compared to the final donor pool used in the analysis, I excluded the following countries from my preliminary set: China, Indonesia, Thailand, Vietnam and Iceland. My main argument for including these countries in the first place was due to their cultural and geographical proximity. Furthermore, in 1997, Asia was hit by a financial crisis and I wanted to include countries in the relevant region in case Japan was still dealing with certain aftermaths of this incident in the treatment period. However, I deem the exclusion of these countries to not affect the main result and validity of my research. This is because the remaining donors share similar GDP trends as Japan and I will still be able to use their co-movements to construct the synthetic control. To add on, other western countries share more similar economic traits with Japan than the countries I excluded from the pool.

The reason for excluding the first four aforementioned countries are mainly due to either one or two reasons; they have extreme variable values relative to Japan and/or experienced similar shock during the treatment period. China was struck by a severe earthquake in Sichuan 2008 (Pletcher and Rafferty, 2021), Indonesia suffered from the Indian Ocean earthquake and tsunami in 2004 (Britannica, 2021) which is the third largest recorded since the beginning of the 20th century (Mat Said, Muhaimin Ridwan Wong, and Ahmadun, 2020). Due to spillover effects from this event I excluded Thailand from the donor pool. On the other hand, Malaysia is kept due to the tsunami having had negligible impacts on the local economy's main industries (Khairi Zahari et al., 2015).[9] [10] Likewise, I decided to keep Hong Kong as a donor unit as the local economy and development differs from mainland China, and the earthquake in 2008 was only felt as a minor tremor with no causalities or damage (Observatory, 2008). Furthermore, I chose to exclude Vietnam for two reasons, the first being spill-over effects from the Indian Ocean earthquake and tsunami in 2004 and the other being that the country characteristics were too different from Japan, which could cause interpolation biases. Similarly, I dropped Iceland due to its uniqueness, small size and proneness to high economic volatility.

Table B in appendix shows an overview of the final countries, as well as the ones dropped from the initial donor pool. It is important to be logically restrictive when choosing the number of donor countries to include in the study. Since there is no

[9]Compared to other local economies, Malaysia was not as severely struck by the tsunami. The Island of Sumatra was hit the worst where local coast communities, with their fishing, agriculture and tourism industry, were deemed to have been subject to the most damage. This incident however, shielded the rest of the country from further destruction from the natural disaster (Mat Said, Muhaimin Ridwan Wong, and Ahmadun, 2020)

[10]The synthetic estimate's robustness to the exclusion of Malaysia from the donor pool is tested in the L-O-O sensitivity analysis. See section 6.3.1.

rule that specifies a specific limit, one could easily create a false positive outcome by including country units until a perfectly significant outcome is mechanically attained (Abadie (2021)).

5.3 Variables

5.3.1 Predictors

Before I begin this section I would like to make a declaration that I have not used the data driven variable selection method mentioned above. Instead, I ground my reasoning in research, models and scientific literature to support my choice of predictors. There are mainly two motives for this decision. First, as previously explained the procedure entails dividing the pre-intervention period in two parts. However, as I only have a total of 12 pre-treatment years to my disposal only 6 years of data would constitute the basis of my control estimate. And since the first 6 years in my data set do not encompass the economic volatility caused by the Financial Crisis 2008 I doubted the quality of the resulting synthetic control. The other reason is a practical matter. In order to exercise this data-driven method I was acquired to download another STATA package which I was not familiar with. Hence, due to time-constraint it was not feasible for me use this mechanism for variable selection.

Moving on, an intuitive starting point for deciding what independent predictors to incorporate in my data set includes an analytical breakdown of the economic definition of GDP per capita. This is why I began by determining the factors that actively contribute and influence this measure. Undeniably, the two main components is clearly gross domestic product and country population. The latter is a fixed number while the former can be broken down into further elements.

Even though GDP is an widely used and cited international indicator of economic development there are several ways to actually calculate and define it. An IMF publication describes it as *"[...] the monetary value of final goods and services—that is, those that are bought by the final user—produced in a country in a given period of time [...]"*(Callen, 2020). The Organisation for Economic Co-operation and Development (OECD) states in a report three different ways GDP can be measured (OECD, 2021):

1. *"As output less intermediate consumption (i.e. value added) plus taxes on products (such as VAT) less subsidies on products."*

2. *"As the income earned from production, equal to the sum of: employee compensation; the gross operating surplus of enterprises and government; the gross*

Table 1: Predictor variables

Variable	Source
GDP per capita (1999)	IMF, WEO databse
GDP per capita (2008)	IMF, WEO databse
GDP per capita (2010)	IMF, WEO databse
Government consumption	World Bank, WDI database
Household consumption	World Bank, WDI database
Expenditure	World Bank, WDI database
Investment	IMF, WEO databse
Industry	World Bank, WDI database
GDP	World Bank, WDI database

[1] GDP per capita (.) are lagged outcome variables for years 1999, 2008, 2010, in PPP constant 2017 international dollars. Government consumption is the government's final consumption as % GDP and similarly household consumption is final household consumption as % GDP. Expenditure is general government expenditure % GDP, calculated as the total expense and net acquisition of non financial assets. Investment is the total investment expressed as a percentage of GDP. Industry is the industry sector's share of national GDP, including construction and manufacturing. GDP is gross domestic product in PPP constant 2017 international dollars.

mixed income of unincorporated enterprises; and net taxes on production and imports (VAT, payroll tax, import duties, etc., less subsidies)."

3. *"Or as the expenditure on final goods and services minus imports: final consumption expenditures, gross capital formation, and exports less imports."*

The third definition is equivalent to the one often found in conventional economic textbooks, and is referred to as the expenditure approach: $GDP = C+G+I+NX$, where C stands for consumer spending, G for government consumption, I for investments and NX for net export (Ilter, 2017). I used this simple yet intuitive definition and calculation of GDP as my foundation for variable selection. Still, there are other predictors, not necessarily directly linked to immediate economic productions that still have significant impact on economic growth that I also incorporated in my data set. These variables include, inter alia, education as human capital, inflation, TFP and trade openess (Barro, 2003; Bassanini and Scarpetta, 2003; Abadie, Diamond, and Heinmueller, 2014). By performing multiple preliminary runs of the synthetic control estimation, I assessed what combinations led to either large or small RMSPE. The final predictors are the ones I found to produce the smallest prediction error and they are shown in Table 1.

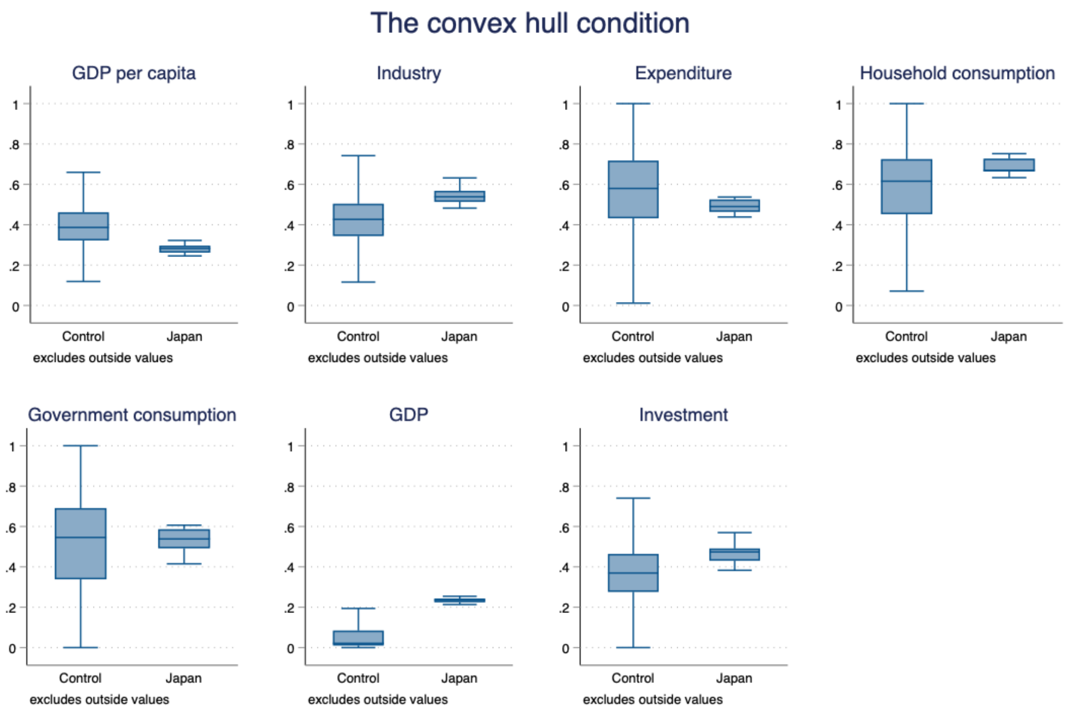


Figure 2: A comparison between Japan and the convex hull of donor pool countries to assess the risk of interpolation bias. Values are normalized.

5.3.2 Lagged outcome variable

A common and established way of attaining a good pre-treatment fit is to make use of lagged values of the outcome variable (Abadie, Diamond, and Heinmueller, 2010; Echevarría and García-Enríquez, 2019; McClelland and Gault, 2017). This is because by including selected years of the lagged dependent variable one essentially exploits its co-movement across countries in the data set to help recreate its historic trend for the synthetic control estimate. It also helps to account for, as well as reproduce the unobserved factor loadings μ_j that are not manually added to the model, thus effectively decreasing statistical noise and the risk for bias (Abadie, 2021). However, Kaul et al. (2015) greatly discourage researchers from using an excessive number of lagged variables, since this would render all other predictors as irrelevant. As I have previously explained, this is also not desirable since it adds more factors into μ_j, leading to greater bias (Abadie, 2021).

Following Abadie, Diamond, and Heinmueller (2010) I decided to include 3 lagged variables that together cover the entire pre-treatment period. The combination of 1999, 2008 and 2010 was chosen since I found it to produce the smallest RMSPE for synthetic Japan. The year 2008 was a strategic choice of mine, since I wanted to capture the fluctuation in GDP across countries during the economic crisis. As the financial shock was not idiosyncratic but affected all units in the donor pool it does not interfere with general inference in this study. The reason is because the economic downturn caused a decline in GDP for all affected countries and thus the co-movement in GDP, which SCM takes advantage of, is not broken. [11]

5.3.3 Time period

The time frame of this study encompasses the period 1999-2018, which totals 20 years of data. The event of interest happened in 2011, meaning 1999-2011 constitutes the pre-treatment period, and 2012-2018 the post-treatment period. I strategically chose 1999 as my starting year due to the Asian financial crisis that happened in 1997. To add on, Japan is a country that regularly suffers from earthquakes and they experienced a similar shock that caused substantial economic damage and thousands of causalities back in 1995. Hence, any further backdating would cause the synthetic control to pick up these idiosyncratic shocks, leading to bias and unreliable estimations.

I decided to end the study period with the year of 2018 for two reasons. One, it would result in an even integer of 20 years worth of information which is graphically more pleasing. Second, I wished to refrain from potential spill-over effects from the Covid-19 outbreak in 2019-2020.

Results

6.1 Main results

In this chapter I present the results from my synthetic control estimation. I display the predictor values for synthetic Japan, donor countries as well as predictor variables weights. Then in later sections I move on to inference analysis and robustness checks of my main results. All data is processed using STATA with the program package "Synth".[12]

Table 2 displays the variable values I obtain after running Synth. Each variable that composes the doppelganger Japan is listed in column one and its respective weight is shown in column two. As expected, the three lagged variables of GDP per capita are given the greatest weights, where the year 2008 makes up for about 75%

[11] Cross-country GDP trend can be compared at https://data.worldbank.org/.

[12] A simple overview of this package can be found at the following website: https://web.stanford.edu/ jhain/synthpage.html.

of the synthetic control's ability to replicate the trajectory of Japan. Industry is one of the additional sets of predictors that stands out with a weight of 0.03. This is probably because the industry sector's share of the annual GDP amounts up to 30%, a number estimated by the data in my thesis and also confirmed by sources such as the World Factbook by CIA (CIA, 2021).

Table 2: GDP per capita predictor means

		Japan		
Variables	Weight	Real	Synthetic	Donor pool
GDP per capita (1999)	0.11885	35324.26	34724.76	40541.85
GDP per capita (2008)	0.75253	38791.51	38938.51	46612.31
GDP per capita (2010)	0.08377	38111.41	37759.34	48135.61
Government consumption	0.00905	18.069	16.736	18.357
Household consumption	0.00254	55.970	55.462	53.074
Expenditure	0.00083	35.479	39.939	39.659
Investment	0.00013	25.878	22.324	23.481
Industry	0.02927	30.259	29.826	25.042
GDP	0.00303	4.68e+12	3.48e+12	1.79E+12

[1] *Note:* The weight column displays the predictor weights used to create Synthetic Japan. As seen in the table, Synthetic Japan does a better job at replicating the trajectory of Japan, compared to the average of all donor pool countries.

According to this table, the synthetic Japan seems to be doing a fair job at replicating the real variable values. Much better so than the average of all donor pool countries, which is shown in the right most column. This again highlights the strength and advantage of using the SCM in comparative case studies; a symmetrically weighted average of all countries in the donor pool will result in a sub-par estimation with large discrepancies, causing the inferential analysis that follows to be inapplicable.

Table 3 shows the countries that were given a positive weight, consequently contributing to synthetic Japan. Italy and Malaysia account for 81% of the control, whereas the United States stands for 13.2% and Denmark only 5.8%. Compared to previous literature, four contributing countries is a reasonable outcome considering that a unique feature of SCM is the sparsity of country weights (Abadie, 2021). Most typically, a synthetic unit will be composed of 4-5 donor entities (for instance Abadie, Diamond, and Heinmueller, 2014; Gong and Rao, 2016; Grier and Maynard, 2016). However, there are also instances where studies have obtained both fewer and more contributing bodies (Born et al., 2019; Barone and Mocetti, 2014).

The non-negative weights ensure no extrapolation, and the fact that the weights are distributed in a sparse matter speaks for transparency because it allows an easier detection and determination of the direction of potential bias. For instance, I can already now suspect statistical noise, since Malaysia may be suffering from spill-over effects from the Indian Ocean earthquake and tsunami back in 2004, as mentioned in section 5.2. This would not have been a problem if Malaysia were given a weight of zero. However, now that it constitutes the synthetic control it is important to check the result's sensitivity of having the country as a donor unit. I do this analysis in the coming sections 6.3.1 and 7.1.

Table 3: Country weights in Synthetic Japan

Country	Weight	Country	Weight
Australia	0	Korea	0
Austria	0	Malaysia	0.307
Belgium	0	Netherlands	0
Canada	0	New Zealand	0
Denmark	0.058	Norway	0
Finland	0	Singapore	0
France	0	Spain	0
Germany	0	Sweden	0
Hong Kong	0	Switzerland	0
Ireland	0	United Kingdom	0
Italy	0.503	United States	0.132

Figure 1 shows the corresponding graphical illustration of the synthetic control outcome in Table 2. It is evident in the pre-treatment period (left side of the dotted vertical line) that, albeit minor noises, the synthetic Japan closely replicates real Japan. This trend is later broken in the post-treatment period where now the two lines distinctively diverge. Whether this discrepancy is statistically significant or not will be discussed in section 6.2.

An interesting observation to note is the fact that real GDP per capita increases immediately after the disaster takes place. My initial intuitive hypothesis and assumption was the contrary. That is, GDP per capita would decrease as a natural consequence of great economic damages caused by the tsunami, earthquakes and aftershocks, as well as the meltdown of the Fukushima nuclear power plant. Nevertheless, seeing how the scientific community is finding ambiguous results regarding natural disasters' affect on the economy, I continue the analysis of this peculiar finding in section 7.2.

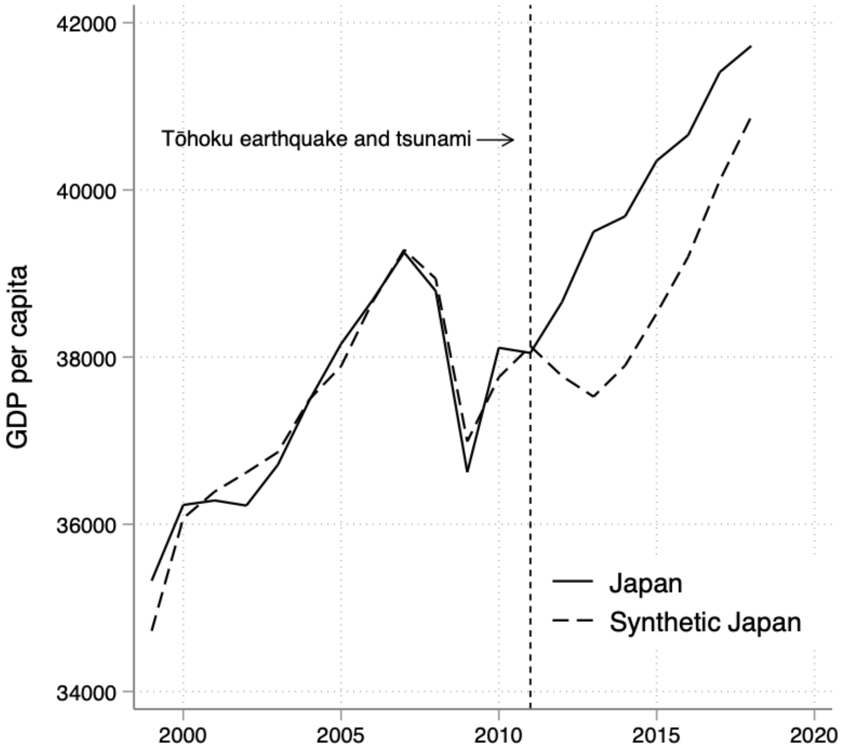


Figure 3: Japan and synthetic Japan's trends in GDP per capita.

Another interesting remark concerns the anomaly that the effect is brought about by a sudden drop in synthetic Japan, rather than the conventional deviation in the treated unit, here real Japan. This is the first time I have seen such a drastic divergence between the two units in a synthetic control paper being caused primarily by the control. Normally, the doppelganger continues the trajectory in a predictive way post-period whilst the real unit diverges gradually after the intervention. My result, on the other hand, produces not only a very sharp division, but the trend also separates in opposite directions. After turning almost every stone trying to find a plausible explanation to this, not much is found that can logically explain this peculiar finding. This is most likely due to the rarity of my outcome, hence it is not commonly discussed in the literature. Nonetheless, I found a few explanations that could add some enlightenment to this dilemma and I present them in the discussion section 7.1. Still, it is evident that neither of these expositions are comprehensive enough to fully account for the behavior of synthetic Japan in its entirety, which is why in the remainder of this paper I simply consider this outcome as an indication of an increase in GDP per capita.

The estimated effect of the 2011 disaster on GDP per capita is measured as the difference between Japan and its doppelganger equivalence in the post-treatment period. Figure 2 highlights how this incident has caused a substantial positive increase in the outcome variable, by plotting the yearly gaps in GDP per capita between the real and synthetic counterpart. In the pre-treatment period, the gap is fluctuating around the x-axis with a value of 0 and a variance ranging from approximately -500 to 500. However, directly after the incident, this difference increased to 2000, a four time increase compared to previous deviations. It also seems like the trend continues to decline towards zero in the post-treatment period, inclining that the gap between the two decreases over time.

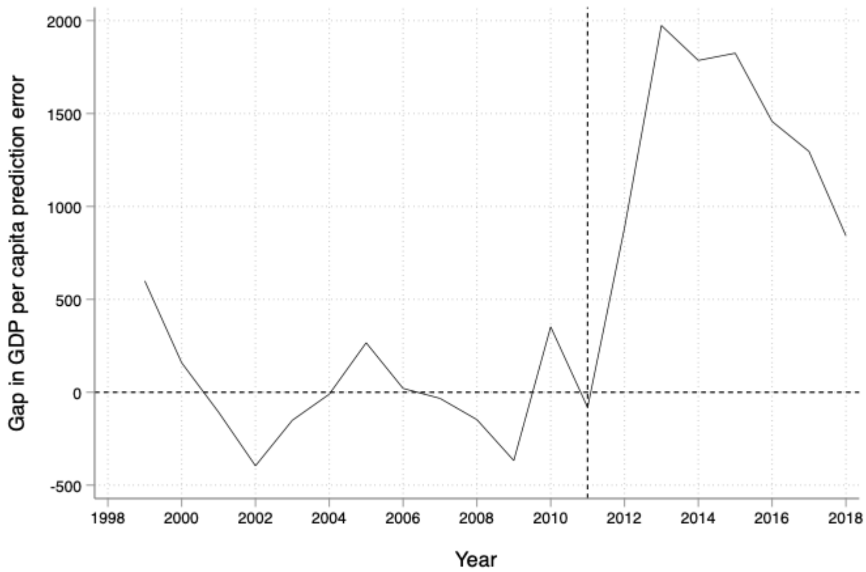


Figure 4: Yearly GDP per capita gap between Japan and synthetic Japan.

6.2 Inference analysis

My inferential analysis is broken down into two parts. I begin with the in-space placebo test, that is a falsification test where I estimate psuedo p-values and associated permutation distribution by re-assigning the treatment to each donor pool country. In each round of estimation, Japan is included in the donor pool. The second part consists of placebo runs, where I plot the placebo distribution for each country and re-do the runs after dropping out countries that have a pre-treatment RMSPE significantly greater than Japan.

6.2.1 In-space placebo test

As described in chapter 4.3, inference analysis for synthetic controls is carried out differently due to the absence of randomization. In this in-space placebo test, as well as the following placebo runs described in the next section, I try to evaluate the significance of the GDP per capita gap obtained for Japan by asking the question: How often would I come by a result of this size if the treatment was allocated randomly? That is, is the result for Japan statistically considerable, or are the results simply driven by pure chance?

The first step of this analysis is to assign the treatment to all countries where no natural disaster took place and attain respective pre/post RMSPE ratios. By ranking countries according to their ratio magnitudes I obtain the permutation distribution shown in Figure 3. As the histogram illustrates, Japan is one of the more extreme countries, ranking 4th place out of 23 countries. The corresponding (psuedo) p-value is 0.1739, indicating that even though my estimation shows a positive gap, it is not statistically significant.

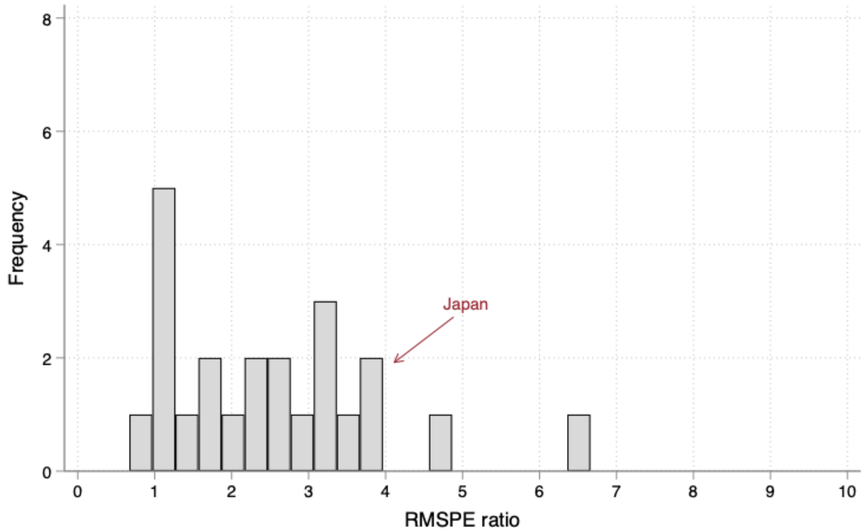


Figure 5: Permutation distribution of post- and pre-treatment ratios of RMSPE.

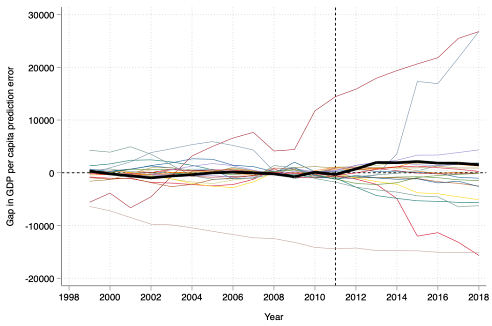
6.2.2 Placebo runs

After taking a closer look at the ranking of countries' RMSPE ratios in I notice that even though Finland, Ireland and the United States have larger gaps than Japan, they have more importantly much worse pre-treatment fit [13]. This indicates a failure and inability for other states to replicate a doppelganger economy for these countries. These miscalculations may arise if units have historically extreme values and unusual trends of the outcome variable. This was the case for New Hampshire in the Tobacco control program paper by Abadie, Diamond, and Heinmueller (2010),

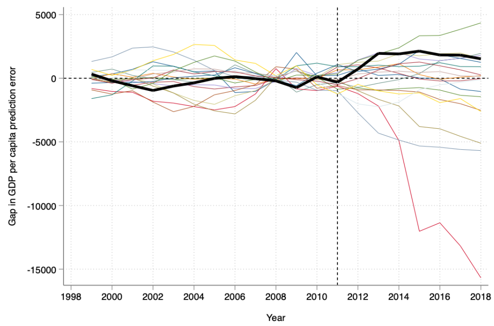
[13]Please refer to A in appendix. I did not include the table here since the size of the table disrupted the flow of the text.

where it was clear that other states were unable to replicate the pre-treatment trend of cigarette sales since New Hampshire was the state in the sample that had the highest annual per capita sales prior to the intervention.

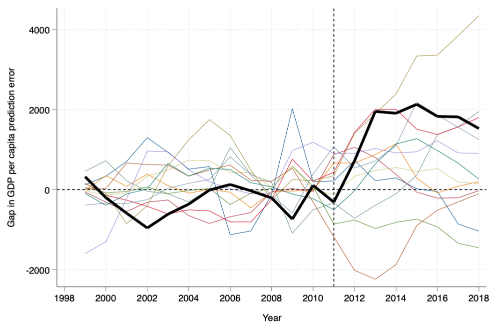
If a country's synthetic control fails to reproduce pre-treatment values, then it is highly unclear whether the consequent gap post-treatment is due to real effect or simply created by a lack of fit (Abadie, Diamond, and Heinmueller, 2010). For the same reason, units with poor fit are not suitable as comparison units in inference analyses. To circumvent this problem, I conduct placebo runs by computing the estimated treatment effect for each country, and successively in incremental steps adopt cutoff points to exclude nations that have 5 times, 2 times and 1.5 times worse pre-treatment fit than Japan.



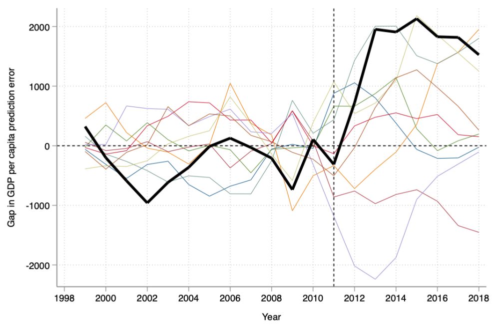
(a) Placebo distribution



(b) 5x cut off point



(c) 2x cut off point



(d) 1.5x cut off point

Figure 6: Placebo runs for GDP per capita gaps in Japan and donor countries.

In the four images above I showcase the general placebo distribution in Figure 4a and the distributions for respective limit points in Figures 4b - 4d. The black bold line represents Japan while all other thinner, colorful lines each illustrates a donor country.

From graph 4a, it is clear that at least 3 countries have a bad pre-treatment fit, seeing how the lines deviate greatly from the x-axis. Indeed, these 3 units are already ruled out in the first stage of exclusion that is also the most lenient one, as shown in graph 4b. The next stage displayed in graph 4c only includes countries with a RMSPE no greater than two times the size of Japan's. By now 10 countries have been eliminated from the pool and yet the effect on Japan's GDP per capita is still insignificant. I should quickly mention that this cutoff point (2x) is the most stringent one used in the original paper by Abadie, Diamond, and Heinmueller (2010), but seeing that I still have 13 countries left in the pool I decide to go one step further and exclude any country that has a pre-treatment fit worse than 1.5 times than that of Japan. Now, Japan is ranked 1st place for its RMSPE ratio size amongst the remaining 10 countries and the probability of estimating a gap of this magnitude under randomization is 10%.

Nonetheless, I dare not say that this is strong evidence for a significant outcome considering how much I had to lower the cutoff point by eliminating more than half of all countries in my data set. To add on, the conventional significance level used is 5%, implying that my finding is only weakly significant. Besides, my first inferential analysis of pre/post RMSPE ratios indicates a negligible effect which again speaks for the fact that the disaster 2011 did not have a positive economic impact on Japan.

6.3 Robustness and sensitivity analysis

There are several ways to do diagnostic checks and sensitivity analyses for synthetic controls. One of them is backdating, also called in-time placebo testing. This exercise is often used if the researcher suspects anticipation effects prior to the intervention, but it can also be used to assess the validity and credibility of the estimated effect. In this thesis however, I will not be doing any backdating since I do not have enough time periods in my data, and because unlike political treatments, the exact occurrence of natural disasters cannot be anticipated as of today. Instead, I suffice with a leave-one-out (LOO) test and a logarithmic re-estimation.

6.3.1 Leave-one-out test

The purpose of the L-O-O test is to evaluate the robustness of my result to minor alterations in the study design and the sensitivity of excluding a particular country from the data set. This is because I want to assess the extent to which my result might be driven by a single donor unit. By leaving out one positive weighted country at a time (Denmark, Italy, Malaysia and USA) and re-estimating synthetic Japan I get the following graph (Figure 5). The bold black line represents the trajectory of real Japan and the dashed grey line is again the original synthetic Japan. The exclusion of Italy (orange), Malaysia (green), United States (blue) and Denmark (red) are illustrated by dotted lines.

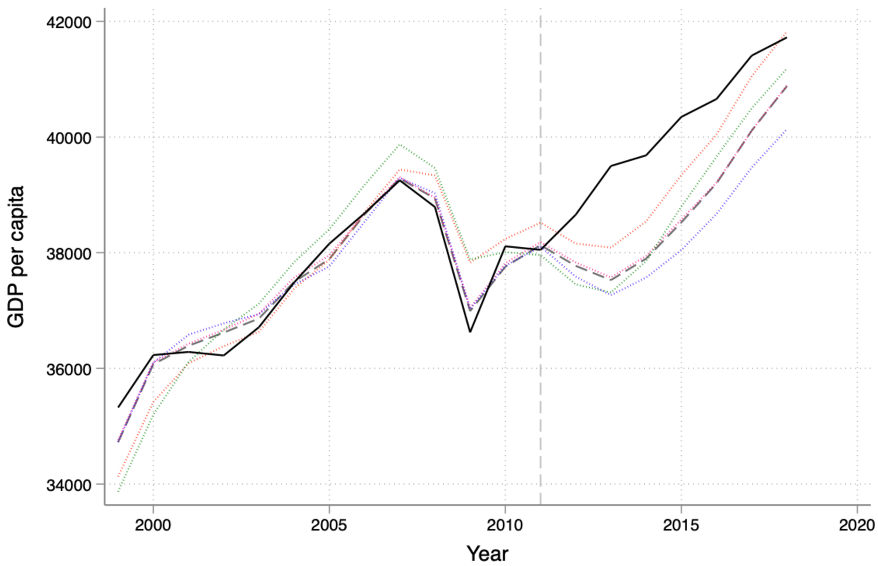


Figure 7: Leave on out sensitivity test.

Trend wise there seems to be no major changes as the new versions of synthetic Japan are all centered around the values of the dashed grey line, suggesting robustness when it comes to the treatment direction. That is, the disaster has caused a positive spur in the Japanese economy. However, there seems to be a sensitivity to the magnitude and size of the treatment. Especially when it comes to Italy, Malaysia. Not only is the estimated effect smaller when excluding either one of the two countries, but the pre-treatment fit is also worse. On the other hand, the result is more robust to the exclusion of United States, seeing how the blue line is able to follow the synthetic trajectory rather closely in the pre-intervention period. It also evident that with the exclusion of the United States the effect size increases, implying that the U.S influences the synthetic GDP per capita trend positively. In comparison, the exclusion of Denmark is the most robust among them all as the red graph is able to almost perfectly replicate the original trend of synthetic Japan for the entire period of study. Though, this is probably because Denmark is only given a weight of 0.058 and leaving it out would not change the original synthetic Japan in any considerable way.

Similarly, it is almost expected that the exclusion of Italy and Malaysia would cause changes in the synthetic control considering that they were assigned significant country weights (50.3% and 30.7% respectively). By excluding either one of them, and thus constraining the synthetic Japan to the remaining three donor countries, would be equivalent to generating a synthetic Japan with an accuracy level of 49.7%

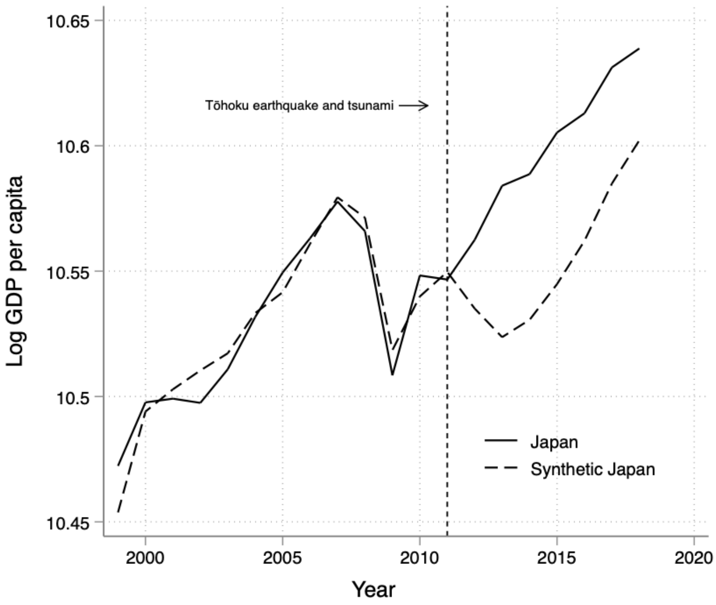
and 69.3% the original estimation. And seeing how the pre-treatment fit worsens, it becomes evident that the effect size is not particularly robust to the countries included in the donor pool. The relative dependency on Italy and Malaysia is therefore yet another indication of my result being statistically insignificant, albeit positive.

6.3.2 A logarithmic re-estimation

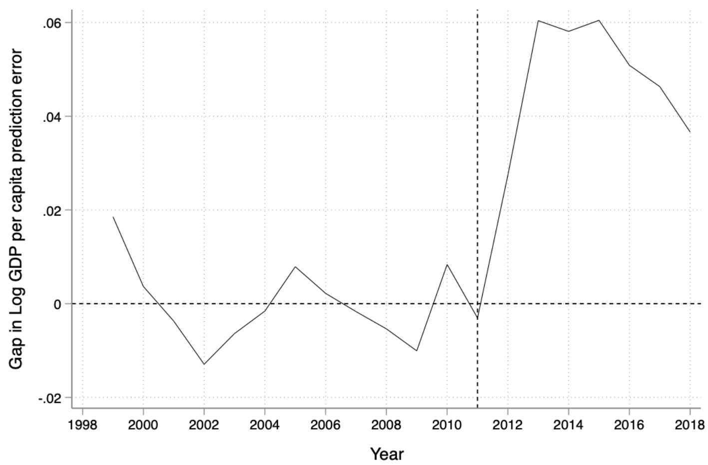
Even though the doppelganger graphically replicates real Japan closely in Figure 1, I am still wary of the fact that the pre-RMSPE value is 450. In fact, the prediction errors of all countries in my data are unusually large compared to previous studies. Optimally, the error should fluctuate around 0. However, this is not a strict rule in the sense that a correctly executed synthetic control estimation is one where the errors are *minimized* in each circumstance; attaining the value 0 is never the goal. Hence errors with 3, 4 or even 5 digit values are not "wrong" in such sense, but it may still be an indication of something being out of order.

One potential miscalculation could concern the growth trend of GDP, whether it can indeed be approximated by a linear function. When looking at historical trends of economic output it seems to be following an exponential growth path compared to a linear one. This is especially the case in the period following the Industrial Revolution (Crawford, 2021). Durlauf, P. Johnson, and Temple (2005) also finds implications of economic growth not necessarily following a linear trajectory, which makes it unfitting to estimate GDP using conventional linear regression models. Of course, the time horizon is an essential determinant here. A wider window is more likely to display an output trend with exponential characteristics and similarly, a shorter time frame is more likely to be linearly approximated. But taking into account that a proportion of studies have adopted a logarithmic approach to their synthetic estimations, I decide to redo my assessments to see if there will be any significant difference in my outcome. [14]

[14]Examples of studies that use log GDP per capita as the dependent variable include Adhikari, A Duval, et al. (2016), Abadie, Diamond, and Heinmueller (2010), Echevarría and García-Enríquez (2019), Gietel-Basten, Han, and Cheng (2019) and Žúdeli and Meliorisi (2016).



(a) Synthetic Japan using log.



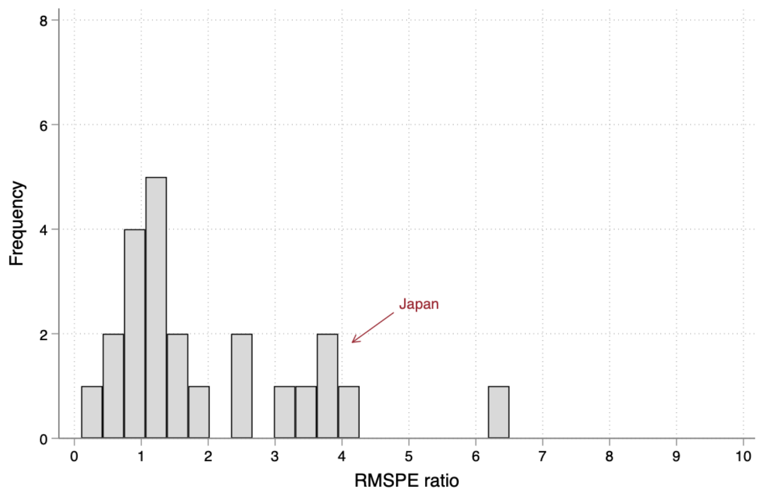
(b) Log gap prediction error.

Figure 8: Synthetic control re-estimation using logs.

Looking at Figure 6, it appears that nothing much has changed in regards to the trajectory of synthetic Japan. However, I do find that by taking log GDP per capita and log GDP the associated RMSPE decreases substantially as seen in Figure 6b. Either, this is a result from a successful attempt of tackling the non-linearity issue discussed above and thus circumventing the risk of interpolation bias, or this is simply the consequence of changing to a logarithmic scale. Nonetheless, it is notable how the volatility window for the prediction error has decreased from ± 500 to ± 0.02 with an average value of 0.0109 prior to 2011.

Another significant change is the distribution of country weights where Italy is now assigned 0.699, Malaysia 0.195, and United States 0.106. Denmark is no longer actively contributing to synthetic Japan as it has been given a weight of zero. It also seems like by taking log, the treatment effect is somewhat greater than before. To see if there is any change in significance and sensitivity I redo the inference analysis and L-O-O test.

As seen in Figure 7, the permutation distribution is different from before where countries have been shifted to the lower end of the spectrum. Japan remains fourth place in the ratio ranking, meaning that the p-value is still 0.1739. Unlike before, I find that no cutoff point yields a significant result for Japan's gap in GDP per capita.



(a) Permutation distribution log Japan

(b) LOO test for log GDP per capita.

Figure 9: Inference and sensitivty analysis of log Japan re-estimation.

Parallel to the previous leave-one-out test, the result is robust to the direction of the treatment, but is sensitive to the magnitude of the effect estimate. Overall, when excluding any of the three positive weighted countries from the donor pool the pre-treatment fit worsens, and the post-treatment effect is scattered loosely around the original synthetic Japan in the post-treatment period. It seems like by taking log, the robustness of my result weakens.

To finalize this chapter, if the main finding seemed ambiguous at first, I believe this re-estimation using log has strengthened the argument for, as well as provided further evidence of, the positive GDP per capita gap being statistically insignificant. Meaning that the Great East Japan earthquake had no large scale impact on the economy of Japan.

Discussion

7.1 The Econometrics of Tohoku Earthquake

Before I begin to discuss the statistical outcomes obtained in the result section, I will first address the puzzle of the sudden dip in synthetic Japan's trajectory immediately after treatment discovered in section 6.1.

7.1.1 An unexplainable dilemma

First of all, the only paper I found to produce a similar result is a study about how the Arab Spring impacted the Tunisian Economy (Matta, Appleton, and Bleaney, 2019). As the authors try to decipher the main channels through which the economy was effected by the event, they re-estimate synthetic controls for economic indicators such as total consumption, gross capital formation (investment) and net exports. The output for investment shows a very similar break of trend between real and synthetic Tunisia where the two graphs separate in opposite direction. However, in their case it is real Tunisia that diverges from previous trajectory and not synthetic Tunisia. The authors also do not comment a lot about this division other than that it implies adverse effects. Applying this understanding of adverse effects to my result, it could be the case that the unusual unfolding of events, where a major natural disaster induced a nuclear accident, could have brought about more adverse and complex consequences than I previously assumed, and that this then is reflected in the peculiar trend post-treatment. The economic rehabilitation of the Tohoku earthquake could also be interfering with the aftereffects of the global financial crisis that happened just three years before, leading to abnormal behavior in the synthetic unit. For instance, the sovereign debt crisis in Italy could be a negative influence that drives down GDP per capita before it rises again as the Italian economy gradually recovers in the subsequent periods. But this is an unsatisfactory answer since my L-O-O test clearly shows that the exclusion of any particular donor country does not remove the dip in synthetic Japan, meaning that this drop is not due to some arbitrary country shock. Also, I find this explanation to be lacking because the main issue is not about the two units' opposite trends, but rather that the *synthetic unit* is the one exhibiting an inconsistent trajectory compared to the pre-treatment course.

Another possible explanation to the observed phenomenon concerns random noise and overfitting bias. A graphical illustration of overfitting bias is given by Facure Alves (2021) where it is seen how the fit is perfectly replicated in the pre-treatment period and later shows great volatility in the post-treatment period. Abadie (2021) describes how a small pre-intervention period together with large transitory shocks can induce such bias. Other factors that may cause such bias is for instance when there is enough pre-treatment periods but the donor pool includes too many countries, making it very easy and flexible to model a synthetic Japan. However, this explanation is too extreme to be fully applicable in my case. First, my pre-treatment fit is not perfect. It is very noticeable that there are statistical noises that generates prediction errors. To add on, the post-treatment trend of synthetic Japan is not volatile in the same way as these authors describe; it is only exhibiting a small dip that is later followed by a steady upward trend that even fluctuates less than the post GDP per capita trajectory for real Japan. Hence, in the end, I am unable to clearly identify the underlying reason for the dip in the outcome variable and this incomprehension constitutes a limitation and shortcoming of this thesis.

7.1.2 Possible violations of assumptions and requirements

Back to the main discussion following my inferential and robustness analyses above. There are reasons to suspect that the underlying assumptions and contextual requirements listed in section 4.1.2 are partly violated. My suspicion concerns the aspects of time horizon, substantial idiosyncratic shocks and the convex hull.

First, I wish to touch upon the time aspect of my thesis. Due to reasons I shall not repeat here (please refer back to section 5.3.3), the period of interest was limited to a span of 20 years. Compared to many other synthetic control studies (e.g. Gong and Rao, 2016; Bilgel and Karahasan, 2019; Vincenzo, Leandro, and Ron P, 2014) the time frame in my thesis is comparatively short. This can pose a problem in two ways. The first one concerns issues that are brought about by having too few pre-treatment periods. In these instances, when there is insufficient information, the main concern is a bad pre-intervention fit which would render the subsequent estimate to be unreliable. This is because it would be too difficult to distinguish real effect from sheer volatility induced by a poor fit. Indeed, graphically I did notice some statistical noise in the fitness of synthetic Japan. Still, the magnitude was never substantial enough to cause an imprecise trajectory, since the control was able to closely track the trend of real Japan. To add on, the estimated effect was sufficiently large to be detected, meaning that the size of variance did not interfere with the inferential analysis or the final result. A different possible outcome of insufficient pre-treatment periods is the risk of over-fitting bias. However, as mentioned above this can only happen in combination with large transitory shocks which there is no sign of in my case. Furthermore, the inclusion of lagged values of the outcome variable helps to dampen the influence of unobserved idiosyncratic shocks since they will be mechanically accounted for.

The other potential problem regards an inadequate number of post-treatment periods. Though, depending on the treatment characteristic this need not be an issue. Because, if the researcher is only looking to investigate the short term effects of an event there is no need to include more post-intervention years. In my case however, I have not specified whether I am evaluating the long- or short-term effects. Rather, the question of interest is *if* the Tohoku Earthquake had an economic impact on Japan. It goes without saying that to answer this question in a comprehensive way it is best to include more post-treatment periods to study potential effects that may be lagging in time.

My second point regards Italy and Malaysia and the probable spill-over effects on their respective outcome variable GDP per capita. This is a relevant problem to discuss because the trajectory of synthetic Japan is highly dependent on these two countries, not to mention that the effect's magnitude is sensitive to the exclusion of either of them. Regarding Malaysia, the worry is that the Indian Ocean earthquake and tsunami in 2004 had a greater impact on the Malaysian economy than what I had initially anticipated. This shock is almost identical in nature and intensity to the Tohoku earthquake, and although Malaysia was only slightly affected compared to its neighbouring countries, it is still possible that the national economy was considerably shaken by this event.

The interference effect on Italy's GDP per capita arises from the Great Recession back in 2008 and the ensuing European debt crisis. Due to the fact that these two financially strenuous events followed each other closely in time the Italian economy went through a double dip recession during the period of study. The financial disturbances caused five respectively seven consecutive quarter-periods of recessions in an Italy that was already suffering from a growth rate below the EU average (WorldBank and OECD, 2021). However, this kind of lagged outcome is not unique to Italy alone. Because, each country affected by the Great Recession used distinct monetary and fiscal policies to counteract the crisis in the following years. With distinct recovery methods that are tailored to their own country's economic situation yields various diverse and delayed economic consequences in the post-treatment period (2011 onward). For instance, it was an unsuccessful attempt by the Italian government to lower their government debt ratio through austerity measures that precipitated the second recession in the 2010s (Krugman, 2013; Orsi, 2013).

Different outcomes of governments' monetary policies, other than the (Italian) backfiring kinds, are those that succeed to stimulate and expand the economy following a deep recession. Similar to how Cavallo et al. (2013) found large political shocks that occurred after natural disasters to be driving the main results, it may very well be the case that the effect shown in my study is nothing but a lingering lagged response of Japan's fiscal stimulus to counter the 2008 financial recession. If this was the case, then the bias would primarily affect the trajectory of real Japan, neutralizing the effects of the disaster 2011 as the negative shock of the incident would be offset by a delayed positive feedback to a past expansion effort prior to treatment. As a result, the effect would appear to be more positive than what it in fact is. Indeed, this drawback of not being able to directly distinguish the channels of influence is an inherit flaw of the SCM's study design.

In the end, the choice of including Malaysia and Italy becomes a question of a trade off between the fit of the control and the size of the bias they may impose. A great advantage the synthetic control method has in these situations is that the sparsity of the weight distribution makes determining bias very easy. When it comes to the direction of bias for Malaysia, I have little academic support to guide me due to the ambiguous findings on the economic effects of natural disasters. However, the outcome of my L-O-O test suggests an upward bias since the synthetic Japan without Malaysia as a donor country has a lower GDP per capita in the post-treatment period. This indicates that similar to Japan, the earthquake and tsunami in 2004 had a positive economic impact and if it were not for the trade off of fitness, perhaps the exclusion of Malaysia would have resulted in a significant positive outcome for Japan. Regarding Italy, the economic consequences from the two financial recessions is naturally negative, hence the bias would in this case be downward. This insight is confirmed by my L-O-O test since the synthetic Japan without Italy has a much higher GDP per capita value than the original synthetic trajectory from 2011 and onward. But, considering that the two biases actually point to opposite directions, it is possible that the net effect of skewness is relatively small. Therefore, it is very likely that the bias has in fact a weaker influence over my final results compared to what their original sizes may be indicating.

Lastly, recall that in order to avoid interpolation bias, the variable values of Japan need to be close to the convex hull of the donor pool. This condition is checked in Figure 2 and it appears that the condition is safely met by all predictors but GDP, where Japan lies slightly above the highest value of the donor pool. However, this is not a significant problem since the discrepancy is very small (it still lies close to the convex hull) and the trajectory of synthetic Japan has a great pre-treatment fit.

All in all, the shortcomings of my synthetic control estimation and the resulting biases are not deemed large enough to have a significant impact on my main result, hence my conclusion remains unchanged.

7.2 Economic Development in the Wake of Recovery

The synthetic control method is a pioneering model in comparative studies that is both intuitive to use and easy to interpret. However, its simplicity comes at the cost of not being able to clearly determine through which distinct mediums of influence the effects were brought about. I have in this study arrived at the conclusion that the Tohoku earthquake had a positive but insignificant impact on the Japanese economy, but I have yet to establish how and why these results might have been realized. Neither the neoclassical theory of growth or the endogenous growth model previously mentioned are able to cover the entirety of this outcome alone. Because for one, there is no immediate drop in GDP per capita as predicted by the former and secondly, there is no sign of a long-term economic growth that is generally demonstrated by the latter. The most similar outcome amongst the previously mentioned empirical studies in the literature review is the one by Albala-Bertrand (1993), which finds capital loss to not have a significant effect on growth even if the size of the catastrophe per se is large.

Still, in contrast to the aftermaths of the Great East Japan Earthquake, the study which is based on macroeconomic modeling additionally estimates that moderate economic responses should be sufficient to counteract any natural disaster (Albala-Bertrand, 1993). Yet, as the Tohoku earthquake is one of the most expensive natural disasters in history, this argument does not seem to hold. Considering the size of the subsequent counter disaster package it is reasonable to assume that the rebuilding efforts that followed the triple catastrophe had a vital role in affecting the GDP measure in the post intervention period. As a matter of fact, the usage of gross domestic product as an estimate for economic growth might be misleading when assessing costs in the context of natural disasters.

Similar to how it cannot perfectly portray the wealth and prosperity of a country, GDP is also unable to give a holistic and realistic picture of the total damage caused by earthquakes and tsunamis. For any economy that is struck by a sudden high impact natural disaster the main destruction happens to existing capital stock, such as people's homes, general infrastructure and production facilities. These are costs and damages directed at physical assets "already produced" at that point in time. GDP, being a flow that measures total value created by domestic production over the course of a year, is consequently not directly or immediately affected by the incident. Instead, due to successive post-disaster activities like production of replacement capital, restructuring of infrastructure, communication and transportation, disaster relief and other cleanup activities it is very much likely that GDP increases following a disaster of such colossal magnitude (Horwich, 2000). When looking at macroeconomic data of Japan this is exactly what is happening. Other than the recession in 2008, the economy only saw a small 0.12% dip from 2010 to 2011, the consecutive years only experienced continuous GDP growth, inflation accounted for. In a similar fashion, investment levels rose about 3 percentage points in the span of four years from 2010-2014 and government expenditure was elevated by 4-5 percentage points from 2008-2014 after which it started to decline. Of course, given the lags of monetary policies, part of this expanding trend is probably fueled by the measures taken against the financial recession of 2008. However, the fact that it persists until 2014 speaks for a positive economic disturbance caused by the Tohoku earthquake in 2011.

Another possible factor driving my result is the idea that different types of natural disaster harm different kinds of inputs of economic growth (Loayza et al., 2012). Relating to neoclassical development economics, the main categories of growth assets are physical and human capital. Human capital is argued to be the more essential source as the destruction of physical capital can be seen as an accelerated depreciation of tangible goods, which precipitates and induces investments and technological advancements. Additionally, a sudden reduction in the return of physical capital can easily be replaced by a substitution towards an increased rate of human capital accumulation (Horwich, 2000; Skidmore and Toya, 2002). This is very befitting considering how the Tohoku earthquake mainly destroyed tangible goods rather than significantly weakening Japan's productive work force. According to

Miyamoto, J. Gilani, and Wada (2012) more than 2.1 million people were directly exposed to the earthquake and tsunami, but considering how natural disasters are local events, more than 98% of Japan's population was in fact not physically endangered. Even though the horrendous disaster resulted in 20 000 mortal fatalities the number still only corresponds to less than 0.1% of Japan's inhabitants. Hence, this shock to the labor force is considered inconsequential, both in absolute and relative terms since the economic costs were in comparison much more substantial.

The substitution effect can also be seen in the data. For instance, the rate at which output per worker grew over the years accelerated in the 2010's, especially between the years 2014-2015 where growth amounted to staggering 22%. This may very well reflect the capital regeneration process as discussed above. The reason why this growth is not observed directly after the disaster is probably because Japan needed time to heal, re-organize, re-prioritize and find structure during a time of chaos. Indeed, it takes time for emigrating citizens of the Tohoku region to settle down in other parts of the country, and for the politicians to execute disaster relief and rebuilding programs. It is also worth noting that the financial recession caused unemployment levels to reach new heights in 2009-2010 at 5.1%. The percentage dropped however in 2011 to 4.52% and continued to decrease in the following years. On one hand, this sustained decline in unemployment rate could be a simple reflection of the actualized monetary and fiscal policies used to combat the previous recession. On the other hand, one cannot distinguish the contributing forces by looking at the numbers alone and it is very likely that the Great East Japan earthquake induced more job opportunities as part of the recovery scheme.

To further expand on the insignificance of my outcome I found the paper by Strulik and Trimborn (2019) to be very useful for analyzing the case of Tohoku. As mentioned in the literature review, their paper proposes a new theory that can explain GDP's various growth patterns following natural disasters. They divide physical assets into two sub-categories, durable consumption goods and productive capital. It is found that disasters that mainly destroy productive capital reduces GDP, but if predominantly consumption goods are destroyed then GDP will be pushed above its pre-shock level. Insignificant effects are explained by both types of capital being equally destroyed, offsetting the negative and positive effects.

As mentioned in the background, the earthquake generated tsunami was the main source of immediate destruction both in terms of deaths and economic costs. And clearly, the physical capital destroyed were the facilities, infrastructures and consumption goods etc. submerged by seawater. As there is no data, at least to my knowledge, that shows the proportion of productive capital loss compared to consumption good loss I do not know for sure the ratio. However, it is a plausible assumption to make, as many households were affected by this incident, that a fair number of consumption goods were effectively destroyed. At the same time still, the Tohoku region is home to a large number of production sites, shops and businesses which all add to the loss of productive capital. Finally, one cannot neglect the nuclear meltdown that caused deadly radioactive waste to contaminate the region. So, even if farm land, plants and fishing ports survived the tsunami, the earth, vegetation, water and cities did not withstand the external blow of radioactive contamination.

Other indirect sources to the loss of productive capital are supply chain disruptions and constrained energy supply. Concerning the former, as explained in the background and estimated by the Japanese Cabinet Office (CAO), the cost of lost economic activities were offset by the production gains generated by recovery and reconstruction projects. The economic harm caused by limited energy distribution were not estimated by CAO due to uncertainty regarding the effects on production. However, it can be assumed that the impact was substantial since the main affected area was Kanto, the industrial heartland of Japan, that accounted for 40% of national GDP. More exactly, there were approximately 1.45 million businesses in the area covered by the Tokyo Electricty Power Company (TEPCO), which is the operator of the Fukushima Daiichi nuclear plants (Fujita et al., 2012). Indeed, a sudden decrease in nuclear power caused a shift in energy consumption patterns as more fossil fuels were imported as a temporary substitute. This increased the economic burden on national electricity suppliers and it was estimated that the associated net loss of suppliers (excluding Chugoku and Okinawa regions) amounted to $20.5 billion and compared to the previous fiscal year the additional cost of fuel increase by $29.5 billion (Hayashi and Hughes, 2013).

Now, coming back to the fact that my synthetic estimate is an insignificant result, it must be the case that the Tohoku disaster caused an equal amount of damage to both types of capital goods. And if I were to refer further back my previous discussion on the observed modest positive shift in GDP per capita, it seems as if the triple disaster most likely reduced the consumption stock more compared to the productive capital stock.

7.2.1 Is Japan different?

Before reading this part of the discussion please have in mind that the following subsection is based on speculations derived from previous academic findings. As the synthetic control does not address underlying mechanisms, the purpose of this analysis is to try and and relate existing scholastic outcomes to my own results for reasons I mention in the following paragraphs. Furthermore, other than illuminating differences between rich and poor countries, this discussion also aims to highlight possible limitations to external validity of my synthetic control estimation. Frankly, the conclusions drawn in this study are more naturally applied to other industrialized nations rather than underdeveloped ones. This is because the results may not be directly comparable due to elemental differences in country characteristics obstructing reliable extrapolations of results.

To begin, compared to the inconclusive findings on natural disasters' economic impact, the empirical research is a lot more unanimous when it comes to the contrasting effect on rich and poor countries. As highlighted in the literature review, papers such as Felbermayr and Gröschl (2014), Songwathana (2018) and Toya and Skidmore (2007) arrive at similar conclusions that a country's resilience increases with economic prosperity and development. Other than being a source of vulnerability, underdevelopment may also generate disaster induced poverty traps (Hallegatte and Dumas, 2009) which could increase the existing inequality between the global north and south. Meanwhile, Japan, being situated in the vicinity of four tectonic plates (Marder, 2011), has a long history of living side by side with both climatic and geologic catastrophes. Still, the country has successfully advanced despite the constant threat of natural disasters. It is therefore of great interest to both try and define some characteristics of poor countries that are regularly struck by calamities and investigate the case of how Japan has developed to become one of the largest economies today. Because, even if the hypothesis of disaster induced poverty traps proposed by Hallegatte and Dumas (2009) is a promising explanation for why affected countries in poor regions have experienced little development, it cannot account for how other countries, like Japan, have successfully made economic progress from a historical perspective.

The fact that all nations have once been poor induces a question of why countries develop differently in the face of natural disasters. It seems like some are successful in advancing economically while others appear stuck in poverty. Cuny (1994) provides some plausible explanations regarding the latter case. First of all, it is important to remember that natural disasters disrupt rather than destroys economies. A poor country that is on the road to development will temporarily lose its momentum as normal economic activities are generally cut back or halted with the occurrence of large shocks. Compared to industrialized countries, the economy of developing nations is usually centered around a few major enterprises, making the system less diversified and thus more vulnerable to external forces. And consequently, when disasters happen they are typically viewed as an emergency and is met by the prompt response of various relief programs. This usually entails emergency medical assistance, basic goods such as personal articles, food and clothes, temporary shelter and so on. These packages are also distributed to the locals for free and is in other words a form of charity. Given that these are delivered appropriately the aid bundles can alleviate emergency needs and necessities, but it cannot address the root cause of why these countries could not handle the situation themselves in the first place. Mainly that they are too poor and underdeveloped to do so.

Furthermore, relief programs are not always as beneficial as they may seem at first glance. Other than not properly dealing with the problem of entrenched poverty, they may in fact postpone the recovery of normal economic activities. The reason is because these aid schemes can generate a sense of dependency, creating a disincentive effect that opposes the initial objective of aid programs aimed to establish a quick recovery. With resources that are already scarce, old development projects must now compete with novel reconstruction plans for limited funds and as the frequency of disasters has been increasing over the years, this may eventually lead to greater strenuous financial situations than before (Cuny, 1994).

Lastly, poor countries seem to often withhold a victim mentality when it comes to natural disasters. Building upon the aid dependency argument above, this behavior has caused a common and widespread expectation to receive aid when in need. So even if they have the potential to deal with the disaster on their own, poor countries might exaggerate their inabilities and distress in order to be eligible for disaster benefits. In a similar way, it is very unlikely that natural disasters induce creative destruction in developing countries since recovery for the most part implies a return to the same normalcy that existed before the incident, without further advancements of communities (Cuny, 1994). Hence, it seems that a great difference between how rich and poor countries tackle natural disasters is the fact that the former actively creates while the latter passively receives.

Some other general factors contributing to the relative vulnerability of poor countries include a lack of resources, poor governance, corruption and inequality (Zorn, 2018). The role of institutions as proposed by Acemoglu et al. (2003) is also highly relevant here as they are significant mediators to the quality of public spending, which directly influences short-run GDP. If properly distributed, reconstruction output could positively influence the economy. However, if corruption and rent-seeking behavior cause misallocation then there is a risk for market distortions and decreasing output (Barone and Mocetti, 2014; Felbermayr and Gröschl, 2014).

The reason why industrialized countries are better equipped to counter the impacts of disasters is also partly because they have reached a certain level of economic prosperity to afford to demand greater safety and insurance against unpredictable future events. Indeed, with a stronger economy comes an abundant source of wealth with which governments and private institutions can use to invest in more secure infrastructure, disaster adapted market goods and resilient industries. These types of demand has even created an insurance market that directly addresses natural disasters in Japan (Horwich, 2000). This is very apposite since on a general level the insurance market has proven to be an effective mechanism to transfer risks and costs associated with natural catastrophes, and thus plays an important part in making societies disaster resilient (McDermott, Barry, and S.J. Tol, 2011).

A particular reason behind Japan's fast recovery is its unique norms and customs that have gradually evolved from and adapted to the constant threat of natural disasters, resulting in a culture that emphasizes unity in times of danger (Group, 2020). This is a distinct difference compared to the mentality mentioned above that can be witnessed in many poor and economically stagnant nations. Social capital, as defined in the social studies, has also proven useful to explain the speed of Japan's recovery post 2011 Great East Japan Earthquake (Olcott and Oliver, 2014). The concept was presented as an underlying factor that contributed to swift cooperative inter-firm behavior as well as rapid large-scale mobilization of resources. It is evident that this social capital is reflected in the Japanese culture considering its definition: "...the reservoir of goodwill within a community of individuals or firms that is characterized by a sense of obligation to assist other members of the community who are in difficulty; by trust that those giving or receiving assistance will not unreasonably exploit the situation to their advantage; and by a high degree of shared knowledge and understanding, accumulated over repeated interactions.".

A last point regarding why some rich countries, especially Japan, have been able to develop under the threat and re-occurrence of natural disasters is due to the manufacturing industry. The manufacturing industry of Japan has been its driving economic force since the Industrial Revolution. Although catastrophes, as expected, cause burden and setbacks in the sector from time to time, public institutions and private firms have constantly worked together to build a more resilient community.[15] This is highly in line with the literature on build back better and creative destruction since historical disasters have become catalysts for innovative solutions, programs and tools (WorldBank, 2020). This is again a stark contrast to what was found by Cuny (1994) about the disaster response in underdeveloped countries that have stagnated in their economic development.

[15] Adding on, the Ministry of Foreign Affairs states that Japan has actively been "implementing measures to shore up both the physical and institutional safeguards against disasters, with particular emphasis being placed on disaster prevention" since the 1960s (MOFA, 2021).

As we are living in a time when the threat of global warming is constantly looming over us, it is more relevant than ever to expand and contribute to the research on natural disasters. It is evident from this final discussion that there is more to be learned about the role and promise of resilient industries, as well as Japan's progressive advancement that happened in conjunction with reoccurring external shocks. And though many elements of resilience are specific to countries' economic structure and local culture WorldBank (2020) considers Japan to be a nation which other countries ought to learn from and take after. Indeed, as the country has been taught to thrive in a hostile environment as well as adopted advanced preventative measures and technologies, there is perhaps no other country in the world that is as good at build back better as Japan.

Conclusion

In this thesis, I explore whether the Tohoku earthquake and tsunami had a significant effect on the economy of Japan. I utilize synthetic controls, as proposed by Abadie and Gardeazabal, 2003 and Abadie, Diamond, and Heinmueller, 2010, to study this empirical question. Data is obtained for a period of 20 years, spanning the years 1999-2018. Several sensitivity checks are implemented to test the robustness of my result. By comparing GDP per capita for Japan with its synthetic counterpart, which illustrates the economic trajectory for Japan if the disaster had not happened, it is discovered that the incident gave rise to a positive but statistically insignificant effect.

Adding to a somewhat inconclusive and ambiguous field of research, my result supports and corroborates findings within disaster and development economics that suggest natural disasters to have a negligible impact on the economy, at least in the case of Japan. Whether this result is directly applicable to other countries is difficult to determine without having conducted country specific analyses. Still, the external validity of my research extends more naturally to industrialized countries compared to developing countries. This is because the difference in income levels causes people and governments to act very differently when facing catastrophes, resulting in disparate economic decisions and political measurements.

Considering how natural disasters are typically portrayed as downright destructive and unforgiving in media, it was surprising to obtain not only an inconsequential effect but also a visible positive shift in economic output. I argue that this may have come about for many different reasons, including using GDP as a measure of economic growth, the substitutability between human and physical capital input, and the type of assets that were effectively destroyed in the triple disaster. Furthermore, this study is not one without shortcomings as I discerned several potential sources of bias. Nonetheless, after careful analysis I proved that these biases most likely eliminate each other up to a certain point, leaving the net effect to be smaller. And even if the biases are greater than first assumed, they would still not be great enough to change the ultimate outcome of this paper.

As this study analyzes the macroeconomic effects of the Tohoku disaster, it could be interesting for future research to examine the microeconomic impacts of this event, especially in the affected regions of Iwate, Fukushima and Miyagi. Indeed, economic costs incurred on a local level may be hidden on national level data, and even if other parts of Japan is able to assist in absorbing the shock, the region itself may experience slower economic growth as a consequence of disaster induced emigration protracting rebuilding programs.

In this study I have also briefly touched upon the subject of how Japan has successfully handled the threat of natural disasters in contrast to low-income countries. It might therefore be of interest to dive deeper into how Japan has, historically, managed to escape poverty traps caused by natural disasters and worked towards becoming both an industrialized and resilient nation.

Last but not least, some drawbacks of my thesis include having a restricted number of pre-treatment periods and not using cross validation to select predictor variables. Even though it is the timing of the Tohoku earthquake that has set the limit to my data, a more accurate estimate would have been obtained if I had the option to incorporate information from the years before 1999. I also believe that if I had used the data-driven method for choosing predictor variables my estimate would have been able to minimize RMSPE further and the result would perhaps be more robust to changes in the donor pool. Another shortcoming is the presence of pre-treatment noise. Compared to control units in some other SCM studies my synthetic Japan has noticeably more variance. A last limitation I wish to mention is the fact that the underlying reason for the sudden dip in synthetic Japan remains unsolved.

And so, with new found insights derived from the flaws in my thesis I will finally recommend two related models for future SCM research in disaster economics that could be of value. The first suggestion is an algorithm created by Amjad, Shah, and Shen (2018) which helps to de-noise the data matrix through singular value thresholding. The other extension is the augmented synthetic control developed by Ben-Michael, Feller, and Rothstein (2021) that deals with finite sample and predictor imbalance bias. Unfortunately, I had not the time nor the right statistical software to use these models in this paper. However, seeing how they address limitations in the SCM design itself, it would be interesting to see whether such bias adjustments ought to substantially improve my synthetic estimate.

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Appendix

Table A: Inference - RMSPE country ranking

Rank	**Country**	**pre-RMSPE**	**post-RMSPE**
1	Finland	1525.844	10163.575
2	Ireland	3414.471	16006.328
3	United States	796.046	3102.873
4	Japan	450.155	1752.235
5	Italy	1383.130	4940.529
6	Belgium	312.286	1035.847
7	France	509.896	1689.201
8	Singapore	6972.308	21445.186
9	Sweden	481.398	1425.125
10	Spain	542.447	1403.313
11	Netherlands	1352.566	3494.996
12	United Kingdom	351.480	827.252
13	Canada	270.841	615.183
14	Denmark	534.661	1133.052
15	Switzerland	2538.556	4654.778
16	Germany	1015.098	1700.813
17	Malaysia	11153.763	14847.711
18	Hong Kong	1353.062	1555.629
19	Korea	859.567	983.036
20	Norway	1419.427	1562.699
21	Austria	502.151	533.702
22	New Zealand	409.444	411.053
23	Australia	889.720	596.650

[1] Comparing the ratio of post-RMSPE to pre-RMSPE it is clear that Japan ranks 4th place. This result generates a psuedo p-value of $^4/_{23} \approx 0.1739$.

Table B: Donor pool countries

Country	Final pool	Comment
Australia	Yes	
Austria	Yes	
Belgium	Yes	
Canada	Yes	
China	**No**	Idiosyncratic shock 2008.
Denmark	Yes	
Finland	Yes	
France	Yes	
Germany	Yes	
Hong Kong	Yes	
Iceland	**No**	Risk of interpolation bias.
Indonesia	**No**	Idiosyncratic shock 2004.
Ireland	Yes	
Italy	Yes	
Korea	Yes	
Malaysia	Yes	
Netherlands	Yes	
New Zealand	Yes	
Norway	Yes	
Singapore	Yes	
Spain	Yes	
Sweden	Yes	
Switzerland	Yes	
Thailand	**No**	Spillover effects 2004.
United Kingdom	Yes	
United States	Yes	
Vietnam	**No**	Spillover effects 2004 and interpolation bias.

Table C: Log GDP per capita predictor means

Variables	Weight	Japan Real	Japan Synthetic	Donor pool
Log GDP pc (1999)	0.1162	10.472	10.454	10.573
Log GDP pc (2008)	0.7105	10.566	10.571	10.764
Log GDP pc (2010)	0.1596	10.548	10.540	10.751
Government consumption	0.0069	18.069	17.295	18.357
Household consumption	0.0008	55.970	57.617	53.074
Expenditure	0.0009	35.479	42.315	39.659
Investment	0.00006	25.878	21.867	23.481
Industry	0.0021	30.259	27.509	25.042
Log GDP	0.0029	29.175	28.414	27.491

[1] *Note:* By taking log GDP per capita I am able to reduce RMSPE from 268.101 to 0.0081374, i.e. a substantially better fit. However, this change does not affect my main results significantly.

Table D: Country weights, log estimation

Country	Weight	Country	Weight
Australia	0	Korea	0
Austria	0	Malaysia	0.195
Belgium	0	Netherlands	0
Canada	0	New Zealand	0
Denmark	0	Norway	0
Finland	0	Singapore	0
France	0	Spain	0
Germany	0	Sweden	0
Hong Kong	0	Switzerland	0
Ireland	0	United Kingdom	0
Italy	0.699	United States	0.106

Table E: Log RMSPE country ranking

Rank	Country	pre-RMSPE	post-RMSPE
1	Finland	0.0255	0.1660
2	Ireland	0.0542	0.2252
3	United States	0.0137	0.0534
4	Japan	0.0109	0.0418
5	Italy	0.0334	0.1165
6	Sweden	0.0123	0.0391
7	Singapore	0.1026	0.2682
8	Spain	0.0182	0.0476
9	Netherlands	0.0205	0.0391
10	France	0.0180	0.0252
11	Austria	0.0089	0.0124
12	Switzerland	0.0440	0.0587
13	Denmark	0.0146	0.0178
14	United Kingdom	0.0069	0.0081
15	Canada	0.0095	0.0107
16	Hong Kong	0.0416	0.0443
17	Malaysia	0.4751	0.4810
18	Norway	0.0252	0.0215
19	New Zealand	0.0138	0.0114
20	Korea	0.0366	0.0293
21	Australia	0.0260	0.0150
22	Belgium	0.0105	0.0059
23	Germany	0.0375	0.0038

[1] Comparing the ratio of post-RMSPE to pre-RMSPE it is clear that Japan still ranks 4th place even after taking logs. This result generates the same psuedo p-value of $^4/_{23} \approx 0.1739$.