The London School of Economics and Political Sciences

The Causal Effects of the Indian Ocean Tsunami and Armed Conflict on Aceh's Economic Development

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Declaration

I certify that the thesis I have presented for examination for the PhD degree of the London School of Economics and Political Science is solely my own work other than where I have clearly indicated that it is the work of others (in which case the extent of any work carried out jointly by me and any other person is clearly identified in it).

I warrant that this authorization does not, to the best of my belief, infringe the rights of any third party.

I declare that my thesis consists of 81,336 words.

Statement of inclusion of previous work

I confirm that the soil chemical nutrient data I used for the analysis presented in chapter 5 was collected by myself, while I was a Masters student at the University of Hawaii.

Abstract

This PhD thesis investigates the causal long-term economic effects of the Indian Ocean Tsunami and the armed conflict in Aceh, Indonesia (chapters 2, 3 and 4). It also contains an analysis of land use change and the consequences for soil-organic carbon (SOC) in Eastern Panama that is unrelated to previous chapters.[1] Chapter 2 stands at the core of my PhD thesis; it is the equivalent of a job market paper.

In chapter 1, I provide an introduction to and summary of my PhD thesis. In particular, I describe why I believe that I make original contributions to knowledge that are significant and rigorous.

In chapter 2, I carry out a quasi-experimental analysis investigating the causal effects of Tsunami flooding on long-term per capita economic output. The existing literature suggests that natural disasters are growth depressing in the short-term, and in the long-term, natural disasters either cause a continued shortfall of economic output, or an eventual convergence to the pre-disaster counterfactual trend. I picked the Indian Ocean Tsunami in Aceh as a case study for this PhD thesis, because I posit that if there is one case for which there is evidence that goes against the conventional wisdom, namely in the form of increased economic output in the long run, it probably is Aceh. The reason why I expect to see creative destruction is that Aceh received a windfall of aid and was the stage of the largest reconstruction effort the developing world has ever seen. I conclude that natural disasters are not necessarily the cause of output reductions and that they can be windows of opportunity for the economy.

In chapter 3, I investigate the reasons behind the creative destruction, and take a closer look at different sectors and subcomponents of the economy. I examine three channels through which the Tsunami may have affected per capita economic output. First, I find that the Tsunami causally accelerated the structural transformation process, a process through which people and the economy move out of agriculture, and into more productive sectors such as services. Second, I show that the Tsunami brought with it a windfall of aid and other funds, which allowed for a building back better of physical capital and increased capital formation. Third, I show that aggregate private

[1] A requirement of my ESRC/NERC scholarship was to produce also a natural science study, which is the reason for the different topic.

consumption not only was smoothed in a reaction to the Tsunami, but even boosted to sustainably higher levels, compared to the no-Tsunami counterfactual.

In chapter 4, I investigate whether the 30 years long armed conflict in Aceh left any negative economic legacy effects, once the fighting stopped and the peace agreement was signed. The separatist war took a toll on the Acehnese economy. Even though the conflict has ended, did the negative economic effects also end? Aceh's economy has higher per capita growth rates in times of peace than in times of war, which can be either a sign of a peace dividend or creative destruction from the Tsunami. But does the armed conflict leave a negative legacy for future growth rates, even after peace has officially been declared? I find that that peacetime growth rates are negatively affected by the wartime conflict intensity. Using violence data on the incidence of killings, injuries, and other 'measurable human suffering', I assess whether districts that were heavily affected by armed conflict grew systematically differently from those that were spared from the brunt of the violence. I find that there are severe negative economic legacy effects of violence, and the more violence occurred in a district during the separatist war, the slower it was growing during times of peace.

Chapter 5, topically unrelated to the previous chapters, is looking at land use change in Eastern Panama and the consequences for soil organic carbon (SOC). In this chapter, I compare SOC concentrations of primary forests to two competing land use alternatives: Forest-to-pasture conversion for cattle grazing versus indigenous forest-to-crop conversion. I find that both land use changes reduce SOC concentrations significantly, yet the pasture land use has lower levels of SOC than indigenous crop cultivation. The soil carbon levels of secondary forests are not statistically different from primary forests, implying that the forest conversions are reversible, in terms of their impact on SOC, which suggests that allowing secondary forests to re-grow in former cultivated areas in the Eastern part of Panama holds promise for climate change mitigation.

In the concluding chapter 6, I present a summary of the main findings and an outline for future research.

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CHAPTER 1

Introduction

Can a natural disaster be a window of opportunity and cause more economic output per capita in its aftermath than had it not occurred? The natural disaster economics literature firmly negates this possibility for the long run. Nevertheless, what would be a good natural disaster candidate that would call into question the generality of a growth-depressing or growth-neutral disaster effect? I pick the most likely natural disaster case to my reasoning; the Indian Ocean Tsunami and the devastation it brought to the Indonesian province of Aceh, on account of it having triggered the largest reconstruction effort the developing world has ever seen.

My second and third chapters investigate the natural disaster effects on economic growth in Aceh and verify whether the Tsunami resulted in creative destruction and why. In my fourth chapter, I examine whether the armed conflict in Aceh has had any economic legacy effects. My fifth chapter evaluates the consequences of different land use strategies in Eastern Panama on soil organic carbon (SOC).[2]

[2] The reason for why the last chapter is topically different from the other ones is that my scholarship from ESRC/NERC stipulated that I had to produce natural sciences based research also. My previous training in soil science and ecology allowed me to take soil samples from several land use alternatives (forests, indigenous crops, and pastures) and compare their chemical nutrient concentrations.

My PhD thesis investigates the dual challenges facing Aceh's economic development in the post-Tsunami and post-conflict era. It assesses the causal effects of the Indian Ocean Tsunami, the ensuing reconstruction effect, and the legacy effects of the 30-years long armed conflict on long-term economic output in Aceh. My Indonesia disaster and conflict chapters examine these causal impact questions in detail by exploiting what can be described as a quasi- or natural experiment, using subnational data, and modern causal inference techniques.

I believe that my PhD thesis makes original contributions to existing knowledge that are significant and rigorous. My original contributions are that I am the first to document the causal case for creative destruction resulting from a natural disaster. I do not stop at showing the significant causal effects alone, but also explore some of the likely channels through which creative destruction took place. To my knowledge, I am also the first to causally identify legacy effects of subnational violence on peacetime economic growth rates. My contributions to both the natural disaster economics field and the conflict economics field are predicated on cutting-edge econometric techniques.

For the natural disaster economic work I present in chapters 2 and 3, in which I investigate the causal effects of the Indian Ocean Tsunami, I heavily rely on the natural disaster economics and the economic growth literature. The literature investigating the causal effects of severe natural disasters on economic activity is not conclusive. It remains torn between whether the affected economy is permanently relegated to a lower growth path (e.g. Hsiang and Jina, 2014), whether the negative effects are only short-term (e.g. Strobl, 2011), or whether it is significantly affected at all (e.g. Cavallo et al, 2013). Most of the underlying analyses were carried out using national annual Gross Domestic Product (GDP) data. However, *"… much of the interesting variation in economic growth takes place within, rather than between, countries"* (Henderson, Storeygard and Weil, 2012, p. 995). Using spatially coarse indicators such as national GDP as impact measures to evaluate the effect of localized events such as natural disasters introduces a lot of noise and masks spatially heterogeneous effects.

I investigate whether the Indian Ocean Tsunami was creatively destructive and sustainably so, by constructing a unique fine-grained dataset linking local level GDP data to physical flooding data. Using modern econometric techniques and a rigorous causal identification strategy, I find that the Tsunami floods resulted in creative destruction, leading to a building back better of physical capital, which in turn allowed the region to "float up" to a higher economic growth path in its wake.

I distinguish between different post-Tsunami periods, the immediate aftermath (2005), the recovery phase (2005-2008), and post recovery (2009-2012). I find that each of them exhibits unique growth trends. The first year was marred with a delay in the reconstruction effort, resulting in a reduced economic activity compared to the no-Tsunami counterfactual. Once the rebuilding after the destruction was in full swing, the region grew significantly faster than the counterfactual (regaining the lost ground in the aftermath year and more) and had higher growth rates during the recovery phase. In building back the physical capital, and in building it back better, the Acehnese economy was boosted onto a higher output path compared to the counterfactual.

Once the reconstruction was completed and the aid funds dried up, did the region remain on this higher economic output trajectory, did it revert back to the counterfactual output path, or even drop below it? The Acehnese economy was not only stimulated by the building back of destroyed capital, but the built back better capital was also used more productively in the post-recovery phase. The economy did not revert back to the counterfactual per capita output path, nor did it drop below it; it remained on a permanently higher path. To be specific, this does not mean that the flooded districts kept growing at higher rates in the long run, but they remained on a parallel, yet higher per capita output path from 2009 onwards.

The Tsunami caused heterogeneous localized responses due to the geography of the districts. Island districts recovered more sluggishly; facing initially severe contractions they ultimately rebounded back to the counterfactual growth path, reflecting the difficulty the donor community had in reaching these remote locations. Urban districts recovered much faster than rural districts, during the recovery period, and then permanently remained on a higher per capita output path. Rural districts recovered a bit slower, but remained on a higher per capita growth path even in the long run. Even though there were indications of spillovers of the creative destruction effect from the stricken districts to the adjacent districts, they were not statistically significant.

Not all destruction is the same; there were heterogeneous treatment effects. Only the more severely affected sub-districts displayed creative destruction. Less devastated districts grew indistinguishably from the non-flooded counterfactual.

The rich heterogeneous and localized effects shown in this chapter indicate the necessity for going beyond national averages in economic impact analyses of natural disasters. The existence of the modifiable areal unit problem, illustrated in this paper, and the existence of creative destruction suggests that some of the disagreements in the literature may very well stem from observing net effects by using crude measures that dilute the signal strength and direction. I show the magnitude and severity of this problem for statistical inference by conducting the same analysis using a coarser level of analysis, comparing the island of Sumatra (the island on which Aceh is one of nine provinces) with the other five non-flooded islands using the same methods. I fail to detect a significant effect of the Tsunami on island level growth rates.

Following up on work that stresses the importance of the distinction between hazards and natural disasters in suggesting that a hazard turns into a natural disaster only if appropriate preparatory steps were not taken (Neumayer, Pluemper & Barthel, 2014) my work suggests that a natural disaster, even one of the worst ones, will only linger if adaptive steps are not taken. Rectifying policies such as aid are of crucial importance in overcoming even the largest adversity, and using it as a window of opportunity. I conclude that whether or not a natural disaster is here to stay and continue to depress an economy ultimately hinges on political (human) will, and not on the destructiveness of its impact.

In chapter 3, I take a close look at the mechanism through which economic growth could have been boosted by the Tsunami. I look at subcomponents and subsectors of GDP. In particular, I focus on aggregate consumption, investment, and structural transformation, as the principal channels driving creative destruction.

I find that the Tsunami triggered an investment bonanza, meaning capital formation rates well beyond those observed from the counterfactual. I also find that aggregate private consumption was not only smoothed, but in fact even boosted by the Tsunami and the incoming aid. I also find that the Tsunami triggered an acceleration of the structural transformation, causing labor and economic activity move to more productive sectors. Many jobs were gained by the service industry, and it contributes significantly more to the sector share of overall economic activity because of the Tsunami.

In chapter 4, I take a granular look at the negative economic legacy effects of armed conflict. The Indian Ocean Tsunami brought devastation and suffering to Aceh. Nevertheless, it also brought peace in that it helped to end the 30-years long civil war. Even though peace was declared after the Tsunami crashed on Aceh's shores, and the conflict ended instantaneously, did the wartime violence keep haunting the province economically even though war was over? In other words, were there any negative legacy effects from the historic violence of the armed struggle on peacetime economic growth rates?

I find that there is in fact a significant reduction in the peacetime growth rates of the districts that were exposed to more violence during the armed conflict. Regardless of how I measure violence and conflict intensity, be it by people killed, people injured or buildings destroyed, I always find a growth-retarding legacy effect in high violent districts. Even though the negative conflict effect dissipates over the course of five years, the wartime conflict affected districts never recover from the conflict-incurred losses, relegating the economy onto a permanently lower output path.

In chapter 5, I dedicate myself to a different issue. I investigate the environmental consequences of certain kinds of deforestation in terms of soil organic carbon changes. The forest of Eastern Panama is converted to agricultural land predominantly for two purposes: cultivating crops and ranching cattle. This chapter studies the relative soil quality impacts of indigenous forest-to-crop conversion versus non-indigenous forest-to-pasture conversion. Soil organic carbon (SOC) concentration levels are measured in forest, crop, and pasture sites to allow for comparative evaluation of land use change impacts. The preponderance of evidence in the literature points to a substantial decrease of SOC following forest-to-crop conversion, but no change in forest-to-pasture scenarios. Studying indigenous crop cultivation techniques, and smallholding colonist cattle ranching activities, this article finds the opposite. Indigenous rice and maize fields are shown to not store significantly less SOC than forest sites. Non-indigenous colonist pasture sites on the other hand do store significantly less Carbon. The results vary substantially with topography. Deforestation on plateaus has particularly adverse effects on SOC, whereas the effects on other slope positions are minor and statistically negligible. The older the pasture sites get, the more SOC they lose, up to almost half of the original Carbon concentration 20 years after conversion. By the same token however the chapter finds evidence that this is reversible and that if allowed to re-grow, secondary forests will revert back to original SOC levels.

CHAPTER 2

The Economic Silver Lining to the Human Catastrophe of a Natural Disaster: The Causal Impact of the Indian Ocean Tsunami on Aceh's Long-Term Economic Development

2.1 Introduction

To argue that natural disasters destroy physical capital (e.g. they destroy roads and bridges), human capital (e.g. they kill and hurt people) or environmental capital (e.g. they flood or scorch ecosystems) is quite straightforward (see e.g. Hochrainer, 2009, and Noy, 2008). What is however still subject to debate in the field of natural disaster economics is whether in destroying capital, they have a positive, negative, or no effect on economic output, and if the effects reach beyond the short-term (see e.g. Hallegate & Przyluski, 2010).

In principle, there are both positive and negative channels linking natural disasters to economic growth:

Natural disasters may enhance growth through several possible channels. Replacing lost capital is increasing the demand for goods and services, boosting aggregate demand in the wake of the natural disaster (Horwich, 2000; Kunreuther et al, 2004). Moreover, if the capital destroyed was old and out-dated a switch to higher productivity equilibrium is possible (Skidmore & Toya, 2002). This is said to hold true as long as the productivity gains from upgrading capital are higher than the productivity losses from losing the old capital (Hallegate & Dumas, 2009; and Cuaresma et al, 2008). Following this logic, the gradual replacement of destroyed capital with modern capital has a positive net effect on long run economic growth (Benson & Clay, 2004; Benson, 1998; and Hallegate & Dumas, 2009). In this line of thinking, the natural disaster performed an economic service in that it tore down out-dated infrastructure. This creates the opportunity to replace roads, airports, bridges and so on with more efficient infrastructure (Skidmore & Toya, 2002). It has furthermore been proposed that natural disasters stimulate innovation (Toya & Skidmore, 2007). In addition, some have argued that even though GDP might decrease, GDP per capita could possibly increase as the marginal productivity of intact capital increases due to capital and labour becoming scarcer in the destructive wake of the natural disaster (see Hsiang & Jina, 2014). Natural disasters may also result in a more trusting and more cohesive society, which in turn may spur economic growth through augmenting total factor productivity (Toya & Skidmore, 2014). The channel through which interpersonal trust is said to increase in the wake of a disaster is that the calamities promote cooperation in rescue operations and rebuilding of the destruction, which is said to strengthen interpersonal ties (Toya, 2014). Disasters may also trigger outpouring sympathy via increased levels of volunteerism and donations, which further bring a society closer together and increase trust (Khalish, 2014), which in turn should also increase productivity.

Natural disasters may reduce growth rates and depress incomes because the productive capital they destroy such as durable assets, lead to expenditure reductions and therefore reduce the consumption component of aggregate GDP (see e.g. Baez et al, 2010; Carter et al, 2007; and Anttila-Hughes & Hsiang, 2013). The idea is that the funds and labour that are used to replace destroyed capital cannot be used on something else instead (Field et al, 2012). For example, a shrimp farmer who is rebuilding his aquaculture after it has been wiped out could have used the funds for constructing an additional pond instead. Conversely, if she decides not to restore her livelihood but switch to an alternative economic activity instead (Jacoby & Skoufias, 1997), one is lead to conclude that the new activity is less productive because had it not been, a rational agent would have switched already before the shock occurred. Other examples of negative channels include reduced productivity because of impaired capital: a destroyed road reduces productivity by increasing transportation costs, a broken arm reduces the output per worker, and agricultural fields flooded with saltwater make it impossible to grow food (see e.g. Hsiang 2010; or Deryugina, 2011), at least for the duration for which it remains in disarray.

To say that the jury is still out on whether natural disasters are by in large negative or positive for economic output would be a misreading of the preponderance of evidence, particularly so for severe climatological disasters in developing countries. While there are a few papers that argue in favour of a creative destruction based on forces at play along the lines of those described above (increased aggregate demand, capital upgrade and innovation), the preponderance of evidence points to negative effects (Cavallo & Noy, 2011). The few studies that have found creative destruction effects only hold under certain circumstances such as high development level of the country, insured losses and most importantly only hold for moderately destructive disasters (or in analyses that include all kinds of disasters irrespective of their intensity). Loayza et al. (2012) and a meta-study by Cavallo & Noy (2011) reconciled the contradictory findings in the literature by synthesizing that only moderately destructive disasters have positive effects in the immediate aftermath of the disaster. In conclusion, the literature suggests that natural disasters are contractionary rather than expansionary for economies in the short-term.

Particularly developing countries are expected to suffer economically from natural disasters (Heger, Julca & Paddison, 2009; Loayza et al, 2012; and Fomby, Ikeda & Loayza, 2009). The mechanisms investigated as to why low-income countries are disproportionately adversely affected are absence of safety nets (Linnerooth-Bayer & Mechler, 2007), insurance schemes (Linnerooth-Bayer, Mechler & Hochrainer-Stigler, 2011; Hochrainer-Stigler, Sharma & Mechler, 2012), fully functioning credit markets (Noy, 2009), and savings (Paxson, 1992; and Mechler, 2009). All these policy tools are less functional or non-existent in developing countries. The absence of such coping mechanisms has repercussions. Noy (2009) for instance found precipitous declines in economic growth in developing countries, but no effect in developed countries. He attributed the difference between developed and developing countries to countercyclical fiscal and monetary policy pursued by developed countries.

Particularly the poor might suffer from uninsured disaster risk. If they cannot smoothen consumption, they are left to cope with strategies detrimental to their human capital such as cutting back on nutrition or taking kids out of school (Baez, de la Fuente & Santos, 2010; Jacoby & Skoufias, 1997; Moser, 1998; Subramanian & Deaton, 1996, Banerjee & Mullainathan, 2010; and Jensen & Miller, 2008). Coping with natural disasters is particularly hard for the poorest in a society, leading them to adopt strategies to overcome the adversity that are costly not only in the short run, but also the long run (Carter et al, 2007).

The few studies that look at long run economic effects of natural disasters report mostly negative effects, and some find neutral effects (Hsiang & Jina, 2014; Cavallo & Noy 2011; Cavallo et al, 2013; Raddatz, 2009; and Noy & Nualsri, 2007). The one notable exception is Skidmore and Toya (2002) who conclude that even though geological disasters are contractionary, climatological disasters are expansionary and bring about Schumpeterian creative destruction to the economy. Cuaresma et al (2008) suggest though that the creative destruction results found by Skidmore and Toya (2002) only apply to moderate disasters. Moreover, they are likely to only hold in high income countries (Cavallo and Noy, 2011).

For the negative short-term disaster-growth nexus examples, there are two possible scenarios for the longer term. A "rebound" case, where after a few years of depressed growth, the output path eventually converges again with the original growth trajectory, also called "recovery to trend" trajectory. The other route is a "no recovery" option, where even after many years have passed the affected area never converges to the income path under the no disaster scenario. The "recovery to trend" hypothesis argues that there is a substantial contraction in output and that over several years the output will remain below the non-disaster trajectory, but eventually it will re-bound and converge to the pre-disaster trend (see e.g. Davis & Weinstein, 2002; or Miguel & Roland, 2011). The "no recovery" hypothesis on the other hand argues that disasters permanently destroy capital, from which an economy cannot recover. An economy might eventually start to grow again, will however never meet its pre-disaster trajectory (see e.g. Burke et al, 2009; Hsiang, Meng & Cane, 2011; and Hsiang & Jina, 2014.

The natural disaster effects on growth depend on several factors such as type of economic sector affected, and type of natural disaster. It is quite likely that natural disasters affect some sectors of the economy differently than others. While a flood for example is contractionary for the industry sector, it can quite possibly be positive for agriculture, through boosting agricultural yields as water is an important input into agricultural yields and production. A drought may have no strong causal effect on the service sector or the manufacturing sector (as those are insulated to extreme heat), but quite severe negative effects on agriculture, through scorching the harvests. An earthquake may not affect agriculture at all, but heavily damage manufacturing through destruction of machines and other capital input to the production. For analyses on sector-specific effects, see Loayza et al (2012) and Fomby, Ikeda & Loayza (2009).

Geological disasters are found to have different effects on economic growth than climatological disasters (see Cuaresma et al, 2008). While climatic disasters have been shown to not only more harshly affect the economy in the immediate aftermath, they have also been shown to relegate the economy to a permanently lower growth path, compared with geological disasters, which after quite moderate and insignificantly negative effects rebound to the counterfactual growth path (Raddatz, 2009).

Floods have been shown to not have any effect on long-term economic growth. Raddatz (2009) found that after an initial depression, compared with the counterfactual, countries rebound to the counterfactual growth path in the second post-flood year. Other studies found that floods did indeed have a positive effect, but only moderate ones and only on agricultural sector growth (Loayza et al, 2012). The positive association was attributed to the higher levels of rainfall that are correlated with floods, which due to agronomical processes are beneficial for yields. It has also been shown that through interlinkages to the rest of the economy and because of growth in the agricultural sector, moderate floods spurred growth in the short run (Fomby, Ikeda &

Loayza, 2009). Severe floods on the other hand were not found to show any positive GDP growth effects, or any subcomponent of GDP (Fomby, Ikeda & Loayza, 2009).

Weaknesses of existing studies

This chapter overcomes the weaknesses of most existing studies, which include: (a) Short time horizons, (b) using endogenous measure of natural disaster impact and lack of a causal identification strategy, and (c) using aggregate data for localized events:

(a) The short-term effects of natural disasters on economic growth have been researched quite extensively (see e.g. Loayza et al, 2012; and Cavallo et al, 2013 for an overview). Nonetheless, short-term effects may simply be adjustment processes for the convergence to the long-term trend. It is important to shed light on whether long-term trends are affected as well. Only a hand-full of articles looked at long(er)-term effects: Hsiang & Jina (2014) find that national economies never recover, and find significantly reduced per capita incomes even 20 years after the occurrence of a natural disaster. Cavallo et al (2013) on the other hand find that there are no long-term effects in national growth, tracking 10 years post disaster. They do not even find significant effects looking only at the most extreme disasters. [3] Looking at US coastal counties, Strobl (2011) also finds only a short-term contraction but no significant effects seven years after the disaster.

(b) Almost all articles in the natural disaster economics literature, with the exception of Hsiang & Jina (2014), Strobl (2011), Bertinelli & Strobl (2013), and Felbermayr & Groeschl (2014) use endogenous measures of the natural disaster impact. Most of these papers use the International Disaster Database (EM-DAT) from the Centre for Research on the Epidemiology of Disasters (CRED) at the Catholic University of Louvain in Belgium. EM-DAT provides measures of total deaths, injured, affected, homeless, total affected and total damage. Others use data from re-insurance companies, such as

[3] Cavallo et al (2013) initially found long-term contracting effects for the most extreme natural disasters. However, after dropping countries that had revolutions following the years after an extreme natural event, this negative effect disappeared. Depending on whether the natural disasters had any effect on the regime changes, one would either conclude that they have growth-depressing or growth-neutral effects in the long run.

Munich Re, which maintains the NatCatSERVICE dataset, documenting the insured losses associated with natural disasters of the last decades. The issue with these variables that use economic or human cost measures of natural disasters as estimates, is that the ensuing analysis will assess the impact of an economic variable on another economic variable, therefore making causal inference murky. The problem that arises is that the natural disaster impact measure might itself be endogenously determined. Most studies attempted to explicitly or implicitly assume away the endogeneity, because in part they concluded that a natural impact measure was "ideal but unattainable" (Noy, 2009).

Purely physical measures of natural disasters have so far only been developed and used for the evaluation of hurricanes, tropical cyclones, and earthquakes (Felbermayr & Groeschl, 2014). Bertinelli & Strobl (2013), Outtara & Strobl (2013), and Hsiang & Jina (2014) use wind-field models, a measure of wind intensity per particular area. Hsiang & Jina (2014) use it to evaluate the worldwide impact on national level economic growth. Strobl (2011) uses it to assess the impact on county level growth in the US, and Bertinelli & Strobl (2013) use it to assess the impact on grid-cell (5 km^2) level night-light intensity in the Caribbean.

Out of the few studies that examine the long-term effects of natural disasters, there are only two that explicitly attempt a causal identification of the economic natural disaster effects (Hsiang & Jina, 2014; and Cavallo et al, 2013).[4] Both explicitly causal papers however come with challenges that I hope to overcome in this PhD chapter. For one, they both use the national level as the unit of analysis, which introduces noise into the estimation and as I argue, is a too coarse level of analysis (for reasons of aggregation and countervailing effects). For another, Cavallo et al (2013) use the estimated costs of a disaster as the impact measure, which introduces endogeneity. Hsiang & Jina (2014) on the other hand use measures of wind intensity (from a physical wind field model) as an exogenous impact measure, which should not have endogeneity problems.

[4] Additionally, Strobl (2011) would also fulfil the exogeneity assumption if one assumes that a priori all coastal districts were equally exposed and equally vulnerable to hurricanes. If those districts that were hit by a hurricane however were also more likely to be exposed in the past and for example have taken better precautious measure, or have more experience in recovery, the exogeneity assumption is threatened.

(c) *"Skeptics charge disaster economists with … seeing illusory effects that stem only from the crudeness of the available economic measuring tools." (NY Times, 2008, para.7)*

The Modifiable Areal Unit Problem (MAUP) has received no attention at all in the natural disaster economics literature. To the best of my knowledge, there has not been any explicit attempt to investigate whether the disaster-growth estimations are influenced by the size or shape of the unit of analysis. The MAUP points out that the results obtained may be impacted in large parts by the choice of the unit of analysis and the delineations of the chosen districts/provinces/countries (see e.g. Briant, Combes & Lafourcade, 2010; and Openshaw & Taylor, 1979). MAUP may be occurring because of aggregation biases, the non-randomness of unit delineations, or by its changing delineations over time. Changing units of analysis are a pertinent concern in Indonesia, because there was a strong push for decentralization after 2001 and the subsequent more than doubling of districts, and their related semi-autarky.

National level aggregates, such as macroeconomic data emerging from the System of National Accounts (SNA) of each country are the units of analysis of the vast majority of studies looking at the disaster-growth links. Yet, the nation-level is a very coarse level of granularity leading to problems of detectability of the effects, and to the implicit lumping together of units displaying heterogeneous, possibly even countervailing effects. For example hurricane Katrina in 2004, the costliest natural disaster in US history (Burton & Hicks, 2005), had caused losses in physical and human capital of about USD 150 Billion (an average estimate), which is about 100 percent of the annual GDP of Mississippi and about 150 times that of Louisiana, the two most affected States. Mixing the economic output of the two directly affected States in with the 48 that were not affected, introduces a lot of noise making a statistical detection of the disaster signal much harder. In fact, while devastating for the two affected States, the US national economy as a whole was barely affected at all (Cashel & Labonte, 2005). There are also issues of spillover effects. Surrounding regions may be stimulated because of the construction boom in the affected area. Lumping together an economically depressed State with an economically stimulated State washes out the effect and makes for murky interpretation.

Here I would like to echo what Henderson, Storeygard & Weil (2012, p. 995) argued:

"Much of the interesting variation in economic growth takes place within, rather than between, countries. Similarly, many of the theories about factors that affect growth—for example, those that look at the importance of geography—pertain to regions made up of parts of one or more countries. For the vast majority of economics research, however, "empirical analysis of growth" has become synonymous with use of national accounts data. We think the tools are available to set aside this limitation."

Precisely because "the tools are available" now, an analysis that zooms in on a unit of analysis that is up to the task of more accurately evaluating the impacts of natural disasters is possible. I focus on district and sub-district level data in this chapter (and province level analysis in chapter 2). In creating a sub-national dataset linking economic indicators to exogenous physical flood measures, I am no longer limited by the aggregation limitations of SNA data and the coarseness of national boundaries to evaluate economic output, and have better ways of establishing counterfactuals that resemble the treated units better. Factors that are usually hard to control for, such as local institutions, ethnicity, culture, and many others that could possibly have an effect on the output measure can therewith much easier be controlled for. Overall, answering the question of how Aceh (or how Louisiana) are faring after the Tsunami (and the hurricane, respectively), is best done with Acehnese and Louisianan data, not Indonesian and US data. A sub-district, district, or province is a much more appropriate level to evaluate the impact of catastrophic events that affect a small area within the country only.

The first papers to investigate the disaster-growth nexus with sub-national data were Strobl (2011) and Bertinelli & Strobl (2013) who used county GDP, and night-lights data as a proxies of economic activity. In Bertinelli & Strobl (2013) the authors linked a night-lights data grid at a resolution of 3.3 square km to a physical measure of the natural disasters intensity in the Caribbean. They found large negative effects and concluded that economic growth is depressed for about 2 years after in the areas struck by the cyclone. In Strobl (2011), he found an initial reduction of US county level GDP of 0.8 percentage points in the first year, and a partial recovery by 0.2 percentage points in the following year and negligible effects thereafter. Sub-national data was subsequently also used in Outtara & Strobl (2013) and Cole et al (2014).

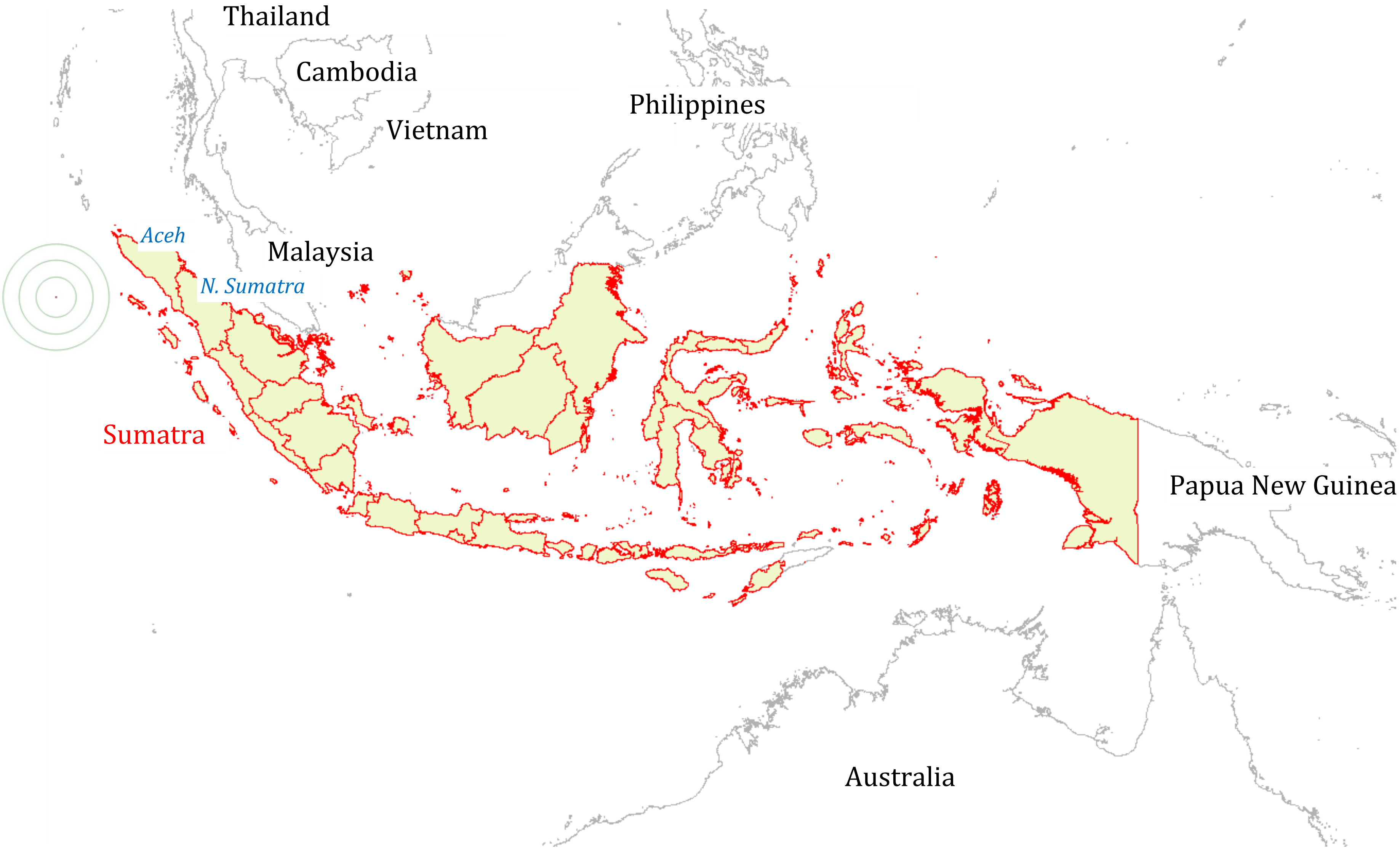
2.2 The 2004 Indian Ocean Tsunami

On December 26, a 9.1 magnitude earthquake off the west coast of Sumatra triggered a giant Tsunami, with waves up to 10 meters high, causing damage up to 9 km inland. A series of devastating Tsunamis hit 14 countries across the Indian Ocean. The worst affected countries were Indonesia, Sri Lanka, and India. It affected Nanggroe Aceh Darussalam, or 'Aceh' for short most severely, but also Sumatera Utara (Northern Sumatra), both are provinces of the Sumatra Island (it is the island of Indonesia that is right next to the epicentre depicted in map 2.1).

The death toll in Indonesia was estimated to be 230,000 people, and the economic costs were estimated to amount up to USD 5 Billion. The initial damage and loss assessment for Aceh was USD 4.5 billion, and for Nias USD 400 Million (BRR, 2006). The only affected island was Sumatra, the easternmost island of Indonesia. Two if its nine provinces were affected by the Tsunami. Aceh, the northwestern Tip of the island was struck the hardest, and North Sumatra, the province just South of Aceh was also affected, but to a much lesser extent.

After the earthquake occurred right off the coast of Indonesia, along the fault line commonly known as the ring of fire, the Tsunami wave reached Indonesia about thirty minutes after it. The wave reached far inland (up to 9km), particularly in geographies with flat topographies. How far it reached at different spots was a function of elevation, vegetation, water depth, and topography (Ramakrishnan et al, 2005; Kohl et al, 2005; Umitsu et al, 2007). It was the deadliest disaster since the 1976 Tangshan earthquake in China and killed almost twice as many people as the Haiti earthquake in 2010 and more than 30 times more than the 2005 Nepal earthquake, and 26 times more than the 2015 Nepal earthquake.

Map 2.1 Indonesia, surrounding countries, and the origin of the Tsunami



2.3 In search of a case of creative destruction: Aceh might fit the bill

None of the natural disaster economics studies focussing on developing countries, to the best of my knowledge, found a long-term creative destruction economic recovery from a severe event. The idea of this chapter is to look at whether Aceh, the westernmost province of the Sumatra Island in Indonesia in her recovering from the Indian Ocean Tsunami of 2004 that crushed on its Sumatra island shores, fits the bill. If there is one example of "building back better" (BBB), Schumpeterian creative destruction, and a higher growth path in the long haul, it probably is Aceh.

"Aceh succeeded in building back better," or a version of this quote was uttered by most stakeholders involved in the construction phase, including, Bill Clinton (UN special envoy to Tsunami recovery in Aceh), the Aceh regional government, the World Bank, UNDP, BRR (the Reconstruction Agency set up by the Indonesian government), several donors, the Guardian, New York Times, and academic scholars (e.g. Duncan Thomas). This PhD chapter aims at putting numbers to these words and attempts to rigorously evaluate whether BBB has occurred and whether it has lifted the province onto a higher and sustained growth path with focus on the long(er) term.[5]

"… an opportunity to build back better and make sure that whatever they do puts Aceh on a higher trajectory of development than before the tsunami."

(Beate Trankmann, Indonesia country director for the UNDP, in The Wall Street Journal, 2014, by Schonhardt, S., para. 4).

The reason why many stakeholders came to the BBB conclusion, which seemingly goes against what one would have inferred from reading the natural disaster economics literature, primarily has to do with the reconstruction efforts launched in Aceh. Aceh was in fact the location of the single largest reconstruction process in the developing world. The aid allocated to the region by far surpassed the monetary damages caused by

[5] The argument of how BBB leads to creative destruction or higher and sustained growth is two-fold. In building back better, Aceh's economic performance should increase beyond what was the counterfactual growth path (the growth path for Aceh in the hypothetical scenario that it had not been struck by the Tsunami), for the time the reconstruction efforts last. Once the rebuilding is finished and the province has been built back better, the new and improved capital should allow the households to be more productive economically, because of the upgraded capital.

the Tsunami (USD 7.7 Billion of aid vis-a-vis USD 5 Billion of estimated destruction costs). On average, for large disasters about 10 percent of the damage costs are compensated for by relief and reconstruction aid (Freeman et al, 2002). In Aceh, the compensation was 150 percent of the destruction. I therefore have reason to assume that even though aid was not potent enough to overcome the negative effect of natural disasters in previous cases, it could be if its magnitude is of such immense size.

Aside from the sheer size of the reconstruction effort, also its quality was to a very high standard, albeit far from perfect.[6] To avoid coordination failures, Indonesia and Aceh set up an agency tasked exclusively with coordinating the relief and recovery efforts, named the Reconstruction and Rehabilitation Agency (BRR). There was very little corruption and waste recorded; USD 7.0 Billion out of the USD 7.7 Billion were actually disbursed and spent. The agency applied sound fiduciary principles (Fengler, Ihsan & Kaiser, 2008), there was very little aid fragmentation (Masyrafah & McKeon, 2008) and aid volatility, normally a huge problem, was kept under control (Masyrafah & McKeon, 2008).

2.3.1 Aid and economic growth

I speculate that aid is the principal driver of the hypothesized creative destruction, yet the literature linking aid to growth is not settled. There is an accounting relationship between aid and GDP. However, aid does not wholly enter GDP, meaning that aid does not translate into GDP increases 1:1. A good illustration of this point is Afghanistan, where 2007/08 aid to the country totalled USD 10.3 Billion, and GDP totalled only USD 8.7 Billion, which corresponds to 118 percent of GDP (see WDI, 2015). It was estimated that only 25 percent of aid distributed to Afghanistan was actually spent "in" Afghanistan as opposed to "on" Afghanistan (see WDI, 2015) resulting in a final aid-in-GDP share of only 34 percent. In Aceh, annual GDP is roughly USD 8 Billion, which is about as much as was disbursed in aid, albeit over four years, which if allocated equally over the four years, corresponds to about 1/4th of annual GDP. Whether it actually also accounts for ¼th of observed GDP is questionable. Probably it accounts for much less.

[6] For sources on what went wrong with disaster-funding in Aceh, see Fengler, Ihsan & Kaiser, 2008.

Some forms of aid disbursed will enter the GDP metric directly such as budget support, which should boost government expenditure, or cash transfers, which enter through private consumption and savings. For a more detailed conceptual and empirical exploration of these channels, see chapter 3. Other parts, such as the USAID financed Aceh-Lamno road, or the charity financed "Jackie Chan Village" (formally *The Friendship Village of Indonesia-China*) only partly enter GDP. The increase in GDP is commensurate with the share of the USD 245 Million for the USAID road and the amount for the Jackie Chan Village that was spent on local production inputs. For example, the majority of the raw materials for the USAID road had to be imported from neighbouring countries, boosting their GDPs rather than that of Aceh. However, the USAID construction employed mostly local contractors therefore positively affecting private consumption, and therefore its own GDP. For the Jackie Chan Village, for example, supposedly an even smaller share of the aid was Acehnese growth promoting as they used a Chinese contractor (Vale et al, 2014). Furthermore, in-kind aid such as emergency food assistance, blankets, and donated machinery also do not appear in GDP figures. The amount of aid that translates to GDP is impossible to identify.

There are also important knock-on or multiplier effects related to aid. These indirect effects may occur concurrently, in the sense that aid may attract investment in new infrastructure, in the form of Foreign Direct Investment (FDI) or domestic investment. The indirect effect may also manifest itself over time. Once the capital is built back better, an upgraded infrastructure for example, it should allow for increase GDP through increased factor productivity. For example, better machinery should allow boosting labour output per person by making the workers more productive. A road that is rebuilt in a better way such that it is wider, faster, and reaches beyond where it originally reached is productivity enhancing because it takes e.g. less time to deliver produce to the market.

There is no automatism between aid and economic growth. There are many scholars that have asserted how aid stimulates economic development, such as, probably most famously, Jeffrey Sachs in his 2005 book "The End of Poverty." Others stipulate that aid flows only stimulate growth under certain institutional conditions (e.g. Burnside & Dollar, 2000). Some scholars even outright contest that aid increases economic growth at all, particularly in the long run (see e.g. Easterly, 2003; and Easterly, Levine &

Roodman, 2004). Proponents of aid argue for its crucial function in supplementing savings and investments, and in building the foundation of long-term growth and smoothing consumption in the short-term through public works and other programs. Critics argue that aid in its myopia rather finances consumption and not investment and, therefore, fails to translate into sustained growth (Arellano et al, 2009). Moreover, they argue that aid crowds-out competitive incentives and stymies the private sector (Easterly, 2003). It has been argued furthermore that the only thing that aid increases is the size of government and not investment and growth (Boone, 1995). The negative relationship between aid and growth has also been attributed to a shrinking tradable sector and an overvalued exchange rate following the inflation brought on by larger financial inflows (Rodrik, 2008; Arellano et al, 2009).

The debate on whether aid promotes long-term growth is anything but settled. Some authors, applying cross-country growth regressions, show a negative relationship between foreign aid/capital inflows and long-term growth (e.g. Rajan & Subramanian, 2005 & 2008). Others, using the same data but a different empirical strategy, as the authors claim the "most carefully developed empirical strategy," come to the opposite conclusion (Arndt, Jones & Tarp, 2010, p. 23).

More recent aid-growth studies attempt to overcome the endogeneity bias inherent to the associative findings of the past. Authors started to carry out instrumental variable (IV) regression methods in an attempt to isolate the causal effect of aid on growth. Even though causal methods were already attempted in the past (see e.g. Over, 1975) they used questionable IVs (Ravallion, 2014). Arndt et al (2015) synthesizing the more recent evidence conclude that it points to a consensus, which is that aid is indeed beneficial for growth, debunking the aid curse hypothesis. While there are still preeminent scholars in the field, such as for instance Angus Deaton, arguing for an aid curse in his book the Great Escape, an "objective review" of the more recent literature points to the opposite (Ravallion, 2014).

Identifying the average causal effect of foreign aid on economic growth by exploiting exogenous variation in in foreign aid flows due to signed Human Rights Treaties at the UN shows that a recipient country's growth rate increases by five percent over the following decade (Magesan, 2015). Others exploit the discontinuity around the income and governance criteria the World Bank uses to decide on concessional lending (Galiani et al, 2014) to isolate the causal average treatment effect. Using lagged aid as an instrumental variable, Clemens et al (2012) also find a positive effect. However, looking also at concessional lending discontinuities, Dreher & Lohmann (2015) find no causal effects of aid on sub-national economic development using night-lights as a proxy.

In summary, the evidence is still mixed and under much controversy, although a review of the recent causal analysis points to a positive effect. Part of the explanation of the heterogeneous results include different types of aid used, different sources of aid used, different aggregation strategies, different econometric methods and different lag structures applied (Berlin, 2015).

Aceh not only benefitted from aid, but also from transfers from central government and remittances. Most of the financial inflows into Aceh were from foreign entities (donors, countries, charities etc…), i.e. aid (see World Bank, 2007). Aceh, however, was also granted an increased share of government revenues in the peace agreements. So on top of the aid inflows, Aceh also obtained higher transfers from the central government, in the form of an autonomy fund and an oil and gas sharing agreement. There were likely also increases in remittances as a response to the Tsunami, however the "data on remittances are extremely difficult to obtain" (World Bank, 2008, p. 23), and I was unable to get them. There might have also been transfers from the central government for the purpose for disaster reconstruction, but there is no data on the geographical targeting of such transfers.

2.4 Research design – exploiting a quasi-experiment

I conceive of the Indian Ocean Tsunami as a quasi-experiment. The empirical strategy of identifying causal economic impacts of the 2004 Indian Ocean Tsunami is based on observing differences in economic activity between flooded districts and non-flooded districts, which serve as a reasonable comparator group to those that have. I exploit the exogenous, because unexpected and unprepared-for nature of the 2004 Tsunami.[7] The

[7] The 2004 Tsunami hit all regions equally 'unexpectedly', therewith constituting a perfect natural experiment for social impact assessment.

reasons why some stretches on Indonesia's island were hit, are because of geographic happenstance, in that they were either close to the natural disaster, or that a barrier island did not protect them. In fact, the UNOCHA map plotting all earthquakes that have happened off the shore of Indonesia from 2000 – 2010, however small, shows that they have been evenly distributed across Indonesia's Southern and Northern coasts, therefore not making it any more likely for one or another district (or province) to be affected by a disaster.[8]

Systematic differences of pre-treatment variables would violate the comparability of the counterfactuals, and therefore foil the natural experiment, such as most importantly the initial wealth (or income) of the treated districts versus the control districts (see Barthel & Neumayer, 2012; and Pielke et al, 1999), as it likely has an impact on how each group recovers from the Tsunami. Furthermore, differences in preparedness and mitigation efforts between the treatment and control group would be a cause for potential systematic differences (Neumayer, Pluemper & Barthel, 2014). I found no indication of different initial GDP levels or historic GDP trends (see the results section), nor did I find systematic differences in preparedness levels. The districts were completely unprepared for the Tsunami (USAID, 2014).[9] The last time a Tsunami struck the shores of Sumatra was during medieval times (Monecke et al, 2008). Other systematic differences are also checked for and by establishing parallel historic trends between the treatment and the counterfactual group (see the results section) I establish a high degree of comparability between the two groups.

[8] See the map here: http://reliefweb.int/report/indonesia/indonesia-snapshot-earthquake-jan-2000-oct-2010

[9] http://blog.usaid.gov/2014/12/lessons-learned-a-decade-after-the-indian-ocean-tsunami/

2.5 The data – going beyond national averages

I link physical flooding measures to economic output, all on a sub-national level. I create a unique dataset containing information on which districts have been inundated and damaged, as a measure of Tsunami impact, as well as local Gross Domestic Product (GDP) data to measure localized economic activity. I carried out the subsequent analysis using a strongly balanced panel dataset from 1999 – 2012. The Tsunami struck on the 26th of December in 2004, giving me eight years after the disaster and five years of pre-intervention data.

2.5.1 Local GDP data

My outcome measure for economic activity is from the Indonesia Database for Policy and Economic Research (INDO-DAPOER),[10] which is maintained by the World Bank. The underlying sources of this data are several datasets provided by the Indonesian Sub-national Bureau of Statistics. DAPOER draws heavily on data collected by the annual National Socio-Economic Survey (SUENAS). SUSENAS is a nationally representative survey consisting of a sample of about 200,000 households that is fielded every year. National level GDP data in Indonesia is calculated in three different ways, which in principle should deliver the same results; the income method, the output method and the expenditure method (see McCulloch & Sjahrir, 2008).[11] The district level GDP data used in this analysis is based on the income method.

The raw GDP district level data is from the Indonesian Sub-national Bureau of Statistics. The calculation of national level GDP on the other hand is usually done by the Central Bureau of Statistics. There are slight methodological differences in the calculation of national GDP and the subnational GDP data. These differences lead to a small gap between the sums of GRDP (*Gross Regional Development Product* - when all regional

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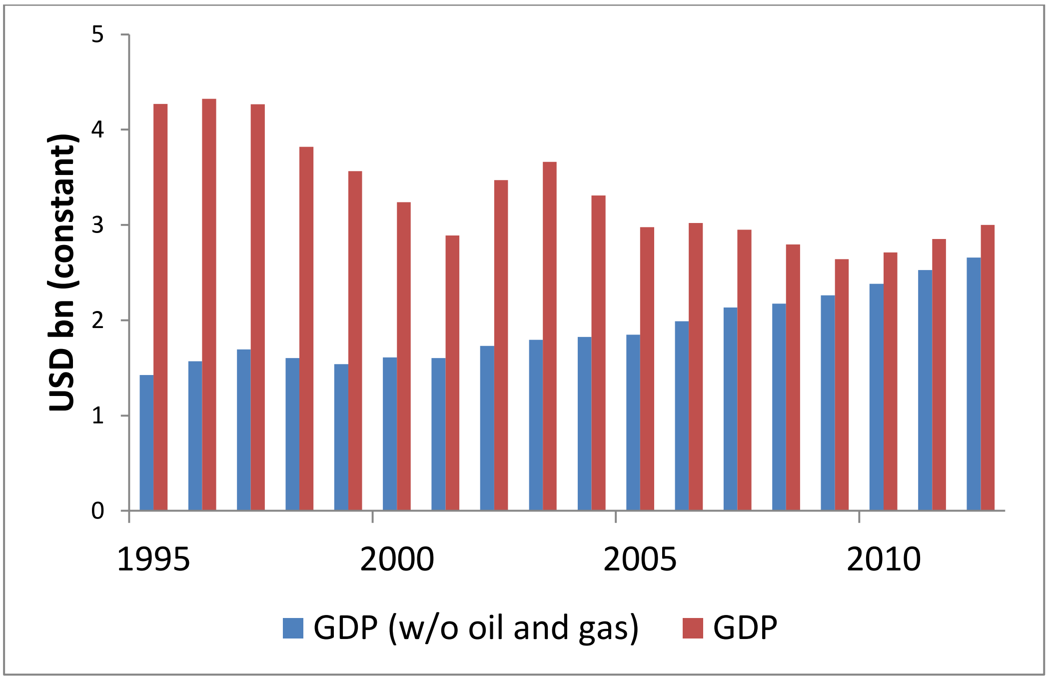
[10] For a more in-depth documentation of the dataset, see http://data.worldbank.org/data-catalog/indonesia-database-for-policy-and-economic-research.

[11] The income method adds up all income from individuals and firms from the sale of goods and services. The output method aggregates up all the values from different outputs in all sectors of the economy. The expenditure approach adds up the expenditures of residents for goods and services, absent depreciation and capital consumption. There is a substantial informal sector in Indonesia, which is not captured by official GDP estimates.

level GDP data are aggregated up to the national level) with the national GDP. The discrepancies have mostly to do with different sector coverage for the accounting. An example leading to the slight discrepancy is that national GDP includes the contribution of foreign embassies to the national GDP, while the subnational calculation does not include it.

The GDP data I use for the analysis exclude the oil and gas sector. There are a series of reasons for why I use GDP data absent of this sector: (a) none of the affected districts have oil and gas resources, and for the purpose of establishing a good counterfactual describing the non-affected districts it is thus much better to look at the GDP without the contribution from oil and gas. (b) The oil and gas sector has very few links with the rest of the economy and employs only very few people (see World Bank, 2009). (c) There seem to be quality issues of data on oil and gas production in that there are discrepancies with data coming from the Ministry of Energy and Mineral Resources and other governmental agencies (see World Bank, 2009). (d) Oil and gas reserves are depleting rapidly, which has direct consequences on the composition of GDP as seen in figure 2.1. In 2012, the latest year available, oil and gas account for less than 10 percent of the economy in Aceh.

Figure 2.1: Aceh's GDP evolution

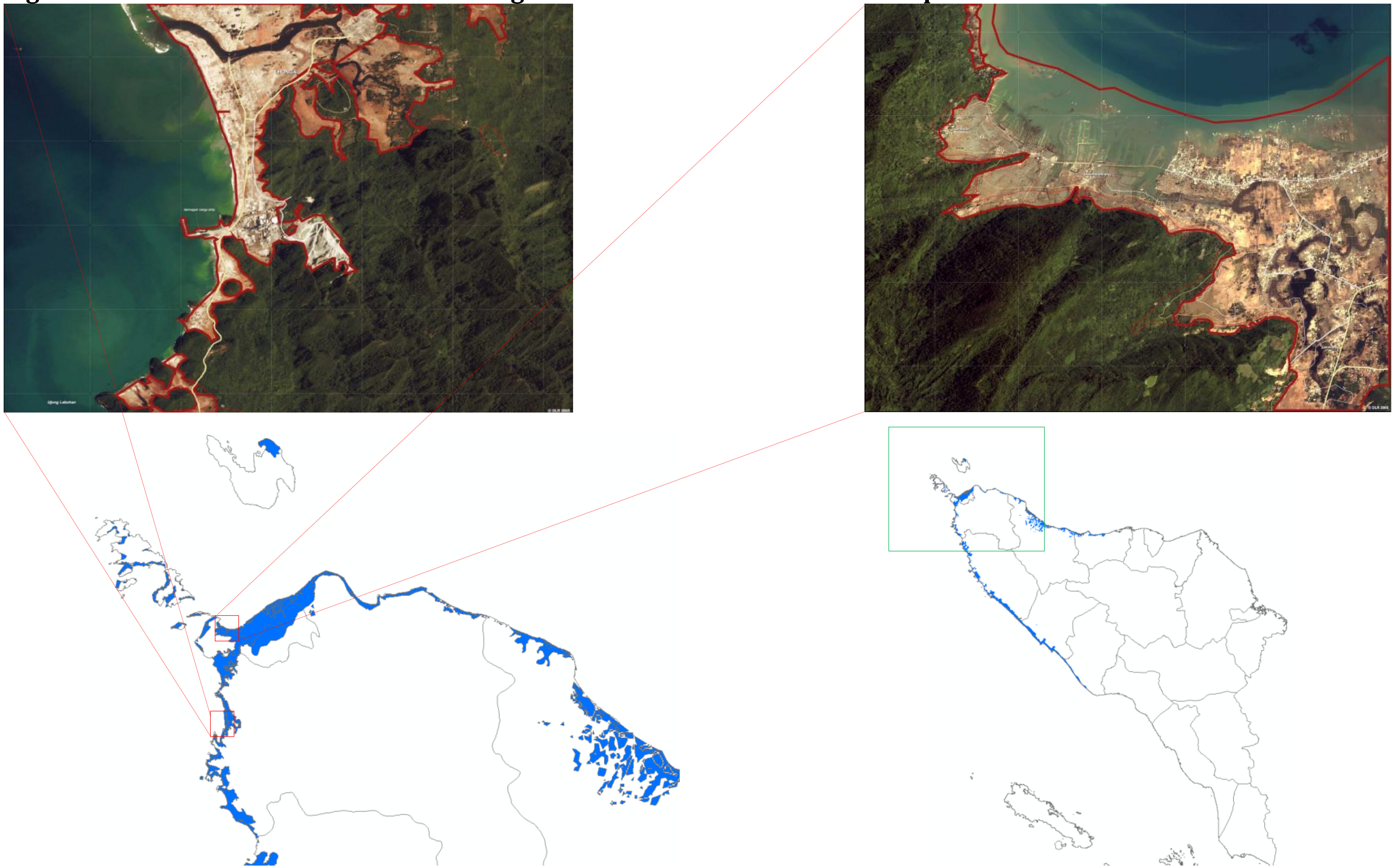


2.5.2 Flood data

I overlapped different inundation maps provided respectively by the Centre for Satellite Based Crisis Information (ZKI) at the German Remote Sensing Data Centre (DLR) and the Dartmouth Flood Observatory (which is based on MODIS satellites). Flood data and maps were produced chiefly to guide on the ground relief and aid efforts. The inundation / damage maps were used to support disaster management operations, humanitarian relief activities, and civil security issues. They were produced in the weeks after the disaster and capture satellite information from 1-5 days after the Tsunami struck.[12] The Tsunami waves, which were up to 10 meters high, inundated areas as far inland as 9km off shore. Flood maps do not distinguish between flooding intensity per area. For example, it could be that further inland the Tsunami wave inflicted less damage, because of less powerful flooding and water volumes. For the purposes of the analysis presented here, I assume no differences in the severity of impact between any of the diverse areas that were flooded. Figure 2.2 shows how damaged areas on images taken by Landsat satellites are converted to maps by using spatial algorithms detecting differences in the colour between before and after (on 29 December 2014) pictures taken from space.

[12] Different days were combined in order to allow for non-intermittent depiction of the entire extent of flood damage, which is necessary because cloud coverage on some days foils a clear depiction of the flooding.

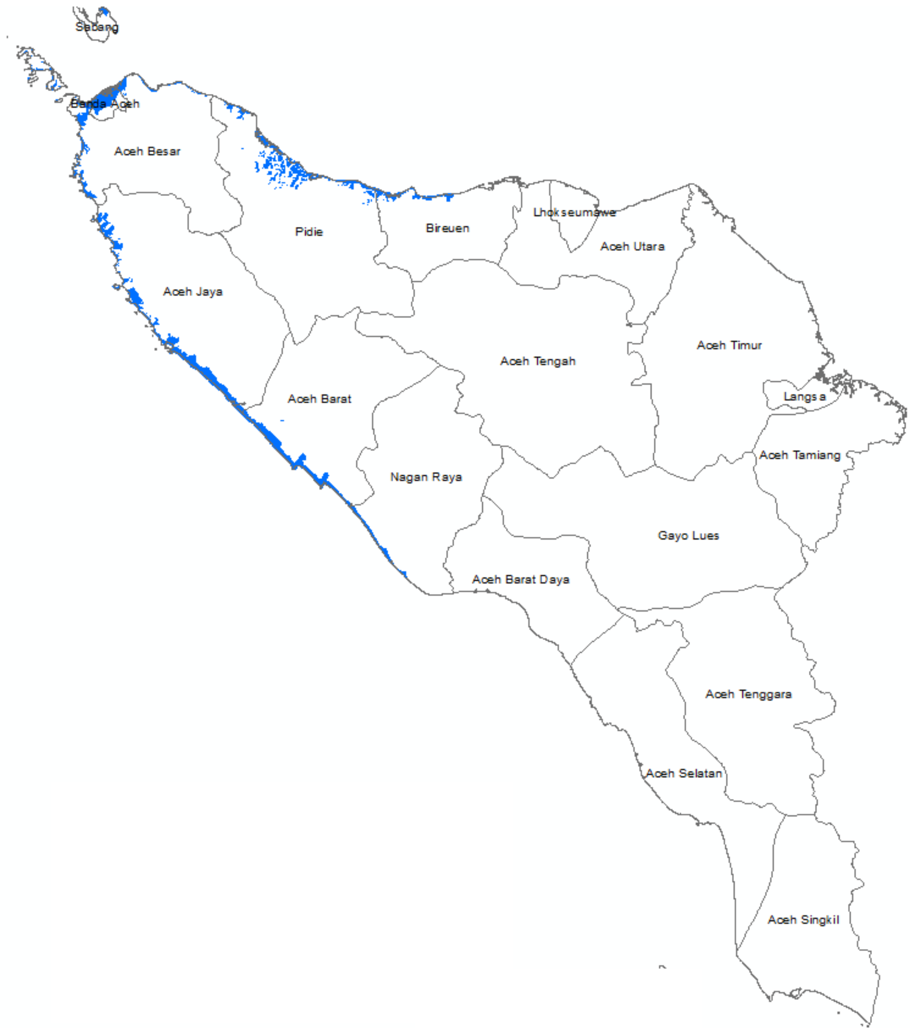
Figure 2.2: Illustration of how satellite images are used to create the flood map



Note: This illustrative map depicts the inundations of Aceh. Aceh's Simeulue islands, which have also been flooded are not depicted in this map.

The equivalent of about 34 percent of the Acehnese shoreline, in total 600km, was flooded by the 2004 Indian Ocean Tsunami. The Tsunami wave went as far inland as 9km. The total area destroyed was 120.295 ha, where about 1/5th was settlement, and 1/3rd was agricultural land (Shofiyati et al, 2005).

Map 2.2: Inundation areas of the 2004 Indian Ocean Tsunami in the Aceh province



Note: Flooded areas according to the German Aerospace maps & the Dartmouth Flood Observatory estimations. The Aceh province has 23 districts, of which 10 were flooded and 13 were not flooded. The above map does not show the two island districts of Simeulue and Aceh Singkil that were also flooded.

2.6 Empirical strategy – Causal method for impact evaluation

To implement the quasi-experimental research design, I carry out difference-in-differences regression estimations with GDP and night-lights data, on the local level. I find evidence supporting the creative destruction hypothesis, not only in the short run but also in the long run. I perform several robustness checks of this causal effect, including using alternative measures, specifications, and methods. I also look at heterogeneous treatment effects as well as spillover effects and the importance of the geographical scale of the units of analysis for the results.

2.6.1 Difference-in-differences analysis of district level GDP data

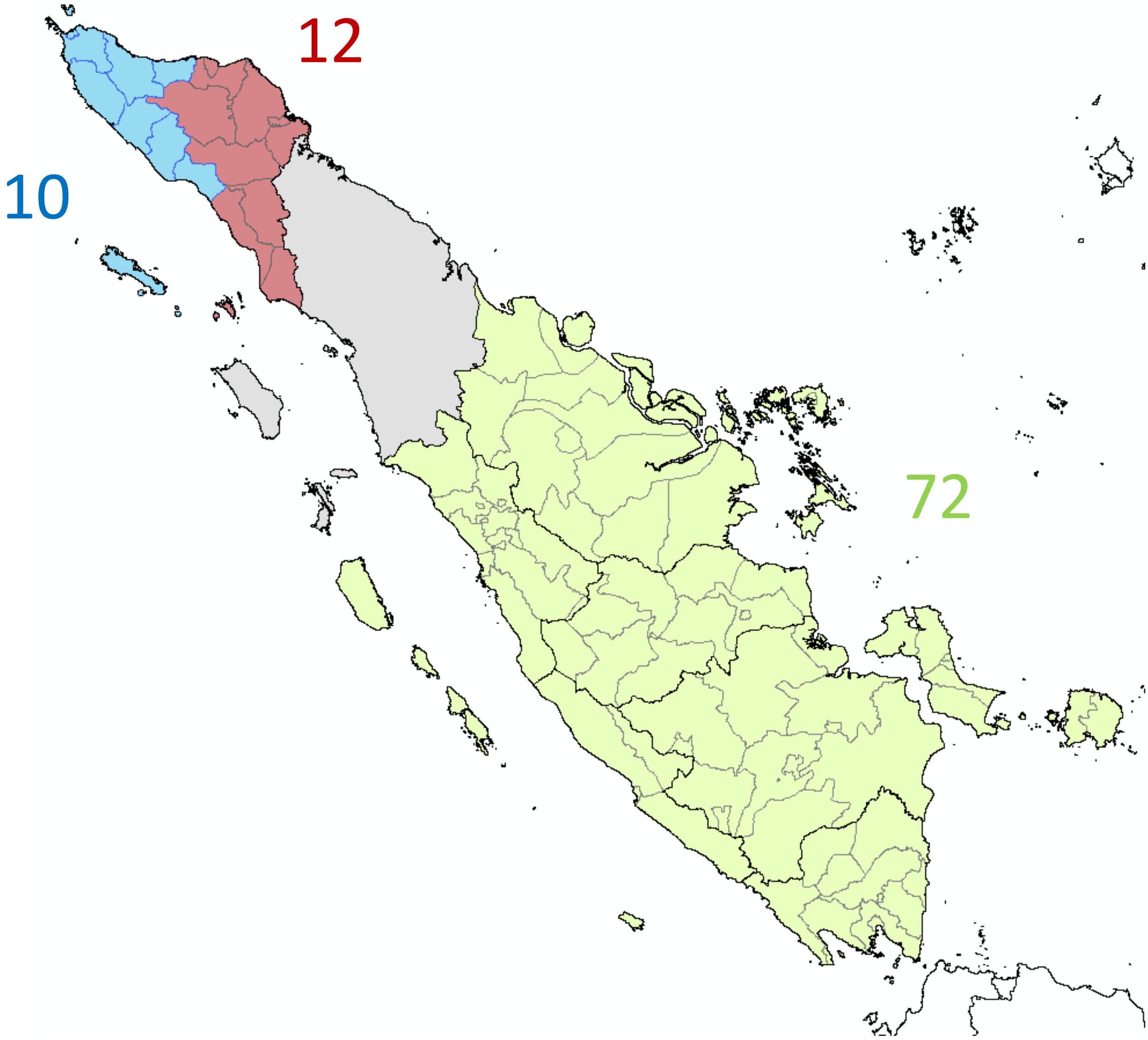
Based on the satellite image analysis of the geographical extent of the flooding, I determined that 10 districts in Aceh were flooded by the Tsunami (see the blue districts in map 2.3). The remaining 13 districts of the province were not flooded, and serve as my counterfactual district pool. Note that by comparing the Tsunami stricken districts of Aceh with other districts from the same province, I am able to control for unobserved heterogeneity in Aceh, a province that is indeed quite different from the rest of Sumatra. Most notably, the province was waging civil war against the central government of Indonesia for 29 years prior to the Tsunami, causing 15,000 casualties.[13] Moreover, the region is much more religiously and culturally conservative. It has become even more so, since the widespread perception that the Tsunami was punishment for not enough Muslim piety within the province, triggering a sharper enforcement of the Sharia law, with the controversial launch of a Sharia police and even the expansion of the law to cover also the 80,000 non-Muslims in the region as of recent. By comparing the ten flooded districts of Aceh with the 13 non-flooded districts of Aceh, these heterogeneous treatment effects along with others that are unobservable and related to the idiosyncrasies of the province are accounted for. A second counterfactual for the

[13] The impact of violence on GDP is explored in chapter 4 of this PhD thesis.

comparative analysis is the remaining part of Sumatra, composed of the 72 districts, depicted in lime green in map 2.3.

The data for North Sumatra, the greyed out province in map 2.3, was dropped for the main part of the analysis, because only two out of the 21 districts of North Sumatra were directly affected and both of which are island districts. The "mainland" districts of North Sumatra remained unharmed. To have an analysis less biased by the island characteristics of the affected districts, the entire province of North Sumatra was excluded. As a robustness check, I included North Sumatra's districts also (see map 2.4).

Map 2.3: Aceh analysis schematic: Composition of treatment group and control groups on the island of Sumatra



Note: The 10 blue districts indicate the Tsunami flood treated districts. The 12 red districts are the counterfactual districts from Aceh. The 72 lime green districts are another set of counterfactual districts from the remainder of the Sumatra Island. North Sumatra districts (grey area) were not included in the analysis, because only the two island districts were struck by the Tsunami. The stricken (blue) districts are Aceh Barat, Aceh Besar, Aceh Jaya, Aceh Pidie, Banda Aceh, Bireuen, Nagan Raya, Pidie Jaya, Sabang, and Simeulue. The comparator (red) districts in Aceh are Aceh Barat Daya, Aceh Selatan, Aceh Singkil, Aceh Tamiang, Aceh Tengah, Aceh Tenggara, Aceh Timur, Aceh Utara, Bener Meriah, Gayo Lues, Langsa, Lhokseumawe, and Subulussalam.

Formalizing the difference-in-differences analysis: There are two groups; Tsunami stricken ("treated") districts and non-stricken ("control") districts: D = 1 means that the district was affected by the Tsunami flood in 2004, D = 0 means that it was not, in other words D = 1 are the treated units and D = 0 are the control units. There are two periods, pre- and post-disaster, with pre-disaster ranging from the years 1990 – 2004 and the post-disaster ranging from 2005 – 2012. T = 0 indicates pre-treatment, and T = 1 indicates post-treatment, where T is short for treatment (flood).

The potential outcome is denoted as $Y_{di}(t)$, where *i* denotes the district, *d*, whether the district has been treated or not, and *t* refers to the time either pre- or post-disasters. *Y* our measure of income is proxied by district level GDP data. I focus mostly on the GDP per capita analysis since this is a better measure of how people are faring, particularly in a region, where about five percent of the population died in the Tsunami waves. Notwithstanding I also present some results using district level GDP data as it sometimes offers an interesting insight into how much of the changes in income stem from population dynamics.

In a perfect world, we would have an outcome of $Y_{1i}(t)$, which we could compare with $Y_{0i}(t)$, for the same unit, and would measure the causal effect for unit *i* at time *t* as $\alpha_i(t) = Y_{1i}(t) - Y_{0i}(t)$. However, a flood can either hit a particular district, or not, there is no parallel universe that allows us to have it both ways.

The estimand is the average treatment effect on the treated (ATET):

$$\alpha_{ATET} = E[Y_{1i}(1) - Y_{0i}(1)|D_i = 1]$$

The estimator of our control strategy is obtained by difference-in-differences computation, which computes the difference of income between treatment and control groups:

$$\alpha = \{E[Y|D = 1, T = 1] - E[Y|D = 0, T = 1]\} \\ - \{E[Y|D = 1, T = 0] - E[Y|D = 0, T = 0]\}$$

where $E[\varepsilon|D, T] = 0$. The above holds under the assumption of parallel trends.

I will exploit the panel data set, by using a fixed effects regression with district and period-fixed effects (which should allow estimating a growth path). The estimation strategy follows a difference-in-differences approach, where I model the first log differences of district level GDP and district level GDP per capita data as an impulse – response function that is linear in contemporaneous and historic exposure:

$$\ln(Y_{i,t}) - \ln(Y_{i,t-1}) = \alpha + \delta(D_i * T_t) + d_t + \gamma_i + \varepsilon_{it} \qquad (1)$$

This impact measure should allow to estimate the average annual impact of the Tsunami on economic growth. Then, I split up the individual years, to get a sense of what impact the Tsunami had in each year, by implementing a distributed lag model of the form:

$$\ln(Y_{i,t}) - \ln(Y_{i,t-1}) = \alpha + \sum_{t=2005}^{2012}[\delta_t(D_i * T_t)] + d_t + \gamma_i + \varepsilon_{it} \qquad (2)$$

Where D_i distinguishes between Tsunami stricken districts (1) and non-stricken districts (0). T_t, also a dummy variable, denotes the Tsunami affected years from 2005 – 2012 with 1 and the non-affected years from 1999 – 2004 with 0. The interaction term $D_i * T_t$ thus denotes the Tsunami stricken districts in the post-Tsunami era with 1 and the rest with 0. Therefore δ is the main coefficient of interest because it captures the causal effect the Tsunami has on growth, if the identifying assumption is met that the treatment is randomly assigned. D_i is uncorrelated with *η(e).*

To correct for unobservable but fixed confounders year fixed effects (d_t) and district fixed effects (γ_i) are included. District fixed effects are included to control for omitted variables such as municipal government quality. By including district dummies, the data are demeaned and any long run trend is removed (see Noy, 2009). Time fixed effects are included to account for common macro shocks that affect secular growth trends over time.

Following Hsiang & Jina (2014) I construct the cumulative effect (ω_i) that the Tsunami had in period *t* on the flooded districts, as a sum of the year-specific disaster-growth effects (δ_t) that are resulting from the estimation of equation (2) from the contemporaneous year plus the historic years : $\omega_i = \sum_{t=2005}^{2012} \delta_t$.

I did not include D_i (as a measure of how similar the treatment and the control group are), or T_t as separate terms, outside of the interaction term specification, because they are both linear combinations of the time and district fixed effects. For the same reasons, I also did not include time-invariant variables. Moreover, I did not include district specific time trends, other than as a robustness check, because the income trajectories of all districts in Aceh followed a similar trend and were curved equally. No additional time varying control variables are included, other than in the robustness checks, since everything measurable could have also been responding to the Tsunami treatment.

With equation (1) I am testing the average annual effect the Tsunami has had on the stricken districts in all eight post disaster years combined. By implementing equation (2), which describes a distributed lag model, where the different lags capture the historical exposure to the Tsunami, I measure the different effects the disaster has had on each year since it happened.

I assume that ε is heteroskedastic and serially correlated within a district for 10 years (Newey and West, 1987). I furthermore assume that there is spatial autocorrelation across contemporaneous districts up to a distance of 100km (Conley 1999 & 2008). The code for correcting the Standard Errors (SEs) for spatial and serial autocorrelation as well as for heteroskedasticity was adapted from Hsiang (2010). The spatial weighting kernel applied was uniform as suggested by Conley (2008).[14] One district being affected is a good predictor for the neighboring district to also being affected; i.e. there is no independence of treated units. Space could thus play a role in determining the economic output measured causing the data to be non-random and making it thus important to correct the SEs for the common factors (the spatial autocorrelation) (see Gibbons, Overman & Patachini, 2014). The reason why I correct SEs for serial autocorrelation is that a flooded district in 2005 perfectly predicts that the same district will be designated to have been flooded in the ensuing years also, since I not only measure contemporaneous but also historic exposure.

Why growth rates instead of levels? I estimate equations (1) and (2) in first log differences because while GDP and GDP per capita levels are not trend-stationary, year-on-year growth is (Hsiang & Jina, 2014). Moreover, taking growth rates should help with temporal dependence. Even though trend-stationarity could be overcome with other alternatives, using growth rates allows me to directly benchmark the estimated effects to those from other studies, as most papers have also used growth rates instead of levels. The most relevant papers to which I will be comparing my results to are Hsiang & Jina, 2014; Cerra & Saxena, 2008; Noy 2009; and Cavallo & Noy 2011. Nevertheless, I also estimate level equations, as a supplement to the growth regressions (see figure A2.2 and table A2.1 in the Appendix).

[14] I also experimented with difference spatial lags, including uniform lags up until a distance of 100km, as well as different duration limits for autocorrelation analysis, as a robustness check.

2.6.1.1 Joint effects: Flood & aid (and other reconstruction funds)

"An analysis of Aceh's economy after the tsunami and the end of the conflict will face a challenge: the confluence of a series of dramatic events with a large impact on the economy, which makes the identification of causes and effects very difficult. " (World Bank, Aceh Growth Diagnostic, 2009, p. 6).

As with any quasi-experiment, the powers of the "experimenter" are limited. Unlike a medical trial in a controlled experimental setting, where some patients of the treatment group receive a physical treatment (Tsunami), some a pharmaceutical (aid money), and others receive both the physical treatment & the pharmaceutical (Tsunami & aid money), I can only evaluate the effect of both treatments combined in this study. The estimated treatment effects do not give us a sense of whether these effects stem from the Tsunami inundation or aid. In other words, it does not show in how far the negative effect of the Tsunami (assuming there is one) is counterbalanced by the positive effects of aid (if there are any). The joint Tsunami & aid treatment effect on economic growth will also not tell us how much of it is due to the direct effect, say from re-building a road, and how much is the result from higher economic productivity, say from making it cheaper for the shrimp farmer to transport her goods to the local market.

Despite the impossibility to disentangle aid from the Tsunami floods, conceptually speaking, the causal identification and the difference-in-differences method I apply in this paper is still sound because the post-treatment measures hypothesized to drive the changes is GDP (aid, etc…) are a consequence of the Tsunami. Without the Tsunami, there would have not been any reconstruction and recovery aid. Therefore, the effects on the economy investigated were strictly speaking brought on by the Tsunami. However, it is quite relevant particularly for policy recommendations to understand the results in their particular aid context.

The Tsunami caused remarkable social change. It mobilized the largest sums of reconstruction aid money ever recorded in the developing world, and it ended a 30 years-long civil war and brought peace to the Acehnese province. As mentioned in the previous paragraph, in this chapter I do not disentangle between the natural disaster treatment and the resulting aid influx treatment, but I am able to control for the effects of peace (see the empirical section for details).[15] In other words, I de facto evaluate the joint treatment effects of the natural disaster and the financial inpouring it triggered, by using the physical flooding measure. In that regard, my study is no different from other international econometric panel studies that compare the impact of natural disasters on economic growth since aid was inherent to these papers' analysis also.

The measures of aid disbursed per person and the measures of flooding intensity used (share of flooded area, share of population flooded, amount of people killed, and amount of people directly affected), have correlation coefficients ranging from 0.84 to 0.92. The reason why I picked Tsunami flooding as the treatment measure, instead of an aid flow measure is that the measure of tsunami flooding is a truly exogenous variable, which can be assumed to have been quasi-randomly allocated. The as-if random assumption cannot be extended to aid. Even though aid seems to have largely followed the needs of the tsunami recovery, as indicated by such high correlation coefficients, the patterns of aid flows cannot exhaustively be explained by the Tsunami intensity. The unexplained remainder, may as well introduce an endogeneity bias if aid instead of physical Tsunami flooding measures had been chosen.

Much of the economic effect caused by the Tsunami was brought on by the aid flows it triggered, as well as by the peace it brought to the region, and with the peace the increased allocation of Indonesian government revenue to Aceh. It may very well be, in fact, it is quite likely that the creative destruction hypothesized in this paper, should it in fact materialize in the data and evidence, could not have occurred had it not been for the unprecedented amounts of aid and revenue obtained by Aceh. This however does not mean that we would have needed a treatment case consisting of districts that did not receive any aid, since this is quite unlikely to ever occur in the real world. As shown by Freeman et al (2002), countries afflicted by extreme disasters receive on average 10 percent worth of damages in compensation.[16] Nevertheless, what the joint treatment

[15] The Tsunami caused the end the 30 years-long conflict between Acehnese separatists and Indonesia's military that caused about 15,000 deaths, which is considered another powerful reason for why the Tsunami may have positively affected Aceh's growth path. The Tsunami brought lasting peace. It ended the conflict between the GAM (Free Aceh Movement) separatists and the government. A peace deal between the rebels and the government in Jakarta was signed less than half a year after the disaster. I specifically look at the effects of conflict and peace in chapter 4 of my PhD thesis.

[16] As mentioned earlier, Aceh received almost 150 percent worth of damages in aid.

effect means is that one has to be careful in interpreting the results, particularly when making policy recommendations.

2.7 Findings

In this section, I am presenting the results of the empirical quasi-experimental analysis. I find that the Tsunami resulted in creative destruction, stimulating short-term per capita growth as destroyed capital is built back better. I also find that the built back better physical capital facilitates increased productivity, which leads to more economic output per capita in the long run. I present several robustness checks to test the creative destruction finding, including alternative measures, alternative units of analyses, alternative specifications, alternative samples, and alternative methods. I also carry out analysis using heterogeneous treatment measures. I find that the more a district was devastated by the Tsunami floods the stronger the creative destruction effect observed. I also present my findings from the spillover analysis, and my analysis of the implications of using aggregate measures for disaster-economic impact analysis. I find no significant spillover effects. I do find evidence for the importance of the choice of geographical units of analyses for the estimated results.

2.7.1 Creative Destruction

Mean comparisons over time between treated and control group

Figure 2.3 displays a simple graphical representation contrasting the mean dynamics of the treated group with the mean dynamics of the control group. It provides a first estimate of the economic impact of the Tsunami. The figure shows an affirmation of the parallel historic paths assumption, which allows the inference that the treatment group is indeed comparable to the counterfactuals, as they behaved historically similarly in the years leading up to the disaster. There is no indication of differences in religion, culture, war, or any other unobservable dimension to have different impacts on the GDP growth paths, as evidenced by parallel historical trends. Following the natural disaster the parallel historic paths are ruptured and significant deviations occur that offer an interesting insight into how flooded districts cope with the natural disaster over time.

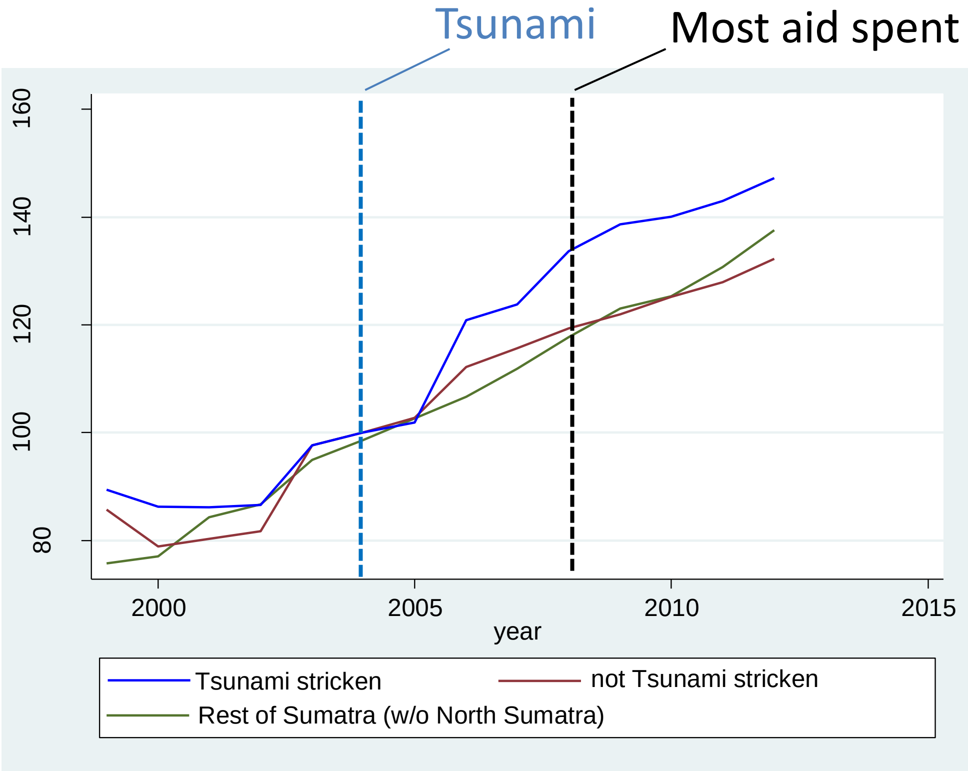
The timeline for aid is quite relevant for the ensuing analysis since it allows to assess whether economic growth patterns change after it has run out. If there is indeed a recovery detectable due to aid as hypothesized, it is interesting to investigate further whether it is sustainable beyond the point when aid stops. Aid totalled USD 7.7 billion and was officially completed by the end of 2008 (Henderson & Lee, 2015; and Masyrafah & McKeon, 2008). Since 2009, there was no more assistance from donors (Vale et al, 2014). The vertical black dashed line in figure 2.3 indicates the year by which most aid had been spent. According to my own analysis of RanD data,[17] 94 percent of aid was spent by 2009.[18]

The trends of GDP per capita group means in figure 2.3 suggests creative destruction, but will be tested more formally in the section to follow. Conducting the same analysis, but with GDP, instead of GDP per capita is in figure A2.1 and figure A2.2 in the Appendix. Unlike GDP, which contracted by about 7 percentage points compared to the counterfactual, GDP per capita does not show to have a contraction in the immediate aftermath (2005) of the Tsunami. The fact that GDP per capita does not show such a contracting effect is an indication that the contraction in GDP was mostly based on the foregone economic activity from the tragically killed population. In other words, the results suggest that fewer people result in less aggregate economic activity within the affected districts, but the average person after the disaster does not seem to engage in less economic activity in the year after the disaster than the average person before the Tsunami struck.

[17] See chapter 4 of my PhD thesis for a detailed description of the RanD database.

[18] Some critical commentators have argued that it would have been better to not spend all of the money within a few years and to set up a trust fund that disburses over the long haul. However, donors like to see concrete results in relatively short time.

Figure 2.3: Parallel paths before the Tsunami: GDP per capita evolution in Aceh's Tsunami stricken districts compared to not stricken counterfactuals



Note: Blue districts (n=10) are those within which territories were flooded by the Tsunami. Red districts (n=12) are counterfactuals within Aceh. Green districts (n=72) depict non-Aceh counterfactuals from the Sumatra Island. GDP measures are normalized at the year 2004. The vertical blue line indicates when the disaster struck and the vertical black line depicts when aid flows dried up (more than 94 percent of total aid committed was disbursed).

Difference-in-differences results

Creative destruction, which I define to mean as more economic output than would have occurred had the Tsunami never struck, was caused by the Tsunami in Aceh. Implementing the regression specification (1) shows that overall, the Tsunami (and the aid it triggered along with the other responses it caused) boosted district-level GDP per capita growth by 4 percentage points annually, relative to how the district would have grown had the disaster never struck (see column 1 in table 2.1).

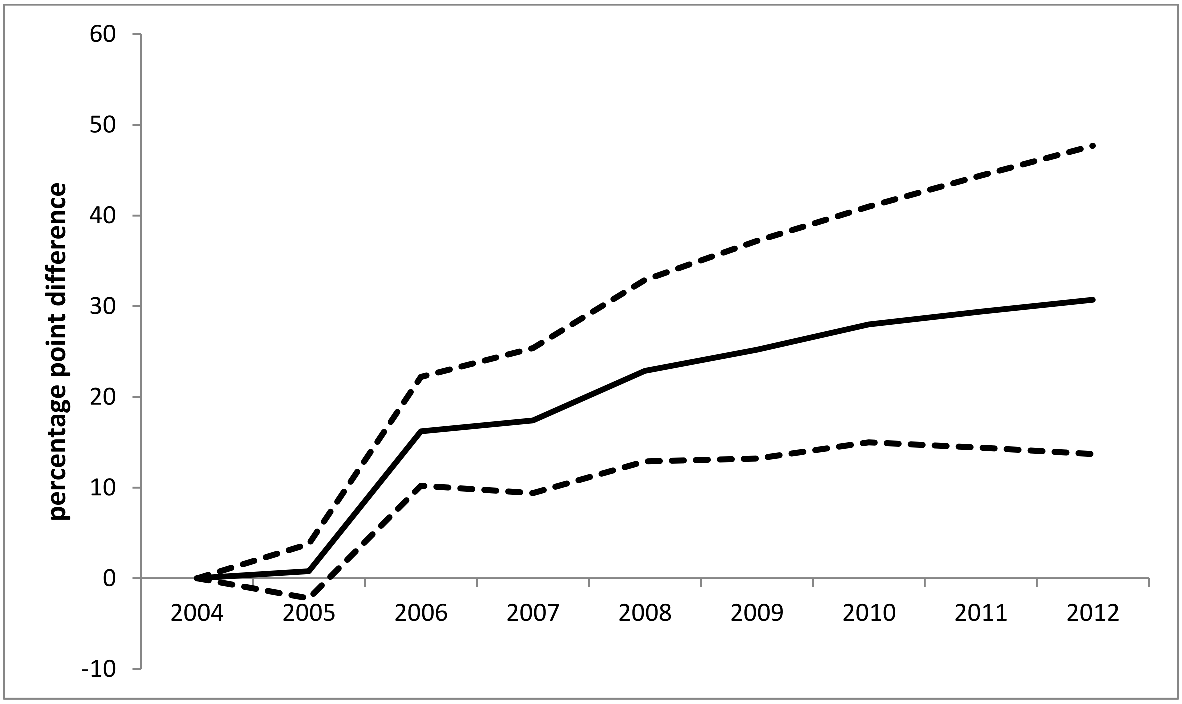
Table 2.1: Aceh's Tsunami-growth causality panel regressions, 1999 – 2012

Treated group:	Tsunami affected districts (blue) in Aceh			
Control group:	Sumatra control districts (red & green)		Non-Aceh districts (green)	Aceh non-flooded control districts (red)
Dependent Variable: GDP per capita growth rate				
Tsunami (average year)	0.041 *			
	(0.020)			
Tsunami_05		0.008	0.011	-0.004
		(0.030)	(0.030)	(0.030)
Tsunami_06		0.154 ***	0.163 ***	0.101 *
		(0.030)	(0.030)	(0.050)
Tsunami_07		0.012	0.014	0.005
		(0.020)	(0.020)	(0.020)
Tsunami_08		0.055 **	0.056 **	0.048 *
		(0.020)	(0.020)	(0.020)
Tsunami_09		0.023	0.024	0.02
		(0.020)	(0.020)	(0.020)
Tsunami_10		0.028	0.033	-0.003
		(0.010)	(0.020)	(0.030)
Tsunami_11		0.014	0.016	0.008
		(0.020)	(0.020)	(0.020)
Tsunami_12		0.013	0.015	0.005
		(0.020)	(0.020)	(0.020)
Year FE	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
SE	Spatial HAC	Spatial HAC	Spatial HAC	Spatial HAC
Observations	1287	1287	1118	299
R-sqr	0.24	0.25	0.24	0.34

Note: GDP refers to district level GDP. Each column is a separate OLS regression. Spatial HAC Standard Errors (SEs) are SEs, which take into account spatial heterogeneity, serial heterogeneity, and heteroskedasticity. SEs are in parenthesis. *, **, *** mean significance at the ten, five, and one percent level, respectively.

Implementing the distributed lag model formalized in specification (2) shows how intricately the effects of the Tsunami on GDP per capita come to bear over time. The cumulative effect of the Tsunami on economic activity is displayed in figure 2.4 (with the underlying regression table 2.1). If there was no effect of the Tsunami on the economic performance of Aceh, such a zero effect would have been shown as tracing the line of origin in the below graph. Moving horizontally in the graph depicts the marginal change from one year to another. The figure shows a monotonically increasing function, which indicates that, the positive Tsunami effect of each year is piling onto the cumulative positive effects of the year(s) before. The largest marginal increase in growth rates occurred from 2005 to 2006, when Aceh jumped by 15 percentage points from one year to the other, compared to the non-flooded counterfactual. The graph shows that the cumulative effect of the Tsunami on economic performance is substantial and reaches about 30 percentage points by 2012. In other words, the observed per capita output in the Tsunami flooded districts by 2012 is about 30 percentage points more than it would have been had the districts not been affected by the Indian Ocean Tsunami. These results allow me to reject the contraction hypothesis and (for now) accept the creative destruction hypothesis.

Figure 2.4: Impulse-responses: Cumulative effect of the Tsunami on GDP per capita growth rates



Note: The dashed lines represent one Standard Error bands. Plotted here is the comparison of the treated group with the two counterfactuals (red & green districts) combined. See the Appendix for a graphical analysis with both of them separately. The SEs depicted are robust to spatial and serial autocorrelation and are corrected for heteroscedasticity. For the annual coefficient point estimates, see table 2.1.

The estimated disaster-growth elasticities do not confirm increased long-term growth rates, but what they do confirm is an increased long-term output per capita. The absence of contracting growth rates of the flooded districts, relative to the counterfactual districts, indicates that their per capita output remains persistently higher in the long term. In further discussing the findings emerging from the dynamic model, I distinguish between the following post-Tsunami periods: immediate aftermath (2005), recovery (2006 – 2008) and post-recovery (2009 – 2012).

Immediate aftermath: The first year after the Tsunami shows no difference in GDP per capita growth rates between the treated and the counterfactual groups (see column 2 of table 2.1). Inspecting the results of GDP instead, shows that GDP in turn contracted substantially in the first year (see figure A2.1 & figure A2.2 in the Appendix). The absence of this statistically negative effect of the Tsunami on per capita growth in the first year after the natural disaster indicates that the reconstruction efforts kicked in pretty quickly bridging and substituting foregone economic activity with reconstruction efforts. It furthermore indicates that the reduced economic activity as measured by the GDP can be explained by the more than 200,000 casualties caused by the Tsunami.[19]

Recovery: While there were virtually no differences in the GDP per capita measure between the treatment and the counterfactual group in 2005, the year after in 2006, the growth promoting effects kicked in, causing the flooded district economies to grow by 15 percentage points more than had they not been flooded (relative to the counterfactual scenario). Looking at GDP only shows that the Tsunami stricken districts bounced back re-gaining the ground they lost in the first year and recovered beyond the counterfactual growth path (see figures A2.1 and A2.2 in the Appendix). In year 2007, the Tsunami stricken districts grew by about 1 percentage point more and in year 2008 they grew by about 6 percentage points more.

Post-recovery: What happens when all the construction dust has settled, the rebuilding efforts have ceased, and aid funds have all dried up? For the long run, I can reject that the growth rates decrease in Tsunami flooded districts as a symptom of converging income levels (as would have been indicated by a reverting to the line of origin in figure 2.4). In other words, the evidence is strong enough to preclude that the flooded districts enter a contractionary spiral after the aid has stopped. Whether the long-term causal effects were such that the flooded districts continued to grow at higher rates beyond 2008 (as indicated by a continued increase of the solid line in figure 2.4), or whether it has reached a parallel higher economic output path (as indicated by a flat line beyond 2008) remains uncertain. Even though figure 2.4 suggests that there is a monotonic increase in growth rates in the post-recovery phase, these positive elasticities are not statistically significant in 2011 and 2012. I conclude that the Tsunami caused economic output per capita to be higher for Tsunami flooded districts even in the long run, but whether growth rates of these districts are also higher in the long run cannot be concluded with any sensible degree of certainty.

Regardless of which counterfactual is chosen to benchmark the flooded districts' economic growth rates, the creative destruction trend holds (as shown by comparing the different columns in table 2.1). The creative destruction effects are less pronounced

[19] This drop in GDP is however counteracted in the years to come with statistically higher economic growth rates, leading to an overall positive effect of the Tsunami on long-term growth rates.

when comparing the flooded districts (blue) to non-flooded (red) districts within Aceh, rather than non-flooded (green) districts in the rest of Sumatra. For instance, while the flooded districts of Aceh grew by more than 16 percentage points faster in 2006 compared to the non-flooded districts of the rest of Sumatra (green), they only grew by 10 percentage points faster compared to the non-flooded districts of Aceh (red). This discrepancy may be explained by positive spillover effects from creative destruction, indicating that the non-flooded districts in Aceh benefited from positive neighbourhood effects. Spillover effects are investigated in section 2.7.4, where I show that there is an indication of the existence of spillover effects to directly adjacent districts, albeit the effects are not statistically significant.

To gain a better idea about the magnitude of the causal Tsunami-GDP effects, I also performed the difference-in-differences analysis in levels. I find that the average annual growth caused by the Tsunami is USD 16 per capita. While the year immediately following the Tsunami shows negative effects, in the year 2006, the extra GDP per capita caused by the creative destruction of the Tsunami is USD 60, a difference that is steadily dwindling over time, to USD 10 in 2010 an then to the single digits for the following years (albeit not being statistically significant). See table A2.1 in the Appendix for the detailed results.

2.7.2 Robustness checks

I performed a suite of comprehensive robustness checks, attempting to put the results indicating a stimulated per capita economic growth rate, caused by the Tsunami, to the test. The thorough robustness checks conducted vindicate the finding of creative destruction and a higher output path. Sensitivity analyses confirm the Tsunami-growth spur result, and find that it is robust to selecting alternative sub-samples, choosing alternative specifications of the regression equation, using alternative measures of the economic output variable, the Modifiable Areal Unit Problem, alternative estimation techniques, and placebo tests. The robustness checks confirm that the Tsunami caused persistently higher per capita economic output in the long run, and shows that higher long-term growth rates are unlikely.

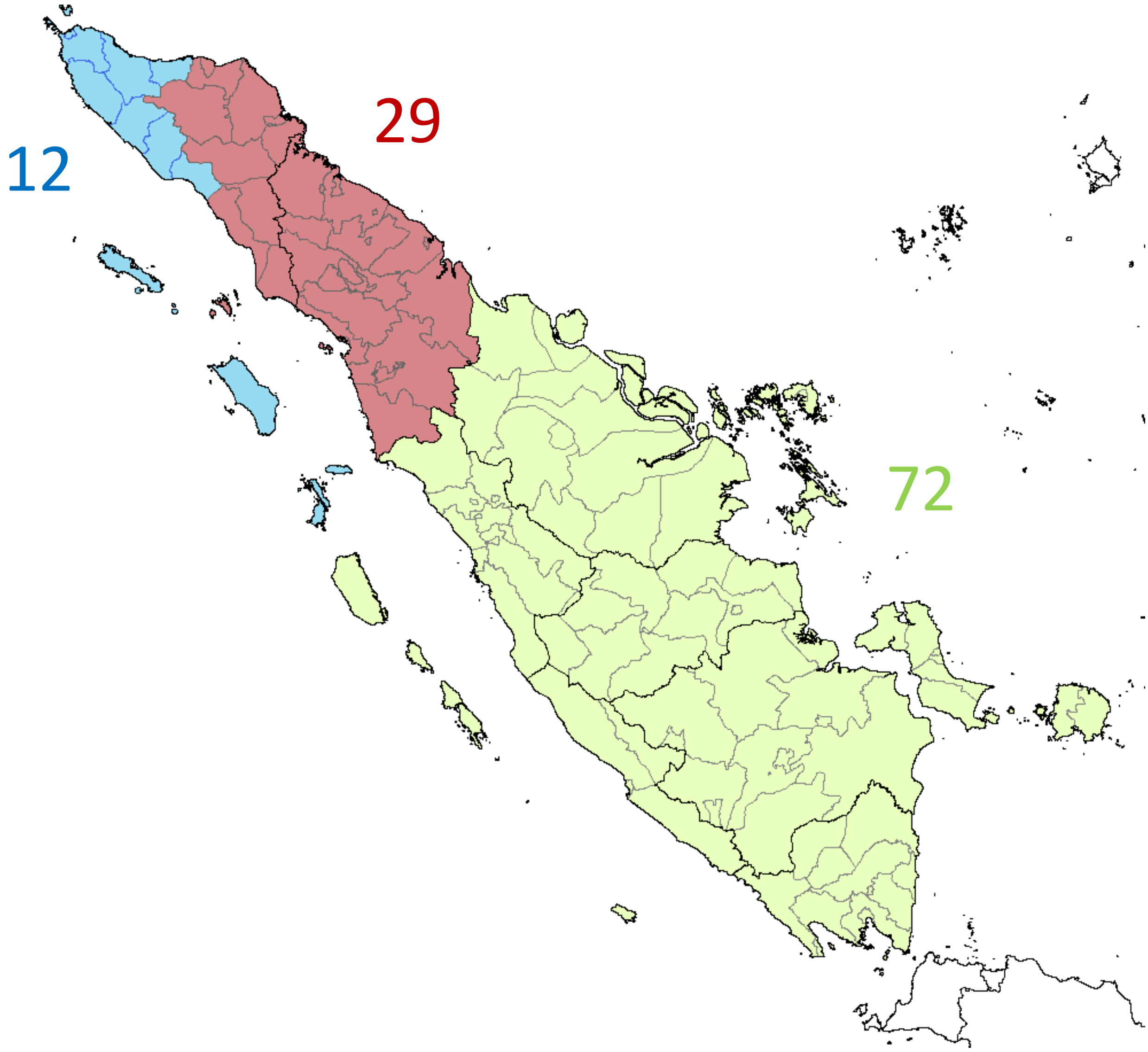
2.7.2.1 Alternative sub samples

Experimenting with different compositions of the sample to base the analysis upon serves not only as a good robustness check, but also offers interesting insights into how the treatment effects are altered by different underlying geographical patters. In this section, I look at how the results change if one includes North Sumatra also, and how they change if one takes into account the island versus mainland, coastal versus inland, and urban versus rural dimensions. I also look at how the results change if the focal point of the recovery effort, the city of Banda Aceh, is excluded. Finally, I also take into consideration the interplay with other socio-demographic and economic factors, and by assuring that both the treatment and the counterfactual donor pool are comparable in their composition in terms of pre-treatment poverty rates, GDP levels, agricultural share of GDP, infrastructure, and human development levels.

Including North Sumatra: Island districts versus non-island districts

In a second round of district level analyses, I also included the Tsunami stricken island districts of North Sumatra. Mainland districts of North Sumatra were not flooded (see map 2.4). For this analysis, there are 12 Tsunami stricken (blue) districts in the treatment group and 29 non-stricken (red) districts in the control group. A second control group is composed of 72 non-stricken (green) districts consisting of districts from the remainder of non-stricken Sumatra districts, excluding the Aceh and North Sumatra provinces.

Map 2.4: Including North Sumatra: Composition of treatment and control group

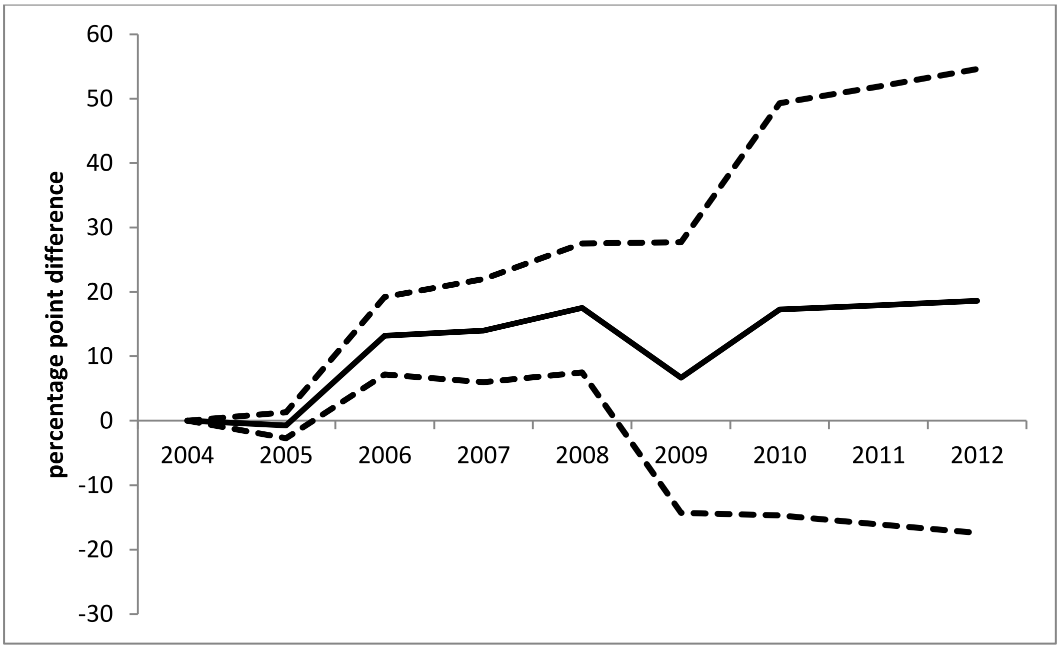


Note: The two Tsunami stricken districts of North Sumatra are Pulau Nias and Pulau Tanahbala.

Expanding the analysis to include also the two affected island districts of North Sumatra and correspondingly also the non-stricken districts of North Sumatra in the counterfactual group, confirms the creative destruction hypothesis, as it shows recovery and growth beyond the counterfactual after 2005 (see figure 2.5, and figure A2.4 in the

Appendix for a simple comparison between the means). Even though the disaster reduced district incomes, relative to the counterfactual, by 1 percentage point in the first year (albeit not statistically significant), it elevated them by 14 percentage points in the year after. The first two years were the only two years that appeared to be statistically significant, the recovery boost obtained in the second year was large enough for the stricken districts to permanently remain above the counterfactual economic output scenario. With aid flows drying up however by the end of 2008, the flooded districts contracted, relative to the not-flooded counterfactual, a drop from which they recovered quickly, and reverted to the increased long-term growth path. A reverting to the pre-Tsunami growth path and consequentially a convergence is rejected. Due to the cumulative error bands increasing significantly from 2009 onwards, it can no longer be asserted with statistical confidence that the long-term GDP per capita output path is different from the counterfactual path.

Figure 2.5: Impulse-responses: Cumulative effect of the Tsunami on GDP per capita growth rates



Note: The dashed lines above represent one Standard Error bands. Plotted here is the comparison of the treated group with both counterfactuals (red & green districts combined). See the Appendix for an analysis of both of them separately. The SEs depicted are robust to spatial and serial autocorrelation and corrected for heteroscedasticity.

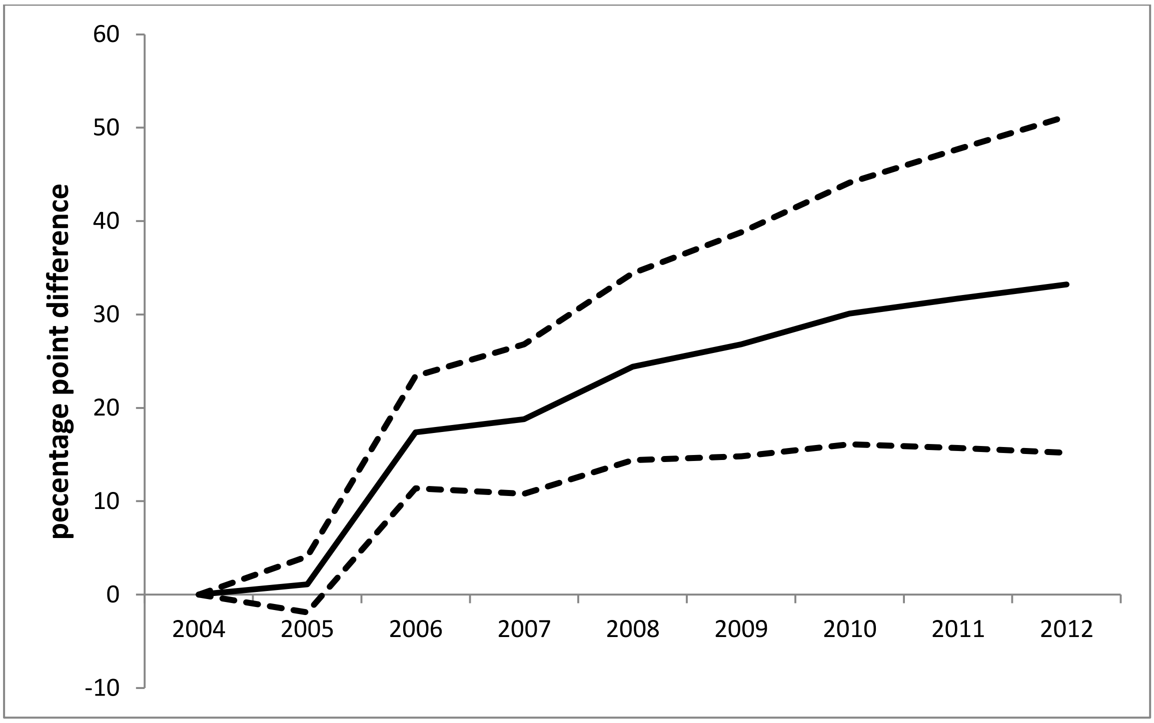
A more sluggish recovery was observed on the island districts compared to the mainland districts. Ruined infrastructure, impassable roads, bad communications, destroyed airports and harbours, among other reasons made it much harder to deliver aid to island districts (Fengler, Ihsan & Kaiser, 2008). To investigate closer whether island districts recovered differently from mainland districts, I looked at them separately (see figure A2.5 in the Appendix). While mainland districts were indeed hoisted onto a higher per capita output path, island districts were not. Notwithstanding island districts still showed a recovery to the counterfactual growth path, with convergence occurring after the first year post disaster. Right after the aid stopped, there was a substantial drop in economic activity, which however only lasted for the duration of two years and then the growth series reverted to the counterfactual growth path.

Apart from logistical issues, there may have been other factors that contributed to the slow growth rate of island districts. Islands may have recovered differently from the mainland because they had much less fatalities. Whereas on mainland Aceh the most recent Tsunami hit the shore in medieval times, Simeulue was hit by a Tsunami in 1907 which spared "mainland" Indonesia (Monecke et al, 2008). The island population, which is culturally different from the mainland population, had retained a collective memory and took proper measures when the water started receding on Boxing Day in 2004. Simeuluans passed on the story of *Smong* (meaning Tsunami in Devayan language) from generation to generation, which functions as an effective early-warning system of collective awareness (Syafwina, 2014). When the island inhabitants saw the water receding they correctly inferred that a Tsunami was to follow, something that mainland Indonesians were unaware of (Gaillard et al, 2008). Countless lives were spared by this cultural memory, and "only" seven out of the 78,000 inhabitants of the island died even though it was physically devastated.

Coastal districts

It may be argued that inland districts do not make appropriate counterfactual candidates, because they are different in many ways (e.g. less likely to be engaged in fishing, less likely to be the centre of tourism, no need for disaster preparedness measures at all, to name just a few). These omitted variables may constitute a bias, despite having shown similar historic paths of the flooded and non flooded districts. To verify that the creative destruction holds, I also performed a robustness check looking only at coastal areas. Broadly speaking, I obtained results comparable to those where inland districts were also included (see figure 2.6 and how it compares to figure 2.4). The magnitude of the Tsunami effects on GDP per capita is only slightly less, with a cumulative growth rate of 33 percentage points more by 2012, as opposed to 42 percentage points in the original estimation including non-coastal inland districts.

Figure 2.6: Coastal robustness check: GDP per capita growth responses to the Tsunami

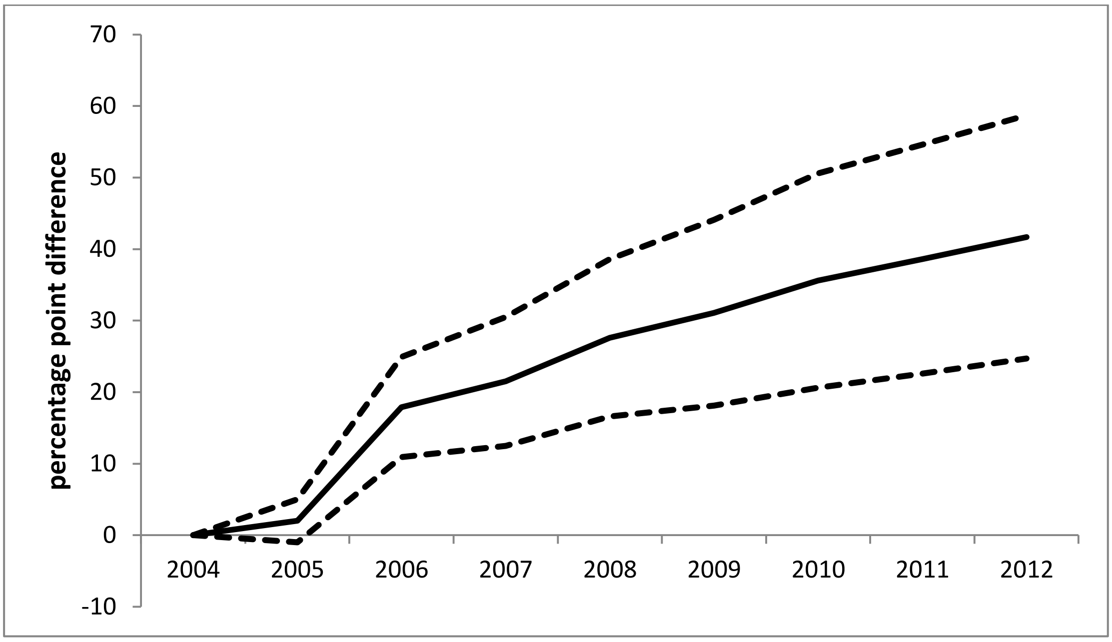


Note: The following districts of Aceh were not included because they were inland: Aceh Tengah, Aceh Tenggara, and Gayo Lues. The following districts of North Sumatra were not included because they were inland: Binjai, Dairi, Karo, Padang Sidempuan, Pematang Siantar, Simalungun, Tapanuli Tengah, and Toba Samosir.

Dropping Banda Aceh

Banda Aceh is the largest city and the capital of Aceh. It was the centre of much of the relief effort and in particular of the first waves of the aid programs, when many of the remoter districts were hard to reach because the Tsunami destroyed much of the infrastructure. Therefore, I exclude Banda Aceh from the analysis and see whether the remainder of the districts still display a creative destruction type recovery. This should allow assessing whether creative destruction was driven only by Banda Aceh. In dropping Banda Aceh from the sample I find that there is not much of a difference from the creative destruction recovery path described by the full sample to the one missing Banda Aceh (see figure 2.7). The cumulative marginal 'creative' effects of the Tsunami by 2012 only dropped from 43 percentage points to 41 percentage points.

Figure 2.7: Excluding Banda Aceh robustness check: GDP per capita growth responses to the Tsunami



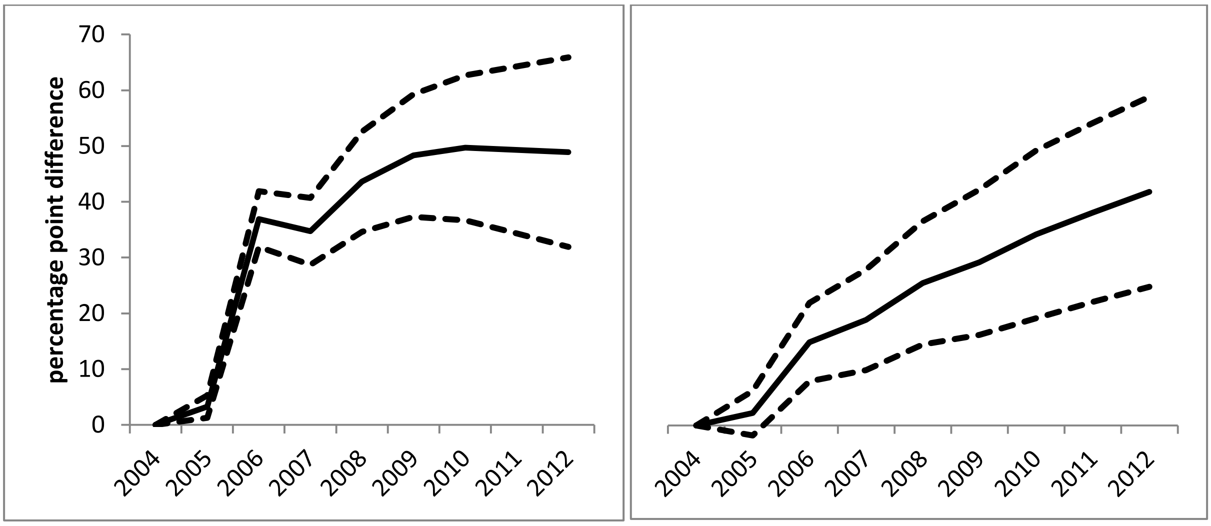
Cities versus rural districts

In this section, I examine whether there are differences in how city districts (the so-called *Kotas*) recover, compared to how rural districts (*Kabupatens*) recover, with a particular benchmarking focus on the general creative destruction finding. I find that both the urban and the rural districts displayed creative construction relative to their non-flooded urban or rural counterfactual, respectively (see figure 2.8). While both displayed creative destruction, the growth trends were quite different.

Flooded cities have taken off instantaneously after 2005, being propelled to a beyond 40 percentage points higher growth path already by 2006. Flooded cities grew significantly faster than non-flooded cities until 2009, beyond which year they no longer grew statistically faster, yet maintaining higher per capita output levels (with no sign of convergence to the counterfactual trend). The effect of Tsunami flooding on villages was quite different, even though also 'creative', and leading to similar growth differentials by 2012 between the flooded and non-flooded groups. Flooded villages show a much slower onset growth differential compared to the non-flooded village counterfactuals. Another difference to cities are that they maintain higher statistically significant annual growth rates until 2012, the last year observed in the dataset.

Figure 2.8: Cities versus villages - robustness check: GDP per capita growth responses to the Tsunami

Panel A: Cities (Kotas) **Panel B: Villages (Kabupatens)**



Note: The Y-axis in panel A also applies to panel B.

2.7.2.2 Alternative specifications

In this section, I show the robustness of the creative destruction result to alternative specifications. Out of a near infinite possibility of specification alternatives, I chose those that could reasonably be argued to make sense from my understanding as well as those that have been used elsewhere in the literature. The dynamic cumulative marginal elasticities between the Tsunami and economic growth in alternative specifications vindicate the creative destruction result (see figure 2.9). Particularly in the short term, the effects measured by the different regression specifications are very similar. They start to digress substantially over the subsequent years, but nonetheless in no circumstance refute the notion of creative destruction. However, while some specifications suggest a levelling off of the marginal growth effect of the Tsunami and an eventual zero marginal effect, others find a continuously increasing marginal growth effect of the Tsunami.

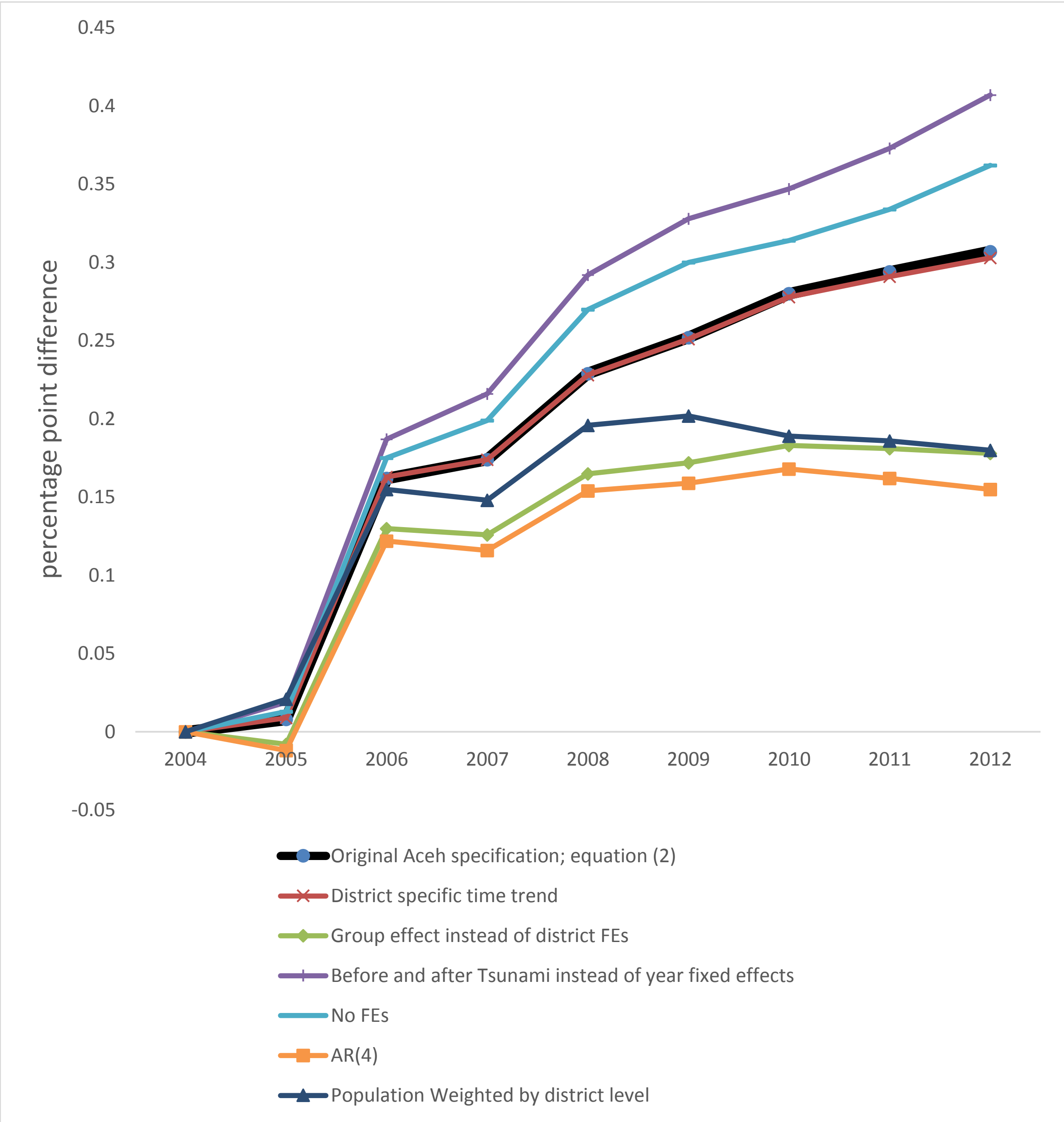
As argued in the core section of the analysis, applying the original distributed lag model, the evidence supports a rejection of a reverting back to pre-Tsunami per capita income levels. Per capita economic output does not converge to the counterfactual level and remains permanently above it. Figure 2.9 also shows that depending on the specification, Tsunami-growth rates are either monotonically increasing in the long run relative to the counterfactual growth, or become insignificantly different from counterfactual growth rates. Therefore, whether or not per capita output increased also in the long run depends on the kind of specification chosen.

The original specification of equation (2) is shown in bold black in figure 2.9. With higher cumulative growth rates of about 30 percentage points by 2012, compared to the counterfactual districts, the results of the specification chosen (see the empirical method section for the rationale on why the particular specification was chosen) are a mean estimate, compared with the alternative estimates. Not accounting for year fixed effects, but only for pre- and post- year period fixed effects results in the highest coefficient estimate, which is 41 percentage points by 2012. Including also the autoregressive components with 4 lags, such as in Cerra & Saxena (2008), yields the lowest estimate of 16 percentage points by 2012.

Including unit-of-analysis specific time trends, as done for countries by Hsiang & Jina (2014) in their cyclone impact evaluation, or Besley & Burgess (2004) for states in India, allows controlling for changes in economic policies on the municipal level and long run conditional convergence (see Barro & Sala-i-Martin, 2003). See Hsiang, Burke & Miguel (2013) for a detailed discussion on the merits of including unit-of-analysis specific linear trends in growth. Including a district level time trend did not alter the results much, and only reduced the long-term impact effects of the Tsunami by a tiny margin (see red trajectory in figure 2.9).

Relaxing the district fixed effects assumption, and only including a measure of fixed effects that all of the districts within either the treatment or the counterfactual group have in common, yields an estimate that is reduced by about half (see neon-green line in figure 2.9). Relaxing the year fixed effects and including only fixed effects for the pre-Tsunami period versus the post-Tsunami period do the opposite, and attenuate the results, yielding a coefficient that is substantially larger (see the purple line in figure 2.9). Taking out the time dummies intensifies the measured Tsunami-growth elasticity, and so do not including fixed effects, be they time dummies or district dummies.

Figure 2.9: Alternative regression specifications - robustness check



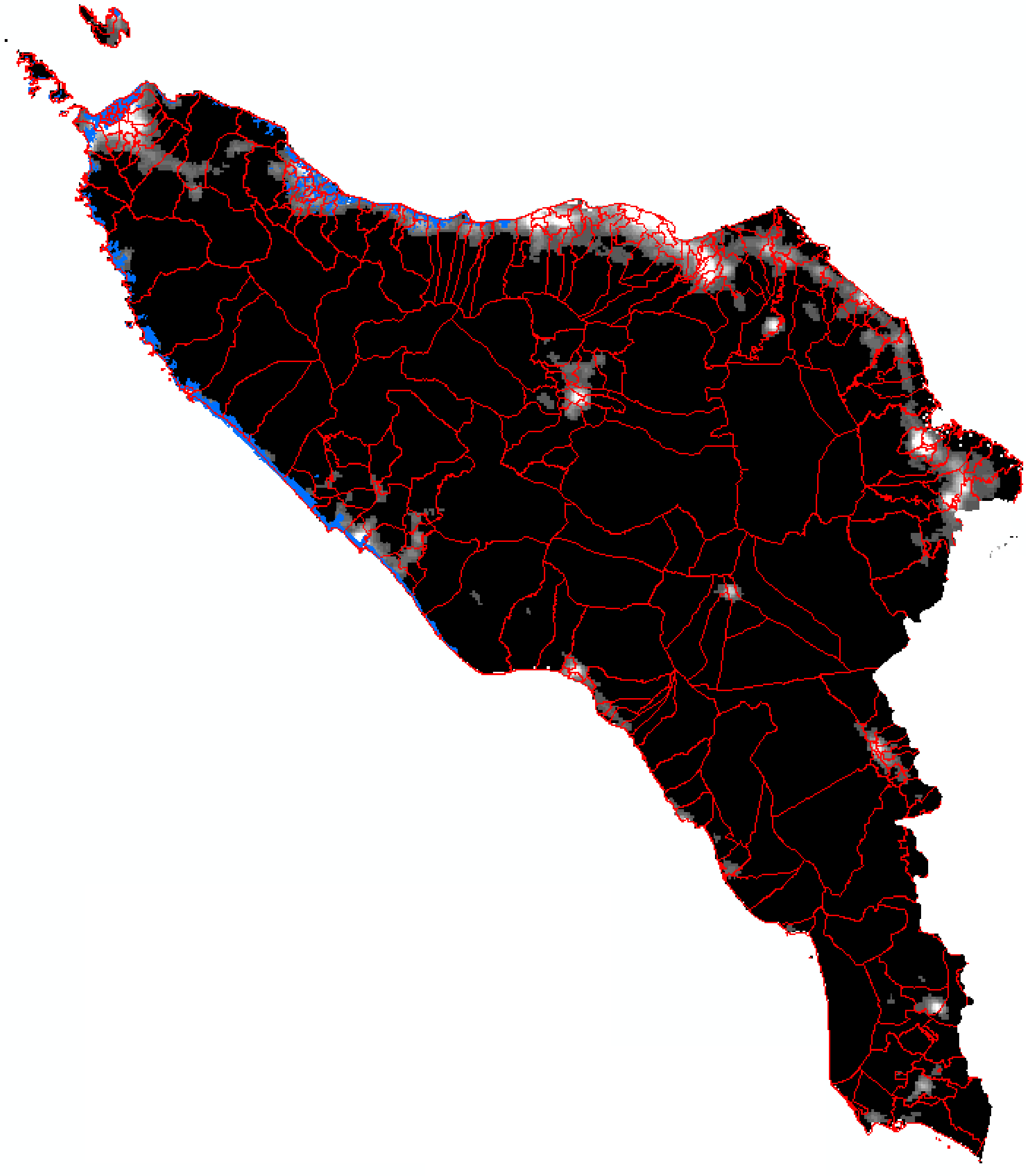
2.7.2.3 Alternative measures of economic output & alternative units of analysis

In this section, I demonstrate that the creative destruction result of the Tsunami also extends to other outcome measures used, as well as to other levels of spatial (dis)aggregation. As an alternative outcome measure, I use night-lights. As alternative spatial units, I use sub-districts (Kecamatans).

The Modifiable Areal Unit Problem (MAUP) is a well-documented problem in spatial econometrics (see e.g. Briant, Combes & Lafourcade, 2010; Openshaw & Taylor, 1979). The problem it describes is that results change when carrying out the same analysis on a different level of spatial aggregation. It describes the distortions that arise from choosing different zoning systems and the challenges this poses for statistical inference. The reasons for why this occurs have much to do with the size of the units of analysis chosen and a little also with their shape (Briant, Combes & Lafourcade, 2010).

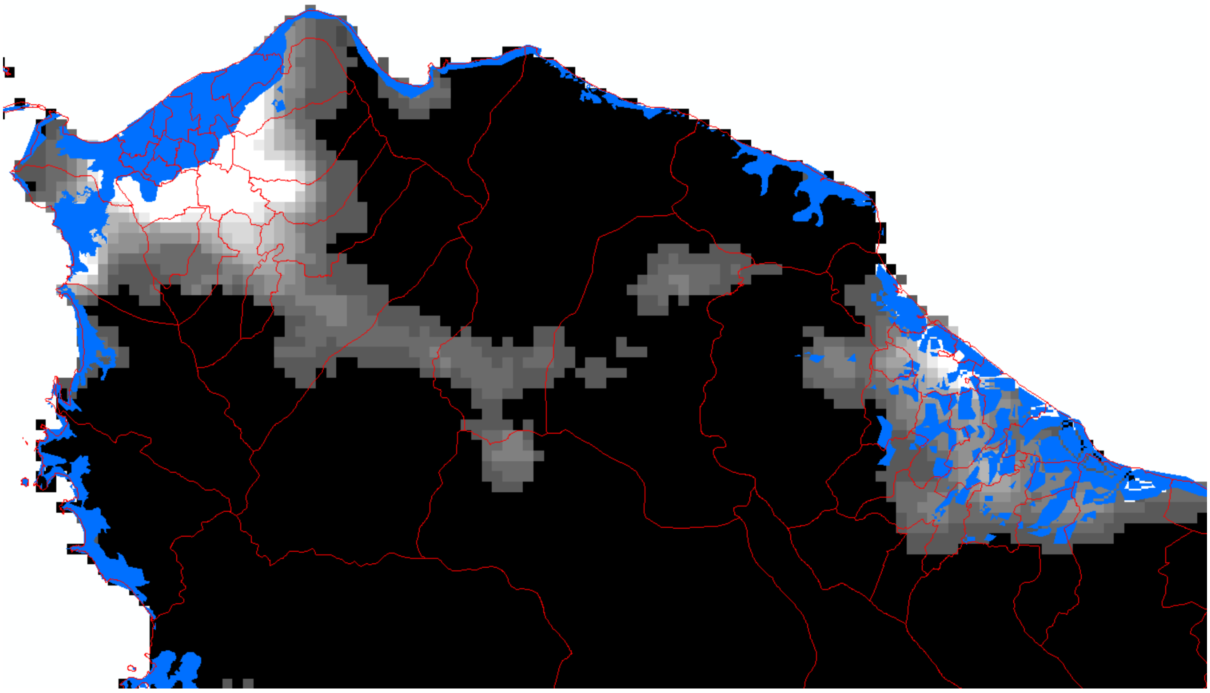
In this section, I zoom in closer to a level of spatial aggregation finer grained than the district level, to the Kecamatan (sub-district) level (see red demarcations in map 2.5). In total, there are 276 Kecamatans in Aceh. The average Kecamatan contains approximately 20 villages and has a population of about 50,000 (World Bank, 2004). Because no measures of economic output, such as the GDP level data, are available on a sub-district level, I use night-lights as a proxy for economic activity and create my own outcome measures for finer grained units of analysis with this data. See map 2.5 and map 2.6 for a visual overview of the geography and spatial aggregation of this level of analysis.

Map 2.5: Aceh by night (showing the lights visible), the areas flooded, and the Kecamatans (in red demarcations)



Note: There are 276 Kecamatans in Aceh. Island districts are not plotted in this map.

Map 2.6: Zooming in on the night-light pixels, the flooding map and Kecamatan borders



Note: The area of the grid-cells is about 10 km^2.

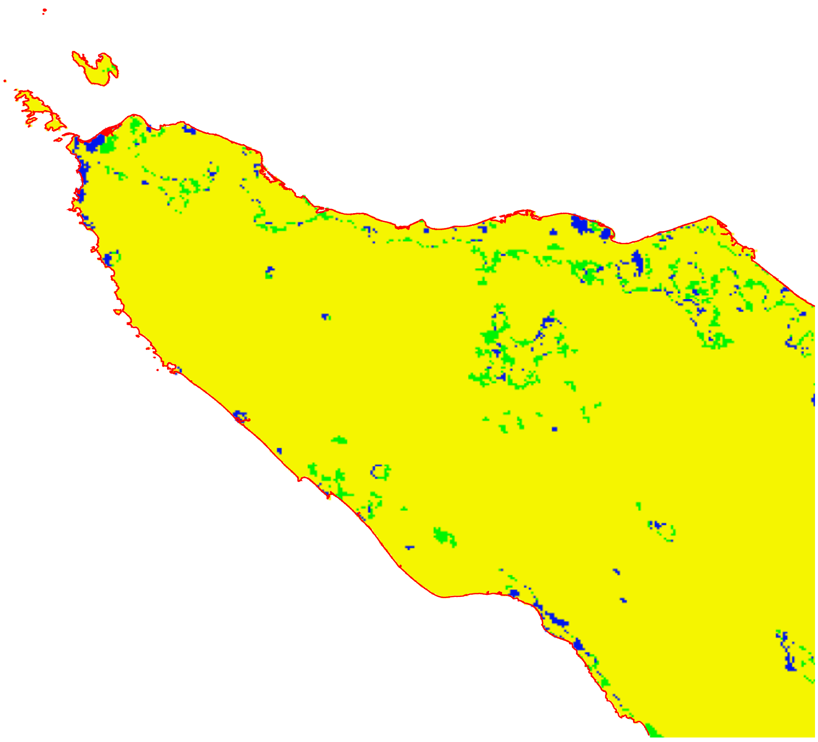
For details on the measurement of night-lights, as well as analytical steps taken to process the luminosity satellite data and generate the Kecamatan level dataset, see the method section of chapter 4 of my PhD thesis.[20] As a brief primer, the Kecamatan level night-lights measure is computed as the sum of all pixel level light intensity measures within its boundaries. Each pixel has a resolution of about 0.8km x 0.8km and ranges on the brightness scale from Digital Number (DN) 0, denoting darkness, to DN 63, representing the brightest light. I create a single night-light measure per Kecamatan that is the sum of the DN of all pixels within its borders. A measure of 100 can therefore be composed of 2 pixels of 50 DN, or 100 pixels of 1 DN. A change in the measure could thus be either due to an increased brightness of the already lit pixels (intensive margin) or from a switching on of previously unlit pixel (extensive margin).

[20] In chapter 4, I use night-lights extensively in investigating whether the 30 year long civil conflict that ended because of the Tsunami, has had any legacy effects on current night-light intensity.

Night-lights as measures of economic activity entered mainstream empirical economics since the seminal work of Henderson, Storeyguard & Weil (2012). It has been extensively shown that night-light intensity is a good proxy for the level of economic development (see e.g. Sutton, Elvidge & Ghosh, 2007; Elvidge et al, 1997; Pinkovsky, 2013; and Michalopoulos & Papaioannou (2011). Although there are also voices challenging the notion of night-lights as a stand-in for GDP particularly for within country analyses (Addison & Stewart, 2015). In this section, I use night-lights as a robustness measure.

Are night-lights responsive to the Tsunami? Prior to using night-lights as a proxy measure for economic activity it is crucial to establish that it reacts to the shock. Map 2.7 illustrates the differences in light intensity in the year before and the year after the Tsunami. Depicting the differences in light intensity between the two years, the map reveals that the areas close to the shore suffered from substantial reductions in luminosity (blue pixels indicating a decrease in luminosity of DN >2), while in contrast, the further inland areas grew (green pixels indicating an increase of luminosity of DN > 2). This selective change in nigh-light intensity close to shore indicates that night-lights are quite responsive to the destructive effects of the Tsunami.

Map 2.7: Difference in night-light intensity between the years 2004 and 2006

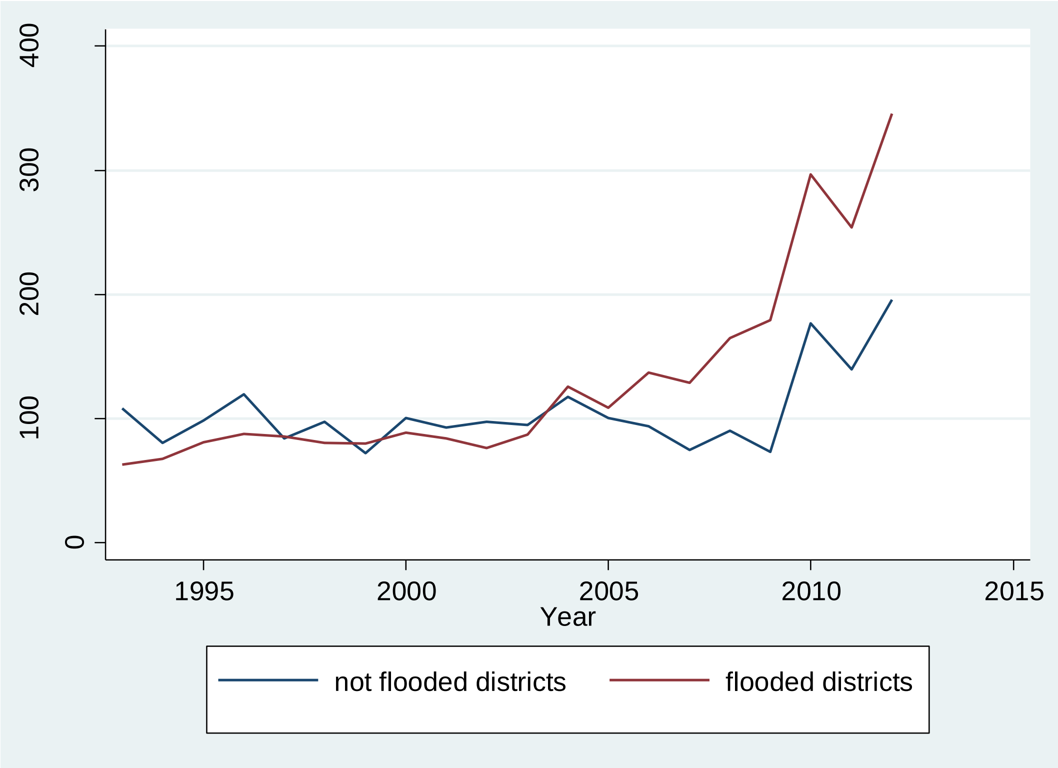


Note: Blue areas represent a drop by more than 2 DN, and a green area represents an area with a gain by more than 2 DN (the yellow areas denote no change or only a minor change).

I repeat the GDP per capita analysis on the district level, with night-lights data on the sub-district level. Looking at the average trends over time I show that the parallel historic path assumption holds, which is that the historic differences between flooded and non-flooded Kecamatans are not systematic and only small (see figure 2.10). Both the treated and the control group of Kecamatan's evolved similarly before the Tsunami intervention. With the onset of the Tsunami, the parallelism of luminosity paths breaks, and they diverge noticeably, so much so that at the end of the period for which we have data, 2012, the average flooded sub-districts shine 75 percent brighter than their non-flooded counterfactual.[21]

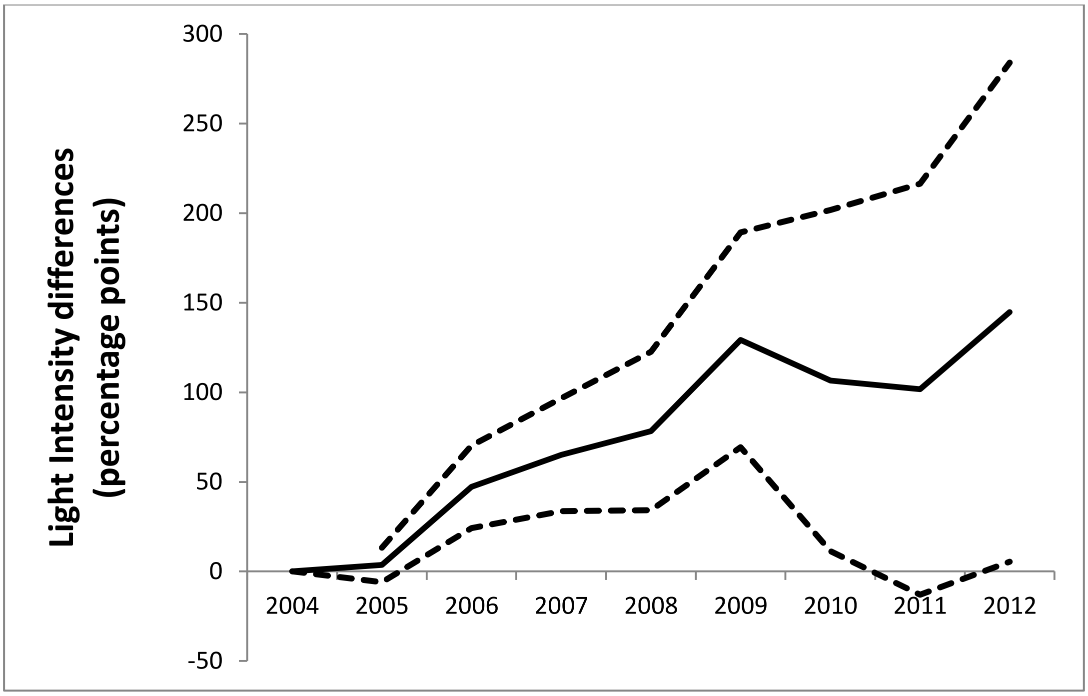
[21] Whereas before the Tsunami intervention the average flooded Kecamatan had a cumulative luminosity measure of about DN 100, just like the average non-flooded Kecamatan, after the Tsunami struck, the paths digressed, ending up at DN 200 for the non-flooded and at 350 DN for the flooded by 2012.

Figure 2.10: Kecamatan level analysis of average night-light intensity: flooded versus not flooded districts



Whether the descriptive average results are also maintained in an econometric analysis shows in a repetition of the difference-in-differences regression estimation outlined in equation (2) on the Kecamatan level with the night-lights data. Implementing the distributed lag model for this finer grained resolution and the alternative data shows that Tsunami flooded sub-districts emanate significantly more light at night than their non-flooded counterparts, which is the corollary to the creative destruction finding using GDP per capita of the district level analysis (see figure 2.11). The flooded Kecamatans grew substantially faster compared to the counterfactual sub-districts in the recovery period until 2009. Similarly to the GDP per capita findings, looking at the elasticities beyond 2009 casts doubts on the persistence of the positive impact. If anything, the figure suggests that there may be a slowing down of the flooded Kecamatan's luminosity growth rate compared with their counterfactual, leading to a levelling off of the luminosity growth path post 2009. These results confirm those from section 2.7.1.

Figure 2.11: Kecamatan level causal analysis: Night-light intensity changes of flooded versus not flooded sub-districts



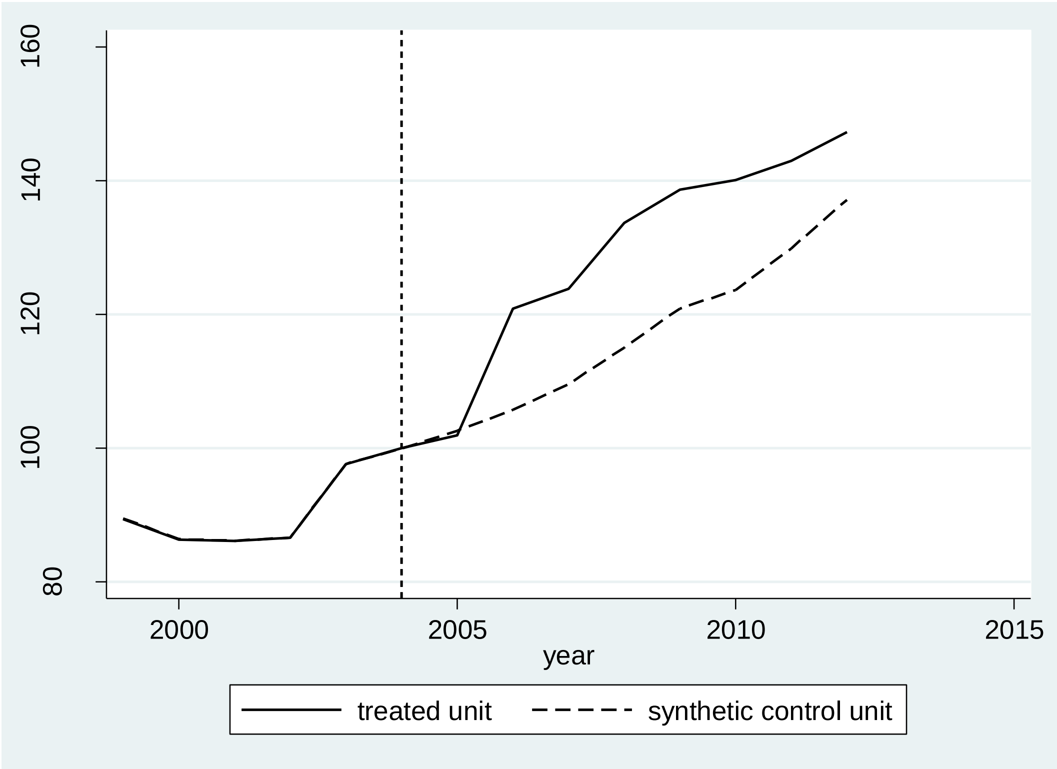
2.7.2.4 Alternative method of causal impact analysis

Here I use the synthetic control method, outlined in detail in chapter 3 of my PhD thesis, as a methodical robustness check. I take the average GDP per capita of the 10 affected districts as the treatment measure. As outlined in the methods section of chapter 3, I construct a synthetic control group based on a convex combination of districts that resemble Aceh in many characteristics of its pre-treatment period. The GDP per capita predictors I chose contain previous levels of GDP per capita, population size, the unemployment rate, the share of agriculture, the share of people living in urban areas, and the number of coastal villages, all of which closely related to the human and economic impact of a natural disaster.

Figure 2.12 vindicates the parallel trends assumption, showing an overlapping pre-disaster treatment effect between Aceh and synthetic Aceh. The estimated effect size of the Tsunami on district level output per capita is represented by the wedge between the treated unit and the synthetic control unit. Aceh noticeably embarks on a different growth path after the Tsunami struck in 2004 and the discrepancy between the two lines immediately after the onset of the disaster suggests a significantly positive and lasting effect of the Tsunami.

The creative destruction results obtained with the difference-in-differences analysis hold true when looking at a close methodological alternative, the synthetic control method. Constructing a synthetic twin to the flooded districts (titled "synthetic control unit" in figure 2.12) reveals quite similar trends and patterns as those in figure 2.4. The exact same conclusion is reached, which is that the Tsunami (together with the aid it triggered) caused economic growth beyond what could have been expected had the disaster never struck. Just as the results of the difference-in-differences analysis suggested, it seems as if the higher growth path is obtained sustainably, but there are some issues of uncertainty around this conclusion, due to a slight convergence trend of the Aceh and synthetic Aceh trajectory post 2009 in figure 2.12 for the per capita GDP measure. For this analysis, the synthetic control unit was created based on the red and green (not flooded rest of Sumatra, including North Sumatra) district donor pool. Figure A2.6 in the Appendix shows an alternative analysis using only the green districts as the donor pool for the creation of the counterfactual.

Figure 2.12: Trends in district average GDP per capita: Aceh versus synthetic Aceh



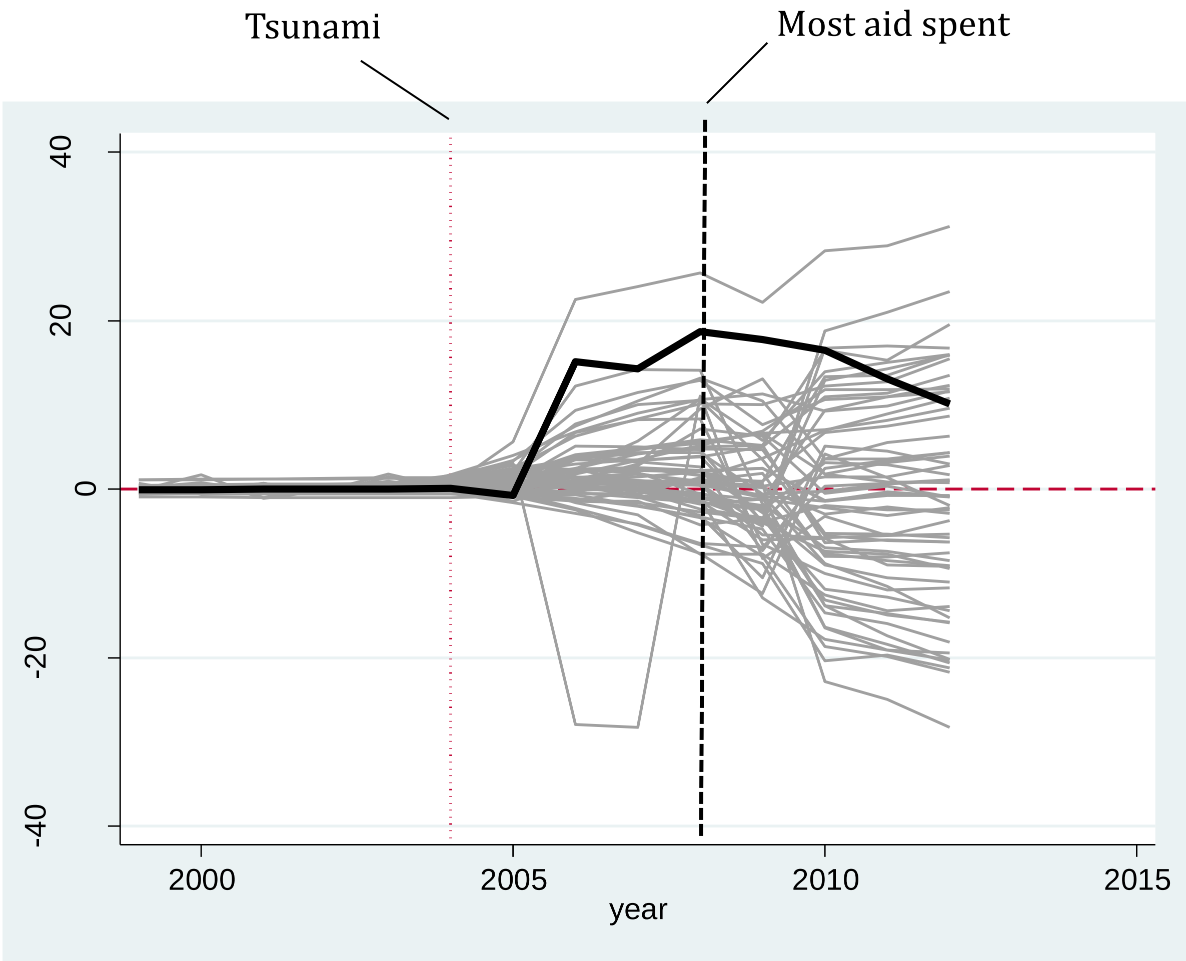
Note: Average GDP per capita of 10 affected districts versus 72 comparator districts outside of Aceh.

Carrying out the same analysis for GDP as opposed to GDP per capita also suggests, just like with the difference-in-differences analysis that GDP significantly contracts in the first year after the Tsunami, before it expands gaining ground and ultimately jumping onto a higher growth path. See figures A2.7, A2.8 and A2.9 in the Appendix.

2.7.2.5 Placebo tests

What would be the probability of obtaining results of the magnitude obtained for Aceh, had the intervention been randomly re-assigned to any other district (where it in fact did not strike)? I iteratively applied the synthetic control method to each of the other control districts and obtained a distribution of placebo effects (see figure 2.13). Comparing the yearly gap between GDP per capita of the average flooded district in Aceh with GDP per capita of synthetic Aceh yields the thick black line in Figure 2.13. In reassigning the intervention to the other non-flooded districts, one proceeds as if they had been flooded. Doing this for all 72 districts of the control donor pool provides a distribution of estimated gaps where no intervention took place (as indicated by the light grey trajectories in figure 2.13).

Figure 2.13: GDP per capita gap in Tsunami stricken districts and placebo gaps



Note: Includes only placebo districts that had a reasonable pre-Tsunami Mean Squared Prediction Error (MSPE).

Placebo gap runs with poor fits do not provide a solid foundation based upon which the rarity of obtaining a sustainably positive long-haul impact of the Tsunami in Aceh can be evaluated. In Figure 2.13, I dropped all regions that had a pre-intervention Root Mean Squared Prediction Error (MSPE)[22] that was larger than fifty times that of Aceh. In doing

[22] MSPE (Mean Squared Prediction Error) refers to the squared deviation between the synthetic control outcome and the treated outcome, summed over all pre-intervention years.

so, I had to drop nine districts. See Figure A2.10 in the Appendix for placebo runs including these nine districts.

The placebo test confirms creative destruction and indicates that during the times of aid abundance there was no other district that had higher growth rates than Aceh, bar one. This one extreme outlier, which even surpasses that of Aceh (the one line that is above Aceh starting with year 2005 in figure 2.13).[23] Another placebo district comes close, but remains shy of the magnitude of Aceh by about one-fifth by 2008. One, arguably two, placebo effects in the ballpark of Aceh's are not enough to refute that Aceh was on a higher than counterfactual growth path during the aid bonanza.

What the placebo test also shows is that there is considerable uncertainty concerning whether the observed creative destruction effects also hold in the long run. In fact, several placebo districts show even larger effects post 2010. This casts doubt on the finding that the Tsunami resulted in a sustainably higher per capita output. For the long haul, based on the placebo results, whether the Tsunami resulted in a sustainably higher per capita output cannot be vindicated at any meaningful level of statistical certainty.

2.7.2.6 Autonomy funding & oil and gas funding

There may be other dynamics put in motion by the Tsunami that may affect the interpretation of long-term Tsunami-growth effects, which makes it important to look at their role closely. The Tsunami ended an almost 30 years-long civil war in Aceh (see chapter 4 for a detailed discussion). After the peace agreement was reached in 2005, the federal government passed a law in 2006 granting Aceh special autonomy status, and establishing two funds, the Special Autonomy Fund, and the Oil and Gas sharing agreement, which started to disburse funds to Aceh in 2008. For more details on this fund, be referred to chapter 4 of my PhD thesis.

The relevance of including an analysis of these two funds for Aceh is that it may have implications for the long-term nature of the GDP per capita trajectory. The finding of a

[23] Curiously, this line represents Padang Pariaman, a district that was affected by an earthquake in both 2007 & 2009, and receiving substantial aid also (which however does not explain why the district started taking off already at around 2005).

long-term higher per capita output in the long run, may be driven by these funds from 2008 onwards. Looking at whether the funding is correlated with the Tsunami flooding, and investigating whether Tsunami flooded districts (the treatment group) received more funding should give us a flavour of whether the results may have been biased in any direction. For example, if the funding allocation was influenced by the level of Tsunami destruction, part of the long-term creative destruction finding could have been driven by this selective funding rather than upgraded capital that allows for more productivity.

Figure 2.14 and figure 2.15 suggest that the autonomy funding and the oil and gas sharing funding were not targeted based on the level of Tsunami destruction. Neither the size of the area that was flooded nor the amount of persons killed by the flooding was systematically related to the amount of funding disbursed to the districts from 2008 onwards. While the districts that the Tsunami spared received and average of USD 252 per person from 2008-2011, the Tsunami stricken districts received USD 278. Looking at the median instead of the mean as a measure of central tendency reveals the opposite trend, one in which the Tsunami spared districts received USD 217 and the Tsunami stricken districts received USD 206. For oil and gas, the Tsunami spared districts received only marginally more: USD 34 versus USD 30 using the mean and USD 26 versus USD 24 using the median.

Figure 2.14: Oil and gas funding versus two measures of flooding intensity

Panel A: Area flooded **Panel B: Tsunami casualties**

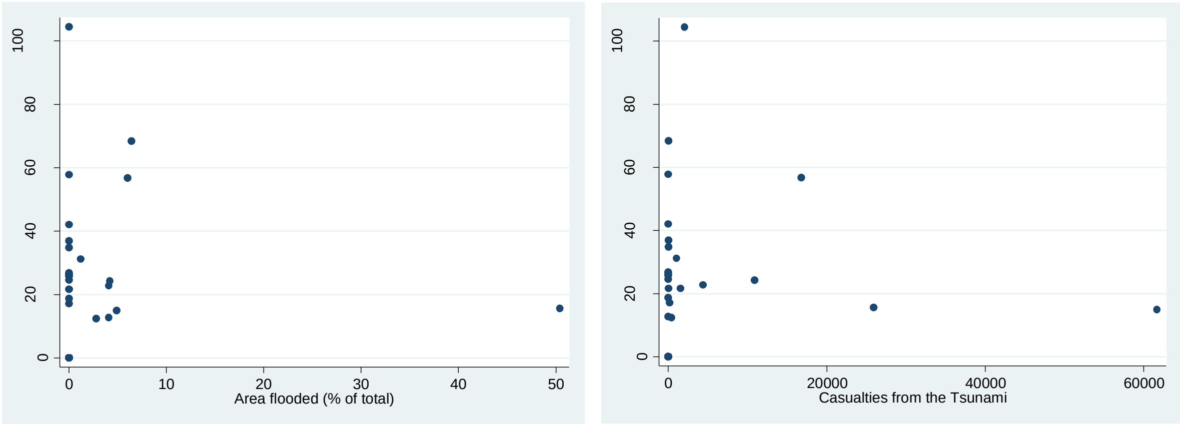
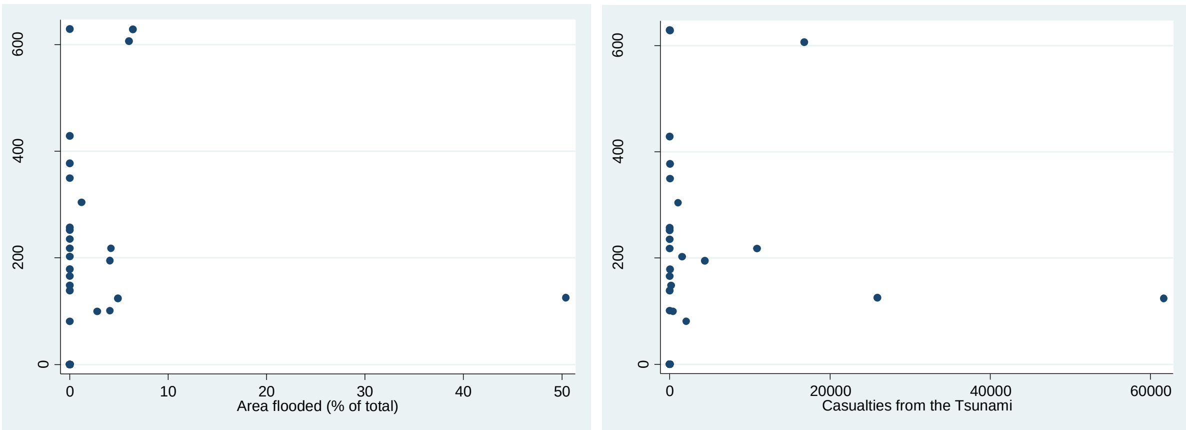


Figure 2.15: Autonomy funding versus two measures of flooding intensity

Panel A: Area flooded **Panel B: Tsunami casualties**



I conclude that neither oil and gas, nor autonomy funding in Aceh are likely to have had any impact on the main findings of this chapter. To be more precise, rather than asymmetric funding from oil and gas or autonomy funds, higher productivity granted by upgraded physical capital is still the more likely explanation for the higher output per capita levels reached.

2.7.3 Tsunami intensity ("the dose")

The severity of the Tsunami impact (i.e. "the flooding dose") and the heterogeneous responses it triggered are the subject of scrutiny in this section. Paracelsus famously said, "The dose makes the poison" (1538), asserting that the harmful effects of many toxic properties on biological systems only manifest themselves in high enough concentrations. Just as the harmful effects of toxic substances on the human body heavily depend on their dose, the impact of the Tsunami depends on its intensity (the level of its devastation). Fomby et al (2009, p.32) for example found that only moderate disasters may have positive effects, but severe disasters "do never have positive effects." Cavallo et al (2013) find that only very severe natural disasters, the most devastating 1 percentile to be exact, show negative short- and long run effects on per capita GDP. For the top 25 percentile or the top 10 percentile of most devastating disasters, the authors did not find a difference between disasters affected growth and the not affected counterfactual. In this section, I come to the diametrically opposed conclusion, which is that the more severe the flooding was, the more the economy grew in the aftermath.

In section 2.7.1, I computed the average treatment effect of the Tsunami on the affected districts ($ATET$), however harshly they were affected; including districts that have been 'tangentially flooded' (as low as 1 percent of the area) as well as others who have been completely inundated (100 percent of the area). As a result, the estimated $ATET$ does not tell us much about the functional relationship between the Tsunami intensity and the economic repercussions.

It is feasible that the creative destruction results observed were mostly driven by moderate Tsunami inundation. On the other hand, it is also imaginable that in order to rebuild capital (say a bridge or a road) it is best if it is completely destroyed, because if it is only partly destroyed additional costs occur in having to destroy it completely before the reconstruction can begin. Similarly, other interplays are also fathomable: there may be intricate nonlinearities and threshold effects characterizing the functional relationship between the dose of flooding and the economic consequences. In this section I scrutinize these heterogeneous treatment and functional form issues, and estimate $ATET(DOSE)$, the average treatment effect given the level of exposure to the flooding.

In carrying out the analysis incorporating information of the Tsunami intensity, I follow two data-driven analytical steps. In step 1, I repeat the analysis from section 2.7.1., including the Tsunami intensity as robustness check of the previous results obtained. I focus on identifying when, if ever, the statistically significant effects – of stimulating or contracting the economy – happened. In step 2, I investigate the effect of the different doses of tsunami treatment during the phases identified to be statistically significant in step 1 and compute *ATET(DOSE).*

Step 1: Incorporating tsunami intensity. Instead of measuring the Tsunami impact with a mere dummy variable, where 1 is for the flooded district and 0 for the non-flooded district, I included a measure of the intensity with which these affected districts were affected; the treatment intensity ($DOSE$). I implement a model that incorporates $DOSE$ into equation (1) yielding:

$$\ln\left(Y_{i,t}\right) - \ln\left(Y_{i,t-1}\right) = \alpha + \delta(DOSE * D_i * T_t) + d_t + \gamma_i + \varepsilon_{it} \qquad (3)$$

To estimate this model I am again using OLS instead of IV estimation, because I extend the assumption that the selection-into-treatment was exogenous also to the intensity of the treatment. Thus, I assume that how badly a district was struck is exogenous, i.e. the treatment intensity is randomly assigned, which implies conditional mean independence.

I then also disentangle the distinct Tsunami periods that I identified in the previous section to look at the different effect of the Tsunami intensity measure during different periods (*p).* The following regression is run separately for each period:

$$\ln\left(Y_{i,t,p}\right) - \ln\left(Y_{i,t-1,p}\right) = \alpha + \delta DOSE_{i,p} * D_{i,p} + d_{t,p} + \gamma_{i,p} + \varepsilon_{it,p} \qquad (4)$$

Here p divides the sample into four distinct periods; it denotes the pre-Tsunami phase from 1999 to 2004 (during which we shouldn't see any impact of the treatment variable), the immediate aftermath in 2005 (during which I expect to see a negative coefficients), the recovery phase from 2006 to 2008 (durich which I expect to see positive coefficients) and the post recovery phase from 2009 to 2012 (during which I expect to see insignificant differences).

I use a suite of different measurement alternatives for the Tsunami intensity (*DOSE*). In a first attempt, I use a measure of human losses, the share of people within a district that have been killed or went missing in the wake of the Tsunami flood. Data on the human tragedy and costs of the Tsunami come from Doocey et al (2007). The human toll of the Tsunami was far from evenly distributed across districts: Five of the 12 affected districts[24] saw less than 1 percent of the population killed or disappearing, another four were below ten percent, and the remaining four had more than 25 percent of the population killed or missing. Implementing equation (3) delivers results comparable to what we obtained with running equation (1). Implementing equation (4), looking at the different Tsunami phases, gives interesting insights into the timing and direction of the Tsunami effects.

Table 2.2 : The effect of Tsunami intensity (as measured by casualties caused) over the different phases of the Tsunami, district level

	Pre-Tsunami (1999 - 2004)	Aftermath (2005)	Recovery (2006 - 2008)	Post recovery (2009 - 2012)
People killed and missing	-0.13	1.05	3.46 ***	-0.30 ***
(% of total)	*0.15*		*0.00*	*0.00*
District fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	No	Yes	Yes
SE	robust	robust	robust	robust
Observation	620	124	496	496
R squared	0.25		0.13	0.09

Notes: Each column represents a separate OLS regression. Standard errors are in italics. *, **, *** mean significance at the ten, five, and one percent level, respectively.

The results in table 2.2 suggest that per one additional percentage of the population killed or missing, the growth rate increases by about 3.5 percentage points annually in the recovery phase between 2006 and 2008. The results looking at the human cost of the Tsunami suggest that once the recovery phase is over and aid funds are dried up, legacy effects kick in, and cause the affected districts to shrink, albeit at a much lower

[24] Doocey et al (2007) report additional districts to those that I have identified with the satellite images of the flood maps. This may be due to people that were registered in these districts actually died in the other district, or because of inaccuracies in the satellite-based maps. Flood maps were created to aid the first responders in the aid and recovery effort. It is therefore quite feasible that they therefore left aside some of the less affected districts.

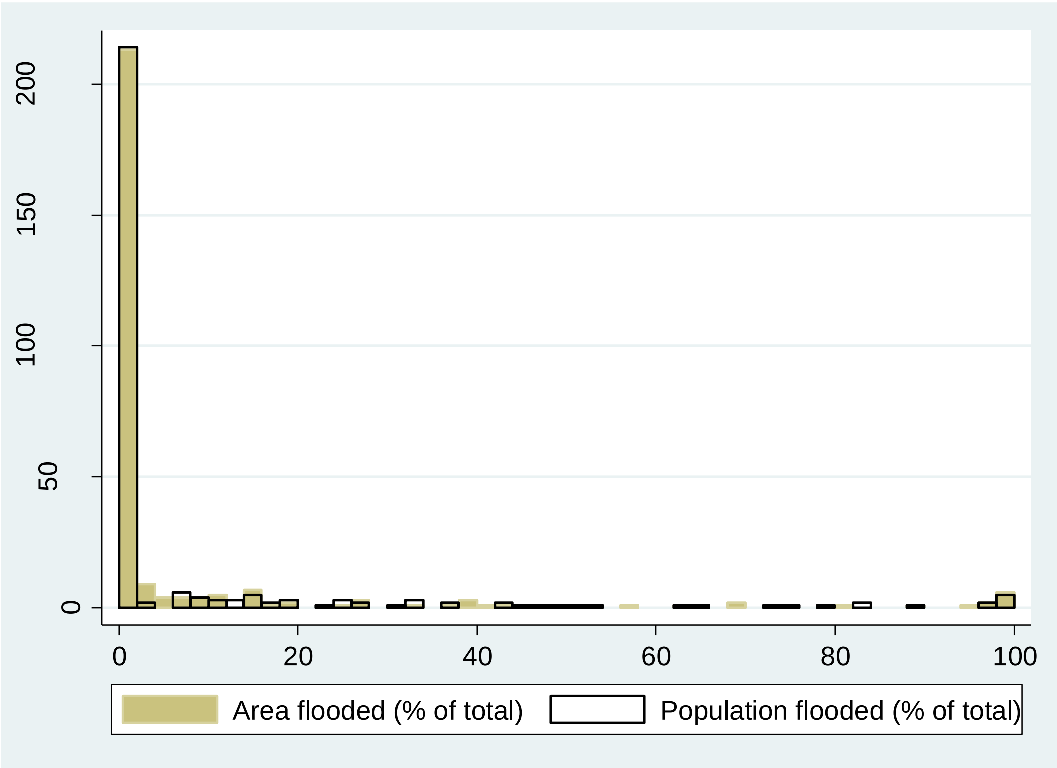
level than they used to grow during the recovery phase: 0.3 percentage points of annual contraction, compared with the 3.5 percentage points annual increase.

However, these results have to be taken with a grain of "endogeneity salt." While the physical characteristics of the Tsunami wave and its reach inland can be safely assumed to constitute an exogenous measure, the amount of people killed in its wake, introduces endogeneity and creates problems for causal inference. Endogeneity concerns inevitably arise with human cost measures (see e.g. Noy, 2009) and in fact one of the main contributions of this PhD chapter is to overcome the limits posed by these endogeneity riddled measures, which are used by most other papers in the natural disaster economic literature, by establishing a measure only relying on the physical characteristics. Nonetheless, using the results more along the lines of a supplementary to the main results driven by physical characteristic variation can only benefit, keeping in mind the limitations of the causal inference.

I create two completely exogenous measures of Tsunami intensity, measures that are based on physical characteristics, to overcome these endogeneity problems with human cost dose measures. I go beyond the district level and present data at the sub-district (Kecamatan). Because there are no GDP figures available for such a disaggregated unit of analysis, I will use night-lights as a proxy for economic activity. The reader may recall that I showed how the results obtained by looking at night-lights are comparable to those obtained by using GDP figures (see section 2.7.2.3.). The method for computing the night-lights measure on a Kecamatan level as well as a detailed explanation of night-lights data is provided in chapter 4 of this PhD thesis.

I use two different measures of flooding dosage with which the districts were treated: (i) I calculate the population that could have hypothetically been affected as a share of the total population within a Kecamatan. By matching Tsunami flood maps plotting the reach of the Tsunami with fine-grained population density maps of the year 2000, I compute the hypothetical amount of people flooded (assuming the population distribution between 2000 and 2004 did not change). I also do the same using sub-national administrative maps, so that I can express the people flooded as a share of those living within each Kecamatan boundary. The population density grid I used had a resolution of approximately five km^2 (CIESIN, Columbia University, 2005). (ii) I calculate the area that was flooded, and produce a measure of the proportion of the total area of each sub-district that was flooded. A distribution of both measures of tsunami intensity is plotted in figure 2.16.

Figure 2.16: Distribution of the physical Tsunami intensity measures of Kecamatans



Note: Bin width corresponds to two-percentile increments of the distribution for both tsunami intensity measures plotted. There are 276 Kecamatans in total in Aceh.

Implementing equation (4) with both of these exogenous measures of tsunami intensity results in table 2.3 and table 2.4. Looking at either measure of Tsunami intensity confirms the creative destruction findings obtained using the Tsunami dummy, and also the timing associated with the effects. Acting essentially as a time placebo test, looking at the pre Tsunami period from 1999 – 2004, shows that the areas that were later to be flooded did not grow faster or slower in anticipation of the natural disaster. In the immediate aftermath of the Tsunami, in the year 2005, the flooded Kecamatans' luminosity decreased at a faster pace than before, albeit not at a statically significant level. During the recovery period, where the Aceh province was rebuilt, luminosity increased causally related to the Tsunami, regardless of how I measure the intensity of the Tsunami impact.[25]

Table 2.3: The effect of Tsunami intensity (as measured by population flooded) on night-lights over the different phases of the Tsunami, sub-district level

	Pre-Tsunami (1999 - 2004)	Aftermath (2005)	Recovery (2006 - 2008)	Post recovery (2009 - 2012)
Population flooded (% of total)	-0.02	-0.13	0.20 **	0.03
	0.05	*0.13*	*0.09*	*0.27*
Kecamatan fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	No	Yes	Yes
SE	robust	robust	robust	robust
Observation	3312	276	1104	1104
R squared	0.08	0.34	0.18	0.36

Notes: Standard errors are in italics. *, **, *** mean significance at the ten, five, and one percent level, respectively.

Table 2.4: The effect of Tsunami intensity (as measured by area flooded) on night-lights over the different phases of the Tsunami, sub-district level

	Pre-Tsunami (1999 - 2004)	Aftermath (2005)	Recovery (2006 - 2008)	Post recovery (2009 - 2012)
Area flooded (% of total)	-2.07	-9.88	22.48 ***	1.42
	6.12	*12.43*	*9.00*	*24.88*
Kecamatan fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	No	Yes	Yes
SE	robust	robust	robust	robust
Observation	3312	276	1104	1104
R squared	0.08	0.34	0.18	0.36

Notes: Standard errors are in italics. *, **, *** mean significance at the ten, five, and one percent level, respectively.

[25] The interpretation of the magnitude of the coefficients in this estimation is not straightforward. For every 1 percent more of the Kecamatans' population flooded the luminosity increased by 0.20 DN and for every 1 percent of area more flooded, it increased by 22.5DN. Transforming the night-lights series so that it would ease the interpretation such as log-transforming the values brings about a host of undesirable problems of the transformed value distribution. For starters, all the pixels that were dark, with a DN value of 0, would have disappeared from the analysis since the log of zero is not defined. The log(0.001 + DN) transformation suggested by Michalopoulos & Papaioannou (2011) produces a multimodal distribution which also comes with a host of problems. In light of these issues, I opted to rather have a harder interpretation than a functional transformation of the series that creates problems, particularly since these results act more as robustness checks complementary to the district level GDP results, which have a straightforward interpretation.

The negative coefficient in the post recovery period suggested by the human cost estimation in table 2.3 and table 2.4 disappear, and the sign even becomes positive (albeit not statistically significant).

The changes in night-lights before the Tsunami struck, from 1999-2004 are very similar across all Tsunami deciles, suggesting parallel historic paths. There are no signs indicating a selection bias. Looking at figure A2.11 clearly depicts how regardless of the flooding intensity the respective Kecamatans, before the Tsunami struck, grew relatively at the same rates. Looking furthermore at the changes in night-lights intensity in the years after the Tsunami struck; see figure A2.13 suggests a substantially larger increase in luminosity the more the sub-district has been flooded. Comparing only the means suggests that the asymmetric luminosity increases stop after 2009 (see figure A2.14).

Step 2: Estimating the dose-response function. From the results emerging from implementing equation (4) I conclude that the Tsunami treatment is affecting economic growth mostly during the recovery phase. Going beyond a mere comparison means, I implement again a difference-in-differences method, allowing me to control for omitted variables.

To investigate the dose-response relationship, and with it *ATET(DOSE)*, i.e. which Tsunami intensity causes which luminosity responses and how these responses compare to one-another, I implement a regression approach where I run the dose-response function (DRF) separately for each quartile of the flooding intensity distribution. I do so looking only at the recovery years (*rec*), which are 2006, 2007 and 2008. The type of DRF I estimate relates the intensity of Tsunami flooding (*DOSE*) to economic (lighting) activities (*Y*) and allows the districts to react heterogeneously to different levels of Tsunami flooding exposure. Instead of exploiting variations across time as in the previous section, I home in on the recovery period only and focus on variations of the treatment intensity instead, which I model as quartiles (q) of the flooding intensity (dose):

$$\ln\left(Y_{i,t,rec}\right) - \ln\left(Y_{i,t-1,rec}\right) = \alpha + \delta_q \sum_{q=1}^{4}[DOSE] * D_{i,rec} + d_{t,rec} + \gamma_{i,rec} + \varepsilon_{it,rec} \qquad (5)$$

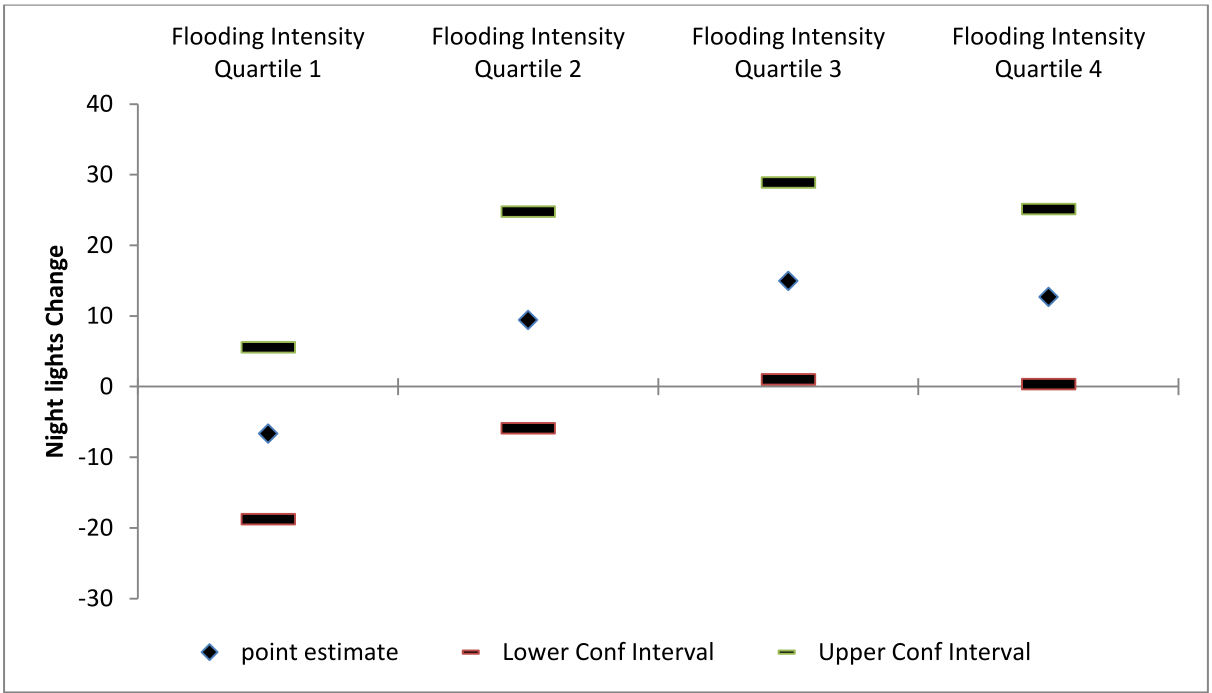
In implementing equation (5) I run separate regressions for each quartile. Here the average treatment effect on the treated districts, $ATET(DOSE) = \ln\left(Y_{i,t,rec}\right) - \ln\left(Y_{i,t-1,rec}\right)$. The doses of flooding administered in this natural experiment correspond to how much of the Kecamatan was flooded (as both measured by the area and the population). Regardless of the flooding intensity to be observed in the wake of the Tsunami, the districts grew roughly at the same rate.

For the population measure, the first quartile (< 25%) corresponds to a share of the Kecamatan population flooded between 1 and 9 percent; the second quartile (25-50%) corresponds to 10 – 20 percent of the population flooded; the third quartile (50-75%) corresponds to 24 – 48 percent flooded and the fourth quartile (75-100%) corresponds to 52 – 100 percent of the population flooded. For the areas flooded, the four quartiles correspond to 1-4 percent, 4-14 percent, 14-39, and 40-100 percent flooded. The reason for picking quartiles instead of other ways to categorize the continuous flooding intensity measure is that they guarantee the statistical power in obtaining the point estimate of the dosage-responses is comparable across the different doses. The counterfactual group, to which the different doses are compared to, comprises the Kecamatans that were not flooded at all (represented by the entire group represented by the zero spike in figure 2.16).

Implementing a more conventional DRF such as the one proposed by Hirano & Imbens (2004) and implemented by Bia & Mattei (2008), is not an option in my case, because the assumptions of this original model do not fit my data very well. The flooding intensity data do not meet the necessary normality assumption and they have a lot of zero-level treatment cases (cases in which there is no flooding, as seen in figure 2.16). Treatment intensity is definitely not normally distributed, and clearly discontinuous as shown by a spike at zero of this distribution.

Scrutinizing the functional form of the flood intensity causal relations to luminosity shows that limited flooding has no significant effect on light emanating activity (see figures 2.17 and figure 2.18). The onset of positive effects associated with disaster destruction start to show at quartile 2 of Tsunami destruction levels, and become statistically significant and sizeable above median levels of destruction (for quartile 3 and quartile 4). Figure 2.17 and figure 2.18 depict the average increase in DN of light per Kecamatan, within the respective flood intensity quartile, relative to the non-flooded counterfactual. It shows that heavily flooded sub-districts (24-100 percent of the area flooded, which corresponds to the third and fourth quartile) gain about 15 DN per annum, or 13 percent of luminosity.[26] Lower flooding intensity levels (quartile 1 and quartile 2) did not cause a significant increase in economic activity (as indicated by the insignificant coefficients of regressions using quartile 1 and 2).

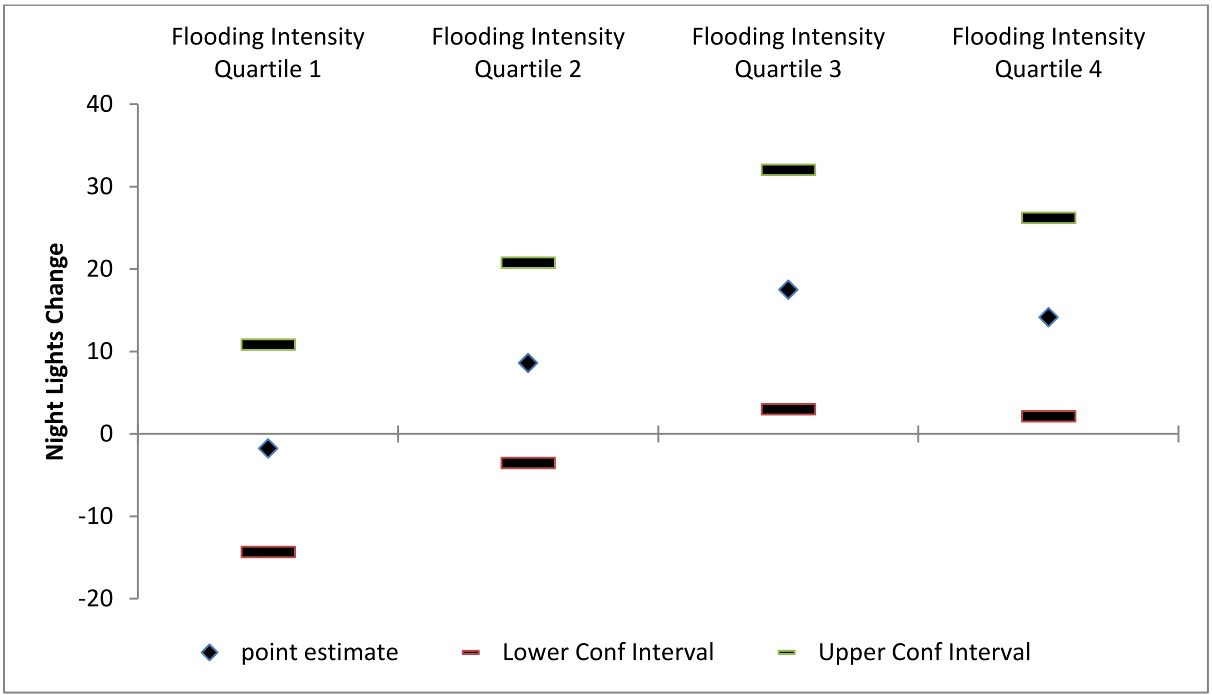
Figure 2.17: Night-light responses to different levels of flooding intensity (percentage of the Kecamatan's population affected) in the recovery period



Notes: Night-lights changes refer to the annual changes in cumulative pixel brightness of the Kecamatan, as measured by Digital Number (DN). The coefficient measured depicts the difference between the treatment and the counterfactual group. Confidence interval plotted is at 95 percent.

[26] These 15 DN in changes may either refer to an already lid pixel that is getting brighter, or a formerly dark pixel that has been "switched on." It is a net measure, meaning that as the sum of a number of pixels, it takes into account pixels within the Kecamatan that have become darker also. The 15 DN are thus the sum of increases in luminosity minus the sum of decreases in luminosity.

Figure 2.18: Night-light responses to different levels of flooding intensity (percentage of the Kecamatan area that was flooded by the Tsunami)



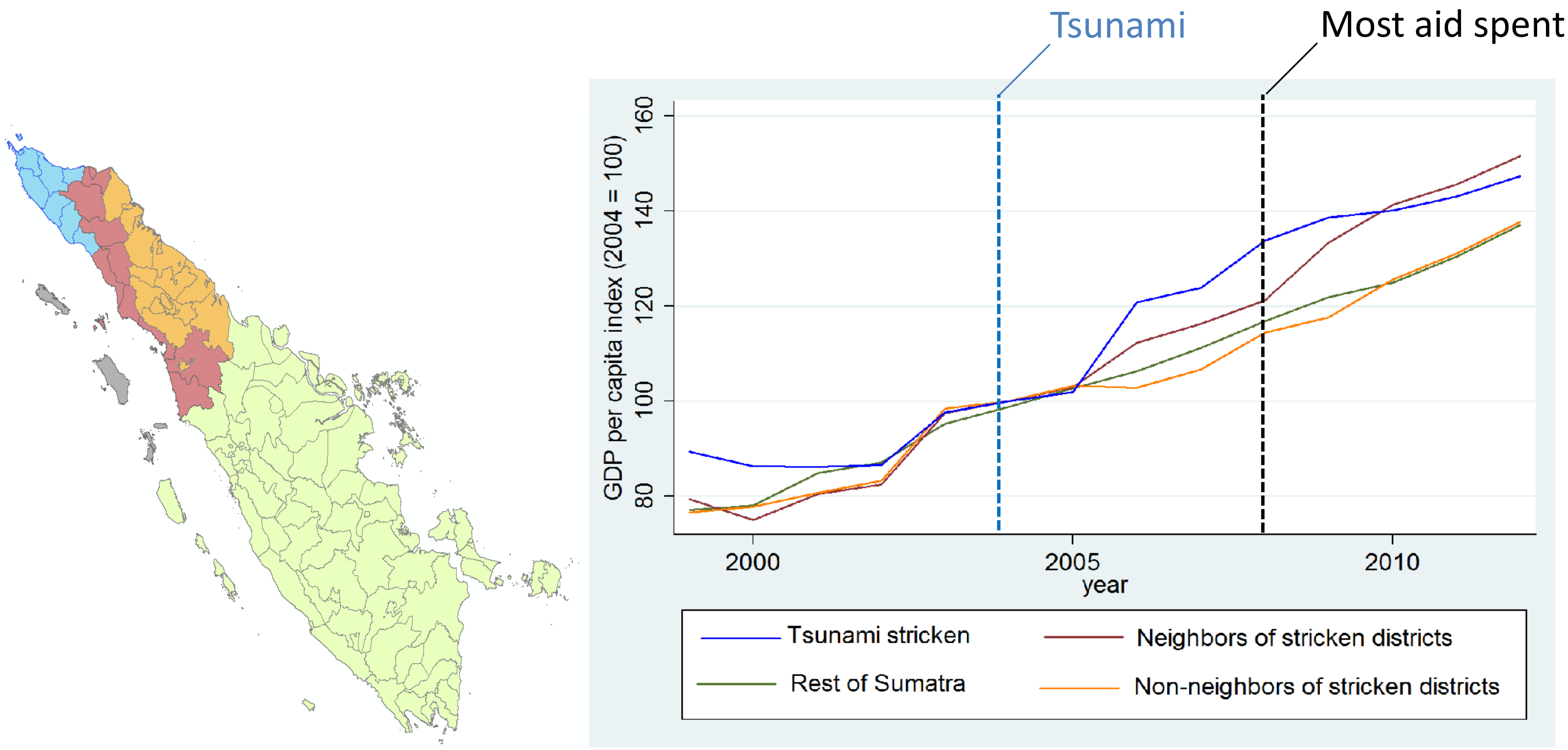
Note: Same as note of Figure 2.17.

Creative destruction is dependent on the level of destruction. Only severely flooded Kecamatans displayed stronger growth performances. Whether this is due to the focus of the international community on reconstruction the most heavily damaged areas, or whether it is because it was easier to rebuild once the infrastructure has been completely levelled, instead of some ruins remaining, is an interesting avenue for future research.

2.7.4 Creative destruction spillovers

There are many channels through which the Tsunami could have also indirectly affected neighbouring districts. Labour markets in surrounding districts may have been affected in the sense that there may have occurred some labour migration towards the flooded areas in the reconstruction effort, which could have registered as a negative economic event for the adjacent district. By the same token, there could have also been stimulating spillovers, because a not flooded business from neighbouring districts may have stood to benefit from increased demands for reconstruction. Because the natural experiment was not a closed system experiment, people could have freely moved out of the affected areas to neighbouring districts and vice versa, with the estimated coefficient depending on the relative strength of each of these diametrical factors. If there were indeed such spillovers, I assume that they should be stronger the closer the district is to the flooded district. The hypothesis is that the neighbouring districts' growth rate has also been causally spurred by the Tsunami, while those that are not bordering are unaffected. I therefore create an indirect treatment district pool of neighbouring districts (red districts in figure 2.19), which I hypothesize should have also been stimulated if there were indeed spillovers, and a district pool of non-neighbouring districts (yellow districts) that I use my counterfactual sample along with the rest of Sumatra (green districts) counterfactual.

Figure 2.19: Spillovers? GDP evolution in Tsunami stricken districts compared with not stricken counterfactuals



Note: Blue districts (n=10) are those within which territories were flooded by the Tsunami, excluding island districts. Red districts (n=29) are the neighbors of stricken districts and in this case the treated districts (treated with spillover effects). Green districts (n=77) depict non-Aceh counterfactuals from the Sumatra Island. The grey shaded area depicts North Sumatra, which only had island districts (2 districts out of 21) affected and is therefore excluded from this analysis. GDP measures are normalized at the year 2004. The vertical blue line indicates when the disaster struck and the vertical black line depicts when more than 96 percent of aid stopped.

Even though the simple graphical analysis, plotting only the means, suggested that there may be positive spillover effects onto the immediate neighbouring districts (red districts), these growth spurring effects are not statistically significant in the econometric analysis (see table 2.5). The direct neighbouring districts to the flooded districts grew in no year statistically significantly faster than their counterfactual districts that are not directly neighbouring the flooded districts. The absence of statistically significant effects justifies a rejection of the hypothesis that claimed that spillover effects have occurred.

Table 2.5: Spillover regression analysis

Treated group:	Direct neigbor districts (red) to flooded district	Direct neighbor districts (red) to flooded district
Control group:	Non-Aceh & non- N. Sumatra districts (green)	Non-neigbor districts (orange)
Dependent Variable:	GDP per capita growth rate	
Tsunami_05	-0.014	0.001
	(0.016)	(0.020)
Tsunami_06	0.026	0.091
	(0.087)	(0.055)
Tsunami_07	-0.015	0.002
	(0.015)	(0.019)
Tsunami_08	-0.011	-0.045
	(0.015)	(0.068)
Tsunami_09	0.066	0.088
	(0.089)	(0.091)
Tsunami_10	0.033	0.001
	(0.021)	(0.026)
Tsunami_11	-0.016	-0.008
	(0.012)	(0.018)
Tsunami_12	-0.014	-0.004
	(0.017)	(0.020)
Year FE	Yes	Yes
District FE	Yes	Yes
SE	Spatial HAC	Spatial HAC
Observations	1235	364
R-sqr	0.24	0.26

Notes: Standard errors are in parentheses. *, **, *** mean significance at the ten, five, and one percent level, respectively.

2.7.5 Scale matters: Lost in aggregation

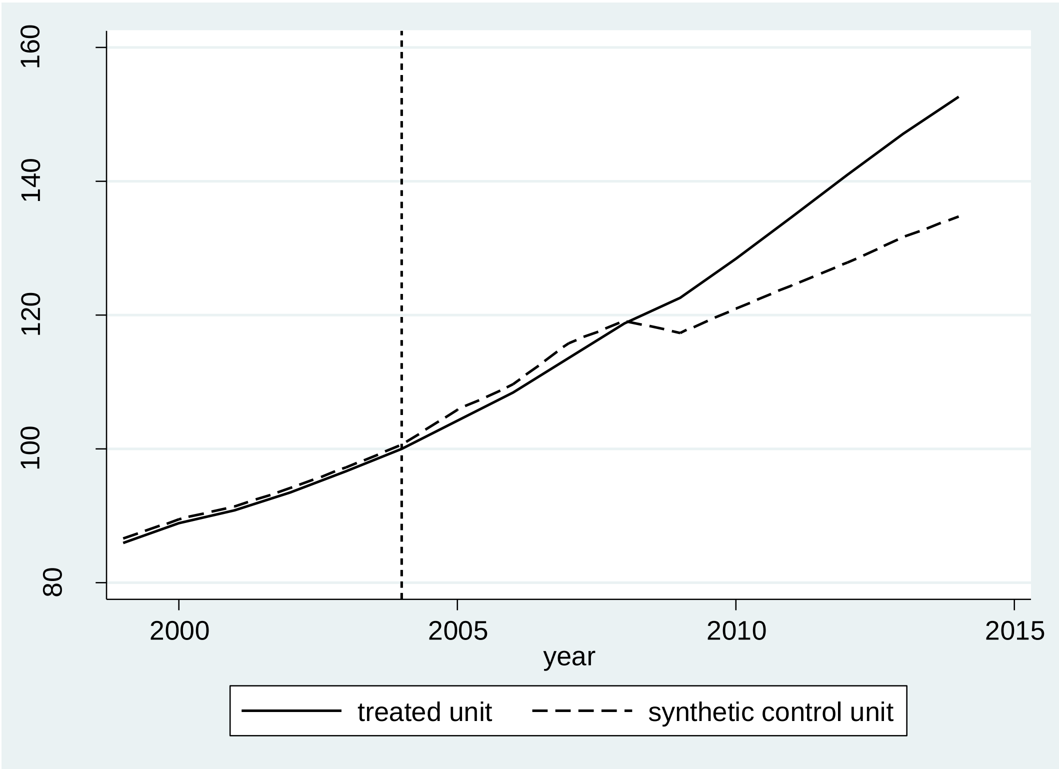
Aggregate figures hide. Carrying out the economic impact analysis using the same method on a country level (and island level) shows how the creative destruction effects disappear. Carrying out the same synthetic control method as done for district level GDP data in this chapter and province level data in chapter 3 of this PhD thesis, which both find creative destruction, illustrates this point quite clearly. Despite the significant divergence in growth paths between the treated and the non-treated (Aceh and synthetic Aceh), when aggregating the economic data up to the country level, even the island level, as most of the other studies investigating the link between disaster shocks and economic growth do, the effects are no longer detectable.

I use countries as the units of analysis, as was done in most natural disasters economics papers (see map 2.8). As an impact measure, I use the national level GDP per capita value reported by the World Bank World Development Indicators (WDI). Carrying out the same specification for the synthetic control method as in section 2.7.2.4 shows that the aggregation results in the creative destruction effect result to be 'lost in aggregation'. Figure 2.20 shows how there is no notable difference in the treatment group and the counterfactual group for the first couple of years after the Tsunami. In 2008, however the counterfactual group seems to have slowed down substantially, unlike Indonesia, which kept growing at a steady rate. The reason for this divergence in 2008 has nothing to do with the Indian Ocean Tsunami, rather with the fact that Indonesia was not adversely affected by the financial crisis of 2008. For a detailed examination of why Indonesia was resilient to the 2008/09 crisis see Tambunan (2010).

Map 2.8: Tsunami stricken country of Indonesia versus countries of the rest of the world

Note: Sri Lanka, India, Thailand and Malaysia were excluded as they were also significantly affected ("treated") by the Tsunami.

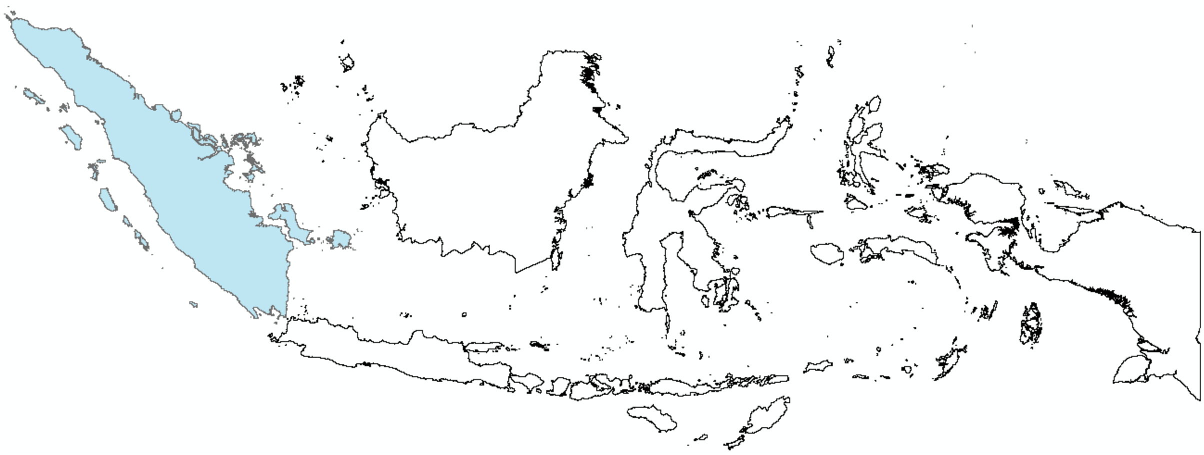
Figure 2.20: GDP per capita of Indonesia versus other countries: National level analysis: Indonesia versus other countries



This “non-finding” suggests that had I done the analysis for the national level instead of the local level, as is the focus of my PhD thesis, I would have just as most other natural disaster economics studies found that the shock did not significantly change the pre-Tsunami growth trajectory. I also reproduce the tried and tested synthetic control method again on the island level.

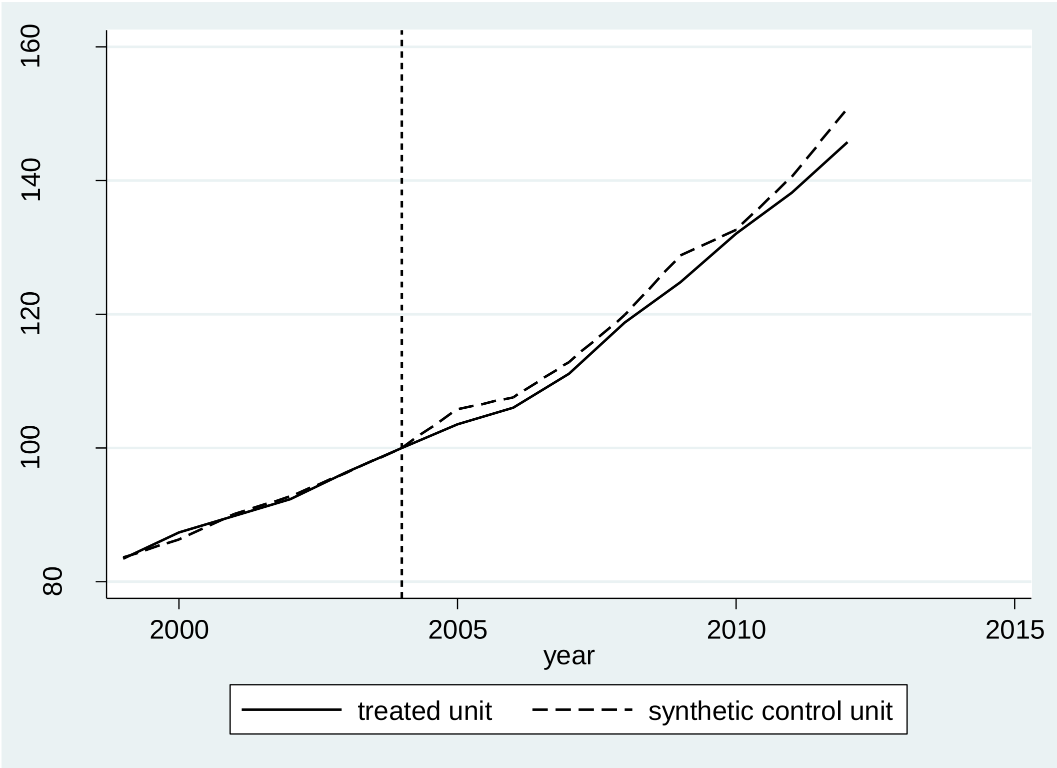
Sumatra versus the rest of Indonesia (see map 2.9). I aggregated the province level GDP data up from the INDO-DAPOER to create island based GDP levels. Comparing Sumatra to the rest of the Indonesian islands, guarantees that I have the same universe as in the district and province level analysis, and that I chose the same datasets, only that I aggregated it to another level. In consisting of 6 islands, I am left with one treated island, the island of Sumatra versus five islands for the donor poll for establishing the counterfactual, which are: Jawa & Bali, Kalimantan, Nusa Tenggara, Papua, and Sulawesi.

Map 2.9: Tsunami stricken island of Sumatra versus 5 counterfactual islands



Carrying out the same synthetic control method specification, reveals that the creative destruction effects disappear when aggregating up to the island level (see figure 2.21). The treated unit and control groups (synthetic control unit) do not differ significantly. The reason why aggregation is likely the culprit for different results is that alternative explanations were ruled out in using the same underlying data and scale. Furthermore, there were no significant spillover effects found in the previous chapter, which may have explained the absence of a significant difference on the island level.

Figure 2.21: GDP per capita of Sumatra versus other islands



Note: Treated unit corresponds to Sumatra Island, and the synthetic control unit is a convex linear combination of the five control islands: Jawa & Bali, Kalimantan, Nusa Tenggara, Papua, and Sulawesi.

Obtaining insignificant differences using coarser data is not only a powerful illustration of the MAUP, but beyond that, the finding also suggests that too coarse data lead to imprecise (possibly even incorrect) findings and conclusions. For example the conclusion that one would have drawn from the above graph, in absence of finer grained information, is that the Tsunami had no discernible impact on economic output, whatsoever. The fact that the costliest natural disaster in the developing world is not picked up in island level analysis, let alone national level analysis casts a shadow of doubt over the results emerging from national level panel regression results.

The missing effect on the national level can, in part be explained because Aceh accounts only for 2 percent of Indonesia's economic growth, and that it is one province out of 34 in the entire country. While the direct impact of the Tsunami on the national GDP growth rate were estimated to result in a reduction of 0.1-0.4 percentage points in 2005, when offsetting activities are taken into account, the net economic impact of the Tsunami nationwide was likely to be close to zero (World Bank, 2006). It was suggested that a main reason for why we find to significant result on the nation level is that the reconstruction activities in rebuilding destroyed infrastructure, played also a major role in the non-finding. I dig deeper into sectoral idiosyncrasies in recovering from the Tsunami, in chapter 3.

In summary of the scale analysis, I find confirmation of what most other studies (e.g. Cavallo et al, 2013 who also applied the synthetic control method) found by looking at the national level only, which is that there are no discernible effects of natural disasters on economic activity, not even in the short run. Nevertheless, I also find that there are substantial localized effects, which paint a picture of creative destruction. I conclude from this scale comparison, that the effects go beyond what it seems at the outset and that most important dynamics happen on the local scale. Similar to hurricane Katrina, which was devastating at the regional level, but barely made a dent for national economic activity, the Indian Ocean Tsunami also did not make a dent traceable in Indonesia's national GDP.

My findings suggest an aggregation bias. They furthermore suggest that a local scale is a more appropriate level to investigate the effects of natural disasters. Perhaps the nation level is an appropriate unit of analysis for investigating the impacts of natural disasters for Caribbean islands (see e.g. Heger et al, 2009) and other smaller nation states. But for a larger country, where even a catastrophic natural disaster killing more than 200,000 people and causing damages well beyond 8 Billion USD, creates too little of a "splash" with 0.02 percent of national GDP lost and the same amount (0.02 percent) of the national population killed, in aggregate national statistics. If a natural disaster leaves the largest part of a country untouched, it is probably a prudent choice for a researcher to switch to a finer grained unit of analysis.

2.8 Conclusion

In this chapter, I showed that the Indian Ocean Tsunami of 2004 was an act of creative destruction. It spurred economic growth and resulted in higher per capita economic output in the short- and long-term. I can therefore reject that natural disasters necessarily lead to reductions of economic output. Disasters can be windows of opportunity that trigger capital upgrading. Thus, whether or not a disaster depresses growth (as shown by most other research work) or whether it stimulates economic output, as was the case in Aceh and is shown in this chapter, is ultimately a human (political) choice.

The Tsunami was only marginally growth depressing in the first year following the disaster. During the subsequent recovery years, growth was boosted considerably by the reconstruction effort, fuelled by massive influxes of international aid and attention. The building back better of destroyed capital resulted in more economic output than would have occurred had the Tsunami not stricken. The built back better capital was used more productively in the post-recovery years, as evidenced by persistently higher per capita economic output. Economic output did not reduce with the aid funds drying up and the flooded districts remained on a higher per capita output path.

The more devastating the Tsunami "treatment", the more people and areas were flooded, the more the flooded district economies grew. Although all flooded districts recovered, those that were most heavily flooded also grew the most. Districts that were moderately flooded only recovered to the counterfactual level, while districts that were heavily flooded not only recovered but also significantly exceeded counterfactual output levels. This indicates that the development efforts were concentrated in the most destroyed areas, or that it was easier to rebuild where the Tsunami completely levelled the infrastructure (by performing the service of destroying out-dated capital).

Regardless of socio-demographic and geographic characteristics, all affected districts recovered. Urban districts, rural districts, island districts, inland districts, and Banda Aceh; all displayed creative destruction. There was some heterogeneity with respect to the level of recovery however. Urban districts (Kotas) for example grew substantially in the immediate Tsunami aftermath, and then eventually displayed a similar growth rate compared to the counterfactual (even though displaying a persistently higher per capita output). Rural districts (Kabupatens) in turn grew steadily and displayed significantly larger growth rates even beyond 2009. Island districts recovered much slower and to a much smaller degree than mainland districts.

I show that it is necessary to choose an appropriately fine-grained level of analysis for a disaster-growth impact evaluation. The devil, in my case the identification of significant effects, is in the details. I obtain significant results suggesting causally growth-promoting effects of Tsunami destruction with district and sub-district (Kecamatan) data. Applying the same causal inference methods to coarser geographical areas, i.e. island level and country level, shows no significant effects.

Regardless of which level of localized aggregation (district and sub-district), which regression specification, which outcome measure, which treatment measure, and which sample I selected, the creative destruction result was robust, suggesting that it can be accepted with a very high degree of certainty. Natural disasters need not necessarily depress the economy. The creative destruction case in Aceh in this chapter shows that even one of the most devastating natural disasters can be a window of opportunity and result in a permanently higher level of economic output.

The creative destruction finding in Aceh is not generalizable to other historic natural disaster cases. Finding externally valid disaster-growth elasticities was never the intention of this chapter. Rather, the intention was to show that the generality of growth-depressing disaster effects need not hold, and that the effects are dependent on other factors. Unprecedented amounts of aid and the largest reconstruction effort the developing world has ever seen caused a growth-stimulating creative destruction episode, which permanently increased output per capita. This result suggests that a natural disaster can be a window of opportunity and whether or not it turns into an economic disaster is ultimately a question of the decisions the international community and the national government take. The next chapter will analyse in more detail the causal mechanisms by which creation destruction took place.

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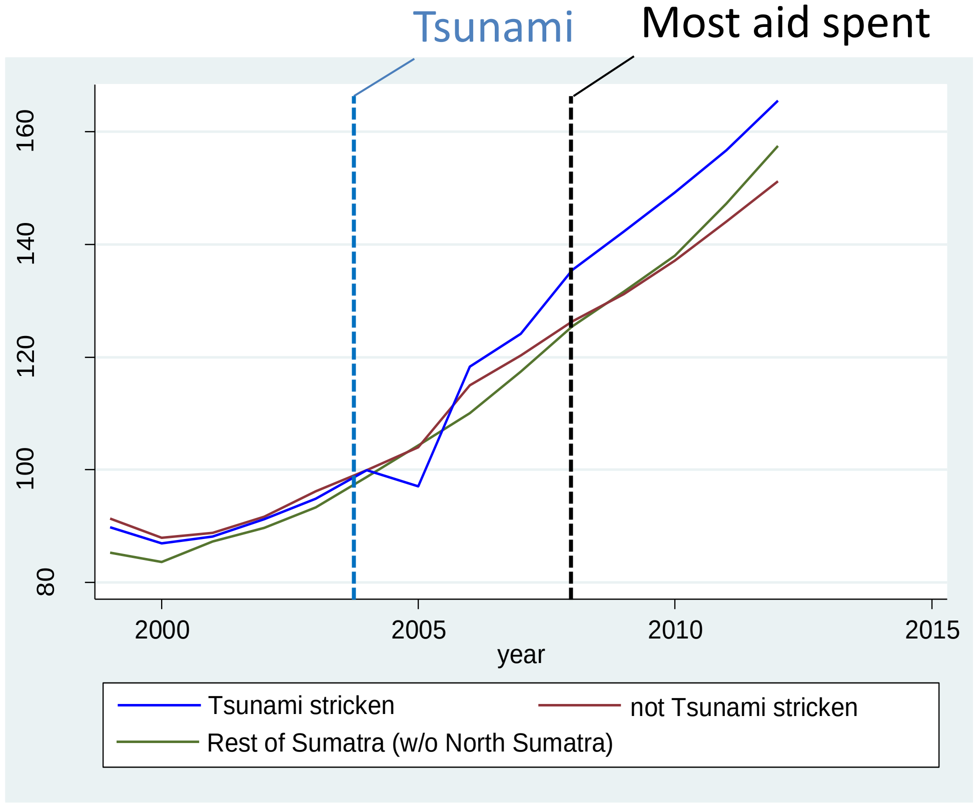
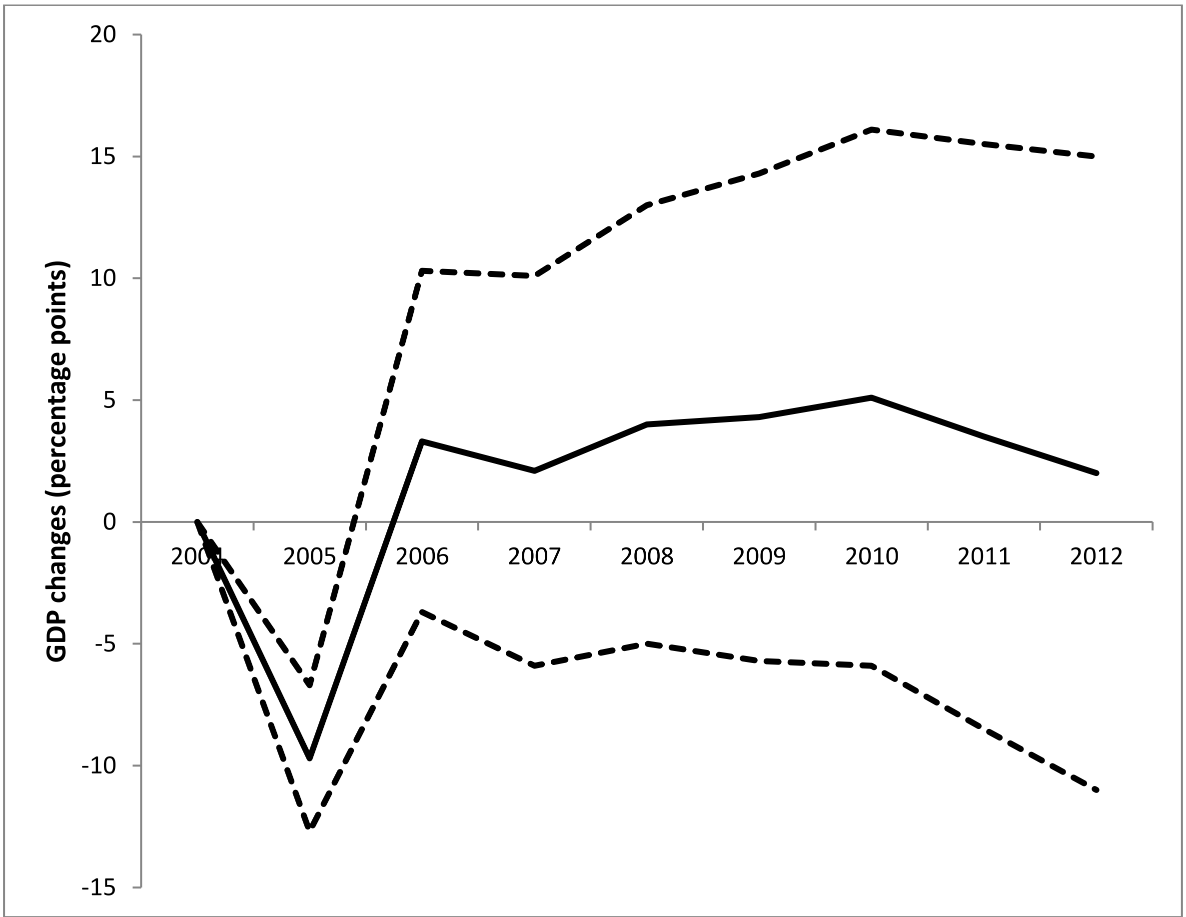
Appendix

Figure A2.1: Parallel paths before the Tsunami: GDP evolution in Aceh's Tsunami stricken districts compared with not stricken counterfactuals



Note: Blue districts (n=10) are those within which territories were flooded by the Tsunami. Red districts (n=23) are counterfactuals within Aceh. Green districts (n=72) depict non-Aceh counterfactuals from the Sumatra Island. The grey shaded area depicts North Sumatra, which only had island districts (2 districts out of 21) affected and is therefore excluded from this analysis. GDP measures are normalized at the year 2004. The vertical blue line indicates when the disaster struck and the vertical black line depicts when more than 98 percent of aid stopped.

Figure A2.2: Impulse responses: Cumulative effect of the Tsunami on GDP growth rates



Note: The dashed lines above represent one Standard Error bands. Plotted here is the comparison of the treated group with the two counterfactuals (red & green districts) combined. The SEs depicted are robust to spatial and serial autocorrelation and are corrected for heteroscedasticity.

Table A2.1: Aceh's Tsunami-output causality panel regressions, 1999 – 2012

Treated group:	Tsunami affected districts (blue) in Aceh			
Control group:	Sumatra control districts (red & green)		Non-Aceh districts (green)	Aceh non-flooded control districts (red)
Dependent Variable: GDP per capita				
Tsunami (average year)	16.027			
	(12.290)			
Tsunami_05		-4.864	-5.207	-3.898
		(11.470)	-(12.270)	-(8.640)
Tsunami_06		59.989 **	61.871 **	48.751 *
		(19.540)	(19.500)	(22.550)
Tsunami_07		6.967	5.612	8.273
		(13.320)	(13.970)	(9.480)
Tsunami_08		36.327 ***	35.618 ***	34.662 ***
		(4.680)	(7.090)	(.)
Tsunami_09		22.286 **	19.765 *	28.569 ***
		(7.950)	(9.250)	(1.380)
Tsunami_10		10.21 *	9.553	4.943
		(12.350)	(12.920)	-(11.330)
Tsunami_11		9.471	6.778	17.312
		(7.500)	(8.850)	(.)
Tsunami_12		4.009	0.932	14.7
		(9.020)	(10.050)	(.)
Year FE	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
SE	Spatial HAC	Spatial HAC	Spatial HAC	Spatial HAC
Observations	1287	1287	1118	299
R-sqr	0.24	0.25	0.24	0.34

Figure A2.3: Impulse responses: Cumulative effect of the Tsunami on GDP per capita

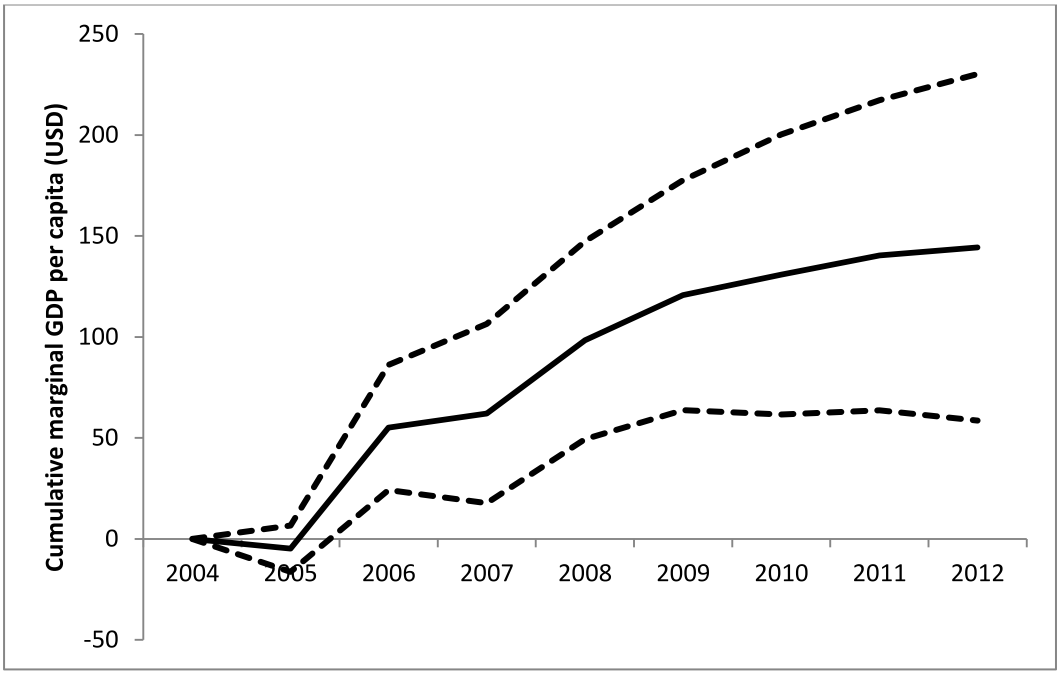
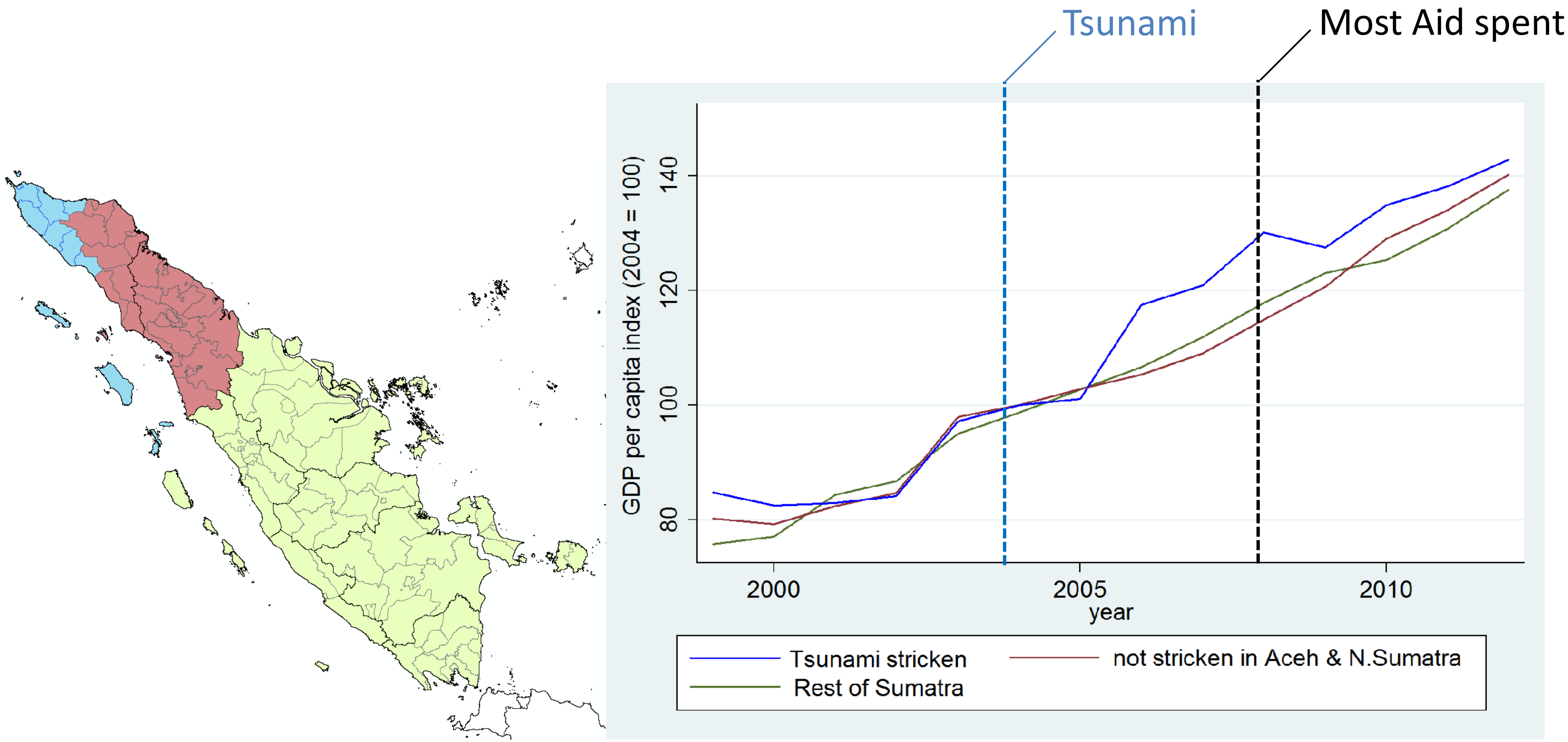
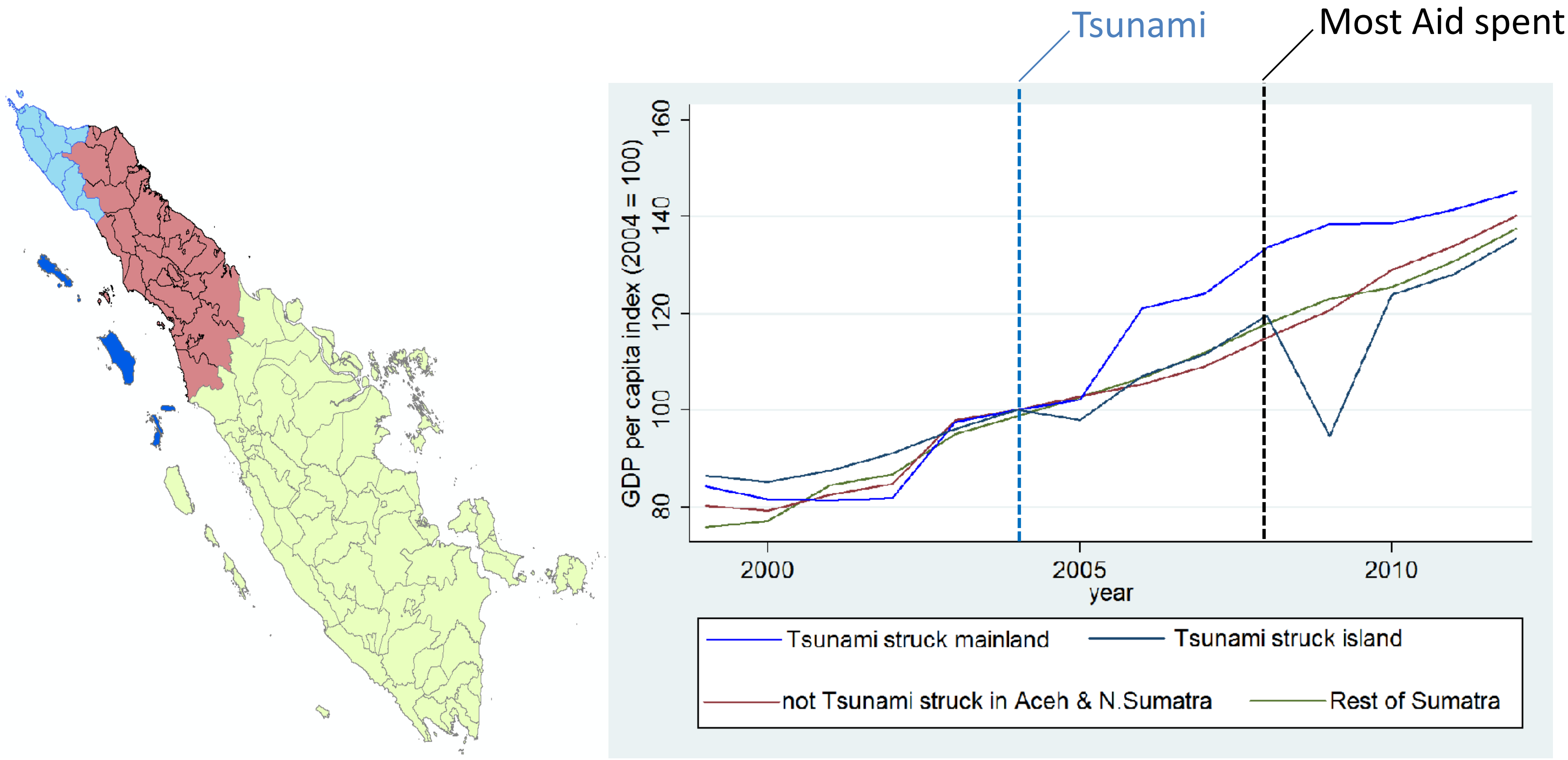


Figure A2.4: GDP per capita evolution in Tsunami stricken districts compared with not stricken counterfactuals



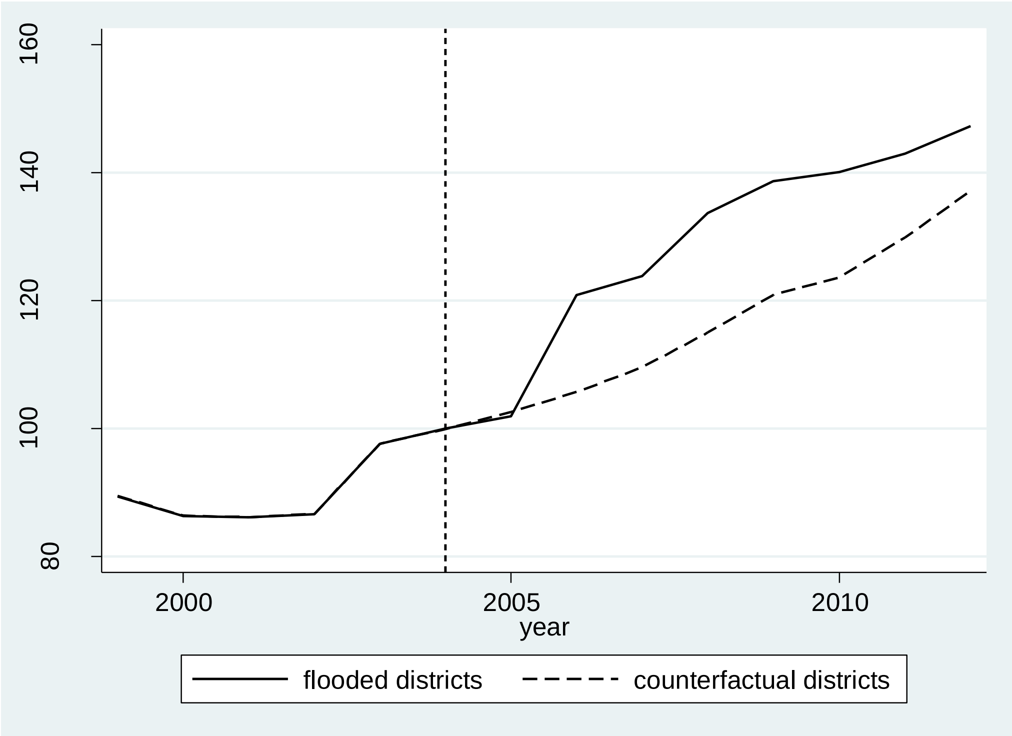
Note: Blue districts (n=12) are those within which territories were flooded by the Tsunami. Red districts (n=29) are counterfactuals within Aceh. Green districts (n=77) depict non-Aceh counterfactuals from the Sumatra Island. The grey shaded area depicts North Sumatra, which only had island districts (2 districts out of a total of 21) affected and is therefore excluded from this analysis. GDP measures are normalized at the year 2004. The vertical blue line indicates when the disaster struck and the vertical black line depicts when more than 98 percent of aid stopped. The Tsunami struck on December 26, 2004. Aid totalled 7.7 billion USD and was officially completed by the end of 2008 (Henderson & Lee, 2015 and Brookings, 2008).

Figure A2.5: GDP evolution in Tsunami stricken districts compared with not stricken counterfactuals



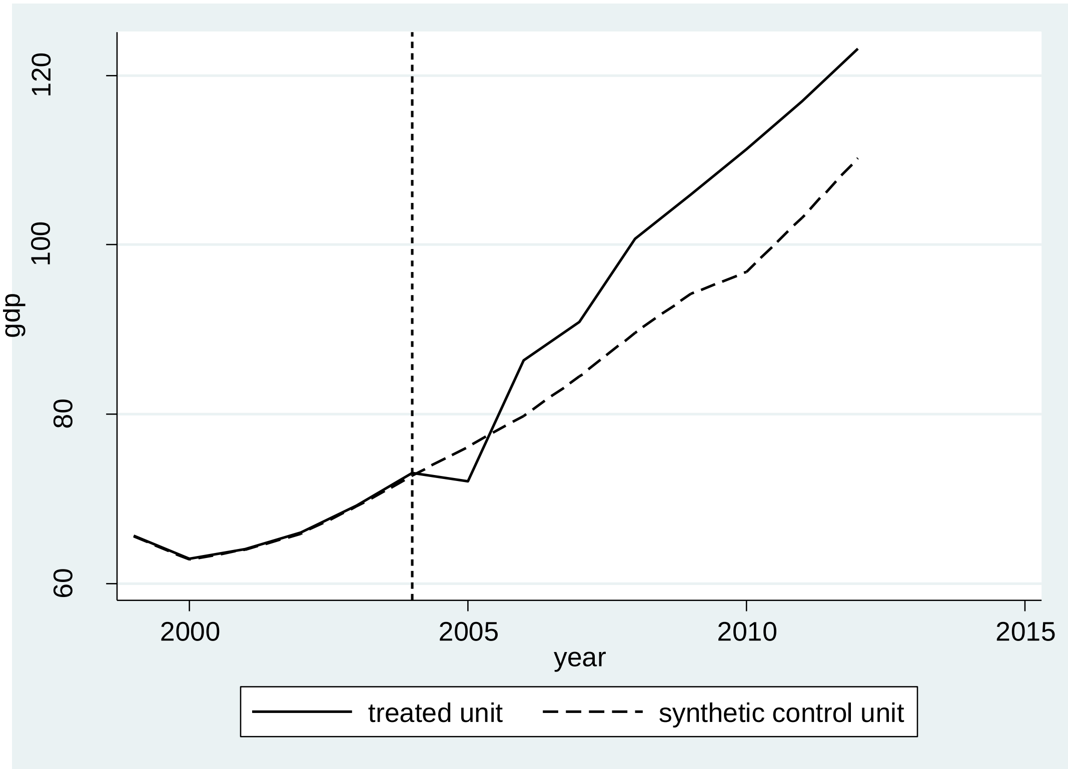
Note: Blue districts (n=12) are those within which territories were flooded by the Tsunami. Red districts (n=29) are counterfactuals within Aceh. Green districts (n=77) depict non-Aceh counterfactuals from the Sumatra Island. The grey shaded area depicts North Sumatra, which only had island districts (2 districts out of a total of 21) affected and is therefore excluded from this analysis. GDP measures are normalized at the year 2004. The vertical blue line indicates when the disaster struck and the vertical black line depicts when more than 98 percent of aid stopped. The Tsunami struck on December 26, 2004. Aid totalled 7.7 billion USD and was officially completed by the end of 2008 (Henderson & Lee, 2015 and Brookings, 2008)

Figure A2.6: GDP per capita trend: Tsunami stricken Aceh districts (red) versus synthetic Aceh districts



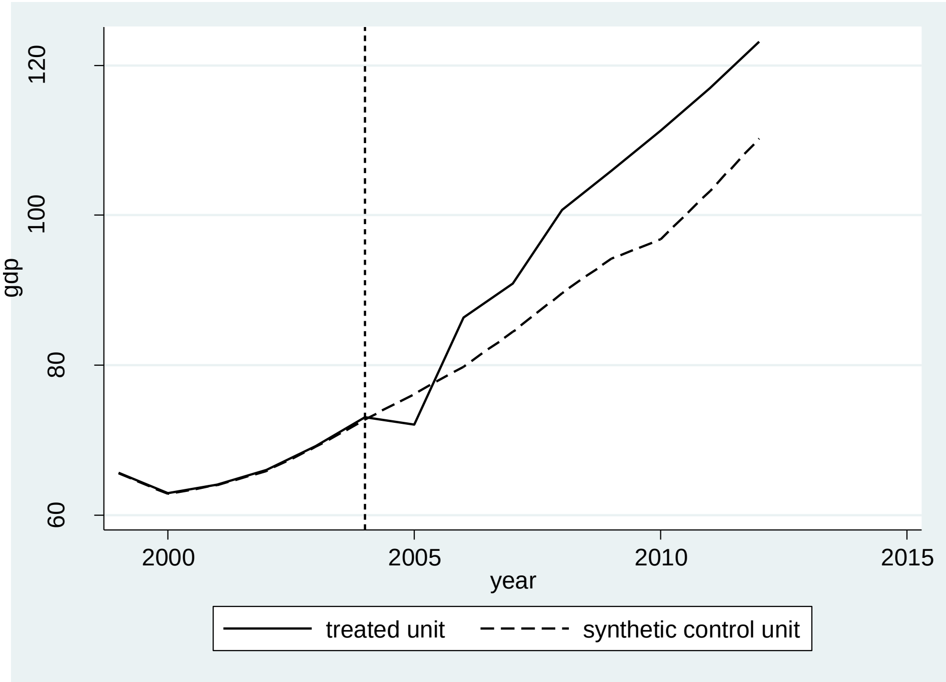
Note: Average GDP of 10 affected districts versus 60 not flooded comparator districts in rest of Sumatra.

Figure A2.7: Trends in district average GDP: Aceh versus Synthetic Aceh



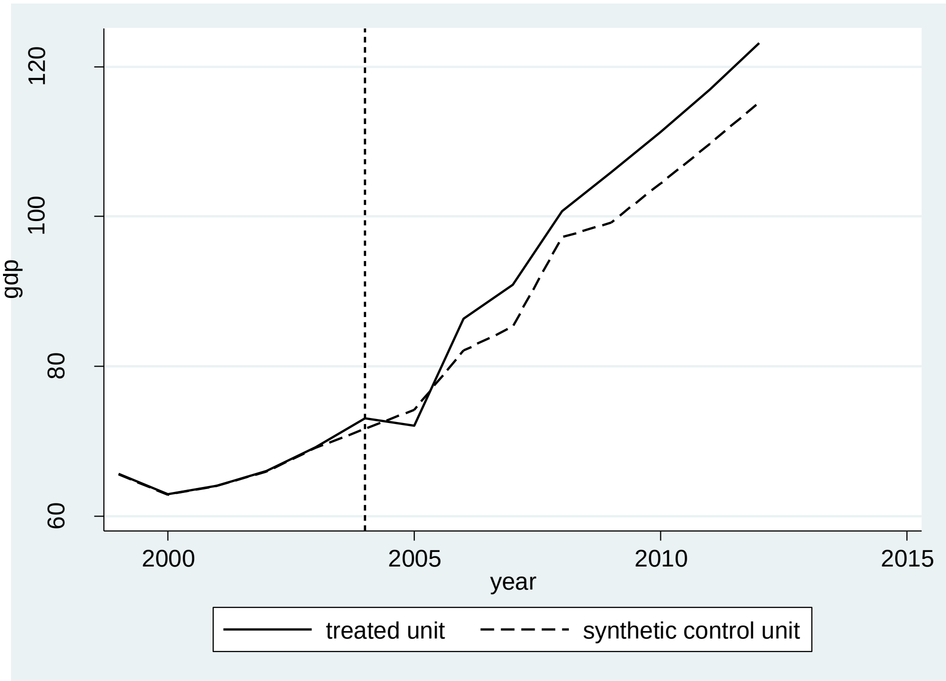
Note: Average GDP of 10 affected districts versus 72 comparator districts outside of Aceh.

Figure A2.8: Tsunami stricken districts in Aceh versus synthetic Aceh districts



Note: Average GDP of 10 affected districts versus 60 not flooded comparator districts in rest of Sumatra.

Figure A2.9: Tsunami stricken Aceh districts versus synthetic Aceh districts



Note: Average GDP of 10 affected districts versus 12 not flooded comparator districts in Aceh.

Figure A2.10: GDP per capita gap in Tsunami stricken districts and placebo gaps in other 72 non-stricken districts

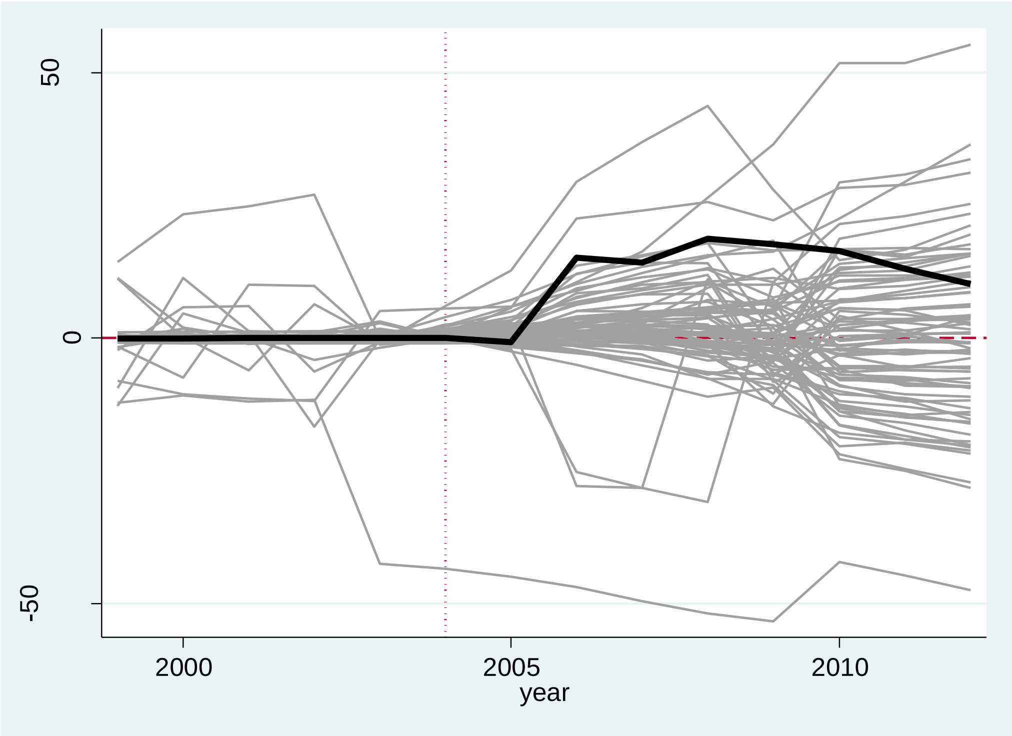
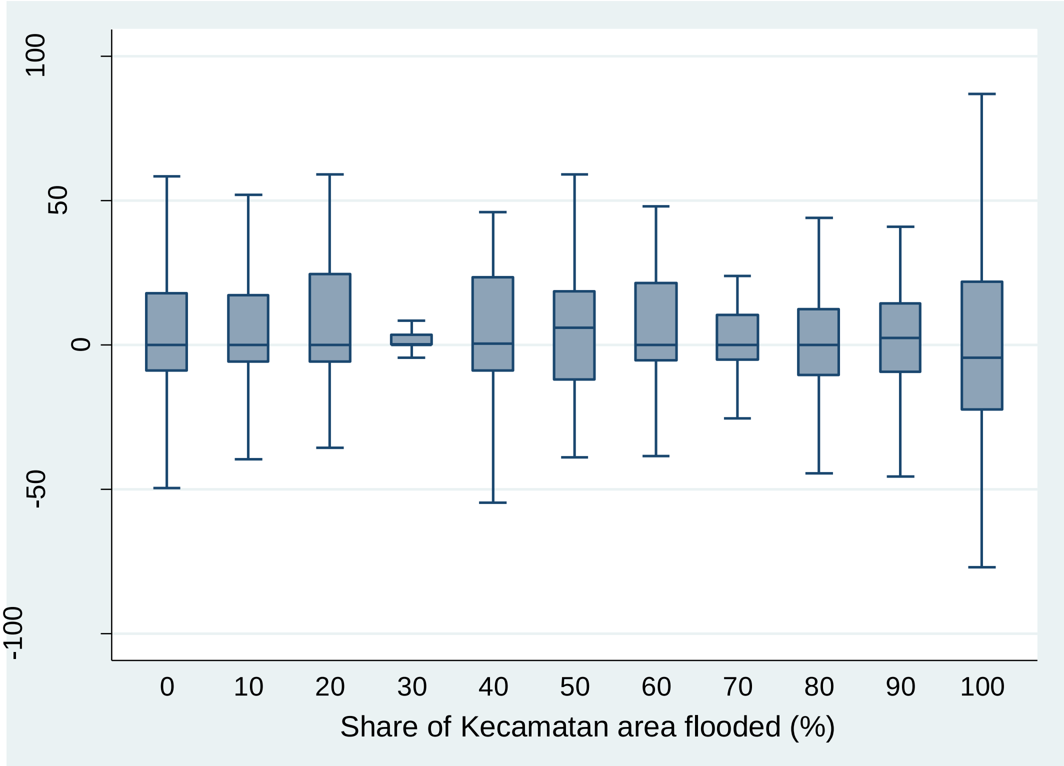
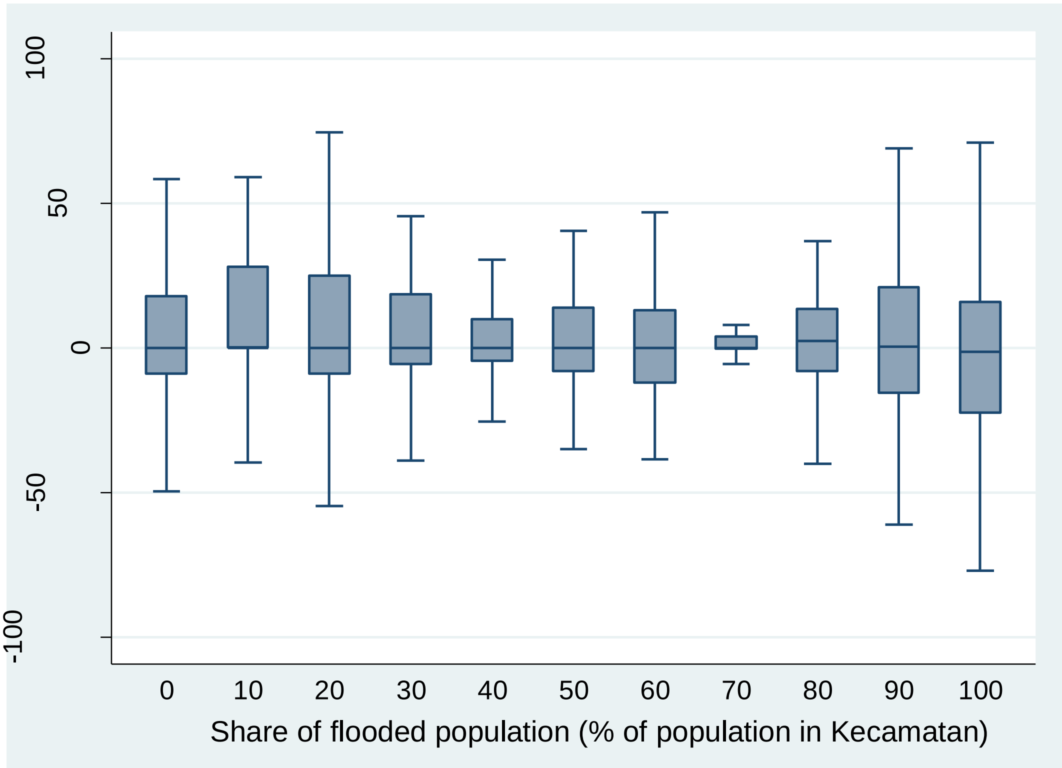


Figure A2.11 – Before the Tsunami (1999 – 2004): Light intensity does not respond to Flood Intensity

Panel A: Area flooded:



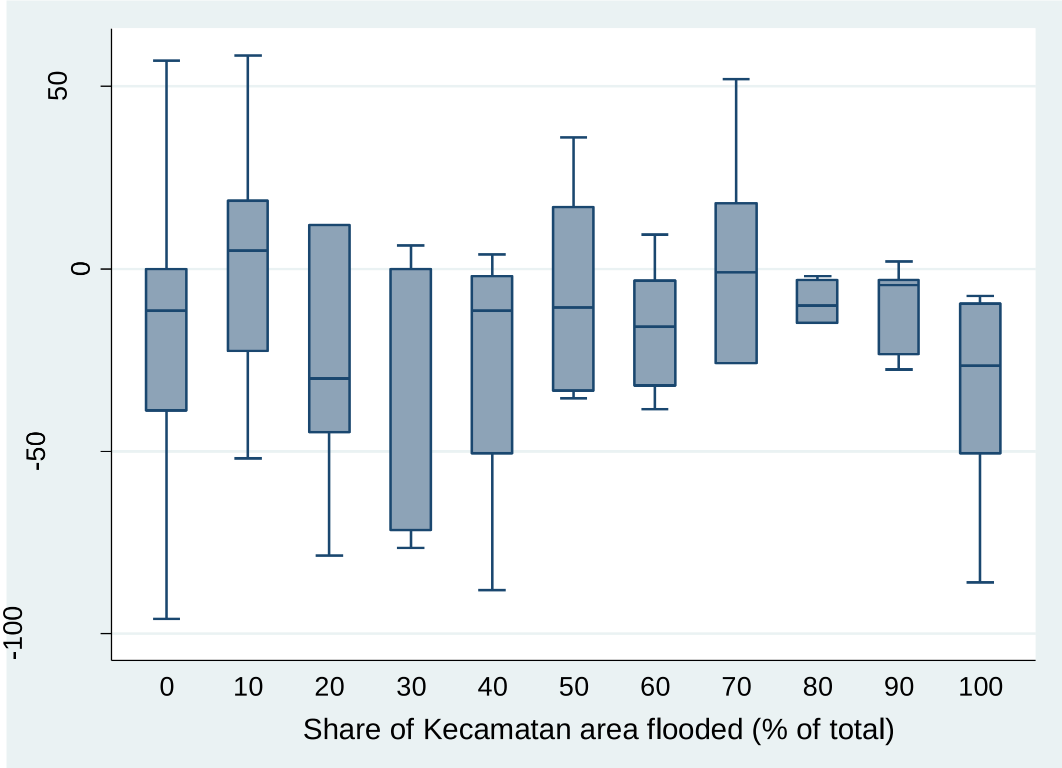
Panel B: Population flooded:



Note: Light Intensity is measured as the cumulative total of the light intensity of all pixels within the Kecamatan. The annual changes are the differences between these total luminosity in period t minus period t-1.

Figure A2.12 – Immediate aftermath of the Tsunami (2005): Light intensity reacts to different levels of Flood Intensity

Panel A: Area Flooded



Panel B: Population flooded

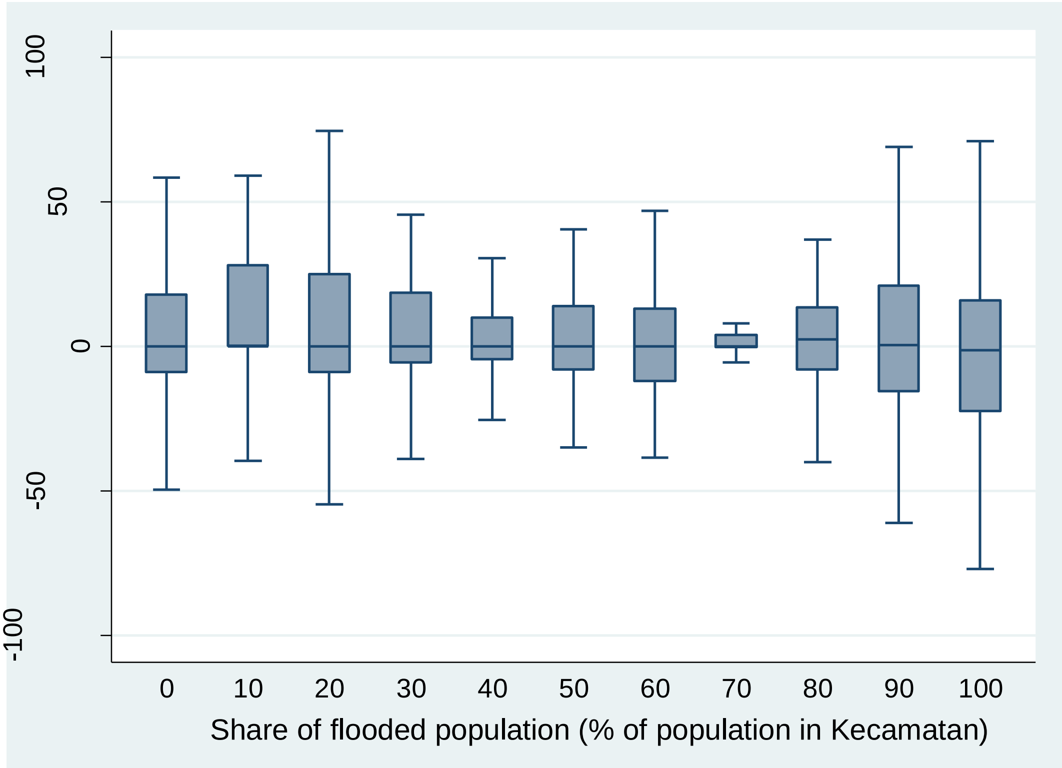
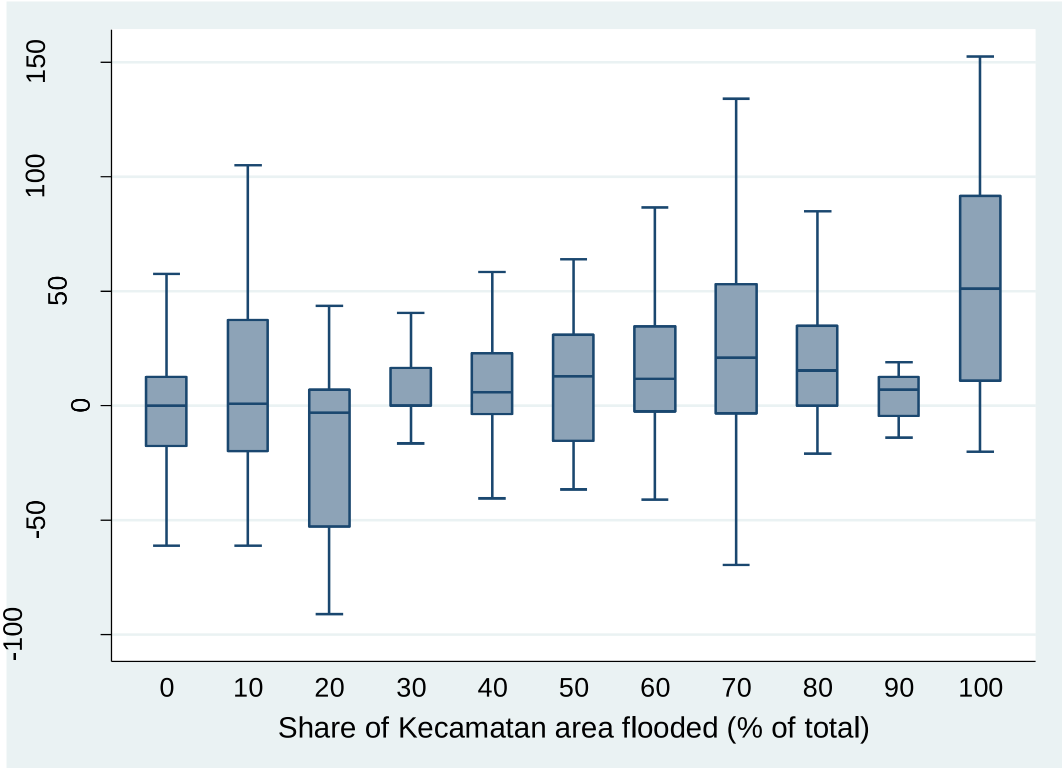


Figure A2.13 – Recovery phase from the Tsunami (2006 – 2008): Light intensity reacts to different levels of Flood Intensity

Panel A: Area Flooded



Panel B: Population flooded

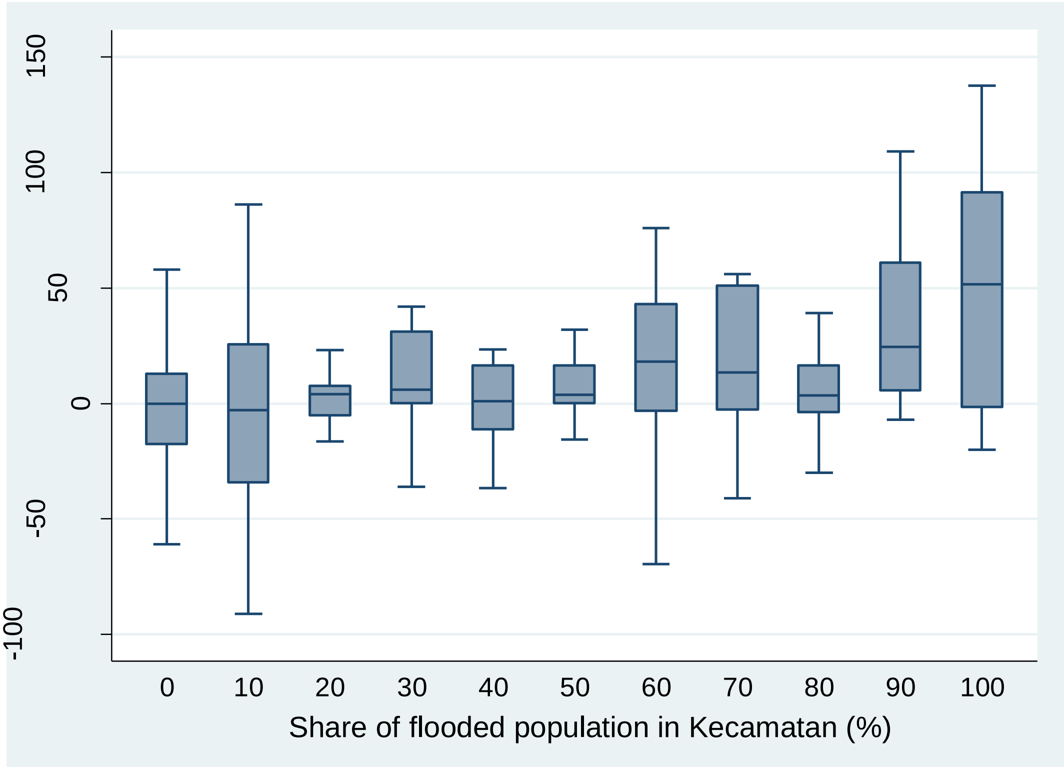
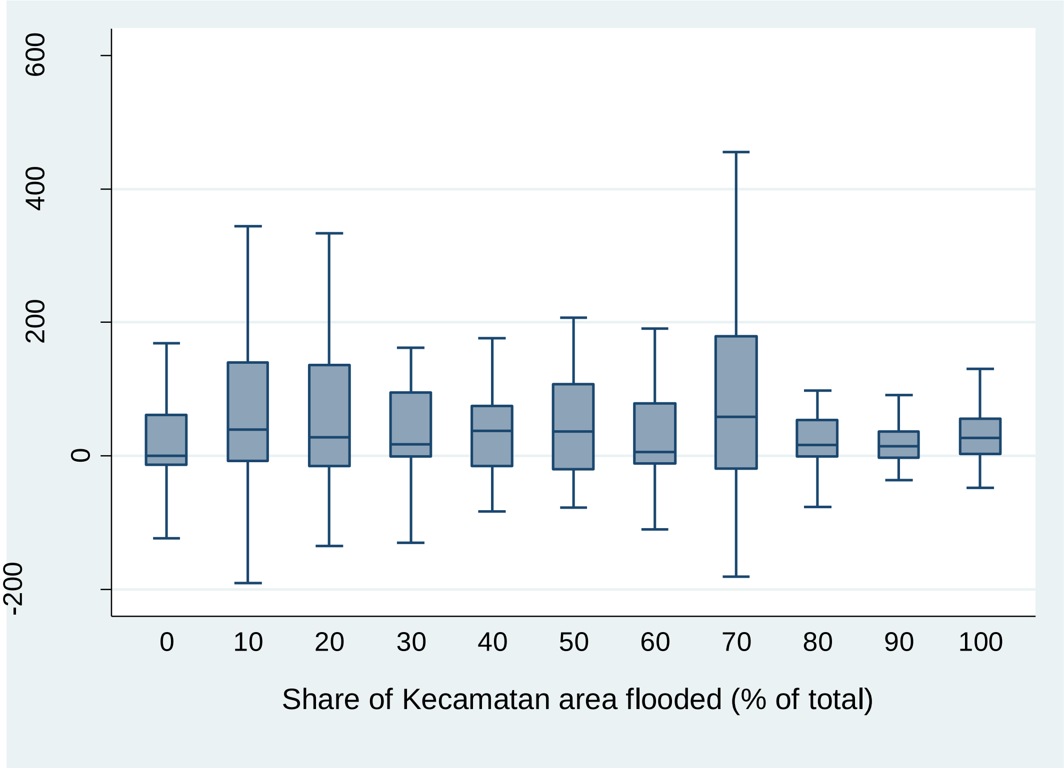
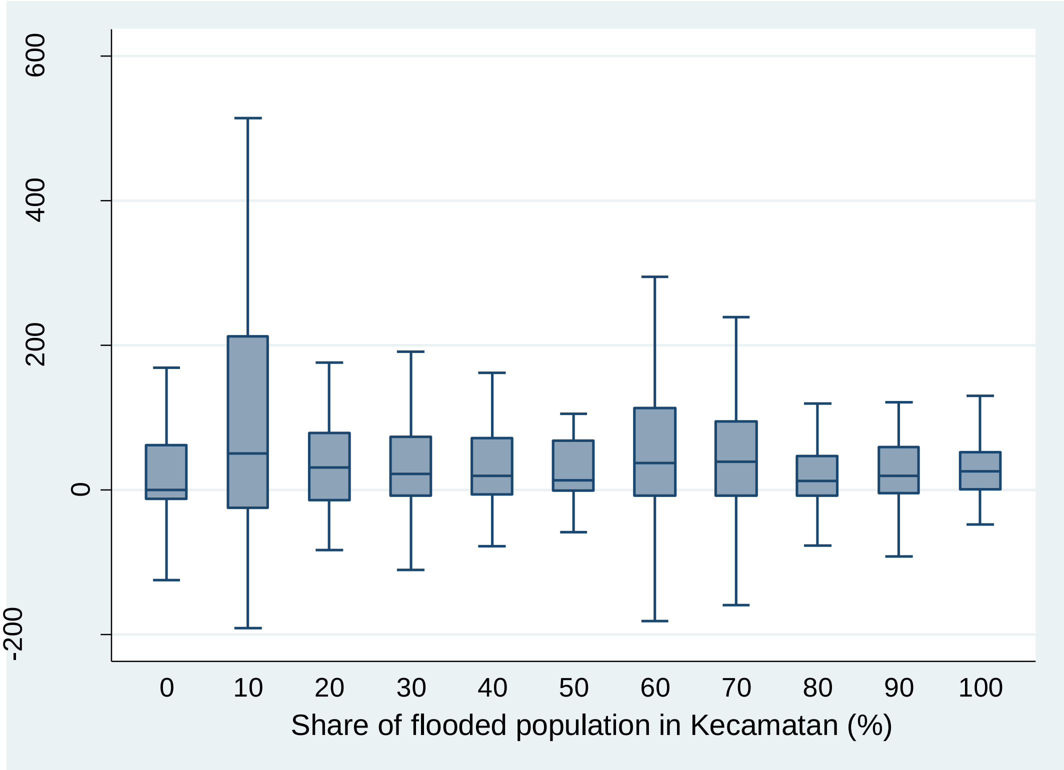


Figure A2.14 – Post-Recovery phase from the Tsunami (2009 – 2012): Light intensity reacts to different levels of Flood Intensity

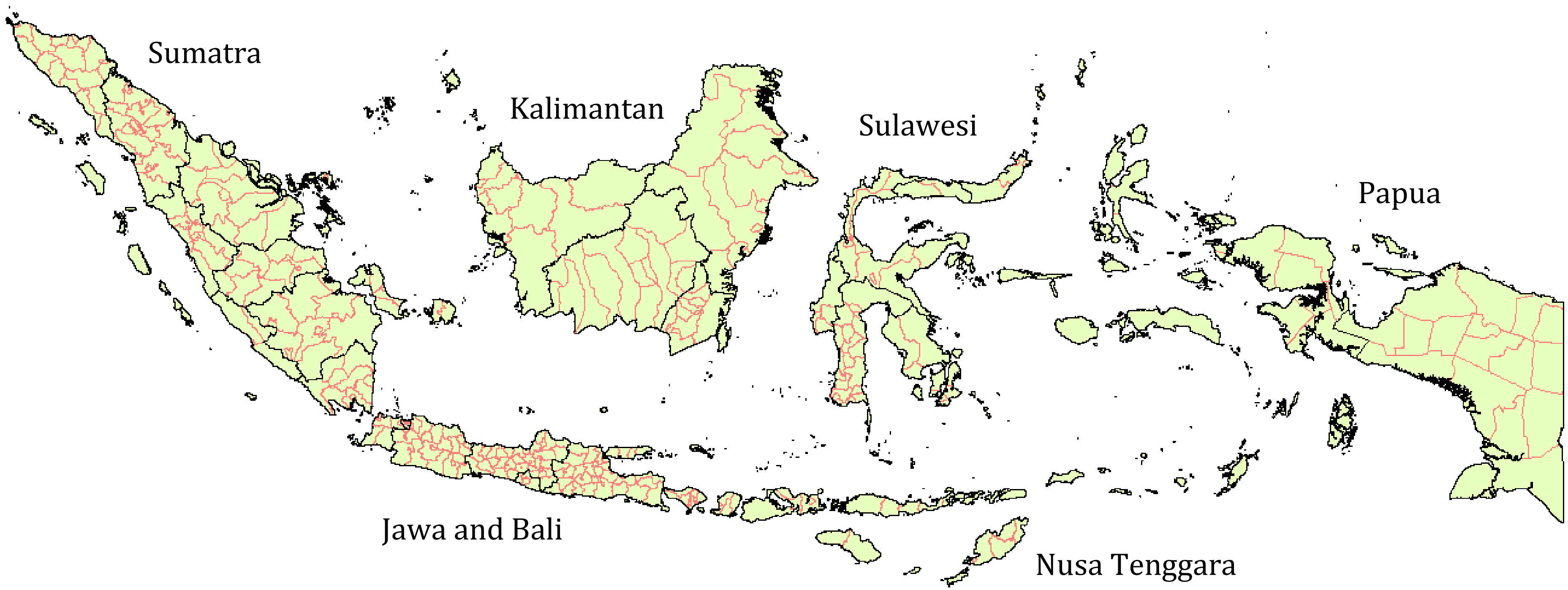
Panel A: Area Flooded



Panel B: Population flooded



Map A2.1: Indonesia with its 6 islands, 33 provinces (black delineations) and 426 districts (light-red delineations)



CHAPTER 3

Why the Indian Ocean Tsunami Caused Creative Destruction in Aceh: An Analysis of Causal Mechanisms

3.1 Introduction

Most studies in the fledgling natural disaster economics literature only look at how aggregate economic activity reacts to a natural disaster, using GDP or a different proxy thereof. In this chapter, I open this aggregation black box and investigate the channels through which growth was stimulated in Aceh. In chapter 2, I concluded that the Tsunami resulted in creative destruction by boosting local GDP per capita growth rates in the short term and by using the built back better physical capital to sustain higher per capita output. In this one, chapter 3, I set out to answer why. For this purpose, I look at the sub-components of GDP with particular focus on aggregate private consumption and investment (capital formation). I also investigate the sectoral dynamics, looking at compositional effects on agriculture, manufacturing and services.

Even though GDP growth was spurred, this positive effect may not have been uniform across all subcomponents. The subcomponents may quite reasonably display varying responses, if not countervailing trends. The GDP boost observed in chapter 2 could have many underlying reasons. It could solely be driven by the reconstruction effort. Given that GDP mashes together all kinds of economic activity, it could quite possibly be that even though, say, investment was spurred by the reconstruction effort, aggregate consumption has collapsed. Looking at the GDP growth alone, would therefore not provide an answer to this, as a substantial enough boost in investments could have quite possibly countervailed and even surpassed a hypothetical depression in aggregate consumption, leading overall to the recorded GDP boost in chapter 2.

The predictions based on the literature with regards to how the GDP subcomponents react to a natural disaster, are by and large that all of them are significantly reduced (see e.g. Auffret, 2003, or Hsiang and Jina, 2014). However, these results probably do not extend to Aceh since the region does not meet the criteria of being an average case for which the statistical findings on central tendencies would be representative for. Due to the windfall of aid and the many development programs launched, as a response to the Tsunami devastation, and not least to the finally reached peace agreement, I would rather expect that capital formation (investment) rates, and possibly even private consumption rates increased in the wake of the disaster.

The predictions in the literature with regards to the different sectors are also diverse and range across natural disaster types. For instance, while a drought was found to be detrimental for agricultural productivity, it was also found to have negligible effects on any other sector. Conversely, a flood was shown to on average actually boost agricultural productivity, while at the same time reducing the performance of the secondary sector (see Loayza et al, 2012).

In the next section, I will elaborate on the empirical evidence in the literature on capital formation and private consumption elsewhere, and contextualize with the idiosyncrasies of Aceh's recovery. Based on this synthesis between literature and Aceh's own unique experience, I form the hypotheses that are then tested in the causal empirical analysis of this chapter. I chose the same approach for the sectoral analysis, focussing on structural transformation dynamics.

3.2 The creative destruction channels – literature, evidence and hypotheses

3.2.1 Structural Transformation

Structural transformation is a crucial factor associated with modern economic growth (Herrendorf et al, 2013). It refers to the reallocation of economic activity from the broad sector of agriculture to manufacturing and services.[27] Small-scale farmers and other low productivity workers move into more modern economic activities, therewith boosting economic growth.

An acceleration of the restructuring between sectors might have been triggered by the Tsunami through a combination of push and pull factors which causally affected structural transformation dynamics. Push factors such as the destruction of agricultural land are driving people out of their original profession of working on the fields. Pull-factors refer to opportunities being created in other sectors such as in the wake of the reconstruction, which focussed particularly on the construction and the service sector, resulting in the development and therefore funding priorities of the donor stakeholders.[28]

Push factors

Agriculture was the most severely affected sector by the Tsunami (Soesastro and Ace, 2005). The destruction of land and agricultural practices was sizeable: Around 70,000 ha (with estimates ranging from 60,000 to 85,000 ha) of agricultural land and 22,000 ha

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[27] Structural transformation is rooted in the dual economy approach of development economics and builds on research by Kuznets (1966), Chennery (1960), Chennery and Syrquin (1975), Johnston and Mellor (1961), and Timmer (1988). In focussing on inter-sectoral relationships and flows it is complementary to the neoclassical growth model that focusses on growth processes within sectors (Rodrik, 2013).

[28] I do not claim that these are the only mechanisms through which the Tsunami could have altered the structural composition and dynamics of the affected region(s). However, I consider them the most likely channels through which a causal effect would have materialized. The presented analysis is not a test of the relative effect of each of these mechanisms; the identified mechanisms rather guide the direction of the hypotheses.

of plantation crops were flooded, and nearly 2 Million livestock animals were killed (Alimoeso, 2006). The Tsunami flood inundated about 30 percent of agricultural land, destroyed the crops that were on it, de-surfaced the land, eroded and scoured topsoil, deposited sand and clay sediments, deposited debris and trash, silted irrigation and drainage patters, destroyed dikes, irrigation systems and roads, increased soil salinity, and permanently altered the coastline (ACIAR, 2014; Moore 2007, Subagyono et al, 2005, New Scientist, 2005). Unable to go about their livelihoods, almost 350,000 people whose livelihood was in agriculture and fishing required food and financial assistance in 2005 (FAO 2005a and ACIAR, 2014).[29]

Is the move out of agriculture long-term? Rehabilitation of soils was a crucial endeavour and large international efforts were launched to repair the destroyed agricultural systems (ACIAR, 2014). Initial fears of permanent decreases in soil fertility and destruction of soil and fields did not hold. Salt pollution of arable fields was flushed out by heavy rainfalls relatively quickly, and more than two-thirds of the fields allowed for farming again in April and May 2005 (see FAO, 2005b). Of the 47,000ha of agricultural land lost in all the affected countries by the Tsunami, 38,000 were able to be used again in 2005. A remaining 9000 ha, most of which in Aceh, remains permanently unusable for farming. This is a relatively small amount seeing that it is less than 0.25 percent of the total 300,000 hectares of rice farms in Aceh. [30]

Despite successful rehabilitation programs, it may have come too late. Former farmers may have permanently moved out of agriculture because by the end of 2007 still only 70 percent of rice paddy fields regained their normal yield in West Aceh. The remaining 30 percent of land yielded lower yields. Lower yields might have contributed to discouraging farmers to return to their old profession (particularly when there were so many other opportunities on the horizon in the reconstruction spree).

[29] A newspaper article by Jakarta Post alleged that food and monetary aid reduced farmer's incentives to return to the fields and that this created a dependency on food aid. Nowhere else, donor reports, academic papers, international organizations, etc… could I find confirmation of this assertion. Here is the link to the article: http://www.thejakartapost.com/news/2014/12/30/agriculture-and-fisheries-after-tsunami.html

[30] Also in the interim, farming was coping relatively well, giving the circumstances. Preliminarily the farmers switched to salt-tolerant crops such as sunflowers and rapeseed, because they did not like the taste of salt-tolerant rice. Soon, Aceh's high levels of rainfall however means that soil salinity was overcome and traditional crops could be cultivated again.

In contrast to the disincentives for going back to agriculture, there were also some incentives, although they did not last. The fields that remained intact, or were refurbished, ultimately recovered in terms of productivity. Over the long haul, agricultural extension work and new irrigation infrastructure installed helped to boost yields beyond pre-Tsunami levels, which could have potentially drawn people back to agriculture (Lassa and Tian, 2014). Many donors launched agricultural, and agribusiness value chain programs, which were focussed on coffee and cacao, leading to increased exports of these commodities in 2006 and 2007. The food, beverage and timber sectors were in fact the only manufacturing sub-groups that actually recorded growth (World Bank, 2007a). And in 2006 and 2007, food and edible oil exports were the only other exports next to chemicals (although quite marginal in size, with an export volume of only 5 Mio USD, which pales in comparison to chemicals, let alone the previous export champions of fertilizers and LNG). In 2008 however, the export of these food products almost came to a complete halt. The recovery of agricultural exports driven by coffee (see World Bank, 2007b) did not last, as illustrated by the almost entire elimination of agricultural exports in 2008. The retardation of the agro-export industry has many underlying reasons, including adverse rainfall patters in 2008, and also the conversion of agricultural land to land upon which settlements are constructed (see World Bank, 2009a).

Pull-factors

Agricultural labour moved in large numbers to the construction sectors because of better wages and opportunities there. Aceh shed almost 70,000 jobs in agriculture, fishery and forestry in the wake of the Tsunami, which corresponds to 6 percent of the labour force, after accounting for those people who tragically passed away. The construction sector absorbed the second-most quantity of labourers by adding about 27,000 new jobs, corresponding to almost a two-percentage increase. Agricultural productivity in 2005 and 2006 was about 750 USD per farmer per year, which was about half of that of a construction worker. Therefore, the hypothetical farmer working on a construction contract, say on an aid financed contract from an NGO, made twice as much rebuilding the field, than he would have made ploughing it.

Agricultural labour also moved to the service industry: predominately hotels and restaurants catering to NGO workers and later tourists, but also transport for all the materials needed in reconstruction and other industries of the service sector. Transportation and telecommunications added almost 20,000 new jobs from 2004 – 2008 by when most of the aid money was spent and continued to add about 10,000 more jobs until 2012, corresponding to job increases by 2 and 1 percent. The gains for the transportation sector mostly stem from transporting reconstruction material.

Hotels and restaurants were booming to cater to the NGO workers, and later the "disaster tourists" and off-the-beaten-path tourists enthusiastic about discovering new dive spots, beaches, cultural experience, food etc. The Tsunami and the peace agreement brought tourists in its wake. While there were practically 0 international tourist arrivals in Aceh, there were already 5000 arriving in 2005, about 12,000 in 2006, and continuously increasing to almost 30,000 by 2011 (Mota, 2014). Domestic tourism also rose substantially since the disaster. From 200,000 domestic arrivals in 2004 and 2005, the number kept on increasing to almost one Mio people by 2011 (Mota, 2014). Dive shops opened up and new hotels were constructed catering to the heightened number of tourists. 70,000 jobs were added to the hotels and restaurants sector from 2008 – 2012 corresponding to an increase of about 3 percent.

Now with the 30-years long war being over, "thanks" to the Tsunami, tourism finally found a foot hole in one of the more remote areas of Indonesia. Due to the natural disaster, Aceh was the centre of international attention. Tourists enjoy a vast array of services, from nice beaches, diving, and jungle exploration to tsunami tourism, where a 2600 ton heavy barge used as an offshore electricity generator washed on shore on top of a building 2 km inland was turned into a tourist attraction and a tsunami museum was opened in the capital, attracting many tourists looking for an adventure off the beaten path.

Hypothesis on causal Tsunami effects on structural transformation*:* Based on the joint push and pull factors triggered by the Tsunami, I hypothesize an accelerated structural transformation process, meaning one in which the movement out of agriculture is sped up, as is the commensurate move into more productive sectors. As to the sustainability of the higher rates of structural transformation, it is impossible to make credible predictions.

3.2.2 Capital formation

Investments are the likeliest out of all GDP subcomponents to have been positively affected by the Tsunami. Most analyses of post-disaster growth rates talk about increased construction activity because of the rebuilding of destroyed capital, regardless of whether overall GDP increases or decreases. Hallegate (2014) argues that if GDP has increased after a natural disaster, which it has in the case of Aceh as I showed in chapter 2, it is likely due to improved investments in construction. Construction is a potent driver for post-disaster growth. One of the very few papers that also suggest a Schumpeterian creative destruction type result for GDP growth, as I did in chapter 2, attributes the findings mostly to the reconstruction efforts post disaster (Skidmore and Toya, 2002).

Capital formation, in the short run at least, should thus have been boosted substantially in the wake of the Tsunami in Aceh, because the region witnessed the largest reconstruction effort ever recorded in the developing world. In total, roughly USD 1.5 Billion of aid money had been allocated to infrastructure projects alone in Aceh (World Bank, 2009b). Advancing the educated guess of investment increases, based on looking at the sheer volume of funds for reconstruction, was also the Economist Intelligence Unit, which corrected its initial forecast of annual increases in gross investments for 2006 from 11.7 percent prior to the Tsunami to 17.1 percent right after the Tsunami.

Noy (2009) argued that in post-disaster economies, both an increased and a decreased investment rate is possible, and which one is the case depends mostly on the future likelihood of disasters and the possibility that the re-built capital might be destroyed yet again by future hazards. In the case of Aceh, there was little doubt that reconstruction was the way to go and uncertainties with regards to future damage were of little concern, as sitting idly on the total of more than 8 Billion USD in collective aid money was not an option.

Finding increased investment rates in the short run is not surprising in light of the enormous scale of the reconstruction effort in Aceh. Despite the sheer size of the collective aid delivered, at one point the funds had to run out, which they did by the end of 2008, and the question remaining is whether the investment volume remained higher than the counterfactual beyond this point. There is evidence in the limited literature that supports both a reverting back to counterfactual investment trends even a decline in investment rates and the opposite, a continued accelerated investment.

Are there long run capital formation effects? Noy (2009) argues that in the short run investments increase as the physical capital is destroyed, but in the long run investments decrease, as funds have just been temporally re-assigned. Hsiang and Jina (2014) for instance show a substantial drop in investments over the long run as a reaction to severe cyclones.[31] Rasmussen (2004) states that reconstruction efforts could crowd out other productive investments and not only increase the rate of interest but also reduce productive investments, leading ultimately to lower rates of economic growth. By this logic, future decreases of investments are the result of tightened fiscal spaces, and funds that were either temporally or sectorally re-assigned to the reconstruction sector. Temporarily heightened investments at the cost of future investments should not have been an issue in Aceh, which received a windfall in funds from the central government and international donors.

Contrary to the resource scarcity argument, there are also good reasons to think that long-term investment rates are positively auto-correlated with short-term investment boosts. Bridges, roads, ports, tunnels, and other infrastructure should have positive economic externalities and boost economic productivity, which in turn should require more infrastructure investment in the future. Albala-Bertrand (1993) identified a high investment rate as a crucial driver of economic recovery, and attributed a high growth multiplier of investment in reconstruction, meaning that once the physical capital is rebuilt, the growth will accelerate due to the better quality capital. Similarly, Auffret (2003) identified replacement efforts to be vital and posited that long-term growth effects are crucially determined by how well reconstruction efforts advance.[32]

[31] Capital formation declined even faster than consumption (Hsiang and Jina, 2014).
[32] He furthermore posited that if an economy did not replace destroyed capital then negative growth effects would materialize.

It is important to distinguish between investments in rebuilding infrastructure, to the same degree or better, and investments in defensive infrastructure (Hallegatte, 2014). In principle, also defensive infrastructure should attract more investment in the future. Defensive infrastructure, such as dikes assure the protection of prospective infrastructure, reducing the risk of prospective construction efforts. Along these lines, Popp (2006) argued that upgraded physical defensive capital, such as improved forecasting and detection technologies, should increase long run growth. In Aceh, about 1.9 Billion USD or one-third of the commitments were specifically earmarked for "building back better" on top of the USD 6.1 Billion for rebuilding (World Bank, 2006).

The availability of complementary recurrent capital to maintain the built back better capital is crucial in assuring long-term heightened investment rates. The oil and gas sharing agreement and the Aceh Sovereign Fund, both started to disburse in 2008 are important guarantors that capital formation is boosted in the long haul.

Hypothesis on the causal Tsunami effects on capital formation*:* Based on the reviewed literature and given the large sums of aid allocated to Aceh, investment rates are expected to have been stimulated by the natural disaster, not only in the short-term, but also in the long-term. An additional contributing factor to increased long term investment rates are the autonomy and oil and gas fund which started disbursing in 2008.

3.2.3 Aggregate private consumption

Aggregate consumption comes closest to a measure of how humans are faring and how they are coping economically, out of all the subcomponents of GDP. It is a summary measures of available household resources and therefore proxies other important measures of human development such as wellbeing and poverty (see World Bank, 2008). By and large, aggregate consumption has been found to contract due to extreme natural disasters (see e.g. Mechler, 2009 and Hsiang and Jina, 2014).

Consumption trends and patterns can be severely altered by a natural disaster and maintaining a stable path of consumption, becomes a challenge. Access to insurance schemes and other forms of financial transfers can enable consumption smoothing as scarce funds intended for consumption do not have to be re-assigned and spent on reconstruction instead (Udry, 1994; Kunreuther and Michel-Kerjan, 2009).

In the absence of risk-sharing mechanisms such as social safety nets, as is the case in most developing countries, households responding to supply side shocks are not able to smoothen their consumption (Gassebner, Kek and Teh, 2010). Looking at earthquakes in El Salvador, Baez and Santos (2008) find that the natural disasters reduced household income significantly, and with it lessened consumption. Household consumption was significantly reduced in the wake of the drought that hit Burkina Faso (Kazianga and Udry, 2006; Fafchamps, Udry and Czukas, 1998). In the Philippines households were not able to smooth consumption in the wake of the typhoon (Anttila-Hughes and Hsiang, 2011). The Economist Intelligence Unit (EIU), after having factored in the Tsunami, corrected its aggregate private consumption predictions for Aceh slightly downwards; pre-Tsunami it estimated a growth rate of 5.2 percent, post-Tsunami 4.6 percent. The forecasting provider attributed their slightly weaker predictions to a weaker consumer sentiment and cautioned that economic growth mainly driven by reconstruction might ultimately be offset a bit by a depressed aggregate consumption.

In lieu of insurance schemes, there are also other ways in which affected private households may finance consumption smoothing, *inter alia* through dissavings, through remittances, through microcredits and direct monetary transfers. In Aceh, all of these mechanisms played an important role, but above all, direct cash transfers were decisive. According to the 2008 World Bank Poverty Assessment in Aceh, dissavings helped selected households to smoothen consumption and that the savings were a substantial buffer between maintaining consumption and falling into poverty (World Bank, 2008a). Remittances also played an important role in smoothing consumption for many families in Aceh (Wu, 2006). After a temporary decrease of formal remittance flows in the months after the disaster, formal and informal remittance flows were restored and recovered beyond the pre-Tsunami level (Wu, 2006).

Cash transfers were a very widely used distribution tool in Aceh. Cash transfers are viewed in the development community as a potent vehicle for stimulating and maintaining household consumption (see e.g. Coady et al. 2010, Bazzi, Sumarto, and

Suryahadi, 2014). Cash transfer programs, where cash was transferred directly to affected households, as opposed to the communities or intermediaries is a recent darling among assistance programs of the development community, particularly among NGOs. The measure came to frequent use in Aceh.

The declared goal by many in the development community, especially in the early stages of the relief effort in Aceh, was to "put cash into people's pockets" (Adams, 2005). The donors implemented a host of different cash transfer programs such as cash transfers to households, cash and voucher projects, cash for work programs, cash grants for livelihood recovery, cash for orphans, cash for shelter, and cash/grant/loan hybrid programmes (Adams, 2005). Particularly cash-for-work programs were a success story in Aceh, and were also described to boost morale and psychosocial wellbeing (Adams, 2005), through which they not only contributed directly to consumption smoothing, but also indirectly, by improving consumer sentiment, one of the major reasons why EIU corrected their consumption forecasts downward in the first place.

Through cash-for-work programs NGOs initially contributed substantially to increasing wages, by offering substantially more than people were paid previously. This should have increased disposable income, which in principle could have even led to an increase rather than just a smoothing of aggregate consumption. As agencies became aware of their programs distorting the local labour market, they reduced wages by limiting the number of days local people could work for them and in some cases even suspended projects for entire periods. This change of collective heart of the donor community could have quite feasibly exerted downward pressures on consumption. For an in-depth discussion on the cash programs and their evolution in Aceh see Adams (2005) and Adams (2007).

Whether the monetary assistance had to be paid back (whether it was a loan, or a grant) should have also influenced consumption rates. The larger the share of grants, the higher the consumption smoothing/boosting effect since the funds do not have to be paid back and therefore future consumption is not in competition with current consumption. Microfinance institutions supplied mostly loans. Humanitarian agencies, such as Mercy Corps, Save the Children, Care, WFP, or Oxfam, to name but a few used a mix between loans and grants. Particularly at the beginning, they used mostly grants, but switched to more loans as the relief efforts transformed into recovery efforts. Depending on the humanitarian agency's philosophy with regards to creating dependencies, distorting local markets, and avoiding poverty traps among others, either loans of grants were chosen.

Overall, cash transfers have proven to be successful, and initial concerns such as corruption and gender imbalances have not materialized (Adams, 2007 & Cole, 2006). Cash transfer programs were however not free from problems and there were a number of limitations and concerns including absent strategic frameworks, limited use of appropriate institutions, limited analysis of cost-efficiency, among several others (see Adams, 2007). Overall, cash transfers were the preferred choice and in-kind transfers were mostly only used in the immediate emergency phase.

In Sri Lanka, the second worst hit country by the Indian Ocean Tsunami after Indonesia, cash transfers were successful in smoothing consumption. Households that received cash transfers in the relief effort had significantly higher levels of consumption than those that did not (Mohiddin, Sharma, and Haller, 2007). Cash beneficiaries were shown to diversify their diets, and also increase their consumption of non-food items. On the whole total caloric intake declined immediately following the Tsunami. However those Sri Lankans that received cash transfers managed to increase their average caloric intake to above 2100 kcal, which is slightly higher than it was even before the Tsunami (Mohiddin, Sharma, and Haller, 2007).[33] Given the prominence of cash programs in Aceh, and a much larger scale of the aid effort, if Sri Lanka showed household consumption smoothing/boosting, so should Aceh.[34]

Under a scarce fund resource premise we may observe lowered consumption rates. There may be the behavioural element of precautionary saving, where people increase their savings rate due to perceived higher uncertainties, in order to have a buffer for future disasters. Another reason for why consumption may not be maintained is asset smoothing, where assets need to be replaced, and in doing so, individuals need to shift away from consumption. Precisely because funds are not scarce however with the

[33] Food-receiving households showed similar yet slightly higher trends in food consumption smoothing/boosting than cash-receiving households.

[34] Even though the outcome measures and the scale of analysis used in the Sri Lanka research are different from the one used in this chapter.

backdrop pf unprecedented aid windfalls and sovereign and oil wealth, I do not expect consumption reduction to have occurred because of these reasons.

Are there long-term consumption effects? Even though I expect to find maintained aggregate consumption rates, as Aceh coped with the natural disaster in the immediate aftermath, longer-term ramifications are more of an uncertain question. The literature reports the adverse effects of natural disasters to be persistent, as they lead to dis-savings that reduce the capital stock and ultimately lower consumption over the long haul (Mechler, 2009). Hsiang and Jina (2014) show after an initial increase in consumption following severe cyclones, which lasts for about three years, the country's consumption rates plummet past that time and consequently deteriorate and decline over the long haul.

Despite the adverse long-term effects on consumption reported in the literature, Aceh may be different. The reason is again the windfall in aid and transfer assistance, which should have delinked consumption from other type of expenditure, and therefore evaporated substitution effects, as there was no limit of financial resources. An increased investment rate and the fiscal stimulus (shown subsequently in this chapter) may have furthermore assured a continuously high rate of aggregate consumption due to positive feedback loops. There are some signs however, that Aceh might have a decline in long-term consumption. The higher unemployment rate causally triggered by the Tsunami (shown in the Appendix of this chapter) may have eroded aggregate consumption, and once the aid programs ran out, consumption would have contracted.

Hypothesis on the causal Tsunami effects on aggregate private consumption*:* The reviewed literature suggests a drop in aggregate consumption, but due to the many cash transfer and other recovery and relief projects launched, in Aceh, consumption smoothing (if not boosting) is expected in the short run. In the absence of fund scarcity in the immediate years following the natural disaster, and an infrastructure that was *built back better*, which should lead to increased productivity, I expect that consumption was boosted also over the long haul. An additional contributing factor to increased long term consumption rates are the autonomy and oil and gas fund which started disbursing in 2008.

3.3 Data and methods

3.3.1 Data – province level GDP subcomponent data

I use province level data because unlike GDP, its composite measures, which I will scrutinize in detail, private consumption and capital formation are not available at the district level. I therefore move up to the next administrative level, the province, which is the smallest unit for which subcomponent data is available. For the sectoral decomposition, into agriculture, manufacturing and services, data on the district level is available, and I conduct a supplementary analysis to the main province method on a district level.[35] The province level GDP data are taken from the same source as the district level GDP data in the main chapter of this PhD dissertation, the INDO-DAPOER dataset. They are computed using the expenditure approach. For more detailed information about the dataset, see the data description section in chapter 2.

The provincial dataset is shorter than the district level dataset used in chapter 2, and ranges only from 2000 to 2010. This means that the provincial GDP subcomponents are available for two years less than the district level GDP figures presented in chapter 2 and only reach until 2010. Furthermore, when deflating the subcomponents, the dataset further reduced in range from 2000 to 2010 because of the absence of deflators prior to 2000, in part owing the political conundrum of the region.

Any analysis of GDP subcomponents lumps together the 10 Tsunami flooded districts of Aceh, with the 13 non-flooded districts which are then compared to the other 31 provinces of Indonesia (including the 8 other provinces of the Sumatra island) that are not affected. Using provincial instead of district level data poses conceptual as well as analytical challenges. The conceptual challenge is that countervailing trends amongst the 23 affected districts are masked in provincial level analysis. Positive spillover effects, as indicated in chapter 1, from the 10 directly stricken districts to others, intensify the interpretation of creative destruction, and negative spillover effects

[35] I chose to highlight mainly the province level analysis in this chapter so that the sector results and method would be consistent with the subcomponent analysis. I did however also carry out a more disaggregated analysis using the district level for the sector analysis, which is also included as a supplementary analysis.

attenuate the interpretation. Therefore in evaluating the results, one should keep in mind that they might be biased because the unit of analysis was not affected uniformly. The analytical challenge is that instead of 10 treated districts I only have 1 treated province, Aceh, and therefore applying the difference-in-differences analysis is no longer possible due to lack of cross regional variation. Consequently I am introducing a new method in this chapter: the synthetic control method, an analytical framework, which perfectly lends itself to tacking this setup forced by the natural experiment and the data limitations.

3.3.2 Synthetic Control and Comparative Case Studies Method

I implement the synthetic control method for causal inferences in comparative case studies *a la* Abadie and Gardeazabal (2003) and Abadie, Diamond, and Hainmueller (2010, 2014) for estimating the Tsunami impact on the Aceh province in Indonesia. The synthetic control method is designed to produce a synthetic comparator, which best mimics the treated (i.e. flooded) region in its pre-treatment characteristics. The counterfactual scenario established by the synthetic control method is constructed to allow inferences as to what would have happened had the intervention not occurred. Essentially the idea is combining regions that have not been affected into one amalgamate, which is designed to resemble the treated Aceh unit as closely as possible (because no one single region can).

Just as in the case of the district level analysis I perform the analysis both ways, first excluding North Sumatra from the analysis, then including it (which also serves as a nice robustness check). Map 3.1 shows an illustration of both ways in which I will carry out the synthetic control method.

Map 3.1: Tsunami stricken province versus 31 non-stricken provinces

Note: Aceh was severely affected, such that 10 out of 23 of its districts were stricken and flooded by the Tsunami. North Sumatra was much less affected in that only 2 districts, the island districts (Nias and Tanahbala) were affected by the Tsunami. Due to this, I drop North Sumatra from the pool of counterfactual regions, which reduces it from 32 to 31.

Formalizing the synthetic control method: I observe $J + 1$ regions (provinces). Let the first region be the one affected by the Tsunami (in our case Aceh), which should leave us with J regions of potential controls. Comparative cases studies assume that the unit continues to be treated over time, which in my case means that I not only estimate the impacts of the year in which the disaster struck, but also the aftermath-years. The estimated results will include only the net effects of the treatment (Tsunami) on Aceh and will not disentangle the effects of possible disaster management and relief intervention taken.

Let Y_{it} be the regional subcomponent of GDP measure (private consumption, capital formation, government consumption, or net exports) or the regional sector measure (agriculture share of GDP, service share of GDP, manufacturing share of GDP) for province i at time t. I deflate all GDP subcomponents, a measure especially important due to surges in inflation caused by the windfall of aid (see World Bank, 2005).[36]

[36] External negative shocks such as the Tsunami can affect the aggregate demand function in various ways. They may affect the classical aggregate demand function endogenously through prices. Increased price levels, such as during inflations, decrease the demand for most goods and therefore depress

Following Abadie et al (2010) and Cavallo et al (2013), Y_{it}^{N} denotes the respective GDP subcomponent absent of the Tsunami flooding and Y_{it}^{I} would be the outcome observed if unit *i* is exposed to intervention in the disaster period and aftermath period (from $T_o + 1$ to T). As I discussed in chapter 2 of the PhD, the Tsunami hit Aceh unexpectedly and there were no preparations taken in anticipation of a possible event. Therefore there are not supposed to be any effects of the Tsunami on the outcome before the treatment period so for $t \in \{1, \dots, T_0\}$ and all $i \in \{1, \dots, N\}$ so one should get $Y_{it}^{N} = Y_{it}^{1}$ for *t* < 2005. $T_0 + 1$ or in our case 2005 is the first year during which we should expect to observe effects of the treatment on Y_{it}^{1}.

The effect I aim to estimate is the local average treatment effect (LATE), the effect of the Tsunami intervention on the treated (flooded) regions $\alpha_1 T_{0+1}, \dots . \alpha_1 T$, where $\alpha_{1t} = Y_{it}^{I} - Y_{it}^{N} = Y_{1t} - Y_{1t}^{N}$ for $t > T_0 = 2004$ or $Y_{it}^{I} = Y_{it}^{N} + \alpha_{1t}$.

Let D_{it} be the indicator denoting whether region *i* was exposed during time *t* to the Tsunami. Because only our first region, i.e. Aceh, is exposed to the treatment, and only after period T_0 (with $1 \leq T_0 < T$), we have:

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

Y_{it}^{I} is observed, we therefore we only need an estimate of Y_{it}^{N} to compute α_{1t}. We obtain the estimation of Y_{it}^{N} by applying a difference-in-differences type factor model (adapted from Abadie et al, 2010):

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

Where δ_t is an unknown common factor common to the not affected group; Z_i is a vector of observable covariates not affected by the Tsunami (such as pre 2004 GDP, pre 2004 population, or pre 2004 level of agricultural concentration); $\gamma_t \mu_i$ is a vector of unobservable common factors interacted with unknown factor loadings; ε_{it} are regional level temporary shocks with 0 mean.

consumption. Because of the surge in inflation caused by aid assistance (see World Bank, 2005), I correct the consumption data and deflate it so that it is inter-temporally comparable.

How do we combine the regions as potential controls? Consider a vector $(J \ x \ 1)$ of weights $W = (w_2, \dots, w_{J+1})'$ such that $w_j \geq 0$ for j = 2, ..., J+1 and $w_2 + w_3 + \cdots + w_{J+1} = 1$. Here every value of W represents a potential synthetic control, or particular weighted average of control regions. Suppose the existence of a set of weights $(w_2^* + \cdots + w^*{}_{J+1})$ satisfying $\sum_{j=2}^{J+1} w_j^* = 1$ such that:

$$\sum_{j=2}^{J+1} w_j^* Y_{j1} = Y_{1,1}$$

.

.

.

$$\sum_{j=2}^{J+1} w_j^* Y_{jT0} = Y_{1,T0}$$

$$\sum_{j=2}^{J+1} w_j^* Z_j = Z_1$$

where Z is a vector of observed predictors of regional GDP (per capita).

Abadie et al. (2010) suggest using $\hat{\alpha_{1t}} = Y_{1t} - \sum_{j=2}^{J+1} w_j^* Y_{j1}$ for the $t \in \{T_0 + 1, \dots, T\}$ as an estimator of α_{1t}.

3.3.3 Methodological Caveat

Similar to chapter 2, the aim of this chapter is evaluating the impact of the natural disaster and aid on, for the purposes of this chapter, GDP subcomponents and subsectors. The effects of the natural disaster absent of recovery aid cannot be assessed, as there is no case in which Tsunami destruction treatment was "given", and aid treatment was not "given". As this chapter uses provincial level data, one level coarser than the district level data in chapter 2, another treatment joins the mix: that of peace. In provincial level data, I have only one observation for Aceh, instead of the 23 districts of chapter 2, and the entire province received the peace treatment. Whereas in the district analysis case I was able to exploit within province variation, essentially controlling for the peace effect, with province level data, this is not possible.

One year after the Tsunami crushed on the shores of Aceh, a historic peace deal was struck ending a nearly 30-years-long civil war. *De facto* peace was attained immediately after the disaster, as indicated by only a handful of separatist conflict-caused mortalities, as shown in chapter 4. A formal peace deal was signed in 2006, halting all conflict and separatist activity and reducing the amount of conflict mortalities to zero.

The relative contributions of physical Tsunami destruction, aid, and peace to creative destruction cannot be singled out and separately quantified with province level data. Due to joint occurrence of flooding, aid disbursal, and peace, all starting essentially concomitantly in 2005, it is impossible to isolate the individual effects with province level data. For example, it cannot be assessed whether a heightened investment activity is caused by the destruction of the Tsunami and the aid disbursed, or because of a better investment climate after the conflict has ended and peace has been restored (both aid & peace being important factors in successful recovery and reconstruction). The estimated causal effects detected with provincial level data are thus a combination of the natural disaster repercussions, aid funds and peace.

Strictly speaking, peace was caused by the Tsunami, and therefore it is an extension of the natural disaster impact and not so much of a problem for a causal Tsunami-outcome interpretation. In order for the results to be somewhat representative to other circumstances however, to be able to assert that peace effects did not play a substantial role in the economic recovery, would be required. Empirical reality however is another, and there are positive effects of peace on economic growth as shown in chapter 4 of this PhD thesis and therefore, the resulting trends in consumption and investment are also to some degree due to peace.[37]

[37] In chapter 2 of this PhD thesis, I looked at the causal effect of the Tsunami along with the aid it triggered on economic growth. I was able to isolate the effect and ascertain to a high degree of confidence that the identification is valid meaning that none of the other factors that started to vary around the same time as the onset of the natural disaster caused the reported treatment effects. The causal identification in chapter 2 was based on using not only the variation within the districts (affected or not) over time, but also the variation between the affected districts and those not affected. I was therefore able to guarantee that the historic peace deal that was struck, which was also caused by the natural disaster did not affect

For the consumption and investment part of the analysis in this chapter, peace effects do play a role in producing the estimated effects. There is no way around it. I do present a discussion however of the role peace plays and the relative size of the peace effects. For the sector analysis, I can control the peace effects by relying on a supplementary district level analysis. Each of the districts received an equal 'dosage of peace', which allows for a controlling for the mitigating impacts of peace in a cross-district analysis. Unfortunately, only GDP sectors are decomposed at a district level, not GDP subcomponents.

A challenge to the long-term effects analysis are oil and autonomy funds that Aceh received, starting with 2008, which cannot be taken into explicit consideration by applying provincial level data. Particularly in light of the fiscal influx in Aceh due to the oil sharing revenues starting in 2008 (and to some degree the peace-funds starting also in 2008), which are delayed consequences of the peace deal, and therefore also of the Tsunami, the interpretation of the effects on each subcomponent has to be done carefully. Interestingly, both investments and private consumption time series display a kink right before the year 2008 (see findings section of this chapter), suggesting that it could have been precisely the autonomy and oil funding, which caused that the higher consumption and investment paths were reached sustainably.

Which recovery policy exactly made the difference? Albeit very interesting in and of itself, the question of which policy measure precisely was the lynchpin in affecting consumption and investment and their relative effects are not the subject of this chapter. This chapter will solely determine if Aceh in a response to the collective of policy measures (most a success, some a failure) following the natural disaster, has managed to smoothen consumption and built back better sustainably.

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the growth stimulating effects reported. In following the same district level analytical approach for a structural transformation analysis, I should also equally be able to control for the peace effects.

3.4 Findings

Investigating the channels through which the Tsunami may have caused a higher growth path, I focus mostly on structural change, aggregate private consumption and investment. In section 3.4.1, I investigate whether the Tsunami has causally accelerated the structural transformation process of the Acehnese economy. I find that the process of structural transformation was occurring in Aceh prior to the Tsunami, albeit at a very slow pace. The Tsunami caused a substantial acceleration of this process and lead to an accelerated shift out of agriculture into services. In section 3.4.2, I verify whether the reportedly largest reconstruction effort the developing world has ever seen is also reflected in the reconstruction numbers, i.e. capital formation levels. This first step is mostly for the purpose of getting a measure of the magnitudes of the recovery, not so much as a test whether or not they have increased, as they 'must' have done so due to the sheer size of reconstruction assistance and aid, absent of measurement errors. I document in detail how the reconstruction effort triggered a boost in investment, as the destroyed capital is replaced. I show that the higher investments lasted even after the reconstruction was finished. In section 3.4.3, I answer the question whether Aceh has managed to smoothen aggregate private consumption. I find that beyond smoothening, private consumption was boosted to a higher long-term consumption path.

To be consistent, I mainly rely on province level analysis using the synthetic control method for both the analysis of sectors (e.g. agriculture and services), as well as subcomponents (e.g. private consumption and capital formation). Because I also have district level data, but only for the sectoral disaggregation of GDP, I also perform a supplementary analysis for structural transformation.

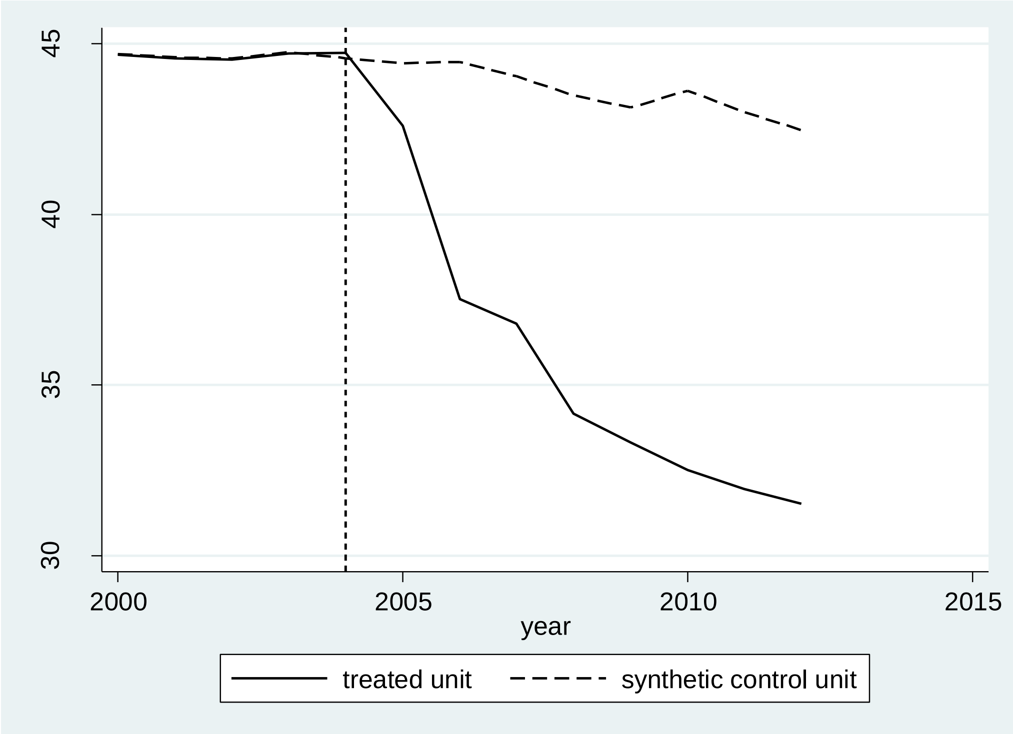
3.4.1 Structural transformation was accelerated

I follow the empirical framework of McMillan & Rodrik (2011) Kuznets (1966), Chennery (1960), Chennery and Syrquin (1975), Johnston and Mellor (1961), and Timmer (1988), in identifying and defining the re-organisation of economic activity as a structural transformation process once it meets the following empirical criteria: (1) declining agricultural share in GDP, (2) service sector growth, and (3) manufacturing sector growth. Based on this verifiable conceptual framework, I evaluate first whether these empirical boxes can be ticked off for Aceh, and second and more importantly, whether the Tsunami caused an acceleration of these transforming processes.

In what follows, I show that the structural transformation process, which was already underway in Aceh, was causally accelerated because of the Tsunami in two of the three yardsticks capturing structural transformation. I show that the Tsunami causally sped up the move out of agriculture (including also forestry and fishing), the move into services (trade, transport and finance). I fail to confirm an accelerated increase of manufacturing (but there was no original transition to manufacturing in the first place) and discuss the reasons.

(1) Agricultural value added (VA) as a share of overall GDP shrunk very little over time in Aceh, if anything at all, in pre-Tsunami times (see figure 3.1). Applying the synthetic control method, I show that post-Tsunami, Aceh would have slowly structurally transformed and reduced agricultural VA by about 2 percentage points, as indicated by the dashed line, representing the counterfactual, arriving at a share of agriculture of the economy of 43 percent by 2012. Instead of the 43 percent share, Aceh in fact arrived at 32 percent, owing to the Tsunami. The Tsunami caused an extra reduction of the share of agriculture of 11 percentage points by 2012, kick starting the structural transformation process. The rates at which Aceh moved out of agriculture accelerated markedly in the years immediately after the Tsunami. After 2008, the rates seem to run parallel again to those of the counterfactual. Correspondingly, employment shares in agriculture also dropped from almost 55 percent of the labour force to about 42 percent since the beginning of the Tsunami.

Figure 3.1: Agricultural share of GDP trends: Aceh versus synthetic Aceh



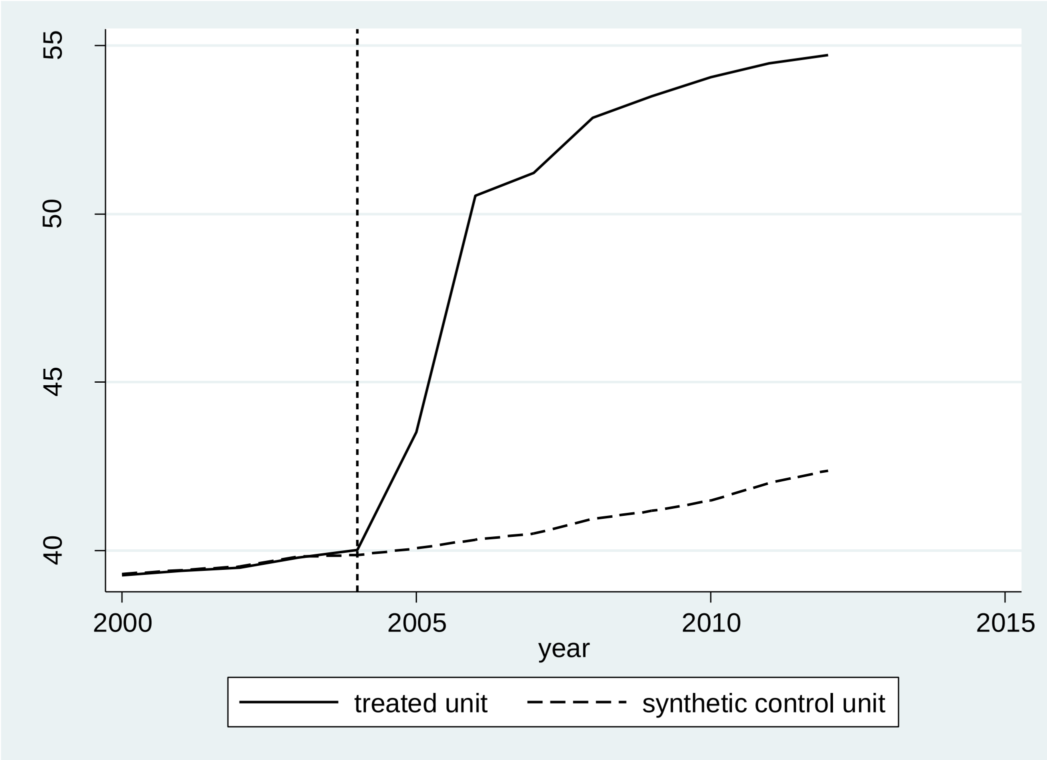
Source: INDO-DAPOER data. For a description of the dataset, see chapter 2.

The effect displayed in figure 3.1 was unlikely observed by chance. Evaluating placebo effects in-space shows that the p-value, comparing the estimated main effect to the distribution of placebo effects, is below 0.02 from 2005 onwards. The affinity between the treated and the synthetic control unit is shown in table A3.1 of the Appendix. Table A3.2 in the Appendix displays the weights of each district in the counterfactual pool.

(2) The tertiary sector (trade, transport and finance), which captured about 40 percent of economic activity before the Tsunami, "now" (in 2012) accounts for almost 55 percent (see figure 3.2). In the absence of the Tsunami, the service sector would have also grown, but at a much slower pace. It would have grown from about 40 percent tertiary VA as a share of the economy, to about 42 percent. Instead of this two percentage points increase, the Tsunami caused an additional increase of 13 percentage points. The agricultural share of the service sector increase from about 18 percent to 20 percent.

The service sector absorbed most of the displaced economic activity from agriculture. Put differently, the tertiary sector's slice of the total economic pie grew substantially, buoyed by the Tsunami, at the expense of the primary sector. As with the agricultural share, it seems as if the change in service share faced an adjustment period mostly in the years following the Tsunami, and further along moved in parallel to the counterfactual trajectory.

Figure 3.2: Service share of GDP trends: Aceh versus synthetic Aceh

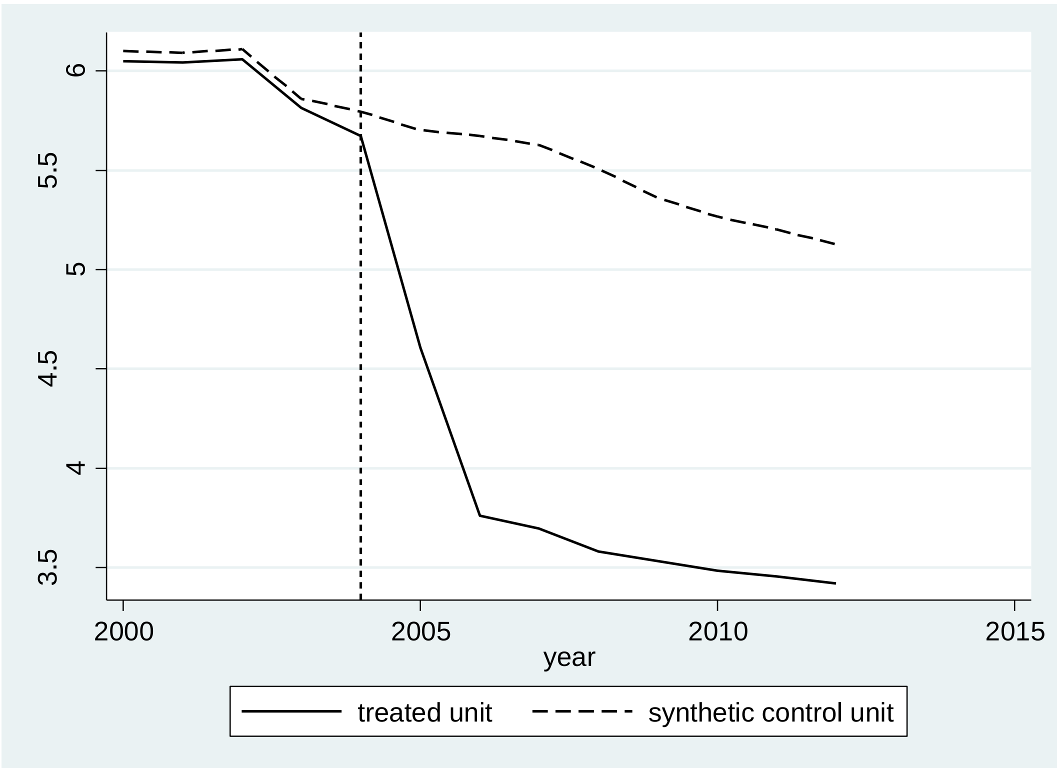


The transport and trade (including hotels and restaurant) sectors (both sub-categories of the tertiary sector) were crucial in Aceh's recovery program, and were probably the key levers that kick-started structural transformation process. While transport almost doubled in size since the natural disaster struck, trade also increased by 50 percent.

The effect displayed in figure 3.2 was unlikely observed by chance. Evaluating placebo effects in-space shows that the p-value, comparing the estimated main effect to the distribution of placebo effects, is about 0.03 from 2005 onwards. The affinity between the treated and the synthetic control unit is shown in table A3.3 of the Appendix. Table A3.4 in the Appendix displays the weights of each district in the counterfactual pool.

(3) Compared with Indonesia, manufacturing in Aceh was always a small sector, accounting for about 6 percent of regional GDP prior to 2004, which contrasts to the national average of about 22 percent. Looking at the historical manufacturing value added evolution confirms the decline of the sector and furthermore highlights the permanence of this decline (see figure 3.3). A poster-child-like structural transformation, one that would have been ticking all of the boxes enumerated by McMillan & Rodrik (2011), would have included an increased manufacturing share. However, Aceh shows the inverse: A decrease in the share of manufacturing, which began already before the Tsunami. The Tsunami certainly did not manage to turn around the manufacturing dynamics and trigger a structural transformation process. If anything, it exacerbated it, where without the Tsunami, Aceh would have a manufacturing share of the GDP of 5 percent. Because of the Tsunami, it only has 3.5 percent.

Figure 3.3: The impact of the Tsunami on manufacturing



The reason why the manufacturing sector was declining in Aceh before 2004 was primarily the running out of oil and gas, which continued to have an impact also in the post-Tsunami era.[38] The Tsunami decimated the manufacturing sector chiefly because of the destruction of one single, but quite important cement factory.

The effect displayed in figure 3.3 is possibly observed by chance. Evaluating placebo effects in-space shows that the p-value, comparing the estimated main effect to the distribution of placebo effects, in no year reaches a value lower than 0.13. The affinity between the treated and the synthetic control unit is shown in table A3.5 of the Appendix. Table A3.6 in the Appendix displays the weights of each district in the counterfactual pool.

Oil and gas: Aceh started running out of oil and gas resources and the first precipitous decline in resource extraction happened in 2002 (which is also mirrored by a synchronous decline in the share of manufacturing in figure 3.3). The closing down of the oil and gas field in Arun is an external negative shock that caused ripples in the entire manufacturing sector of Aceh. Manufacturing relied heavily on oil and gas as cheap production inputs (World Bank, Aceh Economic Update 2007). Declines in production due to missing oil were noted in many industries, including fertilizers, chemicals, cement and others (World Bank, Aceh Economic Update, 2007).

Cement: Aside from the demise of oil and gas, which was caused by triggers unrelated to the Tsunami, the second largest industry prior to the natural disaster, cement, also faced an unprecedented decline; this one was related to the Tsunami however. The physical and human destruction of the Tsunami caused in this sector was very large and equates to a complete destruction. The only cement factory in the area located in Lhoknga, which was operated by Lafarge, a French company, was completely destroyed. Almost all 500 people working in the factory at the time of the Tsunami were killed. The plant was producing about 1.2 million tons of cement a year in Aceh, and only a quarter was sold in the province (Higgins, 2005). It controlled about 96 percent of the local market prior to the Tsunami (Higgins, 2005).[39]

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[38] Partially responsible for the loss of competitiveness of the region were also skyrocketing wages in the wake of the reconstruction process, which disadvantaged the local economy because it made manufactured products more expensive (see World Bank, 2008b). Inflation had likely a big hand in depressing Aceh's competitiveness and ergo its exports in the first year or two after the Tsunami.

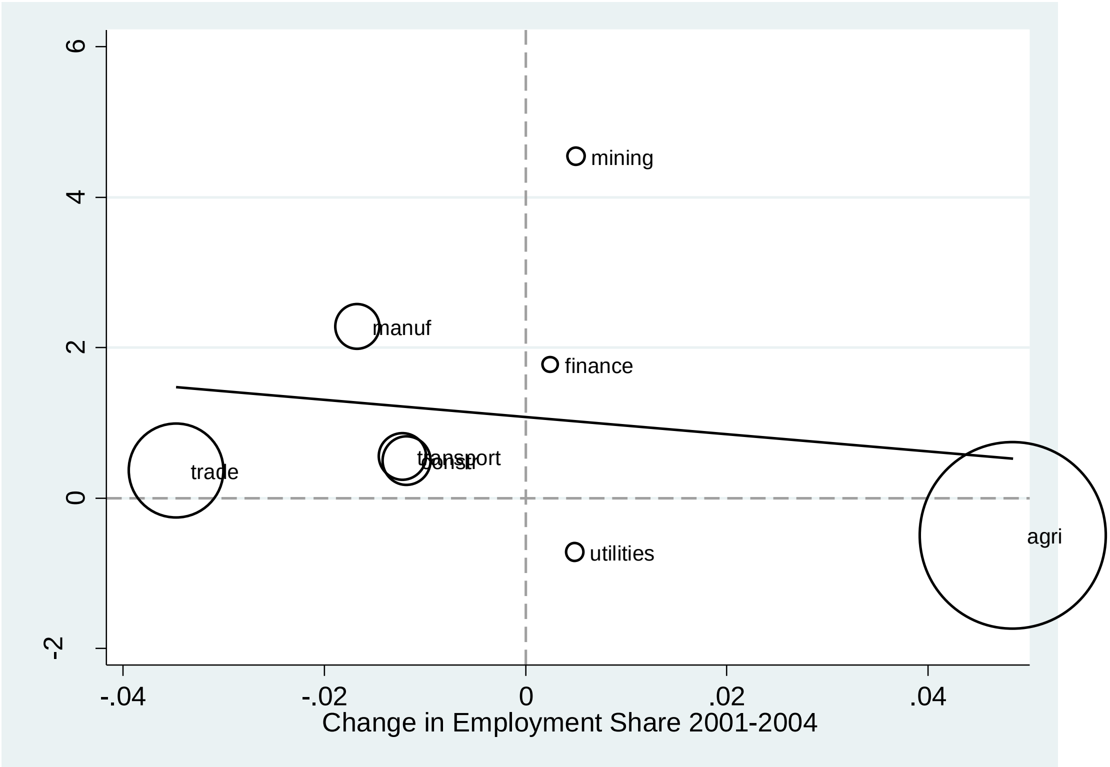
[39] The destruction of the plant caused damages of 220 USD Mio Dollars. The factory is being rebuilt and has yet to start operating again.

3.4.1.1 Linking structural transformation to growth

Production and labour flows from underperforming (low-productivity) activities to high-productivity activities are a crucial feature of development (McMillan & Rodrik, 2011). Nevertheless, how do we know that structural transformation was productivity enhancing; what if the extra labour in services is low-skilled and has an even lower productivity than it had in agriculture? After all, agricultural labour productivity continued to steadily increase by about USD 20 per worker a year after the Tsunami; a rate which has not changed since before the Tsunami.

I examine the question of whether structural transformation was actually growth enhancing, by looking at more disaggregated sectors (see figure 3.4). I find that the Tsunami was a powerful shock nudging the Acehnese economy further towards higher labour productivity. Before the Tsunami struck, the structural change in the Acehnese economy was growth reducing (see figure 3.4). Labour moved from the more productive sectors of the economy, such as manufacturing and also trade, transport and construction to less productive sectors, most notably agriculture, forestry and fishing. During the three years prior to the Tsunami the trade, hotel and restaurant sector shed labour to the tune of about 4 percent. At the same time, agriculture's workforce was gaining workers by more than 4 percent. The only two sectors that are below the average productivity are agriculture and the utilities and electricity sector, both of which increased in jobs from 2001 to 2004.

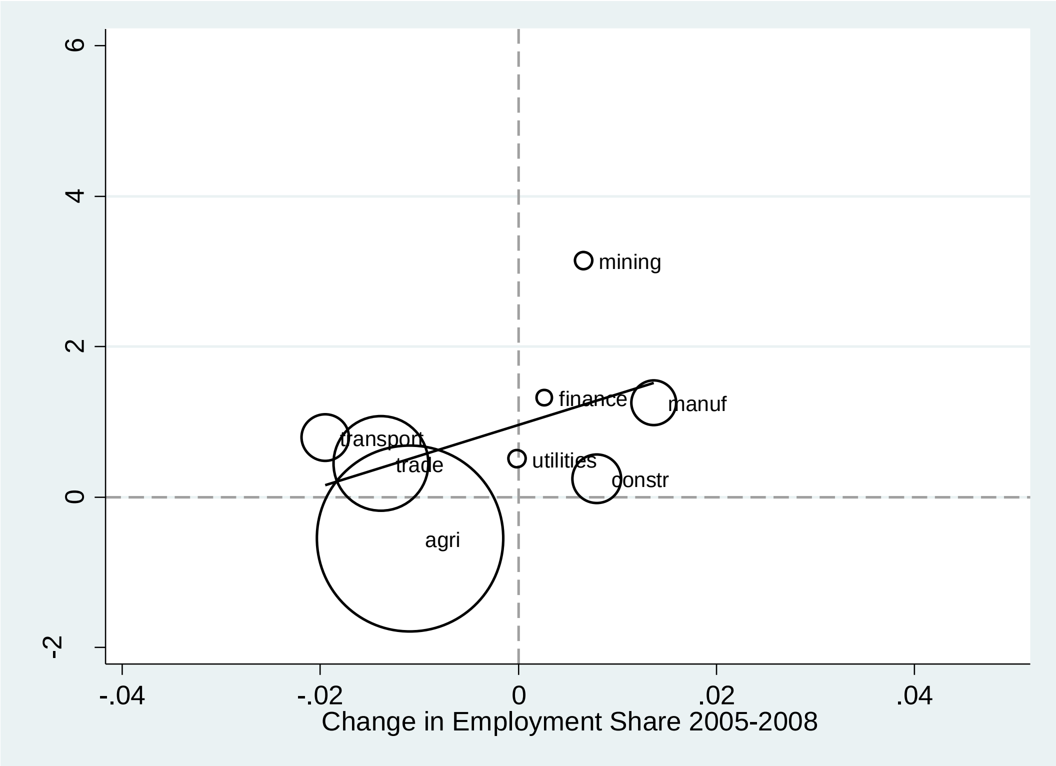
Figure 3.4: Association between sectoral labour productivity and job flows before the Tsunami



Note: Regression equation ln(p/P) = α + β*ΔEmp.Share results in the following estimated coefficient β = -11.4 with associated t-statistic of -0.58. Circle size represents the share of sectorial employment in 2004.

With the timing of the Tsunami came structurally transformative change. Agriculture was now shedding labour and construction and manufacturing were picking up the workers that had just become available. Trade's labour shedding slowed. Together, these dynamics translated into a change from a growth reducing structural change to a growth-enhancing structural transformation (as indicated by the positive slope coefficient in figure 3.5).

Figure 3.5: Association between sectoral labour productivity and job flows after the Tsunami



Note: Regression equation ln(p/P) = α + β*ΔEmp. Share results in the following estimated coefficient β = 41.1 with associated t-statistic of 1.42. Circle size represents the share of sectorial employment in 2008.

Was this switch from growth reducing to growth enhancing structural change causally tied to the Tsunami? The switch per se probably would have also occurred in absence of the disaster, but the magnitude would have been much less as suggested by comparing the productivity dynamics of Aceh to the counterfactuals. Even though the rest of Sumatra also displayed a similar pattern in that the region switched from a growth-reducing to a growth-promoting structural change trend, just like Aceh did, it did so at a much slower pace. The elasticity between employment share changes and share of sectoral productivity, even though also positive from 2005 to 2008 for the rest of Sumatra, was much smaller in size to the tune of one-third of the magnitude (the coefficient was 13.4 compared with the 41.1 for Aceh).

3.4.1.2 Structural transformation also displayed with district level data?

Unlike for investment and private consumption, for the sectoral aggregation I can zoom in closer, to the district level, which should allow me to dismiss the concerns related to biasing peace effects (at least for the structural transformation analysis). Testing for acceleration of structural transformation with a different method, for the district level data, confirms the results attained using the synthetic control method on province level data. Aceh has accelerated its move out of the primary sector into the tertiary sector after the Tsunami. As the economy grew, Aceh moved into the tertiary sector, continuously increasing its share of the overall economic pie.

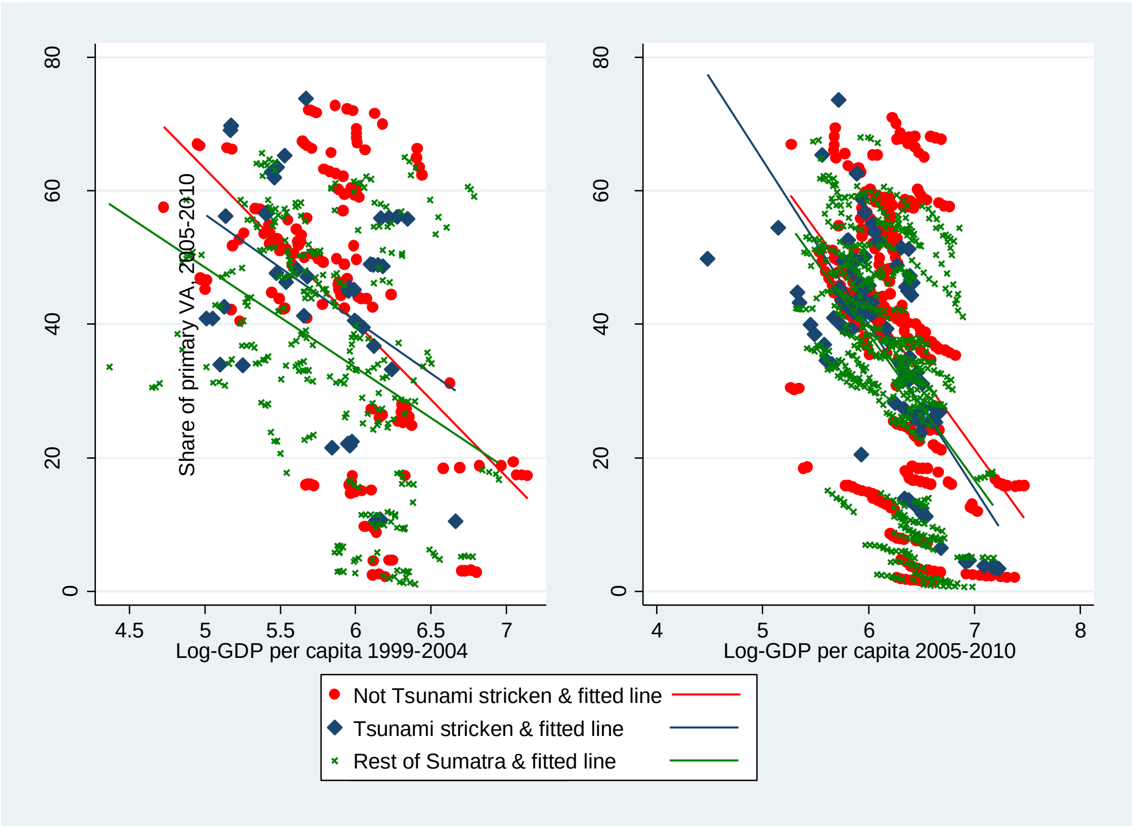
Prior to the Tsunami, the to-be-stricken districts were being structurally transformed at a similar rate compared to the not affected districts, as indicated by the parallel blue and red lines in the first panel of figure 3.6. Both are however steeper than the rest of the island's districts (excluding Aceh and North Sumatra). After the Tsunami however, the rate of change of moving into the tertiary sector did not significantly change in the two counterfactual groups (the green and red lines did not change in slope significantly), whereas it did for Aceh; the region shifted into a higher gear by gradually focussing more on the tertiary sector.

Figure 3.6: Tertiary Sector Value Added - Before and after the Tsunami

Note: The slope coefficient of the fitted linear line for Tsunami stricken districts (blue) increased by 102 percent, comparing before the Tsunami with after the Tsunami. In contrast, the slope of the two counterfactuals combined increased only by about 23 percent.

Corresponding to the move into the service sector was the move out of the primary sector (agriculture, forestry and fisheries). The move out of the primary sector was sped up disproportionately in the Tsunami stricken districts compared to the counterfactual groups, indicating an accelerated structural transformation. The left panel of figure 3.7 shows that Tsunami stricken districts before the Tsunami moved out of this sector at the same pace as rest of Sumatra, and at a slower pace than the stricken districts. The right panel shows however that the Tsunami accelerated the exit of the affected economies out of the primary sector as shown by a steeper slope in the fitted blue line. From 2005 to 2010, the stricken districts displayed the fastest move out of the agricultural sector. From 1999-2004, they moved slower out of agriculture than the non-flooded districts in Aceh.

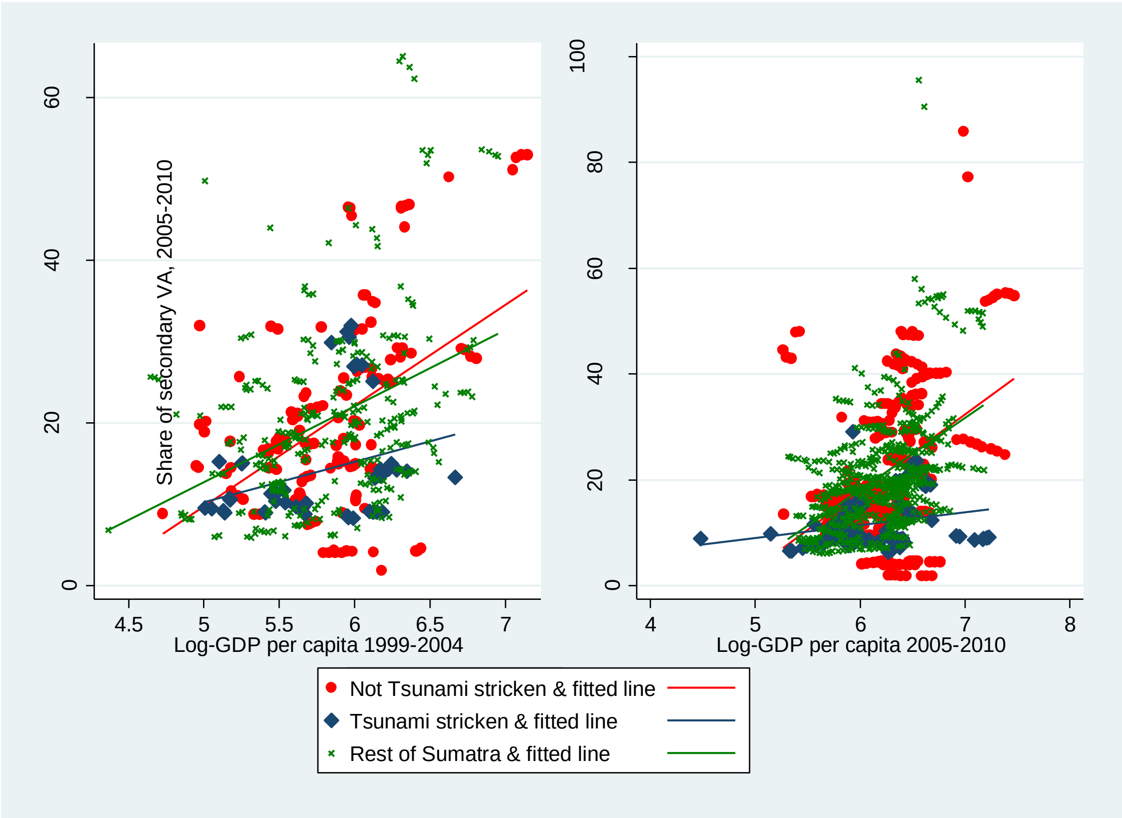
Figure 3.7: Primary Sector Value Added - Before and after the Tsunami



Note: The slope coefficient of the fitted linear line for Tsunami stricken districts (blue) decreased by 55 percent, comparing before the Tsunami with after the Tsunami. In contrast, the slope of the two counterfactuals combined decreased only by about 26 percent.

For manufacturing the Tsunami was also transformative, but not in a growth promoting way. It decelerated the move into the manufacturing sector for the Tsunami stricken districts, much of it had to do with the destruction of certain highly capital intensive factories (as elaborated on in the section on manufacturing). Aceh was moving much slower on concentrating in manufacturing as its economy expanded before the Tsunami, as indicated by a much flatter slope in the first panel of figure 3.8. After the Tsunami, Aceh went the opposite way.

Figure 3.8 : Secondary Sector Value Added - Before and after the Tsunami



Note: The slope coefficient of the fitted linear line for Tsunami stricken districts (blue) decrease by 51 percent, comparing before the Tsunami with after the Tsunami. In contrast, the slope of the two counterfactuals combined decreased only by about 43 percent.

The marginal effects of the structural transformation process are computed in table 3.1. With every one percentage increase of GDP per capita, the tertiary share of the economy increased by 0.097 percentage points. As shown also with the provincial data, most of the changes occurred in the first two years after the Tsunami. Changes to the tune of 10 percentage points from one year (before the Tsunami) to the next (after the Tsunami), were no rarity: e.g. Aceh Barat jumped from 51 percent service share to 61 percent, Aceh Besar jumped from 36 to 47 percent, and Pidie Jaya jumped from 17 to 29 percent. There were also much smaller increases, with e.g. Aceh Jaya increasing from 30 to 34 percent, Banda Aceh from 77 to 81 percent, and Nagan Raya from 41 to 44 percent. No such transformative effects were detectable in the years prior to the Tsunami. No such comparable effects were detected in any of the two counterfactual groups. Commensurately, with every one-percentage growth in GDP per capita in the stricken districts, the economy moved further out of the agricultural sector to the tune of almost 0.08 percentage points per percentage increase in GDP (as shown in table 3.2). The rest of Sumatra also displayed a similar declining trend in the agricultural sector, however it was about half as sizeable and not as accurately estimated (as indicated by it being significant only at the 10 percent level). The secondary sector analysis remains inconclusive.

Table 3.1: Service sector share panel data OLS regressions, 2000 - 2012

DV: Tertiary VA share (% of GDP)	Tsunami stricken districts		Not Tsunami stricken districts		Rest of Sumatra	
	2000-04	2005-12	2000-04	2005-12	2000-04	2005-12
Log GDP per capita	-0.46	9.68 ***	-3.40 ***	-1.68	-1.38 ***	2.27
	(0.45)	(3.66)	(1.29)	(2.44)	(0.49)	(2.14)
FE (district & time)	Yes	Yes	Yes	Yes	Yes	Yes
R squared	0.99	0.96	0.99	0.98	0.99	0.99
Obs	60	96	185	296	380	608

Table 3.2: Agricultural share panel data OLS regressions, 2000 - 2012

DV: Agricultural VA share (% of GDP)	Tsunami stricken districts		Not Tsunami stricken districts		Rest of Sumatra	
	2000-04	2005-12	2000-04	2005-12	2000-04	2005-12
Log GDP per capita	0.01	-7.66 ***	-2.78	4.38 *	1.20 *	-4.07 *
	(0.43)	(2.50)	(2.43)	(2.58)	(0.42)	(2.25)
FE (district & time)	Yes	Yes	Yes	Yes	Yes	Yes
R squared	0.99	0.98	0.99	0.99	0.99	0.99
Obs	60	60	185	296	380	608

Table 3.3: Secondary sector share panel data OLS regressions, 2000 - 2012

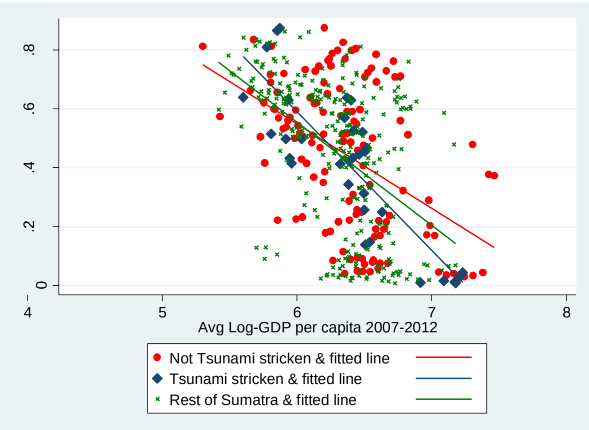
DV: Secondary VA share (% of GDP)	Tsunami stricken districts		Not Tsunami stricken districts		Rest of Sumatra	
	2000-04	2005-12	2000-04	2005-12	2000-04	2005-12
Log GDP per capita	0.43	-1.32	23.32 **	-6.92	0.55	-4.71 **
	(0.35)	(1.68)	(11.31)	(5.49)	(0.74)	(1.94)
FE (district & time)						
R squared	0.99	0.94	0.99	0.81	0.98	0.98
Obs	60	96	185	296	380	608

Notes: Robust standard errors are in parentheses. *, **, *** mean significance at the ten, five, and one percent level, respectively

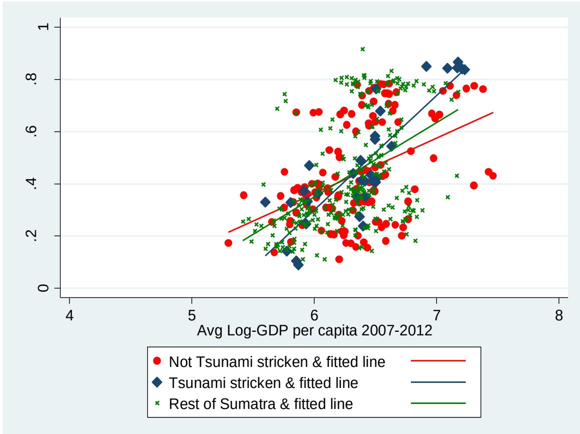
To complement the valued-added analysis, performing an employment share analysis is required. Similarly to the sectoral share analysis, looking at the employment shares also shows that the Tsunami stricken districts move more rapidly out of the primary sector, and also more rapidly into the tertiary sector. Labour followed the tertiary sector, and exited the primary sector as shown by steeper blue lines, compared to the red and green lines in both panels in figure 3.9. This shows that the affected districts are shedding jobs in agriculture and creating jobs in services, at faster rates compared to their counterfactuals. However, what cannot be established is how the elasticity between economic activity and economic composition looked like before the Tsunami struck due to the unavailability of district level sectoral employment data before 2007.[40]

Figure 3.9: Employment share in the Agriculture and Service Sector

Panel A: Agriculture



Panel B: Services



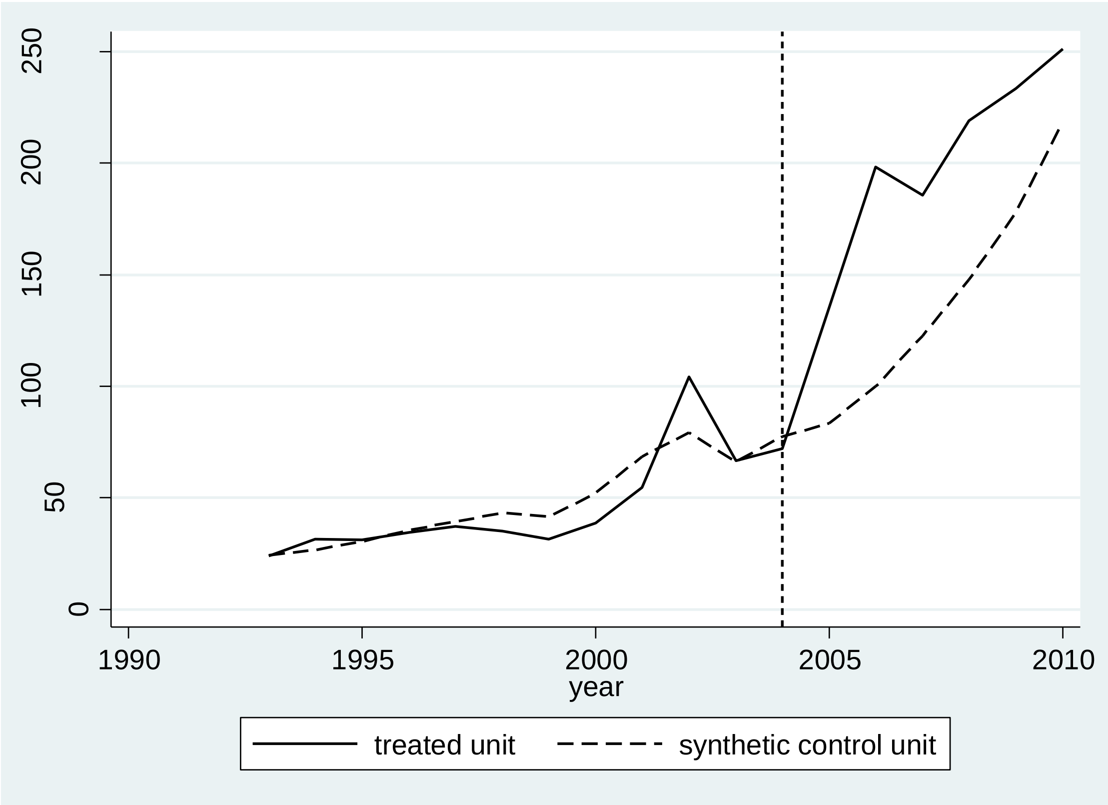
3.4.2 Reconstruction & investment bonanza

The Tsunami struck at the end of 2004 and caused a precipitous hike in capital formation rates in 2005 and 2006 (see figure 3.10). An investment bonanza followed the Tsunami destruction in an effort to rebuild the destroyed capital of the province. Gross domestic investment (capital formation) substantially increased relative to the non-flooded counterfactual, as shown by comparing the solid line (representing the

[40] Using provincial level sector data, I find that the share of persons employed in agriculture in Aceh decreased from about 54 percent just before the floods struck to about 45 percent in the years past 2009. The freed up labour was absorbed mostly by the public sector, but also by the secondary and tertiary sector.

‘treated’ region) with the dashed line (representing the counterfactual, which is assuming the Tsunami has not happened). The wedge between the two lines represents the total extra investment per capita in Aceh in the years following the Tsunami.[41]

Figure 3.10: Capital formation per capita (in current USD) trends in Aceh versus synthetic Aceh



Overall, investments were causally doubled in the immediate reconstruction years, peaking at a value of about USD 200 per person in 2006, compared to USD 100 for the counterfactual (USD 110 per person in 2006 compared to USD 50 for the counterfactual,

[41] The size of the capital formation increases is likely to be an underestimation. Many reconstruction activities (e.g. the Jackie Chan villages) are off-budget and therefore not recorded in the regional accounts because they are not considered by the system of national accounts methodology also used by regional accounting offices. This underestimation however does not put in question the results, if anything, if there was a way to incorporate a measure of these untraced investments, it would result in an intensification of the Tsunami’s effect on investments, leading to an even larger sized effect.

using the deflated numbers, which are reported in figure A3.1 in the Appendix).[42] After this peak, the gap between the flooded and the counterfactual groups continued to narrow to an extra investment of USD 20 (measured in constant USD) in the last year for which there is data available.

So were there long-term effects on capital formation? Investment levels remained high, higher than the counterfactuals', even after the reconstruction was finished. However, there was a drop in capital formation rates in 2007 and seemingly a convergence to the counterfactual investment scenario post 2008. Whether this convergence ultimately lead to say an intersection cannot be answered in the absence of more recent data. Unfortunately, capital formation data is only available up until 2010; therefore whether the treated and the synthetic trajectory ultimately continued to converge can only be conjectured.[43] On average, the annual extra investment per person was roughly USD 40.

Computing the p-values for each period after the Tsunami shows that only the short-term (the two years following the disaster) effects are larger than placebo province's effects. The subsequent years have too high p-values, indicating that the effect may not be significantly different from zero beyond the short-term, as there are enough placebo provinces that showed similar effects to cast doubt on the rarity of the observed effects for Aceh. The affinity between the treated and the synthetic control unit is shown in table A3.7 of the Appendix. Table A3.8 in the Appendix displays the weights of each district in the counterfactual pool.

For the entire region of Aceh, investments rose by a factor of three from 2004 to 2006, from roughly USD 300 Million in 2004 to USD 800 Million in 2006 (see figure A3.2 in the Appendix), surpassing the counterfactual by almost twofold. Measuring the figure's wedge area, by taking the integral, yields an estimate that closely resembles the total amounts of aid allocated for reconstruction, adding confidence in the quality of the capital formation measure.

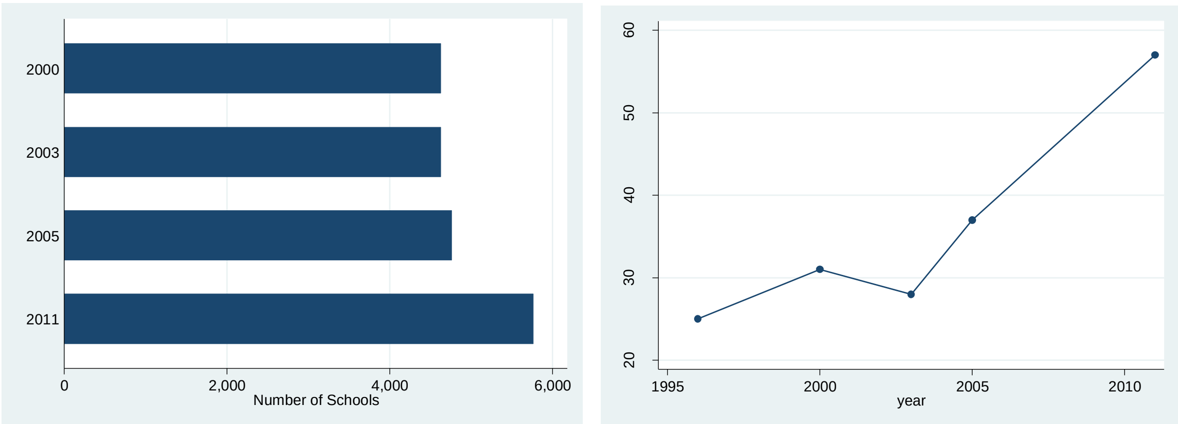
[42] Due to the unprecedentedly high inflation rates after the Tsunami, it is ever more important to deflate the GDP subcomponent figures so they are comparable across time. Unfortunately, the deflators available only date back to as early as 2000, shortening the pre-treatment time series substantially.

[43] An extension with more recent data is most certainly an immediate next step, once the data becomes available.

Spending on infrastructure increased during the decentralization wave in the early 2000s in Aceh (see also World Bank, 2009b), which is also visible in figure 3.11. It reached a preliminary peak in 2002 when the Acehnese regional government received a windfall of funding from the oil share agreement of the same year. Just as the oil revenue agreement came into effect in 2002, resources in the ground started to plummet precipitously, leading a reverting back of the investments in 2003 and 2004.

What was built back? During the reconstruction and investment bonanza, around 140,000 new houses were built, 1700 schools, 1000 government buildings, 36 airports and seaports and 3700 km of roads (at a price tag of USD 12 Billion) by 2008 (BRR, 2009) and 273 bridges (World Bank, 2009b) by 2007. Data availability on rebuilt infrastructure varies across the different examples of rebuilt infrastructure. The years plotted in this section were chosen mainly based on the availability of data. After the reconstruction was completed, Aceh had almost 1500 more schools than before (an increase of about one-fourth) and almost twice as many hospitals than before the Tsunami; from less than 30 to almost 60 in Aceh (see figure 3.11).[44]

Figure 3.11: Number of schools and hospitals in Aceh before and after the Tsunami



Roads are now longer than they were before the Tsunami struck (see figure 3.12). While before the Tsunami, the length of all asphalted roads in Aceh added up to 1300km, the

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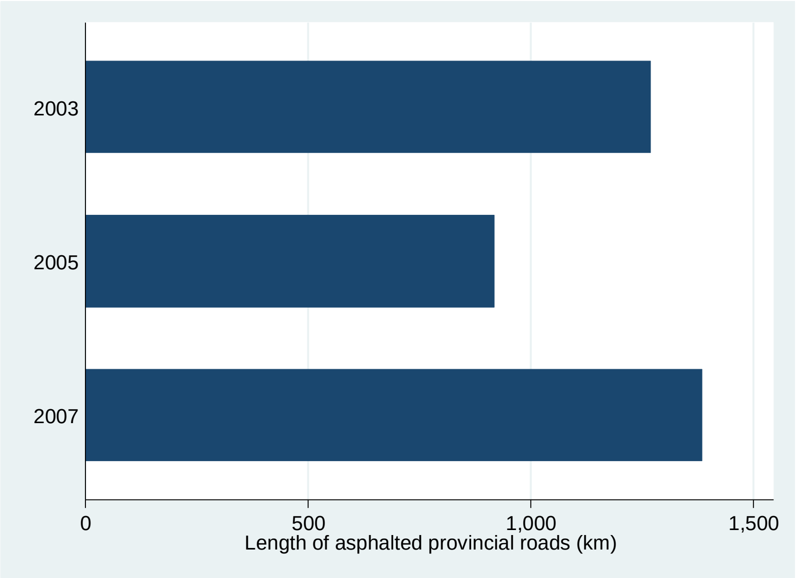
[44] Even though the number of hospitals was growing, the numbers of polyclinics in the province decreased steadily. Health clinics, so-called *puskesmas* on the other hand were shrinking.

Tsunami wiped out about 400km thereof. By 2007, the length even reached 1400 km. The extra roads were built to reach formerly isolated areas (Gelling, 2009).[45] Travelling times have reduced by more than half when travelling between Banda Aceh and Calang on the West Coast of Aceh on an USAID financed highway, which in turn should boost economic productivity over the long haul.

Figure 3.12: Length of asphalted roads before and after the Tsunami in Aceh



Note: There was no data before 2003, which would have allowed looking at how the growth in roads was evolving before.

Physical capital was built back better. Hospitals, schools, roads, and other infrastructure was not only built back, but also built back better. The rebuilt houses for example have improved standards, and consist mostly of cement, which was formerly dedicated only for richer houses and mosques (Steinberg & Schmidt 2009). The roads that were rebuilt are also of better quality, as they were built with better asphalt, they are wider and are further away from the coastline (Jha, 2010). Granted however, not all construction was productivity enhancing. Some of the reconstruction was obsolete and now stands empty (Lamb, 2014).[46]

[45] http://www.nytimes.com/2009/12/26/world/asia/26iht-tsunami.html?_r=0&adxnnl=1&pagewanted=all&adxnnlx=1432659918-UW2rHcz3+9R0JkRBpw/asQ
[46] http://www.theguardian.com/cities/2014/jan/27/banda-aceh-community-spirit-peace-indonesia-tsunami

The construction sector spree also had important spillover effects to other sectors. Many materials supplied for the reconstruction efforts, including sand, gravel, bricks and wood were locally sourced in Aceh (Pribadi et al, 2014). Most of Aceh's imported reconstruction materials came from North Sumatra (Pribadi et al, 2014), which constitutes a positive demand spillover. Other material was imported from further away, such as bricks from Jakarta, cement from West Sumatra, roof tiles from East Java, and metal frames from Australia (Pribadi et al, 2014).

In sum, the reconstruction of destroyed capital, i.e. investment, drove growth after the natural disaster confirming also the main storyline of the seminal Skidmore and Toya (2002) paper. The reconstruction sector was therefore (at least partly) responsible for boosting economic growth beyond its counterfactual growth path. Because capital was built back better it allowed for higher productivity, and contributed to maintaining a sustainably higher per capita output path even once the reconstruction was finished (as shown in chapter 2).

3.4.3 Aggregate Private consumption was smoothed

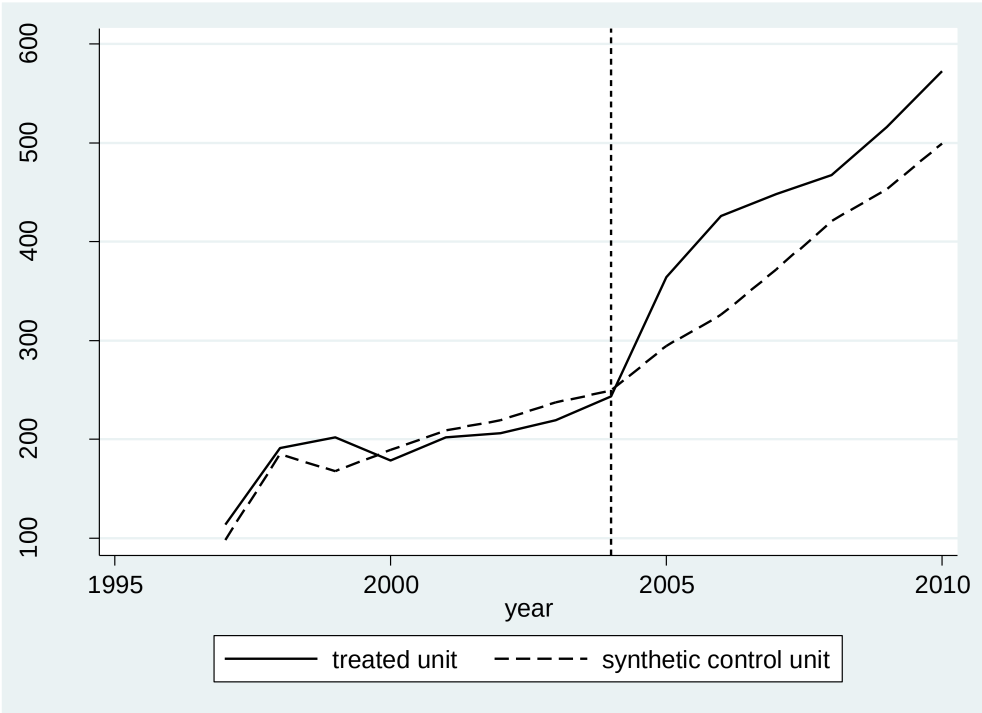
Despite what has been suggested in the development economics and natural disaster economics literature, in Aceh, the Tsunami did not result in a collapse of aggregate consumption. To the contrary, the affected region did not only manage to smoothen consumption to levels similar to the counterfactual, but also reach a higher consumption path (see figure 3.13).

Private consumption experienced a strong boost in the post disaster recovery phase and, from 2006 onwards, reached a growth path which was higher, yet parallel to the counterfactual's path.[47] This mirrors the higher long-term per capita GDP output path

[47] There is an indication that private consumption dropped relative to the counterfactual in the two years after 2006, up until 2008, at which point it picked up again to a level parallel yet much higher than the one of the counterfactual. It is not clear why this drop occurred, and many reasons could be responsible for it such as the running out of the aid funds and a delayed transition into an economy with upgraded capital, or the donor community switching to loans rather than grants. An analysis of household micro data could shed light onto this and could be a promising area for future research.

finding of chapter 2 (as opposed to a continuously increasing per capita growth rate). After an initial adjustment period, the consumption no longer displays higher annual growth rates (which would require the trend to be monotonically increasing compared to the counterfactual), but rather maintain a higher long-term consumption path.

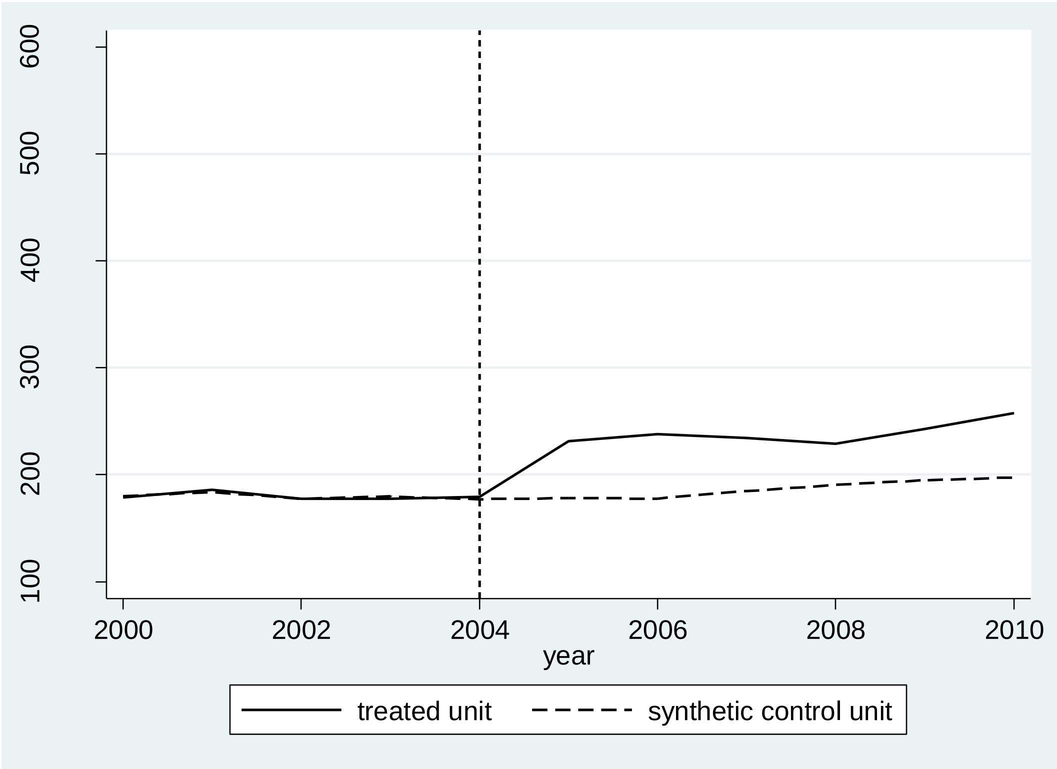
Figure 3.13: Private consumption per capita (current USD) trends in Aceh versus synthetic Aceh



Inflation skyrocketed after the Tsunami; reaching at the highest point 41.5 percent in December of 2005 (World Bank, 2007b). This surge resulted in an inflation rate that was more than three times larger than the Indonesian average. The high price rises were in part caused by high food and transportation costs associated with destroyed roads and higher transportation costs, and by higher demand and an initially limited supply in particular related to reconstruction material. Inflation levels continued to decrease after the peak, to about six percent in 2007, a level that was still far larger than the country's average however. By 2008, inflation was roughly equal to the country's average. Due to this high inflation during the reconstruction period, it is crucial to deflate the prices so they are comparable over time.

The Acehnese consumption path was quite stable in the early 2000s, changing very little and averaging about USD 180 per person, as figure 3.14, which plots constant USD, suggests. While average private consumption before the Tsunami struck was about the same for both Aceh and its counterfactual, it increased to an average of USD 240 in the treated region in the years thereafter, indicating that the private consumption was causally increased by USD 60 (or by 25 percent). These results suggest that not only was a smoothing of consumption achieved, consumption was even boosted, probably owing to the large influx of foreign aid, the fiscal stimulus and the reconstruction efforts, despite the inflationary pressure triggered in part by the inpouring of aid.

Figure 3.14: Private consumption per capita (constant USD) trends in Aceh versus synthetic Aceh



Despite both consumption graphs (figure 3.13 and figure 3.14) indicating higher consumption per capita rates of the treated province, in contrast to the counterfactual, looking at the p-values does not allow to conclude that the increase consumption in the long-term is a consequence of the Tsunami. As with the investment rates, only the immediate years after the Tsunami show that the effect is much larger compared to placebo provinces. From three years post-Tsunami onwards, there are enough placebo-provinces with similar effects to conclude that long-term effects on consumption may not hold true. The affinity between the treated and the synthetic control unit is shown in table A3.9 of the Appendix. Table A3.10 in the Appendix displays the weights of each district in the counterfactual pool.

3.5 Other reasons why the Tsunami may have been "creative" in its destruction

3.5.1 Survival of the economically fittest?

Can compositional changes in the population explain the creative destruction result? Could it be that the economic activity was boosted (not only in district terms but also in per capita terms) because the people that were killed were less productive than those that survived?

Even though the Tsunami was arbitrary, its impact on the population was not. "Natural disasters do not affect people equally," as noted by Neumayer and Pluemper (2007, p. 1), which prompts a careful look into the composition of casualties. GDP per capita could have been (partially) boosted by a compositional change in the kind of people engaging in economic activities. If the economically more productive people survived, an increase in aggregate per capita income could have not only been due to better average economic performance but also an artefact of a compositional change in the population. In other words, if the lower end of the income distribution had died in 2004, the average per capita income of 2005 would automatically have been higher, ceteris paribus.

Physical strength played a role in survival. Children, older adults and females were more likely to die in the waves of the Tsunami, as shown by longitudinal population-based surveys (Frankenberg et al, 2011 and Doocy et al, 2007). On the other hand, there was no difference in survival rates across socio-economic factors (Frankenberg et al, 2011). Assets and income made no difference in mortality rates. Regardless whether the household was poor, middle-class or rich, all experienced similar death and damage impacts (Frankenberg et al, 2009). The fact that people from all strata of society were equally likely to die does not indicate a survival of the economically fittest across different sectors.

However, the fact that physically stronger persons survived in an economy that is still specialized in manual labour (in 2012 about 45 percent of the labour force still worked in agriculture, fisheries, manufacturing and construction), could indicate that within a sector the more productive population segment was more likely to survive. Younger and older persons were more likely to be killed. Moreover, higher levels of education made more resilient (but only amongst males) (Frankenberg et al, 2013). For females, education made no difference in survival. Frankenberg et al (2013) shows that educated males were not only in better physical health, but also able to smoothen consumption better over the five years following the Tsunami, a possible indication that they could be more "economically fit."[48]

The likely direction of this survival bias is that it overestimates the estimated creative destruction effect, and that without it the creative destruction effect would be smaller. How large this compositional effect is, and how much of the creative destruction effect can be explained by the survival bias is hard to quantify. Without being able to say much about the relative size of both effects, I can infer that the survival bias is not large enough to cancel out creative destruction effects, by observing not only creative destruction examining GDP/capita but also GDP data.[49]

3.5.2 Migration

Migration is a key strategy adopted by the survivors of a disaster (Hugo, 2008). One can identify two separate waves of migration that are caused by the Tsunami and could potentially confound the district level analysis, which to recap, concluded building back better (BBB) and creative destruction. On the one hand, internal displacement, where people escape from the hazard and its repercussions and move away from the affected

[48] An initial inkling of looking at the labour productivity figures to find answers, would however be futile, because the productivity measures could have also been affected by aid and extension work.
[49] To further shed light on this question, it would be helpful to conduct the analysis using *GDP/persons in the labor force*, as opposed to *GDP/population*. This will be an interesting avenue for promising follow-up research in the future.

district. On the other hand, people also move towards the hazardous area and participate in labour migration to the stricken districts because of all the job opportunities created there in the wake of reconstruction. Both demographic shifts would call into question the Stable Unit Treatment Value Assumption (SUTVA).

Internal displacement may pose a bias. The income results presented are in per capita terms, which in principle should account for economic activity per resident of the district in question. One may argue however that internally displaced migrants are not accounted for in the recipient district, because they are not formally registered where they fled to, which means that they still are accounted for in the district they originate from which was struck by the Tsunami. This would however not put in question or attenuate the creative destruction result; to the contrary, it would strengthen it. It would underestimate the positive effect of the Tsunami in the affected districts, because it would artificially inflate the denominator of GDP/pop with residents who no longer live there, biasing the overall per capita income statistic downwards.

There is little reason to believe in such an underestimation due to internally displaced people however, because most of the 66,893 displaced households from the Tsunami moved to different villages within their districts (World Bank, 2007c).[50] About two-thirds of them were sheltered by their family and friends (World Bank, 2008c)[51] and the rest relocated first to shelters, tents and public buildings and later to communal temporary housing, most of which were located in the same district. The districts of Pidie, Bireuen and Aceh Besar, all of which flooded, report the largest numbers of Internally Displaced Persons (IDPs) from the Tsunami. By September 2005, only five percent of Aceh's population was still considered internally displaced (see Nazara, and Resosudarmo, 2007). According to another source, by 2006 more than 85 percent of the IDPs returned already to their villages (World Bank, 2007c).

Many survivors moved back to their flooded homes. Although the Indonesian government initially implemented a building ban, preventing survivors to build-back in particularly vulnerable low-lying coastal plains such as e.g. in Lambung, in an attempt

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[50] Estimates of the scale of the triggered population movement vary from 350,000 to 550,000 Indonesians that fled/left their homes (USAID 2005; Robinson 2006; KDP 2007)

[51] http://iussp2009.princeton.edu/papers/90318 claim that most of them stayed in a camp for the displaced.

to shift rebuilding activities further inland, they rescinded that ban as a response to the strong desire of people to move back (Aquilino, 2011). As a compromise, they built escape buildings into the landscape allowing residents to flee vertically. Banda Aceh has 15 of these buildings for example (Vale, et al, 2014). While the merit of repopulating coastal plains is controversially discussed, and potentially lethal, particularly in light of gradual onset climate change and the chaos and havoc that ensued in a "mock exercise" where a magnitude 8.6 earthquake struck in 2012, but eventually did not cause another Tsunami, it is good for the SUTVA assumption of the natural experiment presented in this paper.

Those that moved away from their original villages moved in large parts to areas within the affected districts. An example is likely the best known housing construction efforts the Indonesia-China Friendship Village, or more commonly known as "Jackie Chan Village," after the Hong Kong based actor who mobilized and funded its construction. It is a village built from scratch based on risk adversity standards far from the reach of any future Tsunami wave 300 meters above the sea and 1.5 km inland. The displaced homeowners who decided to locate to this resettlement home, moved essentially within their districts, and therefore do not violate the SUTVA assumption. Additionally conducive for a SUTVA assumption is that many people have since moved back from temporary or permanent villages such as the Jackie Chan village back to coastal communities over time.

If anything, location to resettlement houses/villages like the Jacki Chan village should reduce economic productivity because it is not chosen based on livelihood and economic productivity considerations, but on risk prevention. Many residents of the remote village face quite substantial transportation costs in getting to where their livelihoods are, particularly the fishermen amongst them (Vale et al, 2014). This would not cast doubt on the creative destruction finding, rather it would intensify the creative destruction finding.

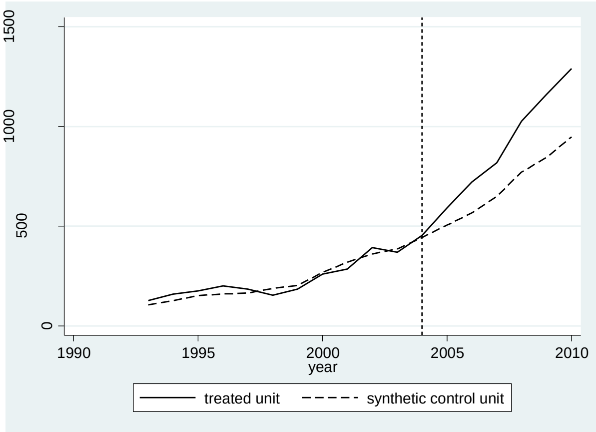
Labour migration. Looking at provincial level population figures shows that Aceh lost about one percent of its population, which almost exclusively is accounted for by the direct casualties the disaster caused. There was virtually no net outward migration (out of the Aceh province).[52] There was however substantial inward migration. The population of Aceh for example grew by roughly five percent in the three years after 2005, which is far above the replacement rate- and even the fertility rate of the region. This is a strong indication that there was substantial inward migration for re-building efforts.

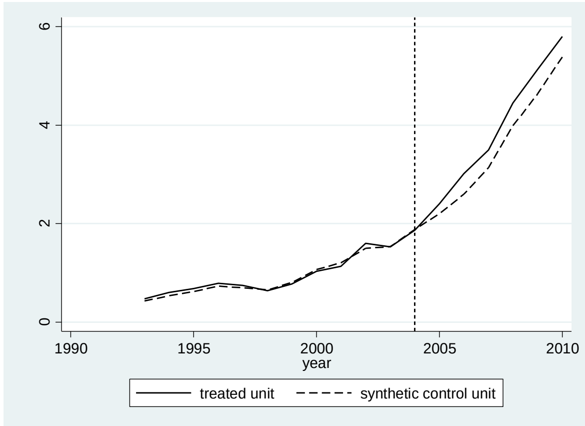
Most of the labour migrants however come from the neighbouring province of North Sumatra. Performing the quasi-experimental analysis with North Sumatra also, took care of this labour migration bias. The robustness analysis of chapter 2 including also North Sumatra as treated area shows creative destruction also, which indicates that if there is a bias due to migration, it is not to the extent that the creative destruction is cancelled out. Furthermore, reproducing the synthetic control method analysis of capital formation, with both Aceh and North Sumatra as the treated districts, also confirms the creative destruction finding (see figure 3.15). Furthermore, the creative destruction growth path is sustainable for the non-island districts, indicating that even if there was population interference between treatment and counterfactual districts and provinces, they would have resulted in a break in time trend in 2008/09, indicating convergence, whenever the majority of reconstruction efforts were terminated. Because there was no such convergence indicating time trend, as we saw in chapter 2, and also figure 3.15, the potential biasing effects of labour migration can be dismissed as marginal at best.

[52] Of course one cannot preclude the possibility of replacement, in that a segment of the population leaves and another one moves in, but that remains essentially unverifiable unless through field interviews.

Figure 3.15: Capital formation trends in Aceh & North Sumatra versus synthetic Aceh & North Sumatra

Panel A: Per capita capital formation **Panel B: Capital formation**





3.5.3 Former volunteer work now priced in the market

Volunteer labour is a crucial part of village life in Aceh, where many public services such as trash pick-up, road sweeping, repair of public infrastructure among other services is part of a moral obligation and performed several times a month (see Freire, Henderson and Kuncoro, 2011). This public service is not remunerated. The volunteer labour system has its roots in Islamic tradition, and dates back to the ancient sultanates and is referred to as "gotong royong."

In a 2014 Guardian article it was alleged that the cash-for-work programmes employed by the donor community to support certain reconstruction programs crowded out communal spirit and undermined the concept of "gotong royong" and made people reluctant to help their neighbours unless they received cash in return (Lamb, 2014).[53] Crowding out of altruistic motives through price incentives is a topic that has received considerable attention in behavioural economics and microeconomics (see e.g. Frey and Oberholzer-Gee, 1997). This claim essentially asserts that after the Tsunami, people only would do community help if they were also compensated for it. By essentially formalizing this informality that was formerly not priced in the market, GDP could therefore also have been boosted, biasing the before and after comparison.

[53] http://www.theguardian.com/cities/2014/jan/27/banda-aceh-community-spirit-peace-indonesia-tsunami

However, looking at boat aid, Freire, Henderson and Kuncoro (2011) find the opposite to crowding out. Looking at the effects of receiving boat aid on the amount of volunteer days put in by the family by applying panel regression methods they find that it affects the amount of volunteer days positively, meaning that the more aid people received the more likely they were willing to give back and work for the community. In a previous cross-village analysis, they found no effect between aid and days volunteered. Granted boat aid is not cash-for-work aid, but there is no evidence to my knowledge investigating crowing-out effects of these programs in Aceh. There is therefore not enough evidence to either substantiate or dismiss the possibility that pricing volunteer work has artificially boosted GDP.

3.6 Conclusion

I investigated three potential causal mechanisms for why the Tsunami was "creative" for Aceh in detail, and find that they jointly contributed to the creative destruction finding of chapter 2. First, the Tsunami caused an unprecedented investment bonanza in the effort to reconstruct destroyed physical capital. Second, aggregate private consumption, against all predictions, did not contract. Private consumption was in fact not only smoothed, but also boosted, due in parts to the many cash programs initiated by the donor community. Third, structural transformation, the reshuffling of economic activity from lower-productivity sectors to higher productivity sectors, was accelerated as a reaction to the Tsunami. Jointly these three factors were in parts responsible for allowing Aceh's economy to buoy the floods and stay above a no-Tsunami counterfactual output path, even in the face of sharply declining tradable exports and decreasing competitiveness of the manufacturing sector, and in the face of increased unemployment rates.

The Tsunami triggered an acceleration of structural transformation, causing a speeding up of the movement out of agriculture and into the service sector making Aceh's economy more productive and growth promoting in its path. Evidentially, aid had a big hand in catalysing these changes, which is also discussed in detail in the second chapter of my PhD thesis. Investigating the varying effect the Tsunami had on the different sectors, I find that the service sector (telecommunications, transport, restaurants and hotels inter alia) and the construction sector flourished in the years after the Tsunami. In contrast, agriculture and manufacturing were stunted. The Tsunami seems to have permanently hurt the manufacturing sector in Aceh, yet due to the small scale of this sector, its reduction in productivity was not severe enough to counterbalance the creative destruction drivers (investment and private consumption).

Other explanations for why the Tsunami might have spurred economic growth in Aceh such as the survival of the economically fittest, inward migration of productive labour, or pricing-out of former volunteer work are also discussed. No evidence was found that these alternative explanations can explain a significant part of the creative destruction effect that was caused by the Tsunami.

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Appendix

Figure A3.1: Capital formation per capita (in constant USD) trends in Aceh versus synthetic Aceh

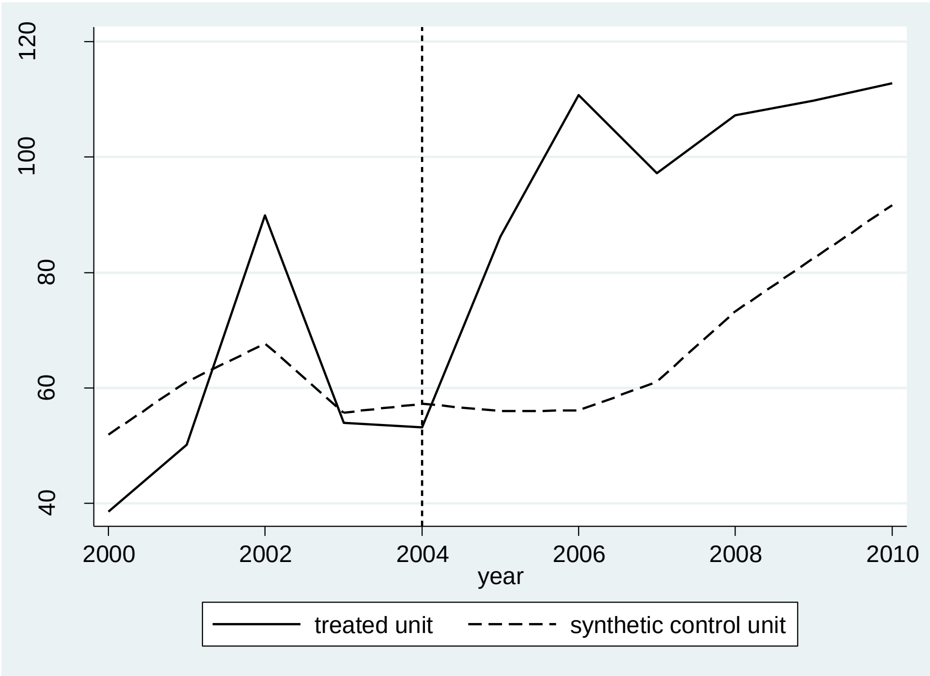

Figure A3.2: Total Capital formation (in current USD) in Aceh versus synthetic Aceh

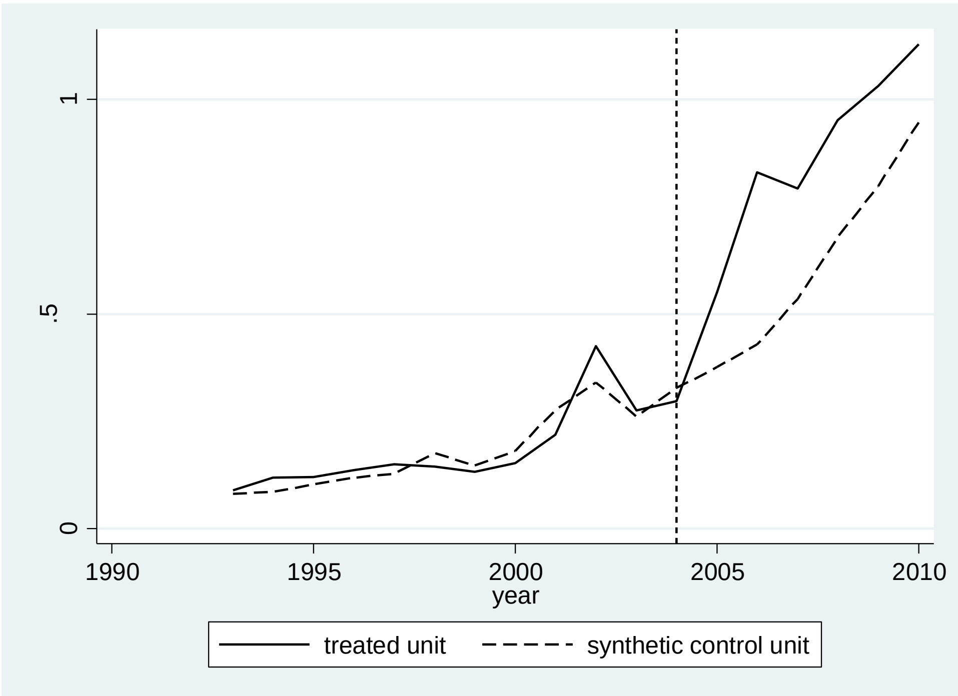

Figure A3.3: Aggregate private consumption per capita (current) trends in Aceh versus synthetic Aceh

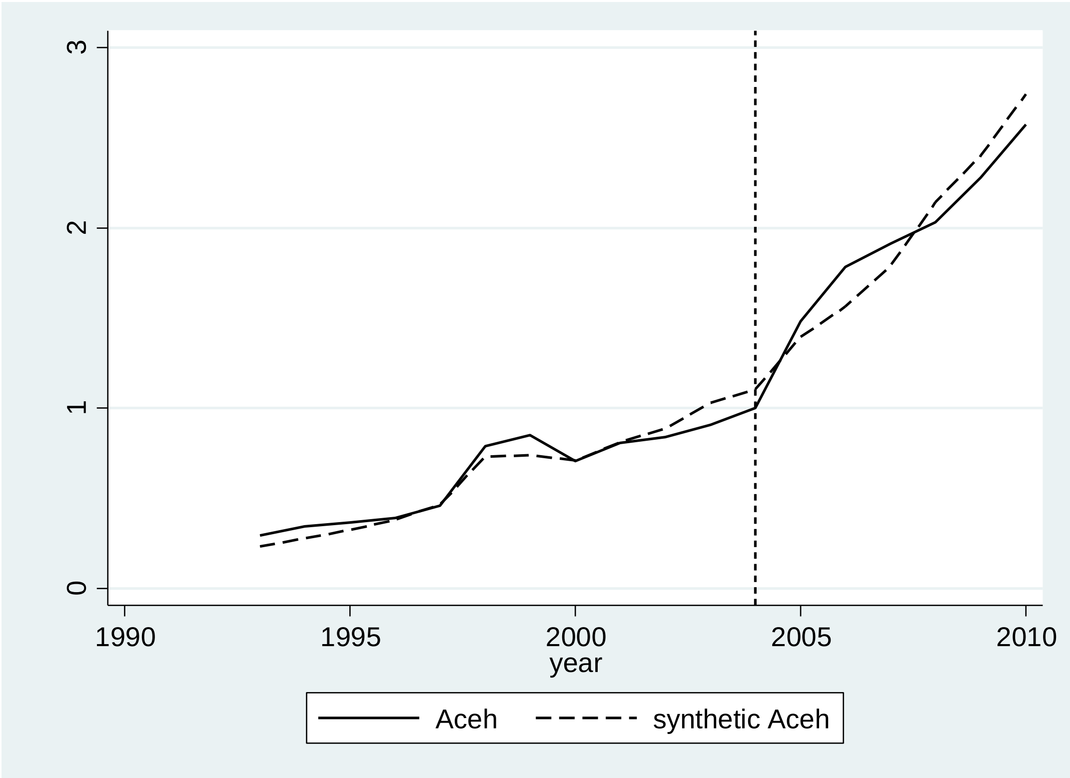

Table A3.1: Agricultural VA predictor means

	Treated	Synthetic
Agricultural VA as a share of GDP (2000)	44.7	44.7
Agricultural VA as a share of GDP (2004)	44.7	44.6
GDP per capita (2004)	427.0	382.6
Poverty rate, % of population (2004)	8.9	18.1
Literacy rate for population 15 and over (in % of total population)	97.0	93.9
Net enrolment ratio (junior secondary), %	86.7	64.1
Net enrolment ratio (senior secondary), %	72.1	39.1
Net enrolment ratio (primary) %	94.1	92.9
Birth attended by skilled health worker (%) (2004)	96.4	73.9
Morbidity rate (%) (2004)	20.6	25.3

Table A3.2: District weights in synthetic Aceh's agriculture VA

District	Weight	District	Weight	District	Weight
Agam	0.01	Lampung Selatan	0.008	Payakumbuh	0.007
Bandar Lampung	0.006	Lampung Tengah	0.05	Pekan Baru	0.006
Bangka	0.009	Lampung Timur	0.072	Pelalawan	0.013
Banyuasin	0.021	Lampung Utara	0.007	Pesisir Selatan	0.009
Batanghari	0.009	Limapuluh Kota	0.011	Prabumulih	0.007
Belitung	0.058	Lubuk Linggau	0.006	Rejang Lebong	0.01
Bengkalis	0.008	Merangin	0.011	Rokan Hilir	0.013
Bengkulu Selatan	0.006	Metro	0.006	Rokan Hulu	0.015
Bengkulu Utara	0.008	Muara Enim	0.009	Sarolangun	0.012
Bengkulu	0.006	Muaro Jambi	0.009	Sawahlunto Sijunjung	0.008
Bukittinggi	0.006	Musi Banyuasin	0.01	Sawahlunto	0.007
Bungo	0.01	Musi Rawas	0.015	Siak	0.007
Dumai	0.006	Ogan Komering Ilir	0.018	Solok	0.012
Indragiri Hilir	0.011	Ogan Komering Ulu	0.01	Solok	0.006
Indragiri Hulu	0.009	Padang Panjang	0.006	Tanah Datar	0.009
Jambi	0.006	Padang Pariaman	0.008	Tanggamus	0.219
Kampar	0.018	Padang	0.006	Tanjung Jabung Barat	0.009
Kepulauan Mentawai	0.024	Pagar Alam	0.008	Tanjung Jabung Timur	0.01
Kerinci	0.015	Palembang	0.006	Tebo	0.013
Kuantan Singingi	0.014	Pangkal Pinang	0.006	Tulang Bawang	0.01
Lahat	0.01	Pariaman	0.008	Way Kanan	0.007
Lampung Barat	0.006	Pasaman	0.025		

Table A3.3: Service VA predictor means

	Treated	Synthetic
Agricultural VA as a share of GDP (2000)	39.3	39.4
Agricultural VA as a share of GDP (2004)	40.0	39.9
GDP per capita (2004)	427.0	408.6
Poverty rate, % of population (2004)	8.9	16.4
Literacy rate for population 15 and over (in % of total population)	97.0	95.2
Net enrolment ratio (junior secondary), %	86.7	65.8
Net enrolment ratio (senior secondary), %	72.1	44.0
Net enrolment ratio (primary) %	94.1	93.7
Birth attended by skilled health worker (%) (2004)	96.4	75.9
Morbidity rate (%) (2004)	20.6	22.2

Table A3.4: District weights in synthetic Aceh's service VA

District	Weight	District	Weight	District	Weight
Agam	0.015	Lampung Selatan	0.011	Payakumbuh	0.013
Bandar Lampung	0.011	Lampung Tengah	0.014	Pekan Baru	0.012
Bangka	0.014	Lampung Timur	0.012	Pelalawan	0.006
Banyuasin	0.022	Lampung Utara	0.011	Pesisir Selatan	0.015
Batanghari	0.012	Limapuluh Kota	0.015	Prabumulih	0.013
Belitung	0.012	Lubuk Linggau	0.013	Rejang Lebong	0.039
Bengkalis	0.013	Merangin	0.013	Rokan Hilir	0.014
Bengkulu Selatan	0.008	Metro	0.011	Rokan Hulu	0.013
Bengkulu Utara	0.011	Muara Enim	0.014	Sarolangun	0.014
Bengkulu	0.013	Muaro Jambi	0.013	Sawahlunto Sijunjung	0.015
Bukittinggi	0.012	Musi Banyuasin	0.015	Sawahlunto	0.011
Bungo	0.014	Musi Rawas	0.015	Siak	0.008
Dumai	0.013	Ogan Komering Ilir	0.017	Solok	0.015
Indragiri Hilir	0.015	Ogan Komering Ulu	0.015	Solok	0.012
Indragiri Hulu	0.014	Padang Panjang	0.012	Tanah Datar	0.014
Jambi	0.013	Padang Pariaman	0.014	Tanggamus	0.062
Kampar	0.014	Padang	0.013	Tanjung Jabung Barat	0.013
Kepulauan Mentawai	0.016	Pagar Alam	0.013	Tanjung Jabung Timur	0.013
Kerinci	0.018	Palembang	0.013	Tebo	0.013
Kuantan Singingi	0.013	Pangkal Pinang	0.012	Tulang Bawang	0.012
Lahat	0.016	Pariaman	0.014	Way Kanan	0.014
Lampung Barat	0.076	Pasaman	0.016		

Table A3.5: Manufacturing VA predictor means

	Treated	Synthetic
Agricultural VA as a share of GDP (2000)	6.1	6.0
Agricultural VA as a share of GDP (2004)	5.7	5.8
GDP per capita (2004)	427.0	367.8
Poverty rate, % of population (2004)	8.9	14.4
Literacy rate for population 15 and over (in % of total population)	97.0	96.6
Net enrolment ratio (junior secondary), %	86.7	74.3
Net enrolment ratio (senior secondary), %	72.1	57.8
Net enrolment ratio (primary) %	94.1	89.8
Birth attended by skilled health worker (%) (2004)	96.4	77.8
Morbidity rate (%) (2004)	20.6	22.6

Table A3.6: District weights in synthetic Aceh's manufacturing VA

District	Weight	District	Weight	District	Weight
Agam	0.003	Lampung Selatan	0.004	Payakumbuh	0.004
Bandar Lampung	0.078	Lampung Tengah	0.003	Pekan Baru	0.003
Bangka	0.002	Lampung Timur	0.005	Pelalawan	0.002
Banyuasin	0.002	Lampung Utara	0.003	Pesisir Selatan	0.003
Batanghari	0.002	Limapuluh Kota	0.004	Prabumulih	0.003
Belitung	0.003	Lubuk Linggau	0.004	Rejang Lebong	0.003
Bengkalis	0.003	Merangin	0.006	Rokan Hilir	0.003
Bengkulu Selatan	0	Metro	0.007	Rokan Hulu	0.002
Bengkulu Utara	0.004	Muara Enim	0.003	Sarolangun	0.006
Bengkulu	0.007	Muaro Jambi	0.002	Sawahlunto Sijunjung	0.004
Bukittinggi	0.003	Musi Banyuasin	0.003	Sawahlunto	0.003
Bungo	0.007	Musi Rawas	0.003	Siak	0.002
Dumai	0.006	Ogan Komering Ilir	0.004	Solok	0.004
Indragiri Hilir	0.002	Ogan Komering Ulu	0.003	Solok	0.004
Indragiri Hulu	0.002	Padang Panjang	0.003	Tanah Datar	0.003
Jambi	0.002	Padang Pariaman	0.003	Tanggamus	0.005
Kampar	0.004	Padang	0.003	Tanjung Jabung Barat	0.002
Kepulauan Mentawai	0.004	Pagar Alam	0.679	Tanjung Jabung Timur	0.019
Kerinci	0.007	Palembang	0.002	Tebo	0.007
Kuantan Singingi	0.004	Pangkal Pinang	0.002	Tulang Bawang	0.002
Lahat	0.004	Pariaman	0.003	Way Kanan	0.003
Lampung Barat	0.01	Pasaman	0.006		

Table A3.7: Capital formation predictor means

	Treated	Synthetic
Capital formation per person, in current USD (1993)	24.0	24.2
Capital formation per person, in current USD (1996)	34.5	35.2
Capital formation per person, in current USD (2000)	38.6	42.2
Capital formation per person, in current USD (2004)	72.0	69.8
GDP per capita (2004)	443.9	298.7
Poverty rate, % of population (2004)	28.5	24.0
Doctors per 10,000 persons (2003)	1.9	1.7
Unemployment rate (2004)	9.3	9.6
Agricultural VA, % (2004)	36.2	35.0
Net enrolment ratio (junior secondary), %	64.5	60.3
Net enrolment ratio (senior secondary), %	34.1	35.1
Net enrolment ratio (primary) %	93.9	91.2
Literacy rate for population 15 and over (in % of total population)	92.5	91.3
Length of asphalted provincial roads (km)	1,269	1,507
Health household expenditutre per person, monthly (in IDR)	1,401	1,580

Table A3.8: District weights in synthetic Aceh's capital formation

	Unit Weight
Bali	0
Bengkulu	0
D I Yogyakarta	0
DKI Jakarta	0
Jambi	0.306
Jawa Barat	0
Jawa Tengah	0
Jawa Timur	0
Kalimantan Barat	0
Kalimantan Selatan	0
Kalimantan Tengah	0
Kalimantan Timur	0
Lampung	0
Maluku	0.106
Nusa Tenggara Barat	0
Nusa Tenggara Timur	0.317
Papua	0
Riau	0.035
Sulawesi Selatan	0.236
Sulawesi Tengah	0
Sulawesi Tenggara	0
Sulawesi Utara	0
Sumatera Barat	0
Sumatera Selatan	0

Table A3.9: Private consumption predictor means

	Treated	Synthetic
Private consumption per person, in current USD (1993)	79.7	64.8
Private consumption per person, in current USD (1996)	98.5	89.0
Private consumption per person, in current USD (2000)	178.7	192.1
Private consumption per person, in current USD (2004)	243.1	254.5
GDP per capita (2004)	443.9	298.7
Poverty rate, % of population (2004)	28.5	24.0
Doctors per 10,000 persons (2003)	1.9	1.3
Unemployment rate (2004)	9.3	9.1
Agricultural VA, % (2004)	36.2	26.0
Net enrolment ratio (junior secondary), %	64.5	60.3
Net enrolment ratio (senior secondary), %	34.1	35.1
Net enrolment ratio (primary) %	93.9	91.2
Literacy rate for population 15 and over (in % of total population)	92.5	91.3
Length of asphalted provincial roads (km)	1,269	1,507
Health household expenditutre per person, monthly (in IDR)	1,401	1,580

Table A3.10: District weights in synthetic Aceh's private consumption

	Unit Weight
Bali	0
Bengkulu	0
D I Yogyakarta	0
DKI Jakarta	0
Jambi	0
Jawa Barat	0
Jawa Tengah	0
Jawa Timur	0
Kalimantan Barat	0
Kalimantan Selatan	0
Kalimantan Tengah	0
Kalimantan Timur	0.153
Lampung	0
Maluku	0.276
Nusa Tenggara Barat	0.493
Nusa Tenggara Timur	0
Papua	0.07
Riau	0
Sulawesi Selatan	0
Sulawesi Tengah	0
Sulawesi Tenggara	0
Sulawesi Utara	0
Sumatera Barat	0
Sumatera Selatan	0.008

Definitions of subcomponents used:

Below are the GDP subcomponent definitions taken verbatim from the Statistics Indonesia government website:[54]

HOUSEHOLD CONSUMPTION EXPENDITURE:
Household consumption expenditure is defined as expenditure on goods and services by households for consumption purposes. In this case, the household as final demand of various types of goods and services available in the economy. Household is defined as an individual or group of individuals who live together in a residential building. They collect income, own property and liabilities, as well as consuming goods and services together mainly food and housing groups (UN, 1993).

GROSS FIXED CAPITAL FORMATION:
Gross fixed capital formation is broadly defined as production unit expenditure to increase fixed assets minus the used fixed assets reduction. Additional capital goods include procurement, manufacture, purchase of new capital goods from domestic and new and used capital goods from abroad (including major repairment, transfer or barter of capital goods). Reduction of capital goods includes sales of capital goods (including capital goods transferred or bartered to other party).
Referred to as gross fixed capital formation because it describes additional as well as reduction of capital goods at a certain period. Capital goods have a life of more than one year and will experience depreciation. The term "gross" indicates that inside it still has an element of depreciation. Depreciation or consumption of fixed capital describe the impairment of capital goods which is used in the production process in one period.

[54] See http://www.bps.go.id/Subjek/view/id/11, which I accessed last on 10 August 2015.

CHAPTER 4

Economic Legacy Effects of Armed Conflict:

Insights from the Civil War in Aceh, Indonesia

"The remnants of conflict in Aceh continue to hamper growth. Conflicts can have a fundamental impact on the political, social, and economic institutions that underlie growth. These impacts affect the way in which an economy functions in the post-conflict period." *(World Bank, Aceh Growth Diagnostic, 2009, pg. 1).*

4.1 Introduction

Wars kill people. In fact, more than 500,000 people died because of armed conflict from 2007 to 2012 (see Geneva Declaration, 2015). Far more than that got hurt. The survivors often suffer from physical, psychological, and mental pain. People get injured, kidnapped, raped, and psychologically traumatized in war. Their civil liberties get restricted, and their human rights violated. Their schools get destroyed and their teachers get harmed. Their houses and durable assets destroyed. They are displaced. Even if they were unharmed, their family, friends, and acquaintances might have suffered. Social cohesion and trust erodes, security wanes, and the social fabric tears. These are just a select few of the horrors of war and its aftermath. Aside from the human tragedy, wars and their social consequences also shatter the pillars of a productive economy. Some destructive interventions may be 'creative' if accompanied by large aid inflows (see my second PhD chapter), and propel the economy onto a higher per capita output path. However, is armed conflict, one of these shocks? Is it a catalyst for economic growth?

There are many studies linking economic growth to armed conflict, looking at both causal directions. There are studies investigating whether economic shocks and economic depressions increase the likelihood of conflicts (e.g. Bazzi and Blattman, 2014; Collier and Hoeffler, 2004; Collier and Hoeffler, 2007; Miguel, Satyanath and Sergenti, 2004).[55] And there are studies investigating the opposite causal direction namely the economic consequences of war (see e.g. Collier and Hoeffler, 2007). Unsurprisingly, by and large, the literature agrees that bad economic performance makes wars more likely and also that war reduces growth (Collier and Hoeffler, 2007). But what happens once war is over?

Do the negative economic consequences of war linger? Put differently, do economies continue to be held back by war even after it is over? Or to the contrary, do they start to develop rapidly, outgrowing their counterfactuals, once they are finally free from the shackles of warfare? We know much less about these so-called *economic legacy effects of conflict.* There is a fair share of studies looking at the long-term consequences of armed conflict through the lens of health, displacement and other measureable human outcomes. Very few research papers however look at economic outcome measures, and even fewer attempt a causal identification (the few that do, are reviewed in the next section).

Aceh is a good testing ground for the economic legacy effects of conflict since the region was in a state of civil war for nearly three decades, and there is a clean cut between war and peace as the war stopped abruptly, lastingly, and exogenously, "thanks" to the Indian Ocean Tsunami on Boxing Day 2004. Moreover, what makes the economic impact evaluation of the Acehnese case so appealing is the availability of a dataset covering conflict intensity with a complete account of all deaths, injuries, kidnappings, rapes, and

[55] A well-tested economic theory of violence argues that poverty and unemployment cause wars because they reduce the opportunity cost of men to fight (Bazzi & Blattman, 2014). Many post-conflict interventions are designed with the looming idea in mind that poor and unemployed men are more likely to fight (World Bank, 2011).

destroyed houses attributed to the separatist armed conflict. All violent incidents were meticulously recorded and geocoded. At the same time, a socio-economic panel dataset at a fine-grained sub-national resolution became available, which was necessary to grasp the economic outcomes related to the violence. Consequently, the sub-national violence-economy dataset created is the most comprehensive and detailed dataset used for the evaluation of *economic legacy effects of violence* to date (to my knowledge), offering an annual panel ranging from 1999 to 2012. In an appeal for more and better research linking civil war to economics, Blattman and Miguel (2010) judge the state of the literature as having produced provocative and interesting ideas, but in order for these ideas to be useful, "more credible econometric methods for establishing counterfactuals" are needed. With this chapter, I am heeding to their call and tackle the methodological limitations identified in the literature full on.[56]

4.2 Literature review on the economic legacy effect of armed conflict

I group the literature investigating economic legacy effects of armed conflict into two broad categories. On the one hand, the macroeconomic literature with its focus on aggregate economic productivity. On the other hand, the microeconomic, health, education, and geography literature and their focus on household (or individual) income or factor of productivity (health and educational outcomes among others). While the evidence from household and individual studies predominantly points to negative economic legacy effects, empirical macroeconomic papers are more ambiguous as to whether the legacy effects are negative or positive. In this section, I will present the results emerging from each of these sub-fields and provide a synthesizing discussion of the findings.

[56] The particular methodological issues of existing studies in the literature the authors take issue with, which I will tackle head on in my study are: providing a convincing causal identification, present robustness to alternative specifications, taking into consideration the time and space dependence of observations, and taking into account aggregation issues.

4.2.1 Macroeconomic theory, hypotheses, and the macro-empirical literature

Macro-economic theory suggests that economic recovery will kick in once peace has been reached. The neoclassical growth model predicts a return to the steady state level of the capital stock with the end of the fighting (see e.g. Barro and Sala-i-Martin, 2003; Blattman and Miguel, 2010). Large rates of return to investment are expected as the capital stock returns to its equilibrium level in the aftermath of the fighting, boosting economic growth. This catch-up growth in the post-conflict period by historically more violent areas (Justino, 2011a), is expected to slow as the initially relatively high rates of return are expected to decline with the capital stock approximating its steady state level.

To better structure the discussion of conflict effects on growth, and the ensuing literature review, I use standard neoclassical models of growth including human capital, in the form they were pioneered by most prominently Lucas (1988) and Mankiw, Romer, and Weil (1992). In a one-sector endogenous growth model, a production function would take the standard form of $Y = AK^{\alpha}(H)^{1-\alpha}$ where $0 \leq \alpha \leq 1$, A refers to technology, K to physical capital, and H to human capital. As in e.g. Barro and Sala-i-Martin (2003), we can think of L as the number of workers, and h as the quality of workers, yielding $H = hL$. In the economic literature h, the quality of a worker is predominantly conceived of as the education level and skills of the person. Human capital however goes beyond that and importantly also includes health (Schultz, 1962; Grossman, 1972; and Becker, 2007 *inter alia*). Differentiating equation (3) with respect to time yields the familiar growth accounting equation $g \equiv \Delta y = \Delta A + \alpha(\Delta k) + (1 - \alpha) * \Delta h$. Warfare destroys physical infrastructure and human capital, and possibly alters some social and political institutions (Miguel and Blattman, 2010). In the empirical section of this paper I will investigate the effects that the destruction of human capital (Δk) and the destruction of physical capital (Δh) have on per capita growth (g).

The prediction from the endogenous growth model is convergence to the steady-state, which implies higher growth rates than the counterfactual, until the pre-war equilibrium is reached again. As an alternative to the neoclassical growth theory, the poverty trap hypothesis posits that conflict depresses the economy, which in turn makes it harder to escape violence, trapping the economy on a lower level equilibrium (e.g. Sachs, 2005). The microeconomic literature, reviewed in detail further below in this section, also finds growth depressing legacy effects of armed conflict. Post-war surveys performed in Aceh conducted in the most violence-affected districts also paint a negative legacy picture: "The nearly 30 years of conflict have clearly wreaked havoc on local economies, preventing villagers from working their land, killing their animals, destroying trade networks, wrecking their houses, and preventing young people from entering into the labour economy" (IOM, 2006). Two rivalling, mutually exclusive hypotheses emerge therefore. One that suggests that there are negative economic legacy effects caused by wartime violence. And another that suggests the opposite, which is that armed conflict is actually growth-promoting for peacetime growth rates, as they trigger catch-up growth. I will test in the empirical section, which one holds true for the armed conflict and economic growth in Aceh.

Barro and Sala-i-Martin (2003) predict in a one-sector endogenous growth model that recovery from destruction is faster, the more asymmetric the destruction of human capital versus physical capital. The authors argue that in both cases, one in which the physical capital was left mostly intact and the human capital was destroyed, as was the case in Europe during the Black Death in medieval times, or one in which the human capital remained largely intact and the physical capital was largely destroyed, as was the case in Japan and Germany after WWII, growth would be faster than had the destruction between the two factors of production been symmetric. The argument made for why an asymmetric destruction was supposedly causing faster growth rates was that the higher marginal product of the relatively scarcer type would spur investment (Blattman & Miguel, 2010).

In the presence of adjustment costs for human capital, post-conflict growth would be faster if relatively more physical capital was destroyed than human capital.[57] The prediction made from the neoclassical economic growth model is that loss of human capital will have more persistent legacy effects than loss in physical capital (see e.g. David, Bastos, and Mills 2011; Blattman & Miguel, 2010 and Barro & Sala-i-Martin,

[57] Put inversely, the disproportionate destruction of human capital should lead to lower growth post-conflict.

2003), indicating disproportionality. Higher adjustment costs for human capital are a sensible assumption for Aceh. Adjustment costs in education, presented by Barro (1992, p 204) as "machines and buildings can be assembled quickly, but people cannot be educated rapidly without encountering a sharp falloff in the rate of return to investment" are a reasonable assumption. Health adjustment costs are also a reasonable assumption is Aceh, given the prevalence of chronic physical health ramifications as well as psychological traumas including depression and post-traumatic stress disorder (more details to come in the health legacy effects subsection).

The empirical macroeconomic literature is sparse, but there is some evidence looking at country level aggregate economic output data. The average post-conflict per capita growth rate accelerates by about 2.4 percentage points after the conflict, compared to before the conflict, mostly owing to increased investment rates (Chen, Loayza & Reynal-Querol, 2008). The authors used an event-study methodology in a cross-section of countries and concluded that post-conflict economies eventually converge to the counterfactual of countries not affected by conflict. A similar acceleration in post-conflict growth rates, one of 2 percentage points, albeit comparing post-conflict with conflict growth rates, was also found by Elbadawi, Kaltani, and Schmidt-Hebbel (2008), but only for the first two years after the conflict ended. Growth rates decelerated markedly after these two years, thus likely not indicative of convergence. Finally, an influential paper by Cerra and Saxena (2008) titled "Growth Dynamics: The Myth of Economic Recovery" finds that output rebounded quickly after civil wars had ended. Using an impulse-response function the authors find that said "myth" actually holds true for all crises (banking crises, currency crises, and twin financial crises), except for civil wars. Civil wars were in fact the only crises for which the authors found that the economy rebounded and recovered.

Mueller (2012) recoded the dataset used in the influential above-mentioned Cerra and Saxena (2008) paper, after discovering a coding error, and re-estimated the original empirical model. He came to the opposite conclusion, which is that civil war shocks are actually the worst shocks, with the average civil war depressing the economy by 18 percent and not recovering. Using the corrected data, he finds that civil war is worse than currency, banking, and twin financial crises.

There is a substantial degree of ambiguity in the empirical macroeconomic literature covering the economic legacy effects of conflict. The microeconomic and household level literature on the other hand is in a more settled state (and will be discussed hereunder). National level data allow us to gain a good assessment of the aggregate economic impact of war damage, but they do not allow us to measure economic legacy effects, which take place on a regional level and imply geographic heterogeneity. For example, it may well be that even though the national economy grows significantly faster in peace times; this may be due to the increased performance of regions that were relatively little affected by the brunt of the violence. It could still be that regions facing the brunt of the violence suffer from significant legacy effects, even if in the aggregate the country grows faster now.

Much of the ambiguity in the literature has to do with the conflation of two different concepts of economic legacy effects, and two different ways of computing them: By either comparing growth: (a) post-war vs pre-war, or (b) post-war & high conflict vs post-war & low conflict. In this chapter, I define legacy effects to mean the lingering effects of the intensity of war (human suffering, and physical destruction) on peacetime growth rates, which squarely puts my definition into the (b) rubric. Concerning (a), I do expect that growth rates are larger in times of peace than they are in times of war; in other words, I expect the economies of peace to be larger than the economies of war, resulting in a peace dividend. But with regards to (b), I expect that the growth rate of the most violence affected areas are slower than the growth rates in less violent areas, indicating *negative economic legacy effects of violence*.

Two seminal empirical economic geography studies find support for the neoclassical steady state prediction, using city size and population trends at the subnational level. The most destroyed cities from World War II, in both Germany and Japan recovered tremendously in the aftermath of the destruction, converging to counterfactual population levels over the mid- and long-term (Davis and Weinstein, 2002; Brakman, Garretsen, and Schramm, 2004). City and population size in formerly war-torn and bombed out cities appeared no different from the unaffected counterfactual more than a decade later. Notwithstanding, even if a city returns to its pre-conflict projected size, that does not tell us whether its inhabitants have lower levels of educational outcome, health status, repaired housing and infrastructure, all of which may still be impeded by the horrors of civil war, and in consequence reduce levels of economic productivity. Moreover, Brakman Garretsen, and Schramm (2004) found that their observation of mean reversion did not hold for Eastern Germany, only Western Germany.

Evidence using economic measures, showing economic recovery and the return to the steady state, comes from Miguel and Roland (2011). Poverty rates, consumption levels, and population density of districts in Vietnam affected by the US areal bombings were found to have converged 25 years later to those of not bombed cities (Miguel and Roland, 2011). The authors show that even areas subjected to the "most intense bombing campaign in human history" converge to their counterfactuals in the long run, and conclude that the poverty-trap hypothesis does not hold in the case of the bombings in Vietnam (Miguel and Roland, 2011, pg. 1). Other empirical economic geography studies find persistent negative effects of conflicts on economic outcome. Applying a synthetic control method to a comparative case study, Abadie and Gardeazabal (2003) for example find long-term reductions in economic growth resulting from terrorist violence in the Basque region of Spain. The negative consequences on economic performance come from the weakening of factors of production by destruction of human and physical capital (Blattman and Miguel, 2010). Fiala (2012) who conducted a causal study on the economic consequences of forced displacement with a regression discontinuity design finds that the neoclassical growth model's prediction of economic recovery, only partially applies to the richest conflict-displaced households, and only pertains to consumption recovery. The top three pre-displacement asset quartiles recovered a portion of their consumption. The bottom quartile was trapped in a lower level consumption equilibrium. All quartiles showed lower levels of human capital.

4.2.2 Microeconomic, health, education, and other micro studies

Human capital accumulation is the "engine of growth" in endogenous economic growth models such as those first developed by Lucas (1988) and used in this chapter, and limits to human capital accumulation or even its destruction, are major threats to economic growth (Lucas, 1988; Lucas 2002; Galor and Weil, 2000). There is a wealth of micro-econometric and other household-level research on the long-term effects of conflicts and violence on human capital measures, including (a) health, (b) education and employment, (c) physical capital indicators, as well as (d) several other effects:[58]

4.2.2.1 Health legacy effects

Devakumar et al (2014) provide a theoretical framework linking health outcomes to conflict and distinguish between several different direct channels through which conflicts affect health, both physical and psychological health, including the channels of mental health, infectious disease, nutrition, and physical damage from violence. They also distinguish between immediate effects and protracted effects. Armed conflict results in high amounts of death and sickness around the world (Sidel & Levy, 2008). Some of these increased mortality and morbidity rates occur through infectious diseases in refugee or IDP camps, others are related to the failing provision of health care in times of war and reconstruction. Oftentimes government decisions to reassign funds from health to security and military affairs exacerbate the already dire health situation (Hoeffler and Reynal-Querol, 2003).

Exposure to violent attacks leads not only to physical health damages, but also have mental repercussions (see e.g. Yehuda and Bierer, 2008). To be a victim does not even require being directly affected by the violence. Psychological traumas can form even from having been witness to violence (Bellows and Miguel, 2006 & 2009). Psychological traumas severely affect living conditions and economic activity and may substantially impair an economic life in the long run. Concrete evidence suggests elevated suicides amongst traumatized women of childbearing ages for example (Ghobarah, Huth, and Russett, 2003).

Conflict effects on health in early childhood are particularly dangerous as they are hard to make up over the course of the rest of the life (Verwimp, Bundervoet & Akresh, 2010). Early childhood health shortcomings cannot be caught-up on is the presented argument. This is particularly important because early childhood development is a good predictor for later levels of human development reached (income, education level and

[58] See e.g. Justino (2012a) for a review of long-term education and health effects as well as ramifications for labour market opportunities.

life expectancy) (see Almond, 2006; Yamauchi, 2006; Alderman et al., 2006; Machini and Yang, 2006). Malnutrition during preschool times had adverse effects on human capital formation (grades completed) in Zimbabwe (Alderman, Hoddinott, and Kinsey, 2006).

Violent conflict effects are truly long-lasting in that they have been found to extend also beyond an individual's lifetime to the next generation (Sonne and Nillesen, 2015). A Liberian child's exposure to the war in utero has significant effects on its height-for-age at birth. Investigating the intergenerational effects of war on children's health, Devakumar et al (2014) found many instances in which the health effects of war propagate across generations through biological mechanisms. Even though they highlight that maternal physiology and behaviour can to some degree shield and protect the offspring from ecological stresses, but not fully so (Wells, 2010).

In Burundi, a study found that children living in violent areas had a lower height-for-age score than those who did not (Bundervoet et al, 2009); they are shorter by 0.35 – 0.53 standard deviations. Akresh et al (2012) finds that Ethiopian-Eritrean children exposed to the violence are substantially shorter than those that were not (by about 0.42 standard deviations). Similar long-term adverse conflict-health effects were found by several other scholars in the recent few years, including Maccini and Yang (2009), Minoiu and Shemyakina (2012), and Barre and Domingues (2013), as cited in Sonne and Nillesen (2015).

4.2.2.2 Education and employment legacy effects

In Timor-Leste, formerly an Indonesian province, since 2002 an independent country, there was also separatist civil war and Indonesian occupation for almost three decades, similarly to Aceh. Contrary to Aceh though, Timor-Leste became an independent country in 2002, while Aceh "only" received semi-autonomous governance status in 2004. Following Eastern Timorese cohorts of students that started primary school during the final years of the civil war and during a particularly abhorrent wave of violence in 1999, and relating their achievements over the short- and the long-term to pupils that were not affected by the violence, Justino, Leone, and Salardi (2013) provide insights into the existence of negative legacy effects. They find not only short-term effects of lower school completion for the pupils exposed to the peak of the violence, but also subsequently, lower school completion rates. The short-term legacy effects of violence were significant for both sexes, whereas the long-term consequences only applied to the boys.[59]

Negative legacy effects of the violence on education were also observed in other countries. Examining the impact of conflict on educational attainment in 25 countries, using household survey data showed that conflict leaves an adverse educational legacy (Bell and Huebler, 2010). UNESCO reported that education was "under attack" in 31 countries, using a three-year time window (UNESCO, 2010). Conflict long-lastingly results in lower rates of formal schooling, fewer years of school enrolment, and decreased literacy rates. Quantifying the foregone educational attainments with a cross-country study found that states in civil war experience a declined enrolment rate of about 1.6 to 3.2 percentage points (Lai and Thyne, 2007). Children in Austria and Germany received significantly less education in the more conflict-affected cities during World War II (Ichino and Winter-Ebner, 1988). Children in the most bombed cities in Germany during WWII received about 1.2 years less schooling (Abbulut-Yuksel, 2009). In Rwanda, the genocide reduced educational attainment by 0.5 years (Akresh and de Walque, 2008). Documenting human capital consequences as a result of the 36-year long civil war in Guatemala, Chamarbagwala and Moran (2011) find that the conflict reduced the level of education (especially of indigenous communities and females). The forty-years of internal conflict in Colombia have left marks on internally displaced children and resulted in lower levels of enrolment and educational accumulation (Wharton and Oyelere, 2011).

The channels through which armed conflicts affect education are manifold. For example, during the Rwandan genocide, two-thirds of the teachers were killed or displaced (Buckland, 2005). Likewise, the Khmer Rouge in Cambodia deliberately targeted and executed teachers. In Somalia, war damaged schools and other educational

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[59] Girls only showed negative short-term effects in that their attendance was affected, but their school attainment was unaffected (in fact they even showed higher completion rates than the violence unaffected control group). The reason for this gender dichotomy mentioned in the paper was that boys were removed from school for "economic survival" during the tough recovery times. Alternatively, the authors also speculate that some young boys may have dropped out of school in order to join armed groups.

infrastructure (Abdi, 1998), likewise in Bosnia Herzegovina where half the schools required reconstruction (Buckland, 2005), in Mozambique where 58 percent were destroyed, or Iraq (Brueck, 1997) where 85 percent were destroyed. In Zimbabwe children affected by the civil war in the 1970s completed less grades (Alderman, Hoddinott, and Kinsey, 2006). Access to school, preventing the opening of schools, threatening the children's security *en route* to school, or at school, and increasing teacher absenteeism, are just a couple of more mechanisms through which conflict directly affects education (Bell and Huebler, 2010 & Shemyakina, 2006). Other hindering mechanisms include shortages in basic needs, such as food and water, or learning utensils, which reduce the effectiveness of learning (Shemyakina, 2006).

There are however also studies that do not find a significant long-term effect on education. Primary completion in Bosnia and Herzegovina for example was no different after the Bosnian war regardless of the level of conflict the pupils were exposed to (Swee, 2009). Similarly, the most bombed cities in Vietnam by the US bombing campaign do not show to have lower literacy rates (Miguel and Roland, 2011).

Combatants or civilians living through the horrors of war suffer from injuries, miss out on education, and valuable job experience (Blattman and Miguel, 2010). Particularly ex-combatants have serious problems joining the civilian labour force. Combatants invest their time in training how to fight instead of acquiring skills for a civilian job in universities, apprenticeships or other forms of on the job training (Annan et al. 2009; Blattman and Annan, 2011). This foregone labour market grooming and homing of skills leads to combatant's lower productivity in civilian jobs, and them earning less (Blattman and Miguel, 2010).

4.2.2.3 Physical capital destruction legacy effect

Violent conflict destroys and damages physical capital such as land, houses, machines, and livestock (see Justino, Brueck and Verwimp, 2013; and Justino, 2011b for a review of the literature).[60] The destruction of physical capital threatens people's livelihood activities and in the aggregate leads to a reduction of economic output. In the wake of

[60] The other cited papers in this paragraph were found in both of these papers.

the 1994 genocide in Rwanda, 12 percent of all households lost their houses. The civil war in Tajikistan destroyed and damaged about 7 percent of houses between 1992 and 1998 (Shemyakina, 2006). Severe asset depletion was also one measured consequence after the conflict in Burundi in the 1990s (Bundervoet and Verwimp, 2005). In Mozambique, the destruction of household assets went as far as 80 percent of farmers' cattle stock being destroyed during the civil war (Brueck, 1996 as cited in Blattman and Miguel, 2010). In Uganda, some farmers lost all of their cattle (Annan, Blattman and Horton, 2006). The genocide in Rwanda reduced the cattle stock by half (Verpoorten, 2003). Armed conflicts do not only destroy private physical capital, but also public one including the destruction of roads, bridges, hospitals, and schools.

4.2.2.4 Other legacy effects

There is a multitude of transmission channels between conflict and its legacy on future economic growth, reaching beyond the purview of the endogenous growth model and with it human capital destruction (and decelerated human capital accumulation), and physical capital destruction. These additional transmission channels include but are not limited to displacement, brain drain, private capital flight, social capital erosion, high opportunity costs of military investments, negative capital stocks from the war (such as mines and destroyed military equipment that needs to be disarmed and recycled), altered savings behaviour, and firm size reduction. In this sub-section I briefly review the most prominent channels mentioned in the literature. For a more complete review of other channels, see Blattman and Miguel, 2010, Justino 2011b and Justino 2012b).

I discuss conflict-induced and forced displacement as a threat to the Sustainable Unit Treatment Value Assumption (SUTVA) in the methodology section, particularly for cases in which the households do not move back from where they fled from. Displacement has permanent effects, even after the households return. Those that do return show lower levels of productivity, therefore posing a legitimate transmission channel through which the conflict may exert a lingering effect on the economy. Causal studies on the effect of displacement on economic activity in Uganda reveal that displaced and returned persons experience a decrease in consumption by about one-third compared to what they would have consumed had they not been displaced, and their assets are lower by about half of a standard deviation compared to nondisplaced households (Fiala, 2012). Two years after the households returned, their consumption was 20 percent less and their assets were one-fifth of a standard deviation less. In Aceh, 38 percent of the respondents to surveys administered in the most conflict-riddled districts reported having had to flee their house, and 47 percent said they had to temporarily flee from their house at some point during the armed conflict (IOM, 2006).

Capital flight and brain drain catalysed by armed conflict are not easily reversible. "It's easier for money and brains to leave than to return" (Bailey, 2006). Private wealth capital flight increases by 11 percentage points from 9 percent of all wealth to 22 percent during war. As part of a "war overhang effect", the rate of capital flight actually increases further to even more than 26 percent (Bailey, 2006). Mobile forms of capital accelerate the 'fleeing' because foreign assets offer higher relative returns particularly once the higher risk due to the war and expropriation has been priced into the expected rates of return to investment (Collier, 1999; Collier, Hoeffler, and Patillo, 2004). Brain drain is also a huge long-term challenge posed, as many of those who fled do not come back (Bailey, 2006).

Military investments are less productive than civilian ones. The opportunity costs of built military capital such as infrastructure and weaponry are high. Lost production is the consequence when government re-prioritizes investments and invests in military rather than civilian human capital or physical capital. It has been shown in the literature that military spending is growth-retarding, as it shifts away the funding for productive investment alternatives (Loayza, Knight and Villanueava, 1999). Collier et al (2003) shows an almost doubling of the public expenditure share on military spending during times of war. As the country enters into war, its military expenditure increases from 2.2 to 5 percent, but upon reaching peace the country does not revert back to the pre-conflict share. To the contrary, the military expenditures remain heighted on average at 4.5 percent of military spending for the decade after the war (see World Bank 2007).

Savings decisions are permanently affected by civil war. Investment decisions were permanently altered in Burundi during the civil war (Voors et al, 2012). Unaffected people are more risk-seeking and have higher discount rates, meaning that they spend more in the present, which could in turn stimulate aggregate consumption. Preference shifts encouraging risk-taking and altruism are arguably positive for economic development, while at the same time discouraging investments and encouraging consumption by reducing patience (Voors et al, 2012).[61]

I just briefly touched upon some of the additional transmission channels of legacy effects of conflict on economic growth here as a longer treatise would burst the scope of this analysis. There are other sources that review this literature thoroughly, including social capital and negative capital overhang and I refer the interested reader to Blattman and Miguel, 2010; Justino 2011b; Justino 2012b).

4.3 The separatist conflict in Aceh, its toll on human and physical capital, and its end due to the Tsunami

Aceh has historically been different from the rest of Indonesia in terms of culture and religion. A more conservative form of Islam is and has been prevalent in the region at the westernmost tip of the Sumatra Island. The tensions between Acehnese independence ambitions and Jakarta's centralist agenda as well as several political, cultural, and religious undercurrents, and crucially also disagreements with how to share the rents from resources extracted in Aceh between the central government and the region of origin, lead to the formation of the Free Aceh Movement, or GAM (short for Gerakan Aceh Merdeka) and the declaration of independence in 1976.

Energy wealth, in particular riches related to oil and gas, increase the risk of civil war (Neumayer and Soysa, 2007; and Fearon and Laitin, 2003). The insurgency in Aceh also had economic roots in that its start had much to do with clashes with the central government about sharing of the resource revenue from oil and gas (LNG) in the region. Besides oil and gas, Collier (2005) identified 5 additional reasons for why the civil war started. (1) Indonesia's democratic institutions, put in place after the demise of Suharto, the country's long-term autarchic leader, were too fledgling and weak to channel Acehnese dissent through nonviolent means. (2) The entrepreneurship of GAMs leader, Hasan di Tiro. (3) Acehnese independence grievances. (4) The symbolic and exemplary

[61] Whether long run behavioural changes triggered by the war have positive or negative net effects on economic development is an interesting avenue for future research.

effect of the East Timor referendum (5) No credible and viable offer of the central government for an autonomous Aceh solution. Other reasons included opposition to inward migration from other islands most notable Java and other parts of Sumatra, which was perceived as a threat to the cultural and religious way of life in Aceh (AKUF, 2007).

The Tsunami brought an end to the civil conflict (see e.g. Aspinall, 2005).[62] When the Tsunami floods engulfed much of the Acehnese coastline, they stopped the violence between the GAM rebels and the Indonesian Army (TNI – short for Tentara Nasional Indonesia). The floods made way for a massive humanitarian response and an unprecedented cooperation between the central government and the rebels as they sought a unified response to the disaster. Jakarta first responded by lifting military emergency law, which paved the way for reconstruction to take place.

Even though the Tsunami was the catalyst for the peace deal struck between the rebels and the central government, there was an array of other factors that aided in bringing about peace. The Indonesian president Yudhoyono extended a helping hand by "call[ing] on those who are still fighting, to come out … [and] let us use this historic moment to join and be united again" (read in Siboro, 2004). Furthermore, his moderate and pragmatic course of action towards GAM in the aftermath of the Tsunami led him to take the GAM concerns seriously, guaranteeing the cooperation from the government's side enabling a ceasefire agreement (Enia, 2008). The situation of the GAM rebels on the other hand was even direr, after much of the province was inundated, and it became much harder for them to operate. Reacting towards a moderate stance of the president, the rebel group signalled an unequivocal readiness to negotiate a peace agreement (Enia, 2008). Additional contributing factors to achieving the peace treaty were the skilled peace negotiators, led by former Finish President Martti Ahtisaari, and the significant international attention brought on by the international community. The presence of humanitarian relief operations in the region, furthermore helped in reaching a consensus between the two sides of the aisle.

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[62] A few scholars have argued that the peace process was already well under way, and would have likely also occurred if it weren't for the Tsunami (e.g. Waizenegger, 2007). The canon in the literature however is that the Tsunami was the essential cause for bringing about lasting peace (see e.g. Aspinall, 2005).

The peace deal, or Memorandum of Understanding as it was called (MOU), struck between the GAM rebels and the central government in Jakarta, included disarmament of the rebels in exchange for self-governance (an important compromising step shy from independence), as well as the formation of a regional political party (Donnan and Bergstrom, 2005). It was also agreed that the Acehnese population should receive 70 percent of the resource revenues exploited in the region. The MOU was signed by the Indonesian parliament half a year after the Tsunami struck Aceh and in entering into force, Indonesia recognized the autonomy status of Aceh.

The impacts of the civil war on Acehnese health were significant. An estimated 30,000 people were killed, and close to 350,000 people were injured during the almost 30 years of the conflict (MSR 2009; IOM, 2008). Surveying the fourteen most affected districts from the violence in Aceh revealed staggeringly high numbers of physical and psychological effects indicating severe traumas (IOM, 2007). The accounts from a total sample size of 1972 interviewed households present a gruesome reality: 74 percent of the respondents report having had a combat experience, 35 percent report having fled from a burning building, 46 percent having been forced to flee danger, 28 percent report having been beaten to the body, 26 percent report having been beaten on the head, 13 percent report having been strangled, 17 percent report having been attacked by a knife or gun, 43 percent report having a family member or friend killed, 5 percent of women reported that their husbands were killed, 45 percent report having a family member or friend kidnapped or disappear, and 31 percent report having been extorted or robbed. Psychological symptoms amongst the Acehnese population were extraordinarily high amongst the sample surveyed in 2006 (IOM, 2006): 65 percent showed depression symptoms, 34 percent showed PTSD symptoms. Out of these symptomatic psychological attests, 18 percent were diagnosed with severe depression and 10 percent had severe PTSD.

Not only was the health of individuals affected by acts of war, and after the war by lingering injuries, but so was access to health in post-war times. In several high conflict districts, particularly in Bireuen and Aceh Utara, only about one-third of the interviewed households signalled a readiness of receiving healthcare delivered by public health clinics (as they are operated by the central government, which the majority of the Acehnese in the affected areas didn't trust).

Physical capital destruction was significant in Aceh. Upon returning to their houses, many temporarily displaced households found their livestock, rice fields, gardens, plantations and tools burnt or pillaged (IOM, 2006). In fact, the phrase "we had to start from zero" was a phrase violence-affected households frequently replied when asked in the household interviews. Overall 43 percent responded that their property was destroyed or confiscated (IOM, 2007).

Former combatants are more likely to be unemployment. In Aceh, according to a World Bank study, almost 75 percent of working-age[63] former GAM rebels were not employed by close to a year after the peace deal was struck (World Bank, 2006). Before the conflict erupted, many of the rebels used to work as farmers, but after the intermission from the civil labour market, they no longer wanted to go back and plough the fields (Said, 2008). Despite still having access to their old land, they rather hold out for a position as a small trader or a similar service-based job (Said, 2008). Reintegration of ex combatants posed a severe challenge (Schulze, 2007), including insufficient reintegration allowances (so called *Jadup*) that were supposed to help the former rebels integrate into the labour market, with the focus on starting business (Schulze, 2007).[64]

4.4 Research design and empirical strategy

4.4.1 Data

I assembled a unique district-level dataset by merging local level GDP measures with local level violence measures. I also included measures of Tsunami flooding and geo-referenced aid flows, as well as other controls. Furthermore, I constructed a second dataset on the Kecamatan (sub-district) level, where instead of using GDP, I use night-lights as a proxy for economic development since GDP is not available at such a fine-grained level of aggregation.

[63] Three-fourths of them were between 18 and 35 years old.
[64] There were several allegations of unequal distributions and corruption of these funds.

4.4.1.1 Violence

The data on violence that I use stems from the National Violence Monitoring System (NVMS), which is an innovative data tool that allows keeping track of acts of violence in Indonesia.[65] The World Bank in conjunction with the Indonesian Ministry of People's Welfare piloted it in 2011; with the aim to precisely and publicly document past acts of violence as well as keeping track of current ones in a mission to better manage and prevent it. The online data portal contains data on where, when, and why violence took place and with which intensity. It contains in total about 180,000 incidents of violence for the entire country and is using official accounts, which are recording incidents since 1999. A detailed elaboration on the construction of the dataset as well as its advantages relative to other prevailing violence datasets in Indonesia can be found in Barron, Jaffrey and Varshney (2014).

As measures of conflict intensity I use casualties as well as other measures of human suffering. The NVMS dataset contains information on the following incidents attributed to the separatist conflict: deaths, injuries, kidnappings, and rapes and it also contains a measure of buildings destroyed or damaged. Separatist conflict refers to "violence triggered by efforts to secede from the unitary state of the Republic of Indonesia." The dataset also records other deaths resulting from violent crime, domestic violence, and violence during law enforcement.

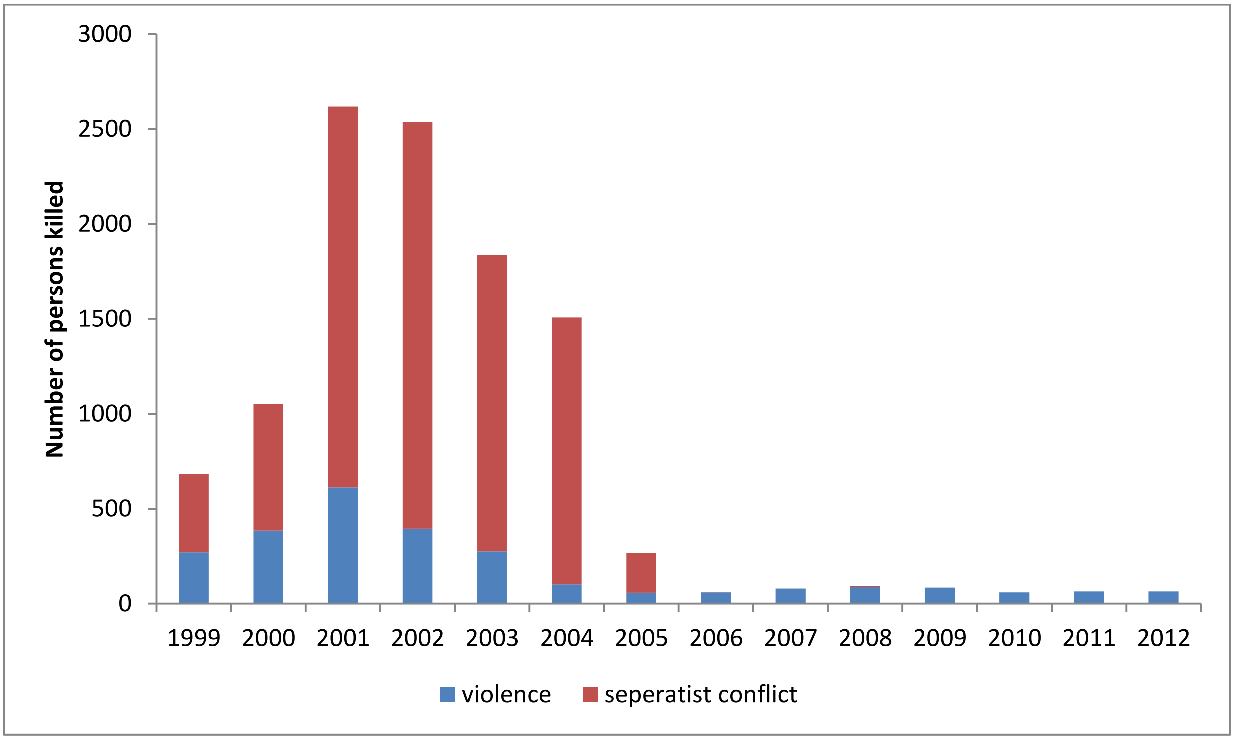
The evolution of deaths from violence and conflict in Aceh shows that before the Tsunami struck in late 2004 and the peace deal came about in early 2005, most deaths were due to the separatist conflict (see figure 4.1). Most of the casualties were civilians (Human Rights Watch 2003; ICG, 2001). The separatist conflict may have spilled over to other forms of violence, as deaths from non-separatist related violence also appeared to have been surging during times of war (see the blue bar sections in figure 4.1).

Separatist casualties came almost to a screeching halt from one day to the next with the Indian Ocean Tsunami striking Acehnese shores on December 26th 2004: from a rough

[65] The dataset could have been accessed at http://www.snpk-indonesia.com/. I accessed and downloaded the data used in this paper on 1 June 2015. The website is currently inactive as it is being migrated to an official government website. Soon the dataset will be available again at the following link: www.snpk.kemenkopmk.go.id. The NVMS dataset will also be uploaded in the World Bank's micro-data catalogue, which the public can also access, in the near future.

average of about 2000 persons a year losing their lives in the early 2000s, to 208 casualties in 2005, to “only” 1 casualty in 2006, and finally 0 casualties in 2007.[66] On August 15, 2005 the Peace Accord was signed in Helsinki. Under the agreement, the Free Aceh Movement (GAM) disarmed and in turn government troops withdrew from Acehnese territory (with the exception of 25,000 soldiers, which remained); moreover, Aceh was granted special autonomous status within the Republic. For a detailed account of the Peace Process, see Kingsbury (2006).

Figure 4.1: Deaths in Aceh over time



Note: The graph depicts the sum of all deaths occurring in all districts of Aceh.

Similar to deaths, injuries from separatist war also came to a complete halt after the peace agreement. See figure A4.1 and A4.2 in the Appendix for a depiction of the trend data.[67] Injuries include bruises, loss of consciousness, broken bones and any issues

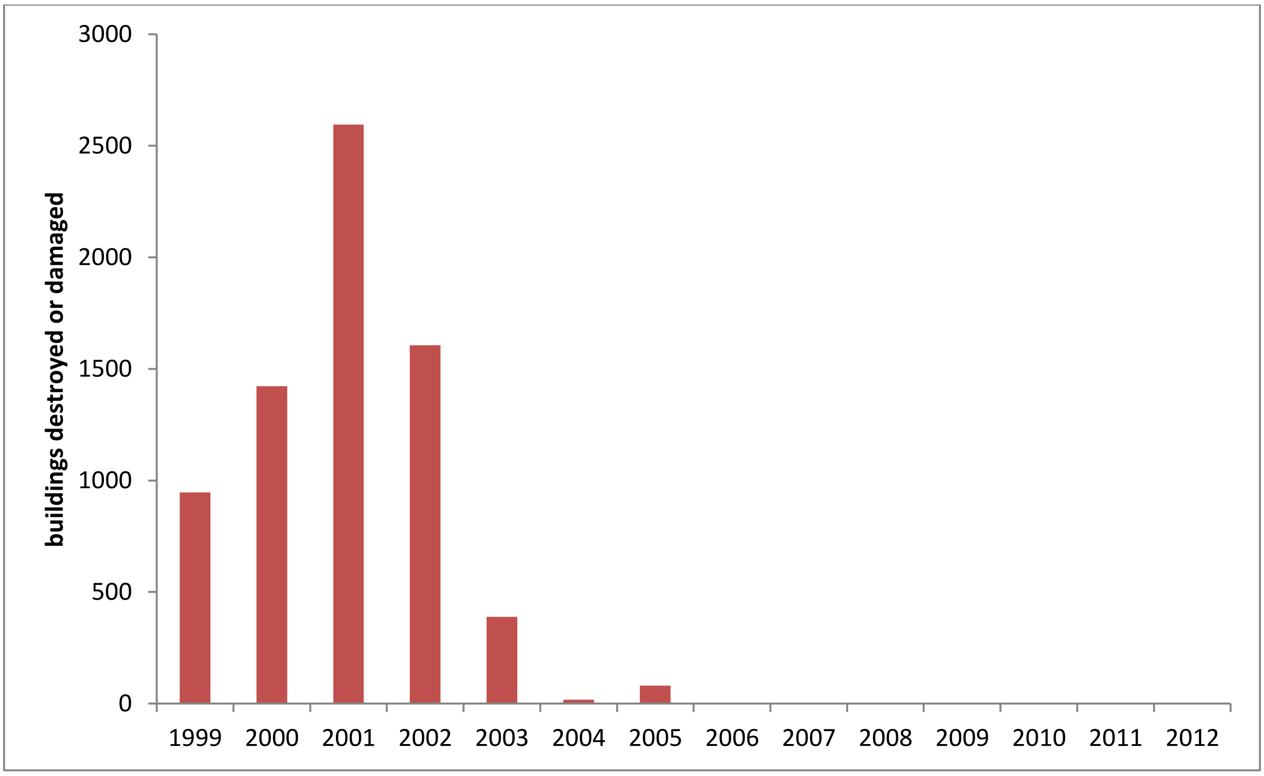
[66] Official statistics pointing to a number of about 13.500 people killed during the violent conflict between GAM rebels and government soldiers (Reid, 2006). The NVMS with its records ‘properly’ starting in 1999 records a fair share of these overall casualties of the 30 year-long conflict, with about 8500 deaths recorded.

[67] There were only very few cases of rape. The year with the highest counts of rape was 2001 with 7 incidents per year. During most years of the civil war period there were no rape incidents at all reported. The rare occurrence of rape is the reason why I did not include it as a separate figure.

requiring hospital treatment. Rapes include men, women, and children raped or molested. Kidnappings denote number of people abducted or taken hostage.

Damaged and destroyed physical capital also came to a screeching halt (see figure 4.2). Thousands of buildings were destroyed or damaged (ranging from broken window glass and shattered doors to the burning down of buildings) before the peace deal was signed in 2005. Unlike the measures for human capital degradation, the measure of physical capital destruction, i.e. buildings destroyed, indicates a stark reduction of destruction already by 2004. This may indicate that the war tactics were shifted. It could be an indication for example that the war in 2004 was mostly waged in remote areas, with GAM rebels hiding in the jungle (Kingsbury, 2006) as a reaction to the military surge of 2002, which could explain why there were still almost 1500 casualties but only 18 houses destroyed or damaged.

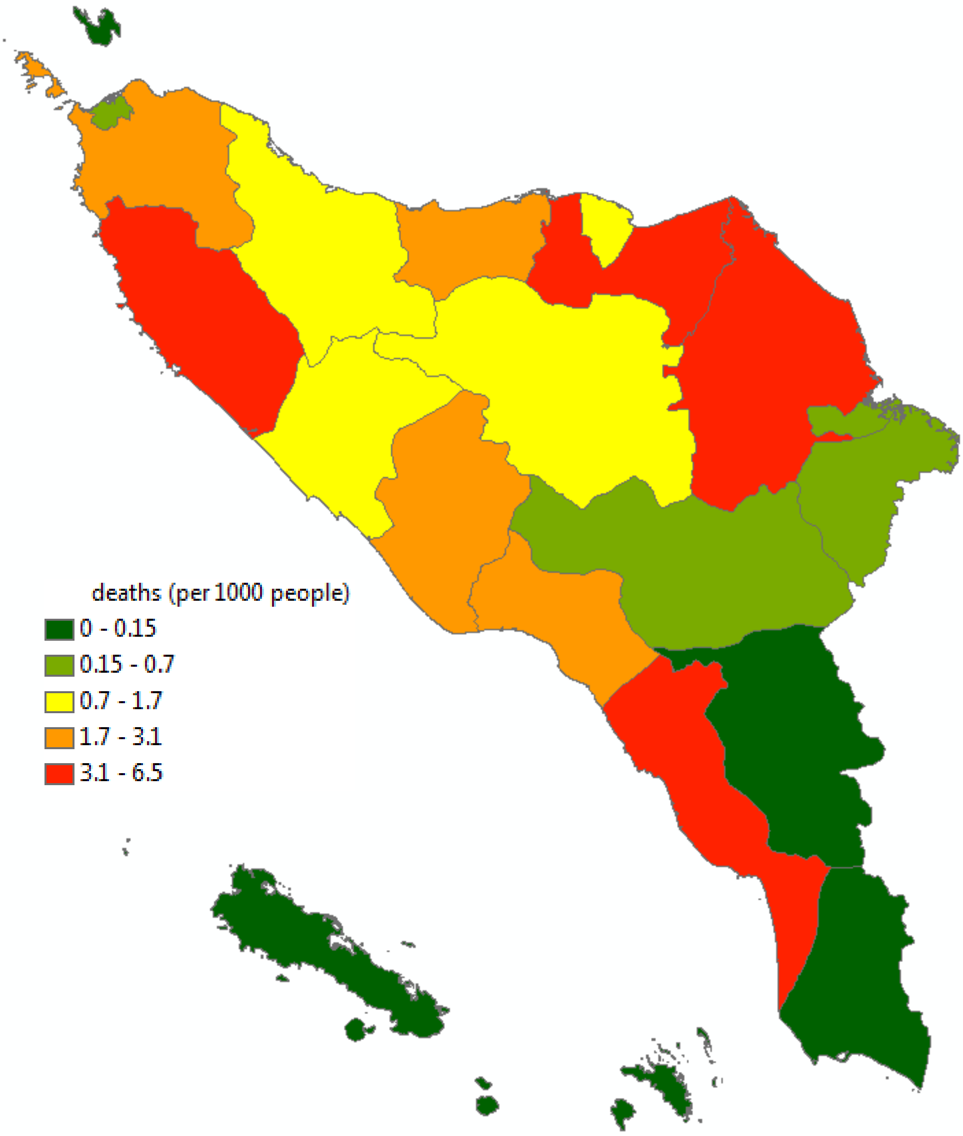
Figure 4.2: Buildings destroyed or damaged from the separatist conflict in Aceh over time



I create three continuous conflict indicators from the NVMS data: (i) number of deaths per capita, (ii) number of injured, raped, and kidnapped persons per capita (adding all incidents up, giving each incident equal weight), (iii) amount of damaged buildings per capita, and (iv) a dummy variable for lots of violence versus low/no violence (splitting the observations in relation to the median). I normalize by population living within the district. For more details on the violence dataset, see the website mentioned in the above footnote.

Violence is not homogeneously distributed across Aceh, meaning that there were certain hotspots of violence, hubs of peace, and grades in-between (see map 4.1 and map A4.1). I exploit this geographic variation for establishing the treatment heterogeneity of violence. The geographical distribution of injuries (see map A4.1 in the Appendix) looks very similar to that of deaths. For a sub-district distribution of total deaths and violent incidents see maps A4.2 and A4.3 in the Appendix.

Map 4.1: Casualties in Aceh from 1999 - 2004



Note: Casualties plotted are cumulative from 1999 – 2004.

To the naked eye, the hotspots of violence and peace are distributed randomly across the province. Geographic factors do not appear to be correlated with violence. It seems that all sides of the island were affected, in the South towards the Indian Ocean and in the North towards the Strait of Malacca. Violent incidences and intensities have a very low correlation with most selected socio-demographic variables that could drive the economic growth potential of the districts. Human capital measures such as number of schools and number of hospitals, as well as sectoral measures such as the share of agriculture look fairly balanced across low conflict and high conflict groups (see table

4.1). Checking whether all growth-inducing factors are comparable across treatment and counterfactual groups is an elusive quest, as there are always limitations on data availability. However, more important than showing that both groups had a similar growth potential in 2004 (before the end of the conflict) in order to establish that they are comparable, is to show that their historic GDP per capita levels and trajectories were comparable, which is shown later in figure 4.5.

Table 4.1: Balance in factors possibly correlated with growth potential

	Median		Mean	
	No/Low conflict	High conflict	No/Low conflict	High conflict
Poverty rate (%)	23	26	23	26
Agricultural share (%)	41	43	37	42
Net primary enrolment rate (%)	96	96	95	96
Net secondary enrolment rate (%)	76	77	76	77
Nr of schools	243	337	246	342
Population	158,169	155,949	186,173	228,443
Nr of hospitals	1	1	3	2
Nr of Doctors	32	24	49	32
Health expenditure per household (IDR)	4394	6256	6240	6920
Births attended by health professional (%)	88	82	84	79

A covariate that violence is correlated to is ethnicity. The ethnic composition of Aceh is rich and includes Acehnese (71 percent), Javanese (9 percent), Gayo (7 percent), Batak (3 percent), Alas (2 percent), Simeulue (1 percent), Aneuk Jamee (1 percent), Taminag Malay (1 percent), Singkil (1 percent), and Mingangkabau (1 percent) (BPS, 2000). Ethnic Acehnese people represent the largest share in most districts. Nevertheless, the districts where the Acehnese represent an exceptionally high share of the population are also the districts where most of the fighting and violence occurred.[68] Not by a huge margin, but noticeably so. Therefore, the ensuing conflict legacy effects are possibly also the effects of being more Acehnese rather than less. To the extent that 'being Acehnese' has growth relevant effects, it may bias the interpretation that the economic legacy effects are due to violence, and not instead to ethnicity. As a counter to this caveat, and more so than simply assuming that productivity is equal across ethnicities, the parallel historic GDP per capita paths shown later in figure 4.5 illustrates how ethnic

[68] Districts with a larger ethnic Acehnese share being more likely to be the stage of armed violence is unsurprising given the fact that the separatist struggle was largely about ethnic identity.

composition was immaterial to growth.[69] If ethnic composition were important for growth it would have already shown before 2005.

Other reasons for why the growth potential may have varied by the intensity of violence are discussed in section 4.5.3., where I examine in detail whether violence is correlated with Tsunami aid, sovereignty funding, oil and gas revenue sharing, as these could have biased the conflict-growth nexus results. I also verify whether geography has any bearing on the estimated effects, as cities were less violent than rural areas. Foreshadowing the ensuing analysis factoring in these potentially biasing factors, I find that they did not.

4.4.1.2 Economic Output

As measures of economic output, I use a district (*Kabupaten* & *Kota*) measure of GDP and a sub-district (*Kecamatan*) measure of night-light intensity. For the sub-district, I had to switch to night-lights data, because GDP was only available as fine-grained as a district. There are 23 districts in Aceh for all of which I have GDP data. This limited number of districts however curtails the statistical power of my econometric analyses, which is one of the main reasons for complementing the analysis with Kecamatan level night-lights data, for which I have 276 sub-districts. I carry out the econometric analysis using both measures and scales, but concentrate the discussion more around GDP, as it is a better proxy of income and welfare, and a more common reference point for economists (even though the attention empirical economists pay to night-lights has increased especially during recent years with several articles being published in major economic journals).[70]

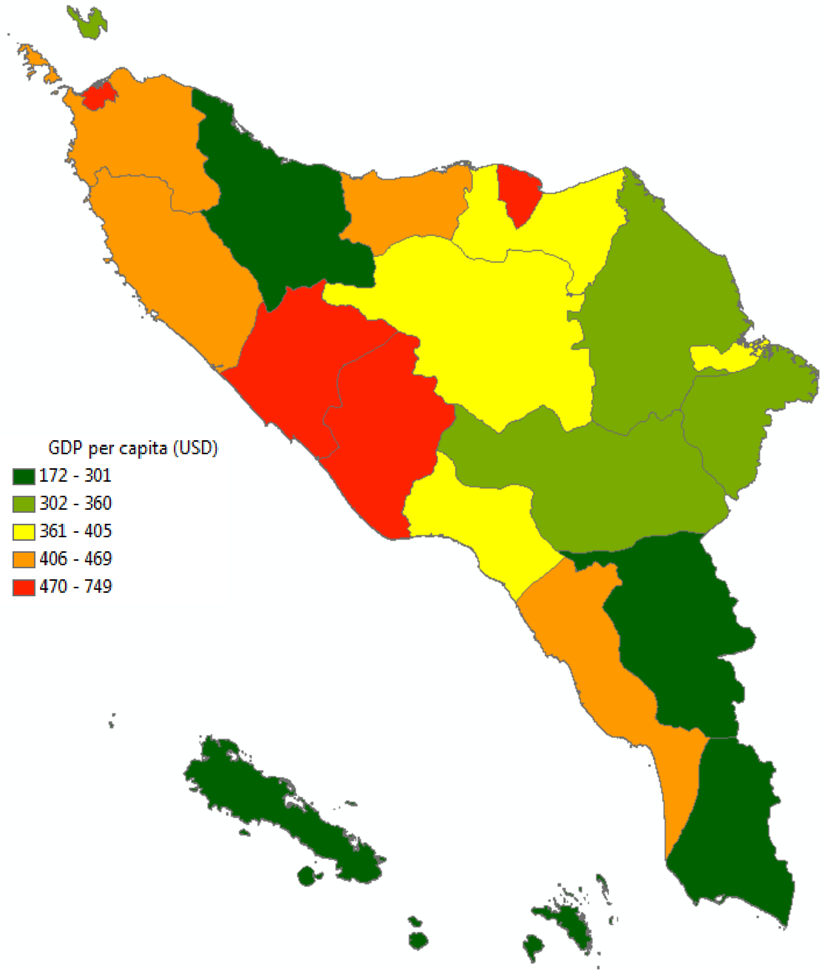
[69] At least in pre-war times there was no ethnic growth differential. There are not many good reasons to believe that that should have changed in times of peace. The few possibly good reasons, not having to do with inherent traits of ethnicities, but rather with their different treatment in peacetimes, including aid disbursements, and sovereign wealth funding allocation, are discussed in section 4.5.3.

[70] Examples of recent papers using night-lights data as a measure of local economic output include: Henderson, Storeygard, and Weil (2012), Chen and Nordhaus (2011), Alesina, Michalopoulos, and Papaioannou (2012), Besley and Reynal-Querol (2014), Hodler and Raschky (2014).

District level GDP data

Map 4.2 shows the geographic distribution of GDP per capita in Aceh. See chapter 2 of my PhD thesis for a more detailed elaboration of the district level GDP dataset. As with the geospatial distribution of the conflict data, it appears as if the GDP data is spatially heterogeneously distributed. In other words, there are high GDP areas to all sides of the coast in Aceh. With Aceh Barat, and Nagan Raya there are district GDP per capita hotspots on the Indian Ocean side to the south and with Lhokseumawe there is a GDP per capita hotspot on the Strait of Malacca side to the North. Furthermore, there is another hotspot with Banda Aceh, where the two bodies of water meet.

Map 4.2: GDP per capita distribution in Aceh during 2004

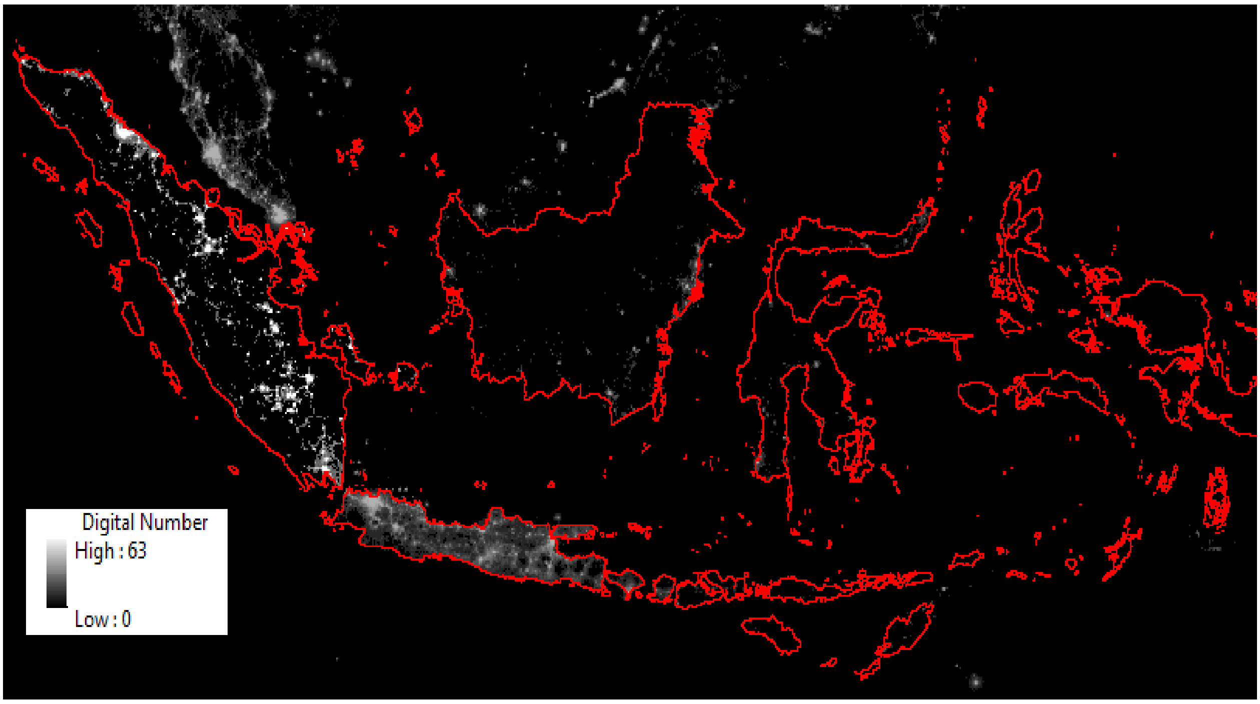


Note: Plotted are GDP per capita quintiles.

Night-time lights

The United States Air Force, as part of its Defence Meteorological Program (DMSP) has satellites circling the earth, capturing images of the intensity of planetary-based lights at night. The night-lights depicted in the daily maps were taken from 8:30pm – 10pm every day. The National Oceanic and Atmospheric Administration (NOAA) processes these data and makes annual average maps available to the public.[71] I converted annual night-light maps of the planet from 1992 – 2012, which were in pixel-format of about 0.86 km to grid-cells of roughly 2.75 km (see map 4.3 for Indonesia by night).

Map 4.3: Indonesia by night in 2004

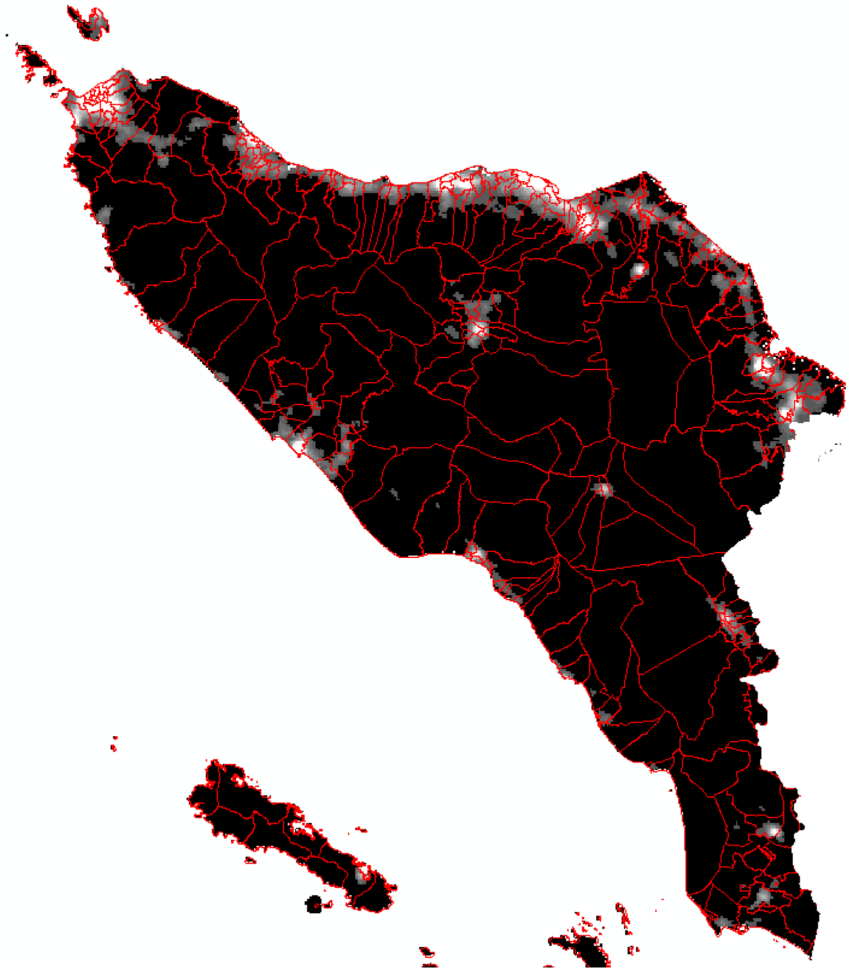


The lights are recorded based on brightness, which is expressed by way of Digital Numbers (DN), which range from 0 to 63, where 0 is darkness and 63 is the highest rate of luminosity. The later represents a censored value, which is top-coded at 63, meaning that there are several extremely high measures of light intensity, which in principle would rank higher than 63 but are truncated at this maximum. Top coding does not present a problem for my analysis, since less than 0.0001 percent of my grid-cells had a value of 63, which is a minuscule frequency. I am not the first to use nightlight imagery

[71] For a more detailed explanation of the night-lights data, along with a discussion of its caveats in using it as a measure of economic performance, see e.g. Small et al (2005) and Henderson et al (2012).

as a proxy for local economic activity (see e.g. Chen and Nordhaus, 2011; Henderson et al, 2012; Strobl & Bertinelli, 2013) for some of the earlier contributions in the field). Homing in closer to the sub-district level of Aceh indicates the 276 Kecamatans for which I produce a single night-lights value per year (see map 4.4).

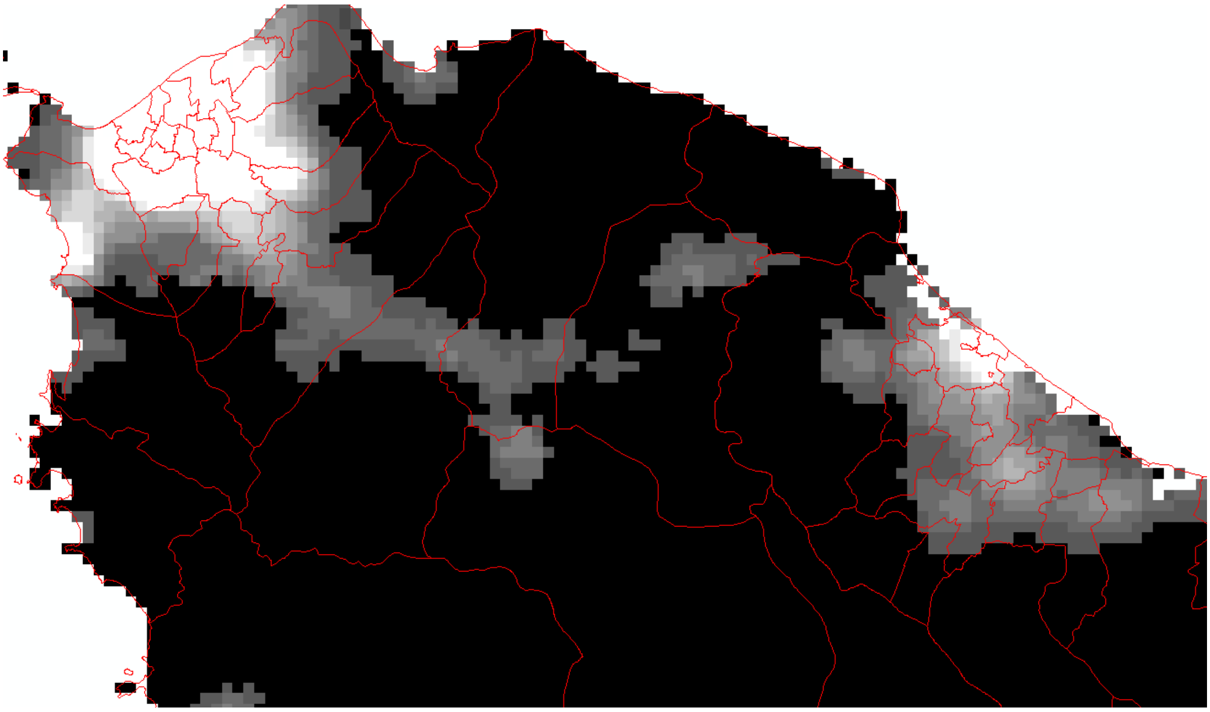
Map 4.4: Aceh by night in 2004 and the 276 Kecamatans



Note: The red demarcations represent the borders of the Kecamatans (sub-districts)

To create the night-light observations per Kecamatan per year, I use the underlying data of night-lights provided in in raster format (see map 4.5), where each pixel represents a unique value of luminosity. I create the measure of the Kecamatan level night-lights, by aggregating the light intensity measure (denoted as DN, which is short for Digital Number) of all pixels within the sub-district's borders.

Map 4.5: Zooming in on the night-light pixels, together with Kecamatan borders



I compute the Kecamatan measure of night-lights (NL) in the following way:

$$\mathrm{NL_{ct}} = \sum_{n=1}^{N} \log(\mathrm{DN} + 0.001)$$

Where *c* denotes the Kecamatan, *n* denotes the number of pixels within such a Kecamatan, and *t* denotes the year. Michalopoulos & Papaioannou (2011) and Lowe (2014) recommend using this log (DN+0.001) transformation, for the purpose of not only capturing already lit pixels but also dark regions (as they would be rendered undefined after a log-transformation) and any changes they might face, and also for reigning in the outliers. Computing the night-lights measure that way assures that that we both factor in the intensive margin (already existing lights getting brighter), as well as the extensive margin (formerly dark pixels lighting up). The changes in lights (as a proxy for the economic growth) are measured as the difference between year *t* minus year *t-1, i.e.* as $\mathrm{NL_{ct}} - \mathrm{NL_{ct-1}}$.

4.4.2 Empirical methodology: Difference-in-differences

The empirical approach applied to assessing whether conflict has any long-term lingering effects on growth is similar to the one I used in chapter 2 for assessing the impacts of the Tsunami flooding: difference-in-differences. There are two periods, war and peace, with the war period ranging from 1999 to 2004 and the peace period ranging from 2005 to 2012. $T = 0$ indicates pre-treatment (i.e. wartime), and $T = 1$ indicates post-treatment (i.e. peacetime) during which a legacy effect may unfold, where T is short for treatment (peace). There are two groups; Conflict stricken ("treated") sub-districts and peaceful ("control") districts, where $D = 1$ means that the district has seen heavy fighting and high conflict intensity from 1999 to 2004, and $D = 0$ means that it was relatively peaceful (the two were split based on the median). For a more advanced diff-in-diff specification, I also use a measure of conflict intensity (e.g. deaths caused), where D_i captures all wartime deaths per district i per year t. Other measure of conflict intensity I used were the number of violent incidences (injuries, rapes and kidnappings), and the number of destroyed buildings by the separatist conflict, as described in the conflict data section.

$Y_{i,t}$ is the outcome measure of GDP per capita for district i during post-conflict year t. Alternatively, for the sub-district case it is the measure of light intensity at night. I will exploit the panel data set, and having multiple time periods by using a fixed effects regression with district fixed effects (γ_i) and period fixed effects (d_t), which should allow estimating a growth path. The estimation strategy follows a difference-in-differences approach, where I model the first log differences of district level GDP per capita data as an impulse – response function that is linear in historic exposure to conflict:

$$\ln(Y_{i,t}) - \ln(Y_{i,t-1}) = \alpha + \delta(D_i * T_t) + T_t + \gamma_i + d_t + \varepsilon_{it} \qquad (1)$$

This impact measure should allow me to estimate the average annual impact of violence on economic growth (night-lights changes). As a next step, I split up the individual years, to get a sense of the impact of peace during each year, by carrying out a distributed lag model of the form:

$$\ln(Y_{i,t}) - \ln(Y_{i,t-1}) = \alpha + \sum_{t=2005}^{2012}[\delta_t(D_i * T_t)] + T_t + \gamma_i + d_t + \varepsilon_{it} \qquad (2)$$

The interaction term between the violent/peaceful district dummy and the wartime/peacetime dummy, $D_i * T_t$, denotes violent districts in the post-war era with 1, and the rest with 0.[72]

δ is the main coefficient of interest because it captures the causal legacy effect of past violence on current growth, if the identifying assumption is met that the treatment is randomly assigned.[73] If δ is significantly smaller than zero then there is a negative legacy effect.

To correct for unobservable but fixed confounders, year fixed effects (d_t) and district fixed effects (γ_i) are included. District fixed effects are included to control for omitted variables such as municipal government quality. By including district dummies, the data are demeaned and any long run trend is removed (see Noy, 2009). Time fixed effects are included to account for common macro shocks that affect secular growth trends over time.

With equation (1) I am testing the average annual legacy effect of violence on peacetime economic growth, and with equation (2), which describes a distributed lag model, I test the effect of wartime violence on each peacetime year growth rate separately.

I assume that ε is heteroskedastic and serially correlated within a district for 10 years (Newey and West, 1987). I furthermore assume that there is spatial autocorrelation across contemporaneous districts up to a distance of 100km (Conley 1999 & 2008).[74] The code for correcting the Standard Errors (SEs) for spatial and serial autocorrelation as well as for heteroskedasticity was adapted from Hsiang (2010). The spatial weighting

[72] I did not include D_i (as a measure of how similar the treatment and the control group are), as it is a linear combination of the district fixed effects. For the same reasons, I also did not introduce time-invariant variables. I also did not include district specific time trends, other than as a robustness check, because the income trajectories of all districts in Aceh had similar trends and were curved similarly.
[73] I assume that the areas where separatist and regime fighters chose to engage in violence are as-if they were randomly assigned, and are uncorrelated with growth promoting factors. There is an argument to be made for why this is not necessarily a good assumption. As suggested by map 1 and map A4.1-A4.3, fighting tends to be concentrated in rural areas, where the separatists could hide easier among other tactical reasons. In the empirical analysis, I control for geographical as well as other growth-promoting factors.
[74] I also experimented with different spatial limits, as well as different duration limits for autocorrelation analysis, as a robustness check. Moreover, I also tested for non-linear spatially decaying functions.

kernel applied was uniform as suggested by Conley (2008).[75] One district being affected is a good predictor of the neighboring district also being affected; i.e. there is no independence of treated units. Space could thus play a role in determining the economic activity measured causing the data to be non-random and making it thus important for me to correct the SEs for the common factors (the spatial autocorrelation) (see Gibbons, Overman, and Patachini, 2013). The reason for why I correct SEs for serial autocorrelation is that a district having been classified as a historically high violence district during year *t* will also be classified being high violence during *t+n*, meaning that one can perfectly predict the treatment intensity from one year to the next.

First, I perform the diff-in-diff analysis on the district level with GDP data. Because of the relatively small sample size and consequentially the limited statistical power, and the high level of variation within each district, as revealed by the sub-district conflict, map A4.3, I repeat the causal analysis for the sub-district level. Formally, sub-districts (Kecamatans) are reflected in the subscript *i* in equations (1) and (2). Because GDP data does not exist on the sub-district level, I substitute it for night-light intensity, a proxy for economic activity. Because of the lack of reliable population data on the Kecamatan level, I use the night-lights measure per Kecamatan without normalizing it for population. Using these differently granular levels of analysis should take care of the Modifiable Area Unit Problem (MAUP), and represent a solid robustness check.

Does displacement pose a serious challenge to causal inference?

It is estimated that the conflict lead to 500,000 – 600,000 internally displaced persons (IDPs) from 1999 to 2004 (IDMC, 2006 & IDMC, 2010). There were two main waves of displacement (Czaika & Kis-Katos, 2009). The first from 1999-2000, where most people only temporarily escaped the violence in their village, to community centres, Mosques *inter alia*, within the province, mostly even within the districts, and returned within one or two weeks to their villages. From 2001 onwards, during the second wave of displacement, when the fighting intensified, a substantial amount of IDPs escaped, reaching almost 180,000 by September 2002, and eventually amounting to more than

[75] I also experimented with linearly decaying kernel spatial weights such as the Bartlett kernel or the Epanechnikov kernel (for a detailed discussion see Anselin and Lozano-Gracia, 2007).

half a Million. The first wave does not really pose a challenge to the SUTVA assumption, the second one in turn does.

There are two types of displacement that may pose a challenge. (a) Internally displaced persons (IDPs) moving from a conflict-riddled district to another district within Aceh. This may bias the estimated economic legacy effect in that those moving to the counterfactual pool of districts were affected by the conflict (their health, their psyche etc.) and are likely not going to be immediately integrated into their labour market in their host district, all of which contributing to lower productivity, which might "contaminate" the counterfactual, and lead to an underestimation of the negative economic legacy effect, as the counterfactual might have been artificially biased downwards. (b) IDPs moving out of Aceh to another province such as North Sumatra also poses a challenge for SUTVA, as those moving may be those most affected, which would lead to underestimations of the economic legacy effects. (a) is likely to pose little inferential trouble as most IDPs that fled within Aceh have since returned, but (b) might result in a bias since a substantial amount of those fleeing to North Sumatra have not yet returned, as elaborated in detail in the following two paragraphs.

(a) Most of the survey respondents in the more conflict prone districts reported only a temporary displacement and a displacement within the district they hail from, often even the same sub-district (IOM, 2006). Many of them were collectively evacuated, leaving their houses jointly. They were also jointly accommodated in government facilities, mostly within their same district, most even the same sub-district (IOM, 2006). IDPs from the second wave of displacement had to stay away from their villages for months in some cases even as much as 2 years, but the great majority of them returned (Ramly, 2005).

(b) Even though many of the IDPs have since returned to Aceh, a not insignificant amount – about one-fourth - has stayed at the destination where they fled to. According to one estimate as many as almost 150,000 IDPs who fled to neighbouring provinces during the separatist conflict are still outside of Aceh by 2010 (IDMC, 2010).[76] The

[76] There was also displacement within the province. A survey from 2008 suggests that the number of displaced people within Aceh still ranges anywhere from 44,000 – 146,000 people (Barron et al, 2009).

majority of these IDPs who have still not returned are ethic Javanese (Hedman, 2005).[77] They fled, occasionally even with military escort, predominantly to Medan in Northern Sumatra (Buiza and Risser, 2003). The ethnic Acehnese who moved outside of the province were met oftentimes with considerable amounts of hostility, risk of arrest, detention and therefore many returned to Aceh.

The non-return of the 150,000 ethnic Javanese people, to Aceh where they had fled from, who were heavily affected by the violence likely leads to an underestimation of the negative economic legacy effects. The implication of this systematic violation of SUTVA for the ensuing econometric analysis is that if I do not find a statistically significant negative legacy effect, it may be because many of the adversely affected people have moved away and are no longer part of the treatment group. If instead I find negative legacy effects, then they represent an underestimation of the true effect size, and the legacy effects would have been even larger had these adversely affected people stayed/returned. To foreshadow the ensuing results, I find significantly negative economic legacy effects for the first five years after peace was struck, and insignificant effects for the years after 2009. The non-return of IDPs implies that if they had not left, the negative effects would be even more sizeable. Furthermore, it also implies that the post-2009 effects could have possibly also been significantly had they never left/returned. The non-returning IDPs therefore increase the confidence in the negative legacy effect finding

4.5 Findings & Discussion

The main finding of this chapter is that there are legacy effects of the conflict and that districts with no or little violence developed much faster after a peace agreement was struck in contrast to districts that had been the centres of violence. Highly violent

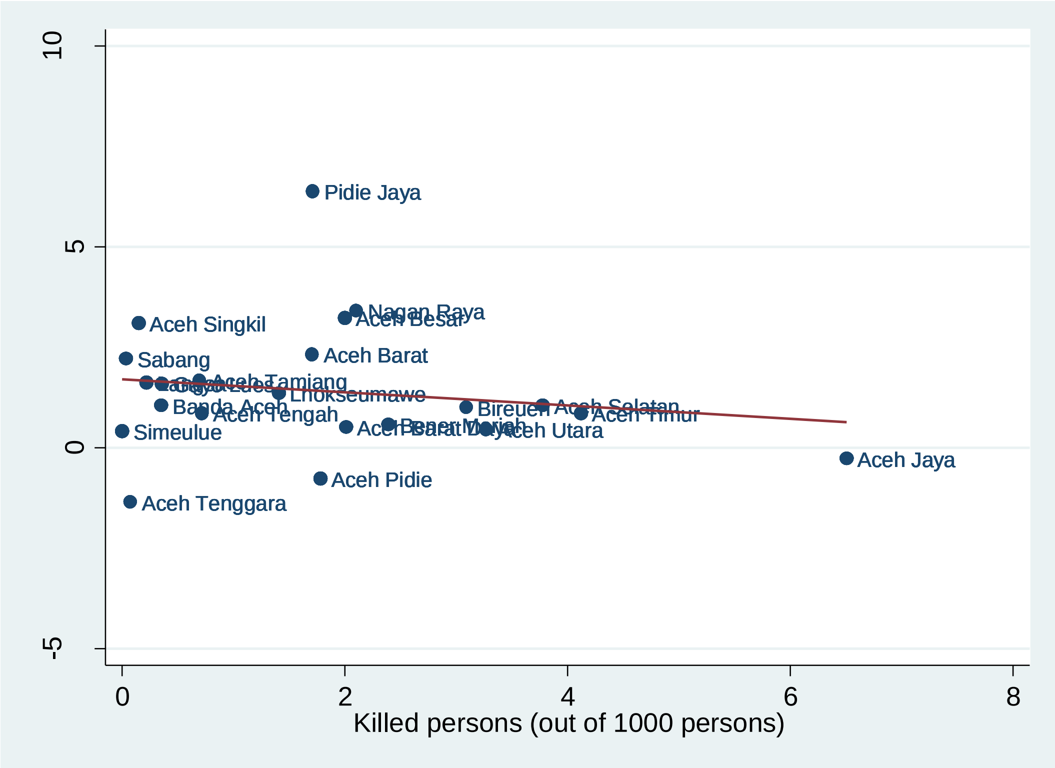
[77] Even though GAM rebels have denied to have systematically attempted to cleanse Aceh from ethnically non-Acehnese, the evidence from other sources observing events on the ground including Amnesty International points to the opposite (Schultze, 2004; Barber, 2000). These sources indicate a disproportional exposure of ethnic Javanese to violence. Similarly, the TNI military attacked mostly ethnic Acehnese, as the GAM rebels were mostly composed of ethnic Acehnese. Which one of these violence asymmetries is larger in the district aggregate, determines whether the absence of mostly ethnically Javanese people from the sample causes an overestimation or an underestimation of the measured negative economic legacy effect of armed conflict.

districts grew by a very similar rate than relatively peaceful districts during wartimes. Once peace had arrived, all districts were growing at faster rates than during times of war. Notwithstanding, districts that had relatively little violence grew disproportionately faster, significantly outperforming districts, which had faced high violence during the civil war. This result suggests that even though peaceful districts were less directly affected by violence during the war, they were indirectly held back by a state of perpetual civil war. It also suggests that there are negative legacy effects, which stymy the growth of formerly violent districts during times of peace. The adverse legacy effects are significant for about five years after the conflict had ended. Within these five years, the negative legacy effects managed to relegate the conflict affected districts onto a permanently lower growth path.

4.5.1 Correlations between economic growth and conflict

In this descriptive section, I show that the more violence districts faced during the insurgency, the slower they grew economically in peacetime. There is not much association between per capita growth rates and violence during the war; see figure 4.3 where the linearly fitted line is almost horizontal. The correlation coefficient between wartime violence and contemporaneous levels of GDP is -0.17 and insignificant. The average annual per capita growth rate was about 3.2 percent per year from 1999 to 2004, across the violence spectrum. In other words, violent districts did not grow differently from peaceful districts.

Figure 4.3: Wartime growth (1999-2004) and wartime conflict casualties (1999 – 2004) in Acehnese districts



Note: GDP per capita growth rate refers to the average annual log growth rate of a constant GDP series during the specified period. There are 23 districts in Aceh. Persons killed refer to victims from the separatist war. The equation for the fitted linear regression line is y = 1.71 – 0.16x, with an insignificant coefficient and an R-squared of 0.03.

The fact that the relatively peaceful districts grew on average by about the same rate as the relatively violent districts may be an indication of spillovers from neighbouring districts. Murdoch and Sandler (2004) found spillover effects for economic growth. They found that the diffusion of negative conflict consequences even affected the economies of neighbouring countries. Similarly, Hegre and Sambanis (2006) found that there are significant spillover effects of armed conflict on contiguous countries. War in neighbouring countries makes it significantly more likely for the country to also be befallen by civil war. For Aceh this would have meant that even though certain districts were relatively peaceful, they grew by less because they are also geographically in Aceh. The sheer threat of violence may be enough to dissuade economic activity. Foreign direct investment, for example, could have been lower in relatively peaceful areas, as many potential investors may have lumped all the districts together, not discerning the geospatial nuances of investment risk.

Peacetime growth rates, with an average annual growth rate of 4.3 percent (from 2006 to 2012), are quite different from wartime growth rates (see figure 4.4). The average per capita growth rate during peacetimes is 1 percentage point higher than that of wartimes. This peace dividend tentatively confirms the findings from Hoeffler, Ijaz, and von Billerbeck (2010), who found that country economies who just came out of war grew about 1 percentage point faster, compared with the average country. All districts that had negative growth rates during the war (Aceh Tenggara, Aceh Pidie and Aceh Jaya) had positive growth rates after the war. Overall, peacetime growth rates are larger than wartime growth rates. There is no exception. Not a single district grew faster during wartimes than during peacetimes, attesting to the benefits of peace for economic activity.

Nevertheless, whether the increase in growth rates is causally related to peace, cannot be established. Higher growth rates may well be due to the Tsunami aid and flooding recovery polices. I have no way of isolating the effects due to conflict and those due to the Tsunami, as both occurred around the same time, during the years 2004/05 and both had a significant effect on the economy. Luckily, comparing peacetime versus wartime is not the subject of my chapter; instead, I want to isolate economic legacy effects of the war, which comes with separate, yet surmountable challenges.

Figure 4.4: Peacetime growth (2006-2012) and wartime conflict casualties (1999 – 2004) in Acehnese districts

Note: GDP per capita growth rate refers to the average annual log growth rate during peacetime. Killed persons refer to the number of casualties during wartime. There are 23 districts in Aceh. Persons killed refer to victims from the separatist war. The equation for the fitted linear regression line is y = 5.98 – 0.91x, with a significant coefficient at the one percent level and an R-squared of 0.41.

Even though all districts increased their average annual per capita growth performance after the war, those that witnessed more violence during the civil war grew disproportionately slower in peacetimes compared to relatively more peaceful districts. This disproportionately low growth rate for relatively violent districts during the war is a strong indication for legacy effects, which are holding the formerly violent districts back. Looking at the three districts that had negative growth rates during the war, Aceh Tenggara, Ach Pidie, and Aceh Jaya illustrates this trend. Aceh Tenggara, recording only a few incidents of violence during the war, improved growth rates by 11 percentage points (from about – 2 percent of annual growth to + 9 percent); Aceh Pidie, reporting a mean amount of violence during the war, increased growth by 7 percentage points (from -1 percent to 6 percent); and Aceh Jaya, reporting a lot of violent incidents during the war, increased by “only” 2 percentage points (from - 0.5 percent to 1.5 percent).

The change in slopes (as illustrated by comparing figure 4.3 with figure 4.4) suggests a possible legacy effect, where districts that saw high conflicts are growing slower than their relatively peaceful counterparts. Whether there is a causal relationship between wartime violence and peacetime growth is scrutinized in the next sub-section.

4.5.2 Economic legacy effects of the conflict: the causal effect of the armed conflict on peacetime economic growth

Is the negative economic legacy effect of the conflict suggested by the descriptive analysis causal? Do conflict-ridden areas grow slower once the conflict has ended, because of the persistent and lingering effects of violence? These questions guide the causal analysis presented here.

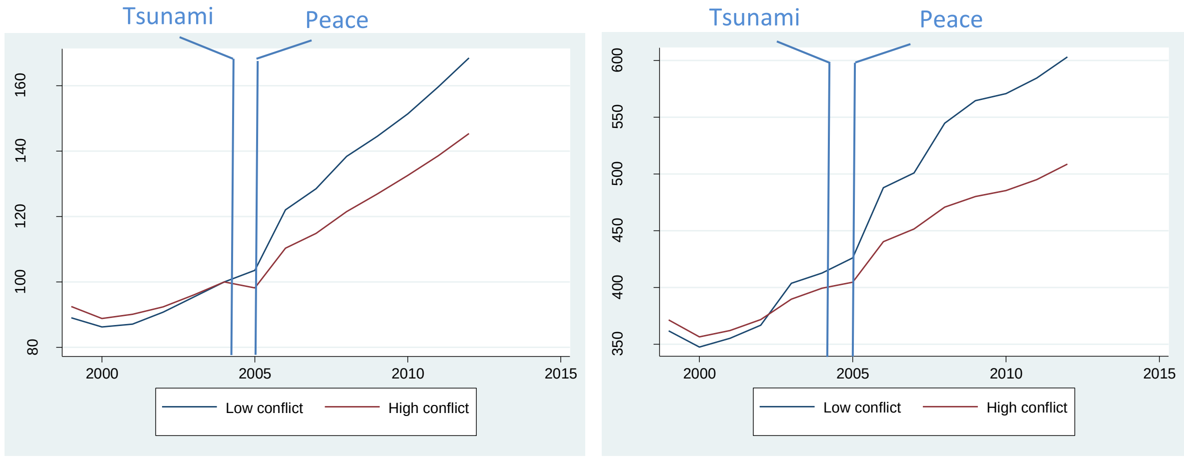
4.5.2.1 GDP per capita district level analysis

Are the conflict-treated districts comparable to the peace-treated counterfactual? Comparing the growth evolution of districts that had a high conflict intensity during the war to those that had a low conflict intensity shows that both developed in parallel during the civil war, confirming the parallel historic paths assumption (figure 4.5).[78] Both conflict groups do not only have a similar dynamism, but also quite comparable levels of GDP per capita from the onset; they both started out at an average of roughly USD 300 in 2000 and by 2004, they were at about USD 400. With the Tsunami striking on the 26th of December of 2004 and the peace agreement being signed in mid-2005, the two groups diverged noticeably. Figures A.4.4 – A.4.9 in the Appendix show the robustness of the parallel trends assessment to the definition of the treatment and the counterfactual groups (median, tercile, quartile and quintile), as well as different measures of conflict intensity (deaths & non-fatal violent incidents).

[78] This is in line with the descriptive findings from the previous section of no relationship between pre conflict growth and violence (as shown in figure 4.3).

Figure 4.5: Parallel historic path of high and low conflict

Panel A: GDP **Panel B: GDP per capita**



Note: The graphs depict the evolution of the mean districts within either the low conflict or the high conflict classification. The high conflict districts are those above the median casualty threshold and the low conflict districts are below this threshold. The graphs look quite similar if instead of deaths per population, I use violent incidents (injured, kidnapped, and raped persons) or damaged buildings, as measures of conflict. GDP measures used are inflation adjusted.

Comparing the aggregate descriptive GDP index shows almost mirroring peacetime growth rates between the high conflict group and the low conflict group. The same almost holds true for GDP per capita also. There is not one year, where they have growth rates that differ by more than 0.5 percentage points, with the exception of the year 2002, which makes them a near-perfect treatment-control group pairing. The reason for the non-similar per capita growth rates (panel B), even though the GDP growth rates (panel A) were very similar in 2002, is an artefact of classification, rather than a different underlying growth pattern during that particular year. District classifications changed in 2002 as part of a wider local democratization process in Indonesia, increasing the Acehnese districts from formerly 14 to ultimately 23 districts. The challenges in estimating new population figures after this administrative change are overall responsible for the marked hike of the low violent districts in the second panel of figure 4.5. The ensuing difference-in-differences analysis will be informed by this anomaly. Figure 4.5 vindicates the key identifying assumption, which is that growth trends were almost the same for both historic violence groups. The deviation from this common trend was induced by the peace treatment and the negative legacy effects of violence.

Caveat of the parallel historic trends assumption

The identification of the estimated legacy effects is based on the assumption that contemporaneous war effects are inconsequential for contemporaneous growth rates, and that the armed conflict intensity effects only manifest themselves historically once the war is over, as so called "legacy effects." I have provided evidence for how the high conflict and low conflict districts have developed similarly during times of war, from 1999 to 2004, as evidenced by similar growth rates across the violence spectrum (as is for example illustrated by figure 4.3 and figure 4.5). The observation of similar growth rates and parallel trends across the high and low violence groups may however not automatically imply that both groups had the same growth potential. It could be for example that the more violent districts would have grown faster than their counterfactuals, had it not been for the violence. This could have for instance happened due to tactical reasons, which could explain why areas with more growth potential saw more fighting.

The true comparability of high and low conflict districts during wartimes can never be exhaustively established, to quell any doubt about the comparability of the two groups. The underlying assumption, which is that war only has lagged (protracted effects) and not contemporaneous effects, is a hard one to accept, and cannot be conclusively confirmed, as there are no historic peacetime trends to which they can be compared. There are however additional facts in support such an assumption: (a) The balance test in table 4.1., for example, shows quite similar growth-related measures such as measures related to human capital and productivity for both the high and low violent groups. That said, although the balance in these growth related factors was established for eleven different measures, to exhaustively establish balance on all possible factors related to growth would burst any reasonable framework, as it would go above the data requirements that could be fulfilled. (b) If it were true that districts that are more violent would have actually grown faster during wartimes, and the reason for why they actually grew similarly to the relatively peaceful districts, is that they were actually held back by the violence, then we would expect that during times of peace they grow faster than the less violent counterfactual. However, the opposite is the case, where they actually grow slower.

I did sensitivity checks on the definition of violence and the way the two groups (violent and non-violent are clustered), in establishing parallel trends, just as figure 4.5. did. I found that regardless of whether I chose deaths as the measure of violence, or violent incidents (kidnappings, injuries, and rapes), and regardless of how I define the cut-offs - above and below the median as in 4.5., or alternatives of that such as bottom versus top tercile, quartile, or quintile – I always get a comparable parallel trends graph. See the following graphs in the Appendix to verify, A4.4 – A4.9. This is furthermore a strong indication for parallel historic paths.

Difference-in-differences analysis

Examples for measures of the depreciation of human capital (ΔH<0) given in the elaboration of neoclassical growth models are often mortality for the degradation of health, and skill deterioration for the degradation of education (see e.g. Barro and Sala-i-Martin, 2003, pg. 240).[79] I use casualties from the separatist conflict per population as the human capital metric for conflict intensity (Δh). It is straight-forward accounting that aggregate economic activity is reduced by less people engaging in it, and therefore I regress mortality per capita on per capita growth (as opposed to district level growth). Aside from this mortality indicator, I also use morbidity measures, including the amount of people injured, kidnapped, and raped, as a direct consequence of the separatist war in Aceh (also population normalized). The results allow some insight into whether the conflict intensity did indeed reduce per capita economic output (y). For physical capital deterioration ($\Delta k < 0$), I use the measure of damaged and destroyed buildings by the separatist war. Due to the unavailability of data allowing me to compute total houses per district, I express the physical capital destruction as a share of total population instead.

The results of the basic difference-in-differences analysis are presented in table 4.2 and table 4.3. They show that across measurement options for conflict intensity, a history of violence is causally stifling the districts in times of peace. Comparing high conflict with low conflict districts shows that areas of low conflict during the war grow on average by

[79] I only use measures of health deterioration because I do not have measures of education deterioration caused by the civil war such as schools destroyed, teachers killed, reduced enrolment or completion rates.

2.9 percentage points faster per year in peacetimes than their rather violent counterparts. Not only the dummy analysis shows this negative legacy effect, but so do all other continuous measures. A single additional wartime casualty per 1000 people causes a 1 percentage point reduction in economic per capita growth during peacetimes. The negative legacy effect is particularly strong during the first years of peace, where such an increase in casualties results in a 2 percentage point decrease of per capita growth in year 2005 and of 4 percentage points in year 2006.

Increased morbidity measures (injuries, rapes and kidnappings) by 1 incident per 1000 people, as well as increased physical destruction also by the order of 1 damaged house per 1000 people, decrease annual per capita growth by about 0.5 percentage points, albeit not statistically significantly so. Nevertheless, looking only at the years up until 2009, the morbidity and destroyed buildings coefficient of the average annual effect is statistically significant (see table 4.3).

Table 4.2: Difference-in-differences regressions of conflict legacy effects on peacetime economic growth rates

DV: GDP per capita growth Measure of conflict:	High Violence vs No/Low Violence		Deaths (per 1,000 people)		Violent incidents (per 1,000 people)		Damaged buildings (per 1,000 people)	
Wartime conflict (average year)	-0.029 **		-0.009 *		-0.005		-0.005	
	0.010		0.000		0.000		0.000	
Wartime conflict x 2005		-0.080 **		-0.021 **		-0.015 ***		-0.012
		-0.020		*0.010*		*0.000*		*0.010*
Wartime conflict x 2006		-0.057		-0.035 **		-0.015 **		-0.024 *
		0.030		*0.010*		*0.010*		*0.010*
Wartime conflict x 2007		-0.004		-0.005		-0.003 *		-0.002
		0.010		*0.000*		*0.000*		*0.000*
Wartime conflict x 2008		-0.043		-0.008		-0.004		-0.012 *
		0.020		*0.010*		*0.000*		*0.000*
Wartime conflict x 2009		-0.025 *		-0.010 ***		-0.006 ***		-0.008 ***
		0.010		*0.000*		*0.000*		*0.000*
Wartime conflict x 2010		-0.005		0.008		0.006		0.014
		0.040		*0.010*		*0.000*		*0.010*
Wartime conflict x 2011		-0.007		0.001		0.001		0.003
		0.010		*0.010*		*0.000*		*0.000*
Wartime conflict x 2012		-0.012		-0.003		-0.002		-0.001
		0.010		*0.000*		*0.000*		*0.000*
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spatial & Serial corr SEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	264	264	264	264	264	264	264	264
R-sqr	0.54	0.57	0.54	0.6	0.54	0.58	0.54	0.57

Notes: *High Violence vs No/Low Violence* is a dummy variable, where 1 is assigned to the districts that are above the median of deaths per capita and 0 to the districts below the median. The reason for why damaged and destroyed buildings are also normalized by district population, is that I was unable to find data on the total number of buildings per district. Standard errors are in italics. *, **, *** mean significance at the ten, five, and one percent level, respectively.

Legacy effects are particularly severe in the immediate aftermath of the conflict, i.e. the first year, 2005, during which peace was negotiated and attained. Independent of which measure of conflict intensity was used, significantly negative legacy effects were registered up until 2009. The year 2009 is the last significant year, across conflict intensity specification, with about 1 percentage point lower per capita growth per additional wartime casualty, violent incident or destroyed house (out of 1000 people). Legacy effects do not appear to be persistent enough to be depressing per capita growth rates in the long-term (see the coefficients from 2010 onwards in table 4.2). Legacy effects do however relegate the violence-affected districts onto a permanently lower output path, as these districts never recover (as evidenced by the absence of positive and statistically significant coefficients in the years after 2009).

Shortening the time horizon for possible legacy effects to manifest themselves only up until 2009 allows me to investigate whether the formerly insignificant average year wartime conflict effects for violent incidents and damaged buildings were insignificant only because of the inclusion of years beyond which any negative legacy effect on growth rates has faded (see table 4.3). Focussing only on the five-year period since the peace deal, shows that the average annual effect of morbidity human capital measures as well as the physical capital damage measures, hitherto insignificant (see table 4.2), are statistically significant (see table 4.3).

Table 4.3: Difference-in-differences regressions of conflict legacy effects on peacetime (until 2009) economic growth rates

DV: GDP per capita growth rate		
Measure of conflict:	Violent incidents (per 1,000 people)	Damaged buildings (per 1,000 people)
Wartime conflict (average year)	-0.009 ***	-0.012 **
	0.000	*0.000*
Year FE	Yes	Yes
District FE	Yes	Yes
Spatial & Serial corr SEs	Yes	Yes
Observations	176	176
R-sqr	0.59	0.59

Notes: Standard errors are in italics. *, **, *** mean significance at the ten, five, and one percent level, respectively.

In summary, the finding emerging from this sub-section suggests that the negative legacy effects on per capita economic growth are short-to-mid-term only. They last for about 5 years, as the last year that showed a negative legacy effect was 2009, after which the negative effects on growth rates have dissipated. The absence of significant negative growth rates post 2009 is however not indicative of an absence of long-term economic effects. In fact, long-term per capita output is persistently depressed, as evidenced by the absence of catch-up economic growth.

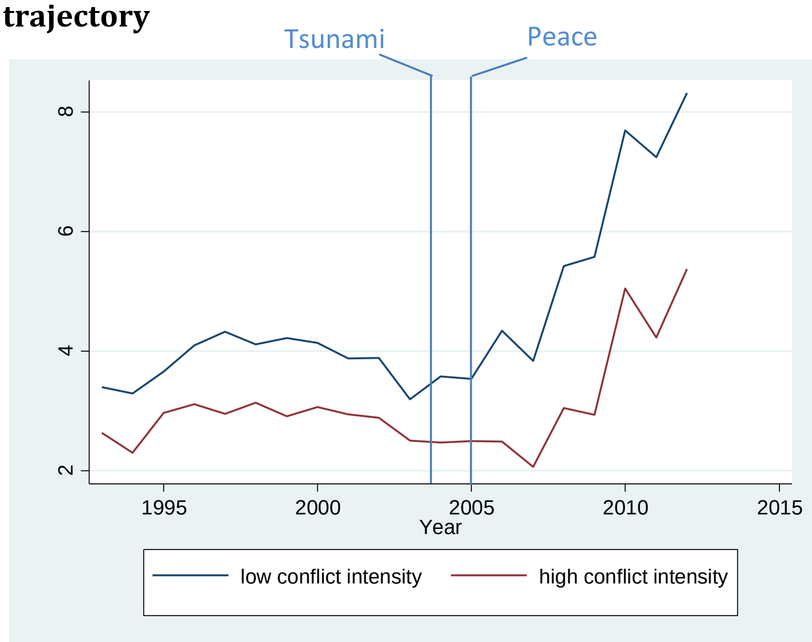
4.5.2.2 Night-lights sub-district analysis

Due to the small sample size of only 23 districts in the previous analysis, and the challenges of the Modifiable Areal Unit Problem (MAUP),[80] it is important to verify and corroborate whether the negative legacy effect also holds true on a sub-district (Kecamatan) level. Since GDP data is not available on this level, I used night-lights as a proxy for economic activity, which adds a fine-grained layer of robustness checking, owing to the usage of a supplementary measure.

Looking at the evolution of night-lights over time shows that high conflict intense sub-districts (above the mortality median) move parallel to low conflict intense sub-districts (below the mortality median) (see figure 4.6). Unlike for GDP per capita, where both trajectories were overlapping, meaning that high and low conflict districts had near identical per capita GDP levels, high conflict intense districts have less light emitting from their areas.[81] In the descriptive figure 4.6, we see a diverging pattern between high and low conflict districts with the signing of the peace agreement in 2005. The difference between both lines has doubled by about 2007; the difference remains the same for the following years up until 2012 (with no convergence in sight).

[80] For a more detailed explanation of MAUP, and the challenges it poses concretely in the district level (Kabupaten/Kota) and sub-district level (Kecamatan) in Indonesia see chapter 2 of this PhD thesis.
[81] The brighter lights in relatively peaceful areas are partly due to the fact that violence was rather taking place in rural areas than in cities, as the separatist GAM rebels hid in the remote jungle area and many TNI military campaigns were launched targeting them there. It may have also something to do with a strategical advantage of keeping it dark at night and better protection from acts of conflict in the dark.

Figure 4.6: High conflict versus low conflict Kecamatans: Night-light intensity trajectory



Note: Plotted is the average light intensity as measured in DN (ranging from 0 denoting darkness to 63 denoting brightness). Low conflict intensity displays the mean of the group that was below the deaths per population median, and high conflict intensity plots the mean for the group above the median.

Taking a causal analytical stab and producing the difference-in-differences analysis for the Kecamatan level with night-lights reveals a confirmatory picture of the negative economic legacy effects of conflict. I use a measure of average night-lights to compute the annual changes, instead of night-lights per population, due to the lack of reliable population data at the Kecamatan level.[82] Regardless of which measure for conflict induced human suffering and killing is used, the effects are statistically significant and negative. This analysis provides confidence that the negative economic legacy effects are not likely due to the MAUP or the particularities associated to the economic growth measure.

[82]In the absence of geocoded and representative (at the Kecamatan level) survey and census data, which would have allowed the computation of a Kecamatan level population measures, the next best option of obtaining population measures is to use the population grid-cells from the Global Rural-Urban Mapping Project (GRUMP) produced by Columbia University's Socioeconomic Data and Applications Center (SEDAC). The population grid from GRUMP is estimated in turn using in night-lights data, which makes it methodologically questionable to use it as the denominator for an index *a la* NL/pop (see http://sedac.ciesin.columbia.edu/data/collection/grump-v1/methods for a detailed elaboration of the method). That said, I used the GRUMP population data to create a Kecamatan level population measure, which I then use to population normalize the night-lights measure and present the results as a robustness check, presented in table A4.2 in the Appendix. The results confirm the negative legacy effects found using GDP data, as well as population un-adjusted night-lights indicator.

Table 4.4: Difference-in-differences regressions: economic legacy effects of conflict on peacetime average Night-light Intensity changes

DV: Light Intensity (annual changes) Measure of conflict:	High Violence vs No/Low Violence		Deaths (per 100 people)		Violent incidents (per 100 people)		Damaged houses (per 100 people)	
Wartime conflict (average year)	-0.015		-0.023 **		-0.013 *		-0.020	
	0.02		*0.010*		*0.010*		*0.010*	
Wartime conflict x 2005		0.038		-0.030		-0.020 **		-0.022
		0.04		*0.010*		*0.010*		*0.020*
Wartime conflict x 2006		-0.037		-0.027		-0.010		-0.039 *
		0.04		*0.020*		*0.010*		*0.020*
Wartime conflict x 2007		-0.019		-0.027 *		-0.005		-0.026
		0.06		*0.020*		*0.010*		*0.020*
Wartime conflict x 2008		-0.11		-0.018		-0.002		-0.007
		0.06		*0.010*		*0.010*		*0.030*
Wartime conflict x 2009		-0.001		-0.025		-0.023 *		-0.003
		0.07		*0.020*		*0.010*		*0.020*
Wartime conflict x 2010		-0.021		-0.022 **		-0.018 ***		-0.029 *
		0.04		*0.010*		*0.010*		*0.010*
Wartime conflict x 2011		0.046		-0.012		-0.012 *		-0.016
		0.04		*0.650*		*0.000*		*0.010*
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4428	4428	4428	4428	4428	4428	4428	4428
R-sqr	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18

Notes: Night-lights are available for one year less than the GDP data. Buildings destroyed or damaged was not available at the Kecamatan level, which is the reason for the lack of an additional column containing it. Standard errors are in italics. *, **, *** mean significance at the ten, five, and one percent level, respectively.

Contrary to the GDP per capita growth analysis, the night-lights change analysis indicates that the negative legacy effects from violence may also perpetuate into the long-term. For less wartime violence riddled districts, the GDP per capita analysis finds that even though output per capita is persistently higher also in the long term, the growth rates are no longer different post 2009. The night-lights analysis suggests that not only are the lights permanently brighter post 2009, but they possibly also keep getting brighter post 2009. In other words, using the sub-district level night-lights analysis suggests that the negative marginal effects keep dragging on, while the district level GDP analysis indicates a statistically significant depression of growth rates only up until 2009.

In conclusion, both measures show a negative economic legacy effect of violence. Regardless of which measure was used, there is no indication of catch-up growth (or light activity), pointing to a permanently lower level of economic activity in both cases. Whether the negative legacy effects on growth rates also linger in the long-term has something to do with either the unit of analysis or the different measure.

4.5.3 The mitigating effects of aid, autonomy funding, oil revenue sharing, and geography.

In peacetimes, Aceh received substantial amounts of funding. Starting with 2005, right after the Tsunami crashed on Acehnese shores on 25 December 2004, the region received unprecedented flows of aid money. Starting with 2008 the province received, as negotiated in a revenue sharing agreement from 2006, a part of the oil and gas rents from the resources on its territory. Furthermore, a separate Acehnese Sovereignty Fund was established, which also started disbursing in 2008. These exceptional financial inflows may have biased the results and forced the negative legacy effect finding, if they were systematically targeting the least affected districts. Therefore, it is crucial to closely examine their relationship with conflict intensity. As most of the fighting happened in rural areas as opposed to the cities as shown earlier, it is important to investigate if the rural-urban dichotomy could have driven the negative legacy effects finding.

4.5.3.1 Are the negative economic legacy effects due to selective aid allocation?

To answer this question pertaining to a systematic bias of the conflict intensity measure due to possibly asymmetrical aid allocations, I turn to the RAND (Recovery Aceh Nias Database)[83] aid dataset, which recorded aid flows into the province. RAND was managed by the Rehabilitation and Recovering Agency (BRR) in Aceh. The dataset contains information of project level aid at the sub-district level. Part of the dataset's purpose was to track funds in order to assure a proper spread of donors and funds across the region. RAND was set up to track the work and funds of more than 500 agencies and to offer an effective tool for monitoring and evaluating reconstruction spending. In the words of UN Under-secretary Jan Egeland, RAND was set up with the idea in mind to "…not only getting relief to the needy parties, but also in keeping track of every penny" (UNOCHA, 2005).[84] Although its purpose was to take account of all financial aid flows, in praxis, that high goal missed the mark, as it lacked the methodology for classifying reconstruction funds, had no rigorous system for quality control, and relied on self-entry by individual agencies (Fengler, 2007). With USD 5.3 Billion accounted for in the dataset, it covers about 70 percent of the total aid of USD 7.7 Billion. There is no indication that the remaining unaccounted for 30 percent are any different, and in particular any more likely to introduce a bias than the accounted for 70 percent.

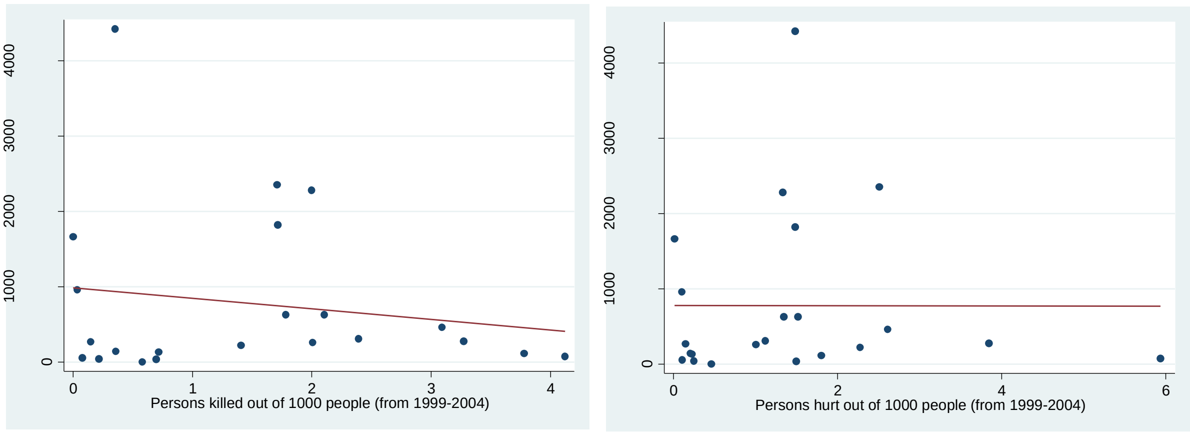
There was a concern that aid would have been distributed unevenly such that conflict affected districts would have gotten less (Barron, 2008). This uneven allocation could have many reasons. For example, the central government could have been trying to punish the former rebel strongholds by channelling less aid to selected districts. Another example for why particularly violence-affected districts may have received less aid has to do with their impaired absorptive capacity on account of a degraded institutional quality or a torn social fabric. There was also a contrasting allegation, which was that former GAM combatants' networks used their political influence, colluded, and corrupted in obtaining inequitable access to more Tsunami aid (IRIN, 2014).

[83] What is now called RAND was first introduced under the name of DAD (Development Assistance Database), in an effort to track and take stock of international aid flows in Afghanistan in 2003.
[84] http://www.un.org/press/en/2005/Egeland_Briefing_050314.doc.htm

The evidence dismisses these aid-confounding concerns, regardless of the direction, as there seems to be no systematic relationship between intensity of the conflict and aid allocated (see figure 4.7).[85] It therefore seems quite unlikely that aid has influence on the legacy effects since it was relatively evenly allocated, as also indicated by the Kecamatan aid distribution (figure A4.3 in the Appendix).[86]

Figure 4.7: Tsunami aid versus human suffering caused by the armed conflict

Panel A: Aid vs. conflict casualties **Panel B: Aid vs. conflict injuries**



Note: Aceh Jaya, the district that received the most amounts of aid was not plotted, for graphical scaling purposes. Aceh Jaya received an average of USD 7,024 per person, and would have resulted in a fitted regression line with a positive slope. The remainder, 22 districts, are plotted. Aid data is taken from the RAND dataset, which is a dataset that records the amount of aid committed and disbursed per Kecamatan and per year. Persons hurt in panel B refer to persons with injuries, persons who were kidnapped, and persons who were raped. I applied equal weighting to these different measures of human suffering. The equation for the fitted linear regression line of panel A is $y = 986.4 - 140.1x$, with an insignificant coefficient and an R-squared of 0.03. The equation for the fitted linear regression line of panel B is $y = 740.9 + 32.4x$, with an insignificant coefficient and an R-squared of 0.00.

Including Tsunami aid flows into the diff-in-diff specification should allow controlling for the effects of disaster recovery aid. Even though the bivariate scrutiny in the above scatterplots does not indicate a systematic relationship between Tsunami aid and conflict intensity, it is best to control for Tsunami aid as part of the diff-in-diff

[85] The underlying assumption of course is that the GAM rebels fought in the districts they lived.

[86] Another measure related to aid, the area actually flooded by the Tsunami, which should have partially determined where aid goes, was also used to assure that the violence was not related to aid. The flooding analysis is in some ways a corollary to the aid analysis as aid was allocated based on necessity and how heavy the area was affected as shown in chapter 4. Flooding results reveal the same picture as the aid results did, which is that there is no significant covariation between area flooded and conflict intensity.

regression analysis. Including Tsunami aid as covariate is kosher, as it does not respond to the conflict casualties (as shown earlier). In other words, aid allocation was not dependent on conflict intensity. If it were, it would be what Angrist and Pieschke (2009, p. 47) term a “bad control.” Aid per capita is a time-varying variable, which was 0 before 2004 and rose to its peak in 2005. Over the next four years, substantial aid funds were channelled to Aceh for the reconstruction effort and by 2008, most of the funds (96 percent of it) have been exhausted.

As indicated by table 4.5, the inclusion of Tsunami aid per capita did not affect the conflict intensity coefficients by much. Tsunami aid per capita has a negative and significant coefficient. This however does not mean that Tsunami aid per capita depresses GDP per capita growth, as it could be an indication that more aid was allocated to areas that were more affected by the Tsunami, which is what could have caused the negative coefficient instead of aid.[87] Important for this section is rather whether the inclusion of aid had any effects on the conflict-growth relationship. The wartime conflict – peacetime growth coefficient dropped by negligibly little after the inclusion of the aid variable in the dummy variable violence specification (columns 1 and 2), the conflict deaths specification (columns 3 and 4), the violent incidents specification (columns 5 and 6), and the damaged buildings specification (columns 7 and 8). The robustness of the estimated conflict-growth elasticity to the inclusion of an aid indicator is a strong sign for the robustness of the negative economic legacy effect to possibly biasing effects of Tsunami aid.

[87] For a more detailed discussion about the effects of aid see chapter 2. Disentangling the reverse causality of aid allocations in Aceh merits closer scrutiny and would be an excellent topic for a future research paper.

Table 4.5: Difference-in-differences regressions of conflict legacy effects on peacetime economic growth rates with aid covariate

DV: GDP per capita growth Measure of conflict:	High Violence vs No/Low Violence		Deaths (per 1,000 people)		Violent incidents (per 1,000 people)		Damaged buildings (per 1,000 people)	
Aid per capita	-0.017 ***		-0.016 ***		-0.016 ***		-0.017 ***	
	0.000		*0.000*		*0.000*		*0.000*	
Wartime conflict (average year)	-0.028 **		-0.008 *		-0.003		-0.004	
	0.010		*0.000*		*0.000*		*0.000*	
Wartime conflict x 2005		-0.072 **		-0.017 ***		-0.015 *		-0.007
		0.020		*0.000*		*0.010*		*0.010*
Wartime conflict x 2006		-0.055		-0.034 *		-0.015 **		-0.023 *
		0.030		*0.010*		*0.010*		*0.010*
Wartime conflict x 2007		-0.004		-0.005		-0.003 *		-0.001
		0.010		*0.000*		*0.000*		*0.000*
Wartime conflict x 2008		-0.043		-0.009		-0.004		-0.012 *
		0.020		*0.010*		*0.000*		*0.010*
Wartime conflict x 2009		-0.025 *		-0.010 **		-0.006 ***		-0.008 **
		0.010		*0.000*		*0.000*		*0.000*
Wartime conflict x 2010		-0.005		0.008		0.006		0.014
		0.040		*0.001*		*0.000*		*0.010*
Wartime conflict x 2011		-0.007		0.000		0.001		0.003
		0.010		*0.000*		*0.000*		*0.000*
Wartime conflict x 2012		-0.012		-0.003		-0.002		-0.001
		0.010		*0.000*		*0.000*		*0.000*
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spatial & Serial corr SEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	264	264	264	264	264	264	264	264
R-sqr	0.56	0.58	0.56	0.6	0.55	0.58	0.55	0.58

Note: Aid per capita is measured in thousands of USD per person. Standard errors are in italics. *, **, *** mean significance at the ten, five, and one percent level, respectively.

4.5.3.2 Are the negative economic legacy effects driven by oil revenue sharing or autonomy funding?

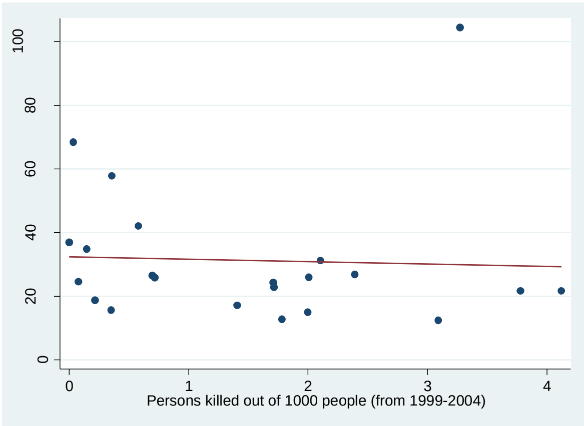
Following the peace agreement, Aceh received special autonomy status, and an agreement with the federal government was struck in 2006 according to which the province would get more funding, in the form of two sources, the Oil and Gas Revenue Sharing Fund and the Special Autonomy Fund, both starting to disburse in 2008.[88] In this section, I examine whether these funds have been systematically differently allocated based on the level of violence and conflict. Wartime violent Kecamatans receiving less funding because they were being punished for being rebel strongholds, for example, would pose a challenge to the interpretation and identification of the economic legacy effects of violence starting from 2008 onwards. It would be equally problematic for causal inference if conversely, for example, the violent districts received more funding, due to political influence of its political leaders.

To dismiss concerns that oil or sovereign wealth funding could have systematically biased the legacy effects found, I investigate whether the level of violence was correlated with the level of funding (see figure 4.8). I find that irrespective of the degree of violence observed, oil and gas revenues were distributed relatively equally across the spectrum of wartime conflict intensity.

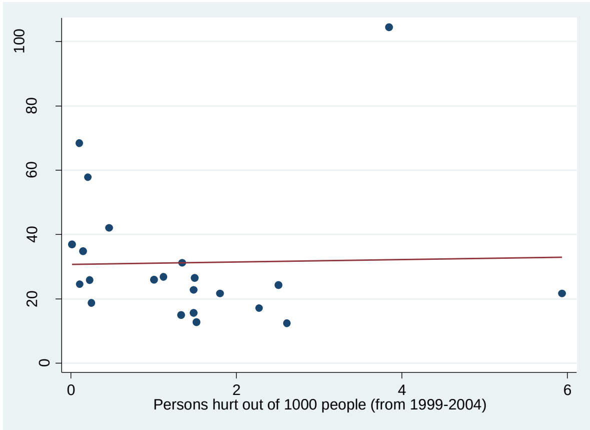
[88] Legal basis for the revenue sharing is Law No. 11 from 2006, which establishes the oil and gas revenue sharing, in the amount of 40 percent of the oil and 55 percent of the Gas profits made from the resources originating in Aceh.

Figure 4.8: Oil and gas revenues versus two human measures of conflict impact

Panel A: Casualties



Panel B: Injuries



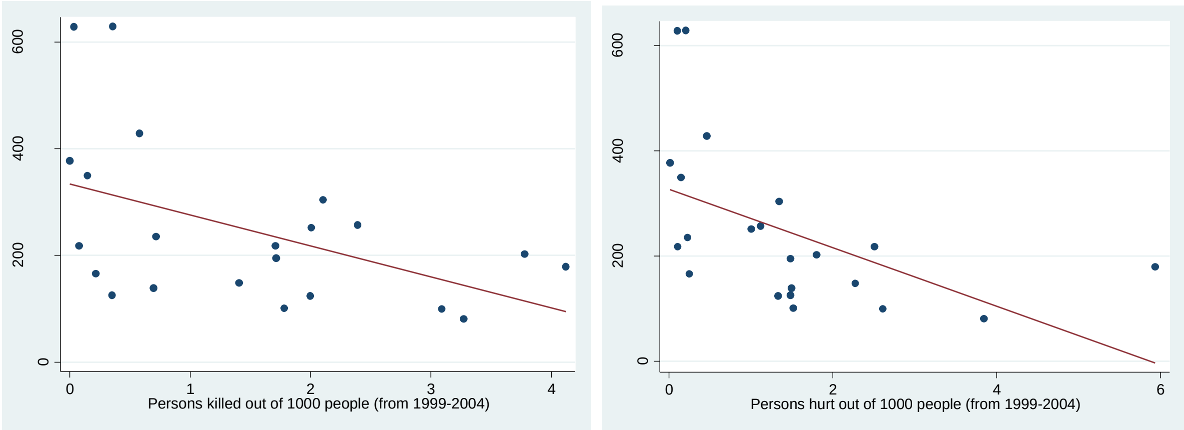
Note: Persons hurt in panel B refer to persons with injuries, persons who were kidnapped, and persons who were raped. I applied equal weighting to these different measures of human suffering. The equation for the fitted linear regression line of panel A is y = 32.3 - 0.75x, with an insignificant coefficient and an R-squared of 0.00. The equation for the fitted linear regression line of panel B is y = 30.0 + 1.0x, with an insignificant coefficient and an R-squared of 0.00.

Paradoxically however, the districts that were the stage of most of the violence and conflict, meaning those that bled the most for secession, received the least amount of financial returns from the autonomy fund (see figure 4.9). While this is a very interesting pattern, prompting closer investigations as to why this happened in the future,[89] for the purposes of the interpretation of the conflict legacy effect on per capita growth for this chapter it has concrete implications. The implications do not affect the size of the estimated effects in the short-term, as the autonomy funds were disbursed only in 2008. Nevertheless, the implications are crucial for long-term legacy effects.

[89] Potential drivers of unequal revenue allocations include punishment of rebel strongholds by the central government, limited absorptive capacity by conflict affected districts because of tears in the social and institutional fabric, amongst many other possibilities.

Figure 4.9: Autonomy funds versus two measures of human conflict impact

Panel A: Casualties **Panel B: Injuries**



Note: Persons hurt in panel B refer to persons with injuries, persons who were kidnapped, and persons who were raped. I applied equal weighting to these different measures of human suffering. The equation for the fitted linear regression line of panel A is y = 333.9 – 58.1x, with a significant coefficient at the five percent level and an R-squared of 0.23. The equation for the fitted linear regression line of panel B is y = 320.4 - 61.7x, with a significant coefficient and an R-squared of 0.24.

For the long-term effects these autonomy funding asymmetries strengthen the conclusion that the legacy effects are only short term, as over the long term, conflict riddled districts get significantly less autonomy funds, which could explain why they were less likely to recover and display delayed catch-up growth rates. The difference in autonomy funding between the highest recipient quintile and the lowest recipient quintile was about USD 12 on average per capita per year, which is a bit more than 2 percent of the average GDP per capita. The relative size of the autonomy funds is thus not large, though not negligible either, calling for a wartime conflict – peacetime growth relationship assessment where peace funding is controlled for.

Like with aid, the inclusion of peace funding – from autonomy funding or oil revenue sharing – did not have much of an impact on the estimated effects between wartime conflict intensity and peacetime economic growth per capita (see table 4.6). Even the estimated effect for the year 2009, right after the first tranche of peace and autonomy funding was disbursed in 2008, did not show any signs of changing. The statistic changing the most after the inclusion of the two peace funding covariates is the degrees of freedom metric estimated, which decreases automatically with the inclusion of additional variables, and therefore is a good sign with regards to the robustness of the estimated negative legacy effect of conflict to peace funding.

Table 4.6: Difference-in-differences regressions of conflict legacy effects on peacetime economic growth rates with peace funding covariates

DV: GDP per capita growth Measure of conflict:	High Violence vs No/Low Violence		Deaths (per 1,000 people)		Violent incidents (per 1,000 people)		Damaged buildings (per 1,000 people)	
Oil revenue per capita	-0.820	-0.863 *	-0.859	-1.047 *	-0.88	-1.03 *	-0.974 *	-1.095 *
	0.480	*0.410*	*0.450*	*0.430*	*0.490*	*0.430*	*0.460*	*0.430*
Autonomy funding per capita	-0.012	-0.010	-0.028	0.000	0.000	-0.039	-0.019	0.008
	0.170	*0.170*	*0.170*	*0.130*	*0.160*	*0.110*	*0.180*	*0.150*
Wartime conflict (average year)	-0.028 **		-0.009 *		-0.005		-0.005	
	0.010		*0.000*		*0.000*		*0.000*	
Wartime conflict x 2005		-0.080 ***		-0.021 **		-0.015 ***		-0.012
		0.020		*0.010*		*0.000*		*0.010*
Wartime conflict x 2006		-0.057		-0.035 **		-0.015 **		-0.024 *
		0.030		*0.010*		*0.010*		*0.010*
Wartime conflict x 2007		-0.004		-0.005		-0.003 *		-0.002
		0.010		*0.000*		*0.000*		*0.000*
Wartime conflict x 2008		-0.041 *		-0.008		-0.004		-0.012 *
		0.020		*0.010*		*0.000*		*0.000*
Wartime conflict x 2009		-0.023 *		-0.010 ***		-0.005 ***		-0.008 ***
		0.010		*0.000*		*0.000*		*0.000*
Wartime conflict x 2010		-0.004		0.008		0.006		0.014
		0.040		*0.010*		*0.000*		*0.010*
Wartime conflict x 2011		-0.006		0.001		0.001		0.003
		0.010		*0.010*		*0.000*		*0.000*
Wartime conflict x 2012		-0.012		-0.003		-0.002		-0.001
		0.010		*0.000*		*0.000*		*0.000*
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spatial & Serial corr SEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	264	264	264	264	264	264	264	264
R-sqr	0.54	0.57	0.54	0.59	0.54	0.58	0.54	0.57

Note: Oil revenue per capita is measured in thousands of USD per person. Autonomy funding per capita is also measured in thousands of USD. Standard errors are in italics. *, **, *** mean significance at the ten, five, and one percent level, respectively.

4.5.3.3 Are the negative economic legacy effects due to geographic factors?

The conflict hotspots were rural areas, rather than cities as shown in map 4.1, and maps A4.1-A4.3. GAM rebels located preferentially in rural districts, as it was easier to hide in the rural jungle than in the cities, among other tactical reasons. The fact that all three main cities (*Kotas*) in Aceh displayed relatively little violence could potentially violate the as-if randomization assumption. Part of the reason for why the more conflict-affected districts grew slower could have something to do with the fact that their counterfactual contains city districts that have a different growth potential than rural districts (*Kabupatens*). To test whether the negative economic legacy effects still hold, despite the possible rural-urban bias, I exclude the three *Kotas* and repeat the diff-in-diff analysis without them.

I find that the negative economic legacy effects of conflict finding is robust to restricting the sample only on rural areas (see table 4.7). The effect size is reduced by a tiny margin, from a 2.9 percentage points slower growth rate comparing high to low conflict districts (see table 4.2), to a 2.6 percentage points difference. All other measures of conflict intensity in the remaining columns are also smaller only by very little. These smaller effect sizes indicate that the asymmetrically affected rural areas do not introduce a substantial bias to the estimation.

Table 4.7: Rural areas: Difference-in-differences regressions of conflict legacy effects on peacetime economic growth rates

DV: GDP per capita growth Measure of conflict:	High Violence vs No/Low Violence		Deaths (per 1,000 people)		Violent incidents (per 1,000 people)		Damaged buildings (per 1,000 people)	
Wartime conflict (average year)	-0.026 *		-0.008 *		-0.004		-0.004	
	0.010		*0.000*		*0.000*		*0.000*	
Wartime conflict x 2005		-0.087 *		-0.021 **		-0.015 ***		-0.011
		0.040		*0.010*		*0.000*		*0.010*
Wartime conflict x 2006		-0.033		-0.030 *		-0.012 *		-0.017
		0.040		*0.010*		*0.000*		*0.010*
Wartime conflict x 2007		-0.010		-0.007		-0.003		-0.003
		0.010		*0.000*		*0.000*		*0.010*
Wartime conflict x 2008		-0.017		-0.004		-0.004		-0.010 *
		0.020		*0.010*		*0.000*		*0.010*
Wartime conflict x 2009		-0.020 *		-0.008 **		-0.005 ***		-0.006 *
		0.010		*0.000*		*0.000*		*0.000*
Wartime conflict x 2010		-0.020		0.006		0.006		0.014
		0.050		*0.010*		*0.000*		*0.010*
Wartime conflict x 2011		-0.009		0.000		0.001		0.003
		0.010		*0.000*		*0.000*		*0.000*
Wartime conflict x 2012		-0.016 *		-0.004		-0.002		-0.001
		0.010		*0.000*		*0.000*		*0.000*
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spatial & Serial corr SEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	216	216	216	216	216	216	216	216
R-sqr	0.51	0.54	0.52	0.56	0.51	0.56	0.51	0.54

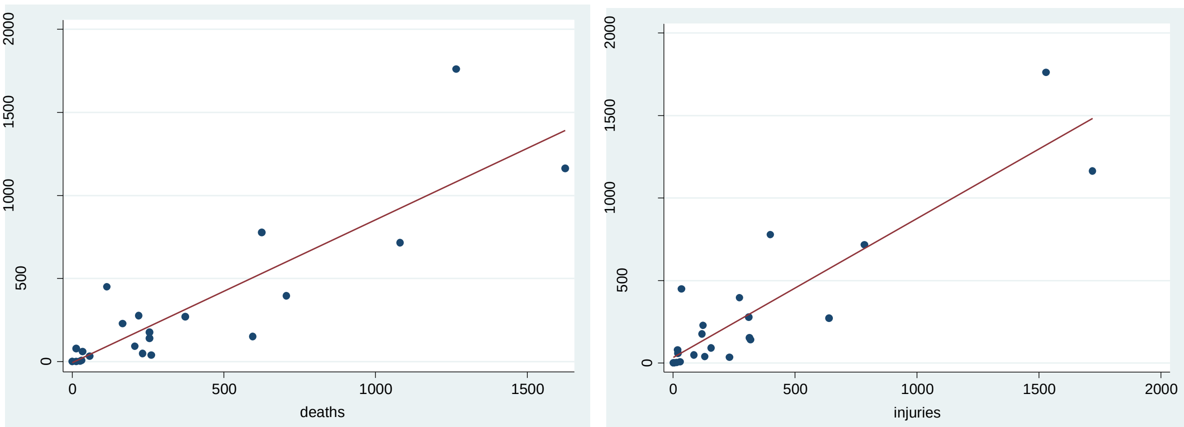
Notes: Standard errors are in italics. *, **, *** mean significance at the ten, five, and one percent level, respectively.

4.5.4 Economic growth impacts: human capital destruction versus physical capital destruction?

As suggested by the difference-in-differences analysis, the destruction and the damage of physical capital during wartimes causes growth to be slower during peacetimes. The reasons why the destruction of physical capital registered negatively in the regressions presented in table 4.2, likely have to do with physical damage being related to human suffering (see figure 4.10), not due to the physical destruction effects themselves. In other words, where bombs and guns destroy houses, they also kill and maim people. The killing and hurting of the people reduces economic growth, not the destroying of buildings. It is thus crucial to look at the effects of physical capital degradation once having controlled for human capital degradation, and vice versa.

Figure 4.10: Human capital destruction and physical capital destruction are closely related

Panel A: Deaths **Panel B: Injuries**



Note: Buildings damaged also refers to buildings destroyed. All measures (deaths, injuries, buildings damaged) refer to the cumulative count of conflict incidents from 1999 – 2004.

The destruction of physical capital may have diametrical effects on economic growth relative to the degradation of human capital. While the destruction of infrastructure and housing could actually trigger investment and growth through the reconstruction process (similar to what I have shown in chapter 3 of this PhD thesis), the destruction of human capital is probably growth-retarding (due to many of the reasons I have mentioned in the introduction, including physically and psychologically hurt persons who are less productive as a consequence of their injuries) and high adjustment costs (see e.g. Barro and Sala-i-Martin, 2003). Carrying out an OLS regression analysis including both the destruction of physical and human capital, shows that while human capital destruction caused by the war depresses peacetime per capita growth rates, the destruction of physical capital actually has small growth-promoting effects, albeit not statistically significantly so (see table 4.8). For an increase in the casualty rate by one-in-one-thousand, the GDP per capita growth rate reduces by 1.5 percentage points. In fact, after controlling for wartime physical capital destruction, the effects of wartime human capital destruction become larger, changing from a decrease of per capita growth of 0.9 percentage points (as displayed in table 4.2) to a reduction of 1.5 percentage points (see column 2 of table 4.8). The increases of the destroyed building-per-person rate by one-in-one-thousand on the other hand increases economic output per person by 0.7 percentage points. The reason why overall separatist violence and conflict were growth retarding is that the net effect of conflict, the negative effects of human capital degradation minus the positive effects of physical capital degradation, is negative (as the human capital effects outweigh the physical capital effects).

Table 4.8: Human capital destruction versus physical capital destruction

DV: GDP per capita growth				
Destroyed buildings (per 1,000 people)	0.007	0.003	0.003	0.001
	0.010	*0.010*	*0.010*	*0.010*
Deaths (per 1,000 people)	-0.015 *			
	0.010			
Violent Incidents (per 1,000 people)		-0.006 *		
		0.000		
Injuries (per 1,000 people)			-0.005 *	
			0.000	
Kidnappings (per 1,000 people)				-0.068 **
				0.020
Year FE	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Spatial & Serial corr SEs	Yes	Yes	Yes	Yes
Observations	264	264	264	264
R-sqr	0.44	0.43	0.43	0.44

Notes: Standard errors are in italics. *, **, *** mean significance at the ten, five, and one percent level, respectively.

All specifications in table 4.8 provide a confirmation of the hypothesis that losses in human capital are more growth-depressing than losses in physical capital. Moreover, physical destruction was actually growth-promoting after controlling for human capital degradation. The positive, albeit not statistically significant legacy effects of the physical capital degradation run counter to the premises of the endogenous growth model (Barro & Sala-i-Martin, 2003), where the destruction of physical capital is assumed to have negative consequences for economic growth.

4.6 Conclusion

In this chapter I bridge the gap in the conflict-growth literature between the micro-studies showing persistently negative legacy effects for the finer grained agent of the economy (individual, household, or group) and the macroeconomic (cross-country and cross-city) studies that find rebound effects and catch-up growth. I reconcile these seemingly contradictory findings by using the same dataset and two different ways of performing comparative growth analyses. Comparing growth rates before and after the war shows that peacetime growth rates are higher, for each and every district in the sample, which may indicate catch-up growth. By the same token, I also compare peacetime growth rates of wartime high conflict areas with peacetime growth rates of wartime low conflict areas, and find that there are indeed economic legacy effects of armed conflict because the districts exposed to more violence during the war grew significantly less in times of peace. In synthesis, even though all districts grew faster once the armed conflict was over (possibly related to positive effects from peace, yet also to other reasons), the ones that were exposed to more violence during the war grew significantly slower in peacetimes than the ones that were relatively unharmed.

For how long do these negative economic legacy effects last? I can assert with a high degree of confidence that they last for at least five years after the peace-deal has been signed as the coefficients are statistically significant and negative for both measures (GDP and night-lights) and both scales of analyses (district and sub-district). Whether the negative economic legacy effects reach beyond these five years cannot be answered with much confidence. However, the absence of economic catch-up growth after the several years-long negative legacy effect indicates that the armed conflict and its legacy effects have permanently relegated the Acehnese economy onto a lower output path.

Isolating the effects of violence on human capital destruction from the effects of physical capital destruction shows that while the destruction of physical capital is possibly growth promoting (even though not statistically significant), the destruction of human capital certainly is growth depressing. Reconstruction of destroyed physical capital consequentially can lead to higher growth rates than in the absence of destruction, as the growth rates do not distinguish between rebuilding and building anew. The destruction of human capital to the contrary leaves a persistent negative legacy, depressing future per capita output, not only in the short- and medium term but also over the long haul.

I examine the role of other factors that may have also played a part in causing the negative legacy effects, such as asymmetric Tsunami aid disbursal, asymmetric distribution of oil and sovereign wealth revenues, and geographic biases, as they pose a challenge to causal identification. After examining the extent and effect sizes of these systematic biases, I conclude that none of these factors biases the estimated effects enough to call into question the negative legacy effects of conflict, for the short-term. Receiving less peace funds may have contributed to why we do not see catch-up growth rates of the more wartime conflict-riddled districts.

In conclusion, the violence during armed conflict caused a reduced per capita growth rates during peacetimes in the short-term. These negative economic legacy effects last for about five years after peace had been established, enough to permanently relegate the wartime violence affected districts onto a lower output path during peacetimes. It is very likely that the negative legacy effects are at play also in other armed conflicts around the globe, as the mechanisms (inter alia reducing productivity by hurting people and breaking up social cohesion and trust) should not be any different in Rwanda, or Guatemala from Aceh. However, many mediating factors may be at play, which may substantially interact with the negative legacy effects. Future research, looking into the causal effect of armed conflict onto economic growth in other places is thus necessary to gain insights into how externally valid the negative legacy finding is.

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Appendix

Figure A4.1: Injuries from separatist conflict in Aceh over time

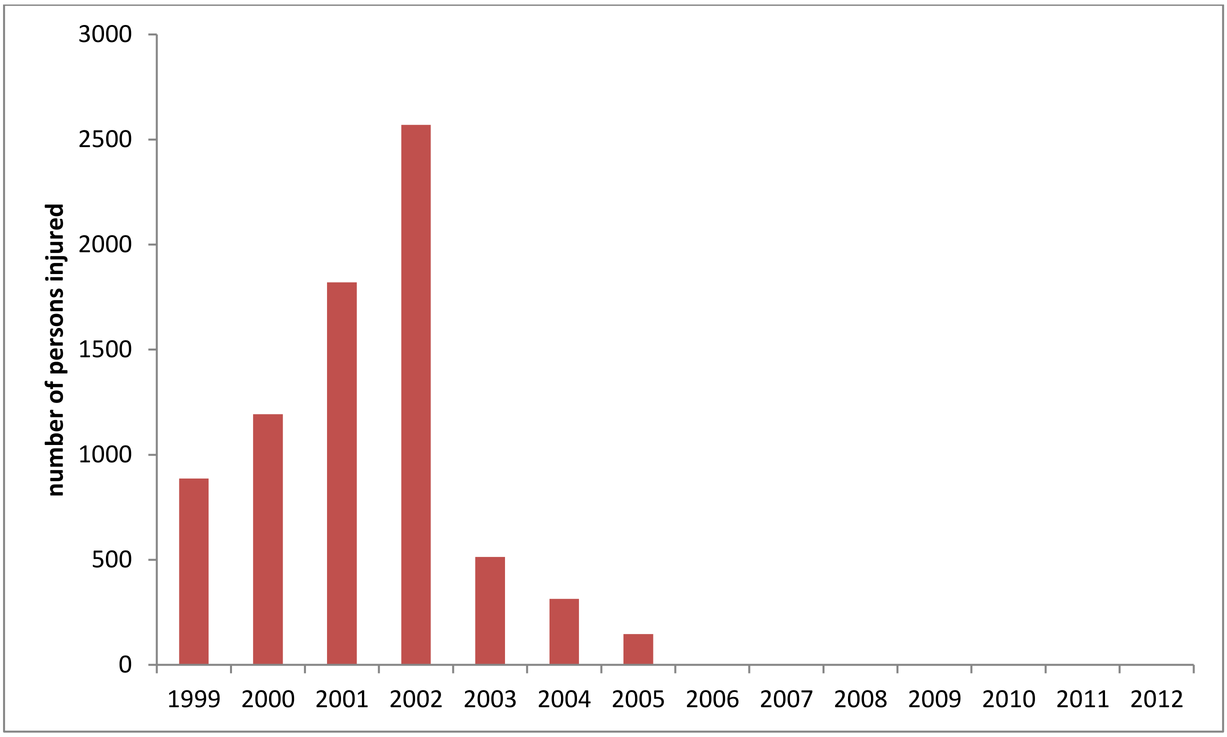


Figure A4.2: Kidnapping trend in Aceh

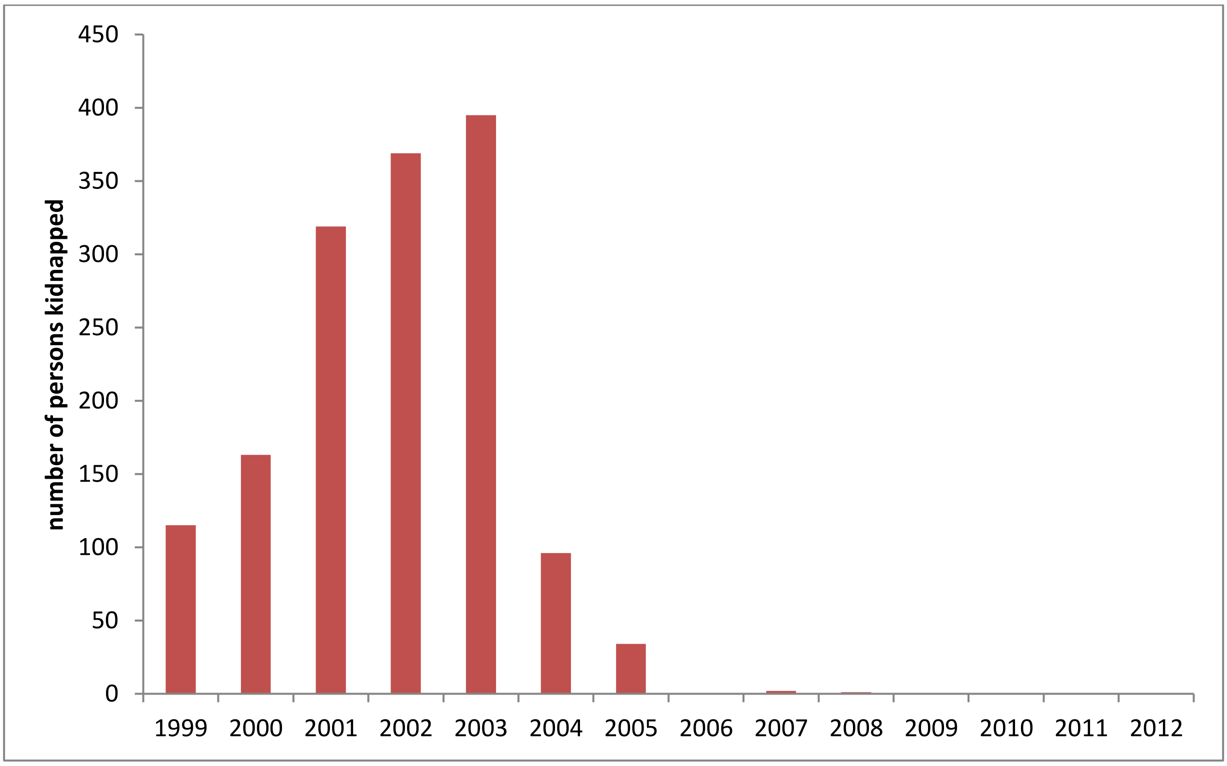
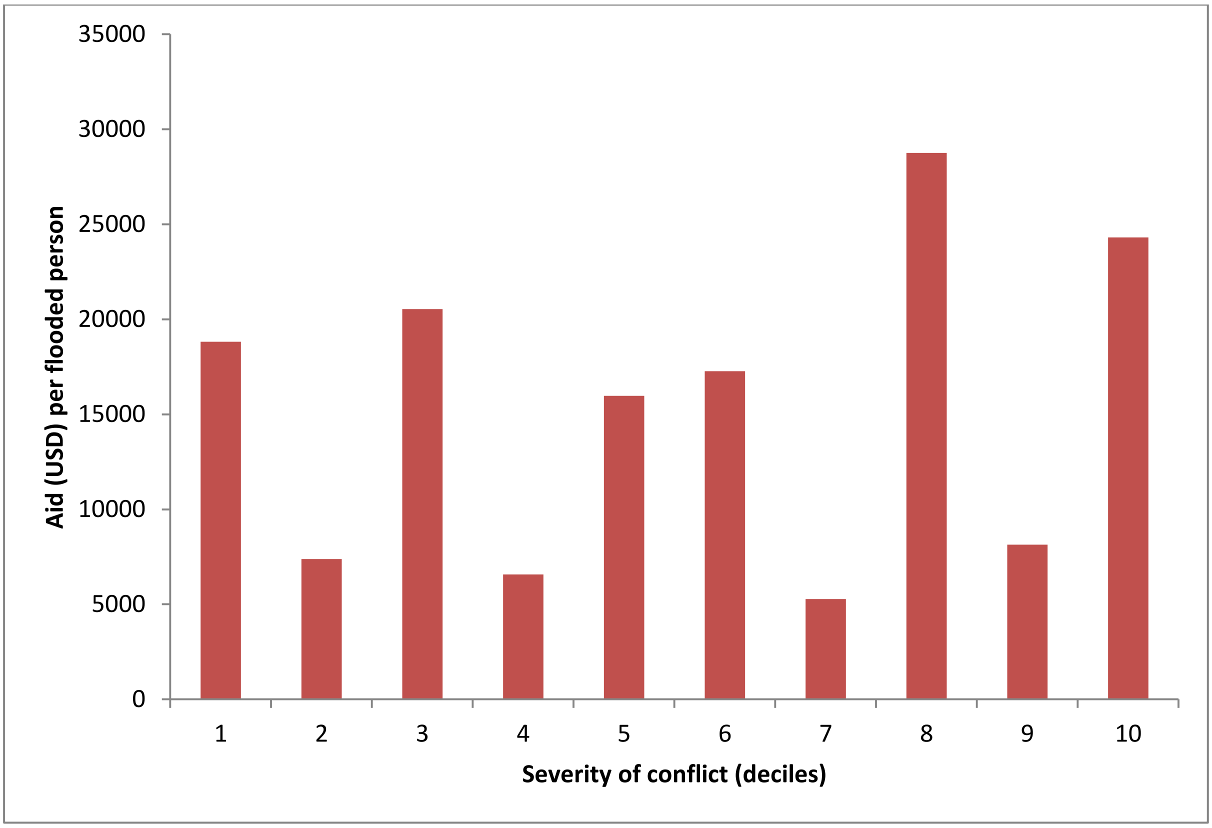


Figure A4.3: Distribution of aid by conflict intensity



Note: This only includes the aid earmarked for Kecamatan specific projects. 72 Kecamatans (sub-districts in Aceh) were flooded. It includes all aid categories; no distinction is made between aid that was earmarked to promote growth, and aid that could possibly be reasoned to directly translate to growth and other aid.

Figure A4.4: Parallel historic path of high and low conflict intensity robustness check, using deaths as the measure and quintiles as the categories

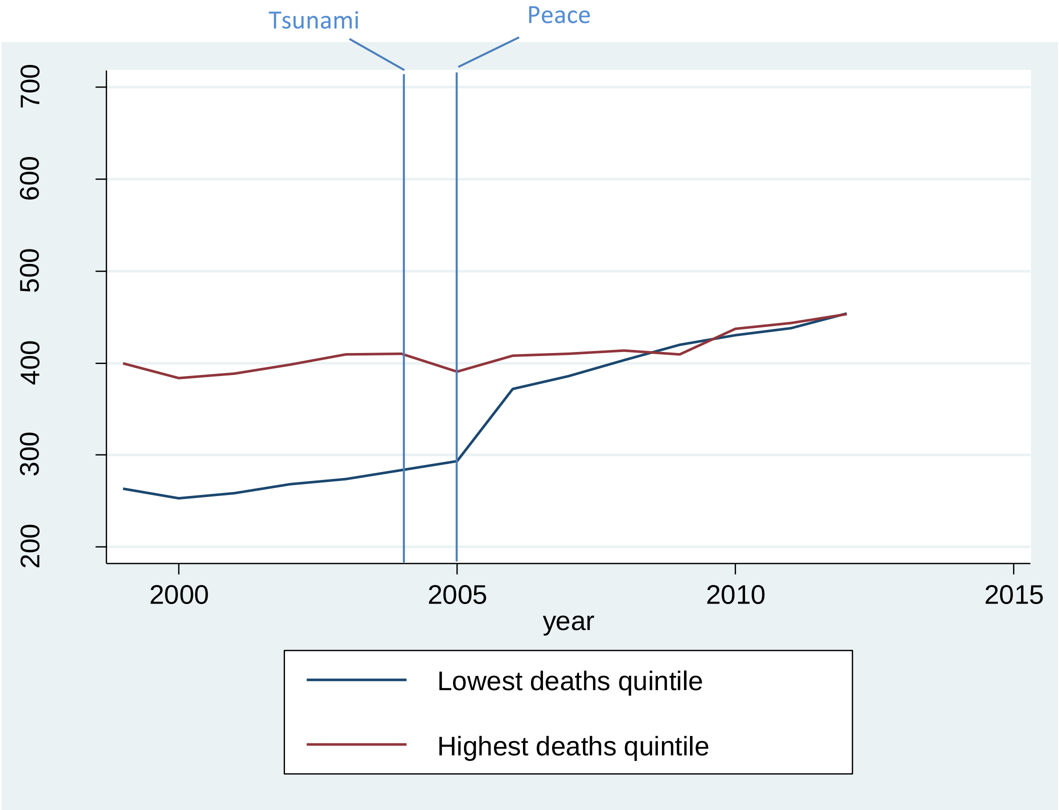


Figure A4.5: Parallel historic path of high and low conflict intensity robustness check, using deaths as the measure and quartiles as the categories

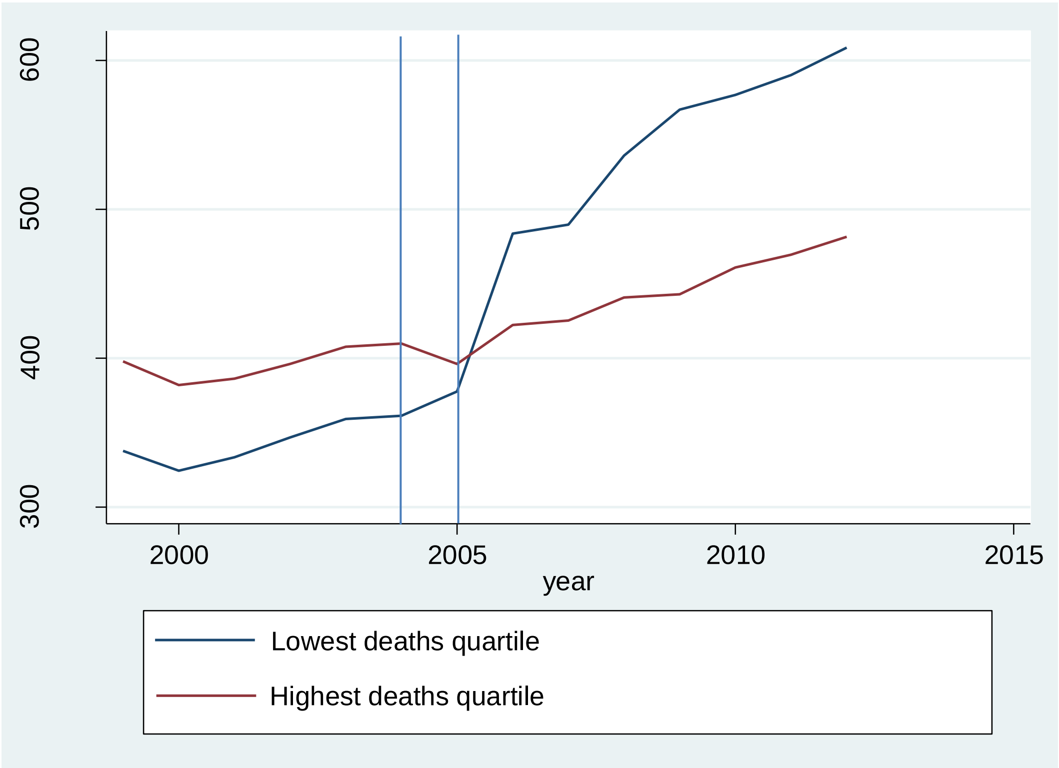


Figure A4.6: Parallel historic path of high and low conflict intensity robustness check, using deaths as the measure and terciles as the categories

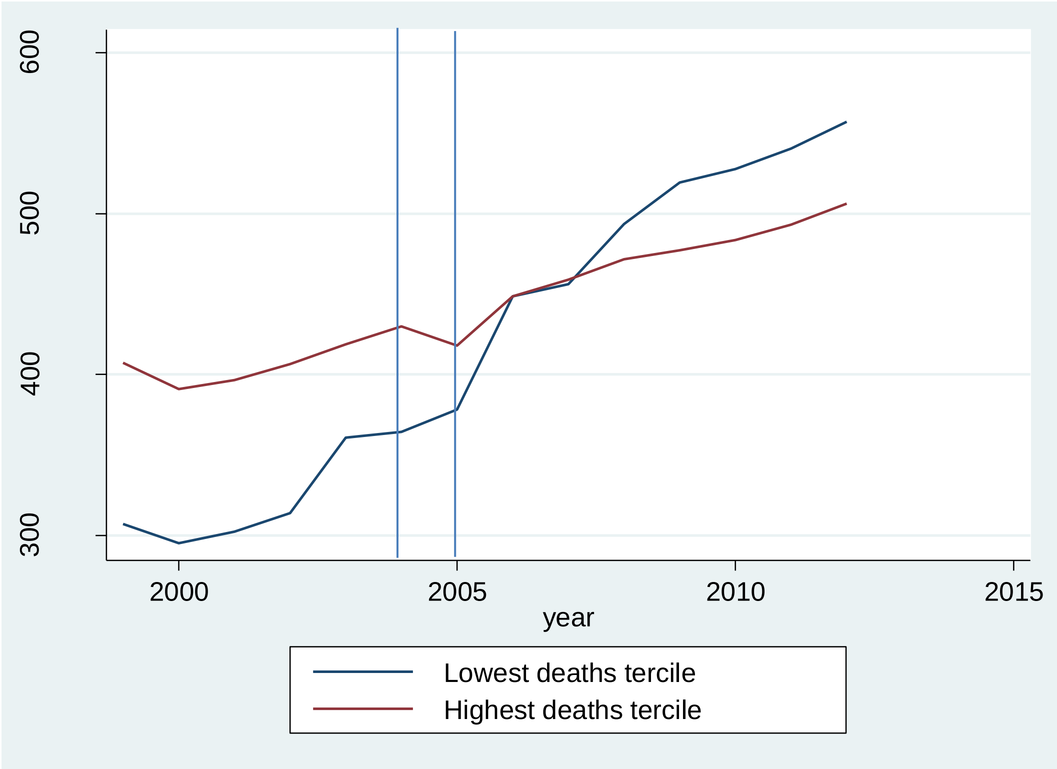


Figure A4.7: Parallel historic path of high and low conflict intensity robustness check, using violent incidents as the measure and quintiles as the categories

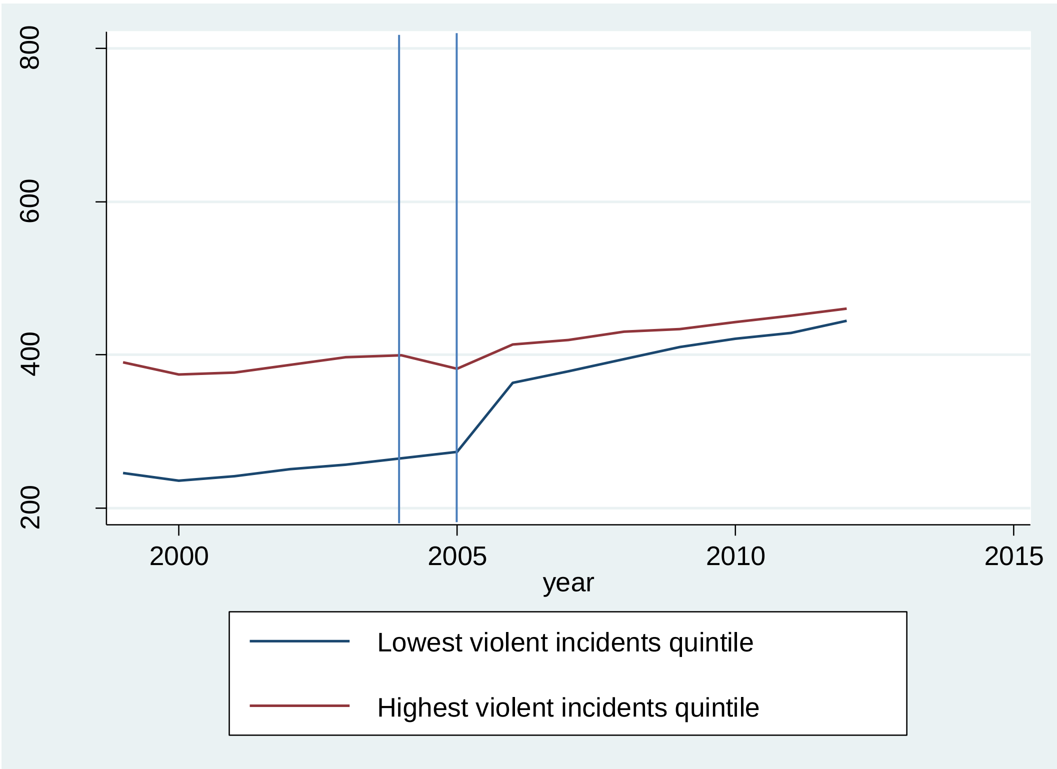


Figure A4.8: Parallel historic path of high and low conflict intensity robustness check, using violent incidents as the measure and quartiles as the categories

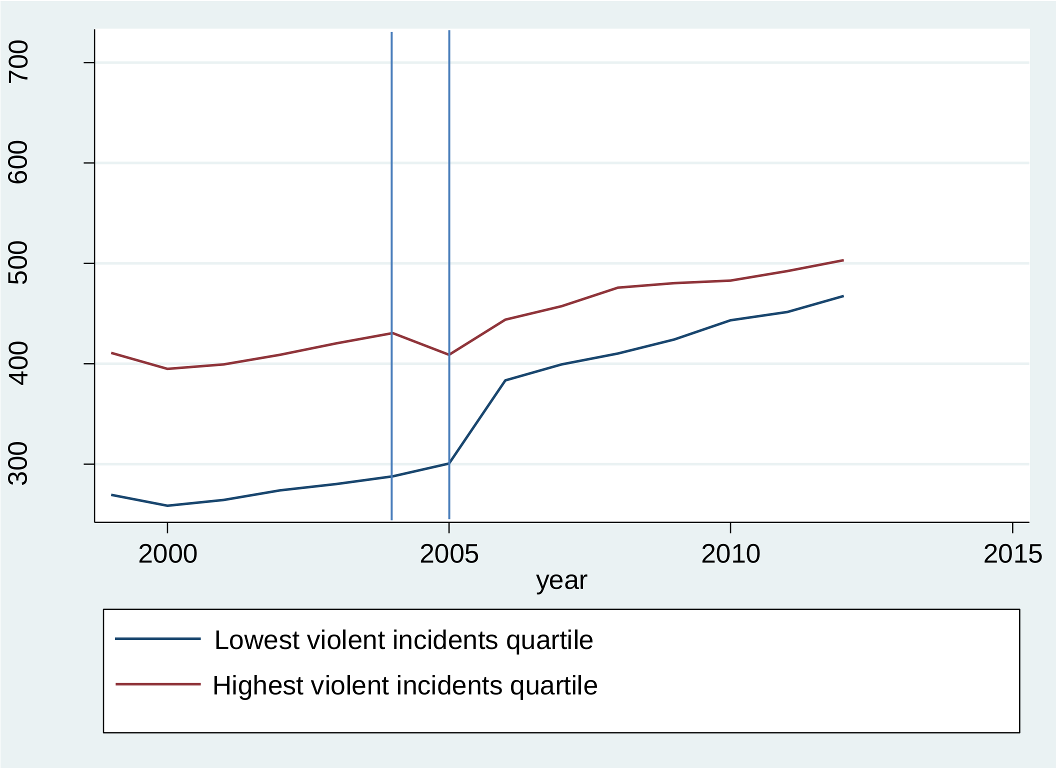
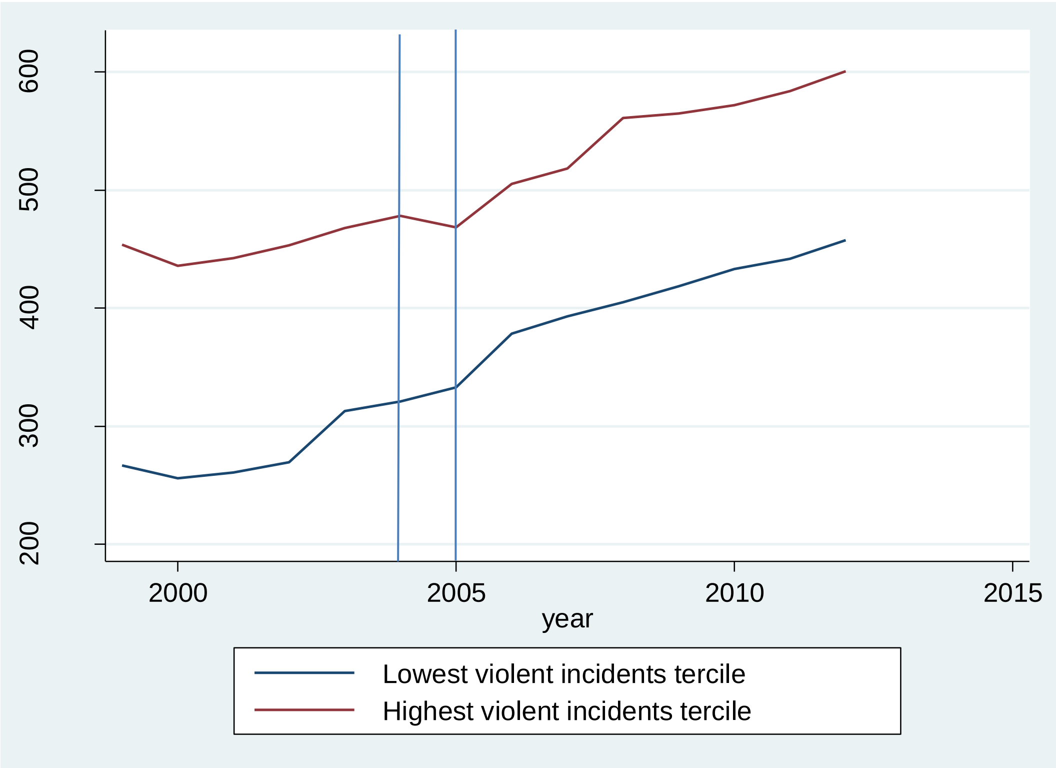
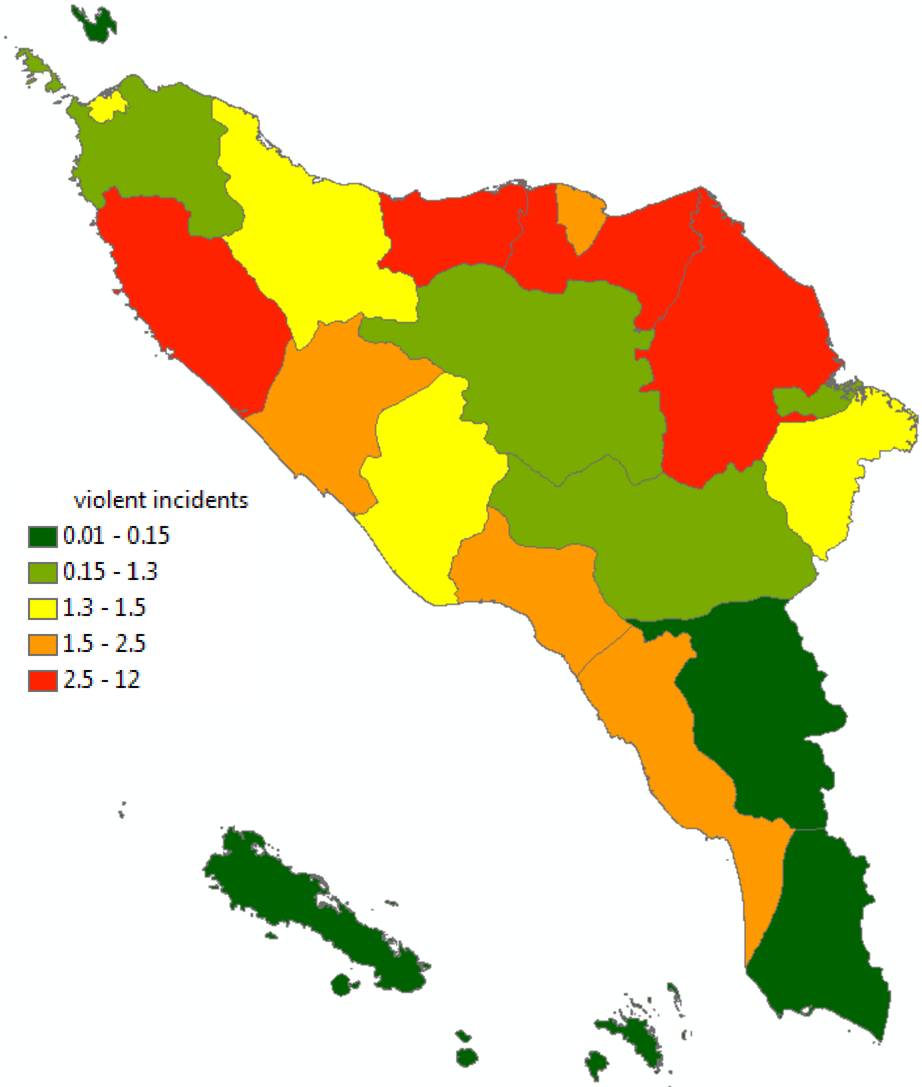


Figure A4.9: Parallel historic path of high and low conflict intensity robustness check, using violent incidents as the measure and terciles as the categories

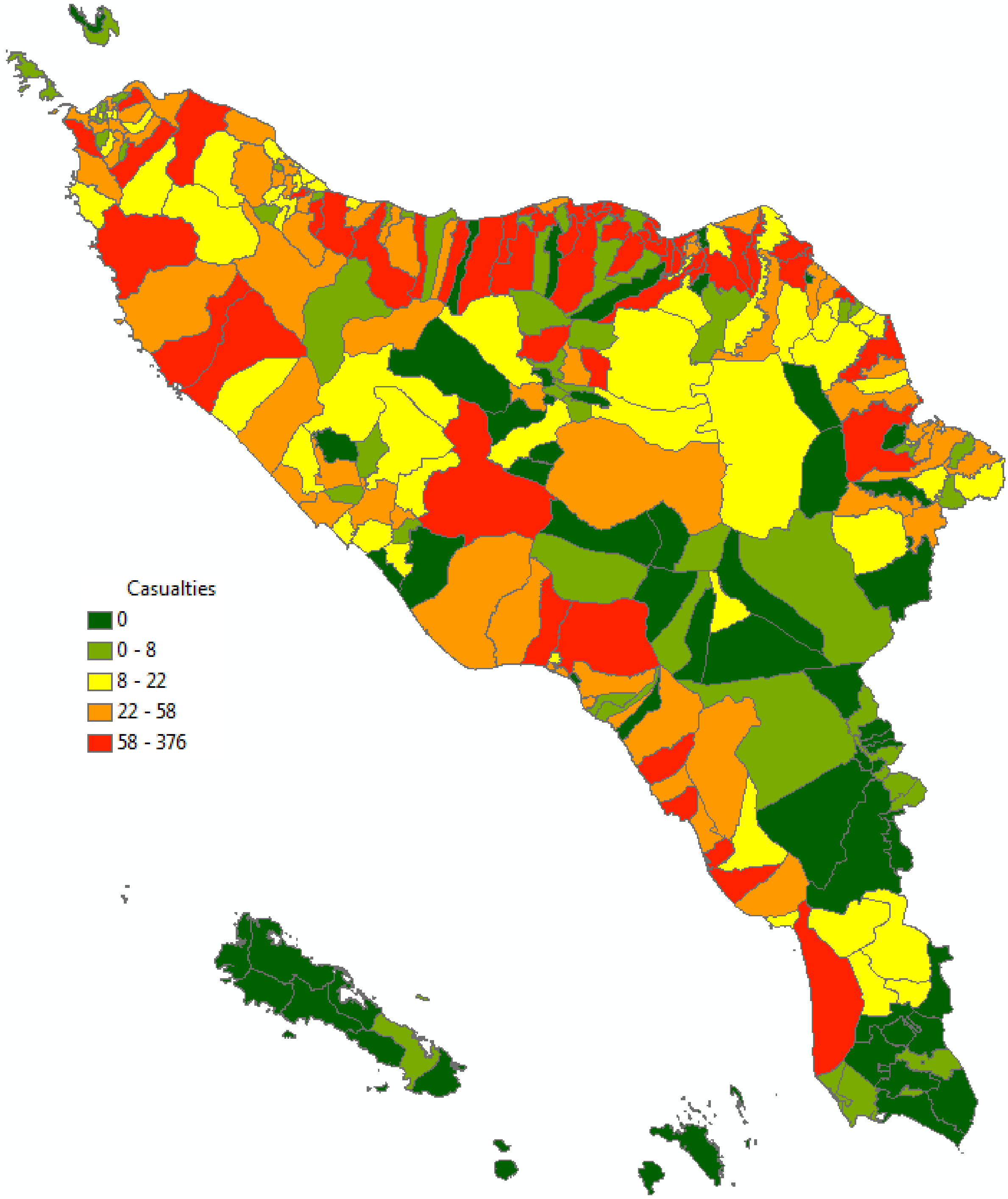


Map A4.1: Violent incidents in Aceh from 1999 – 2004



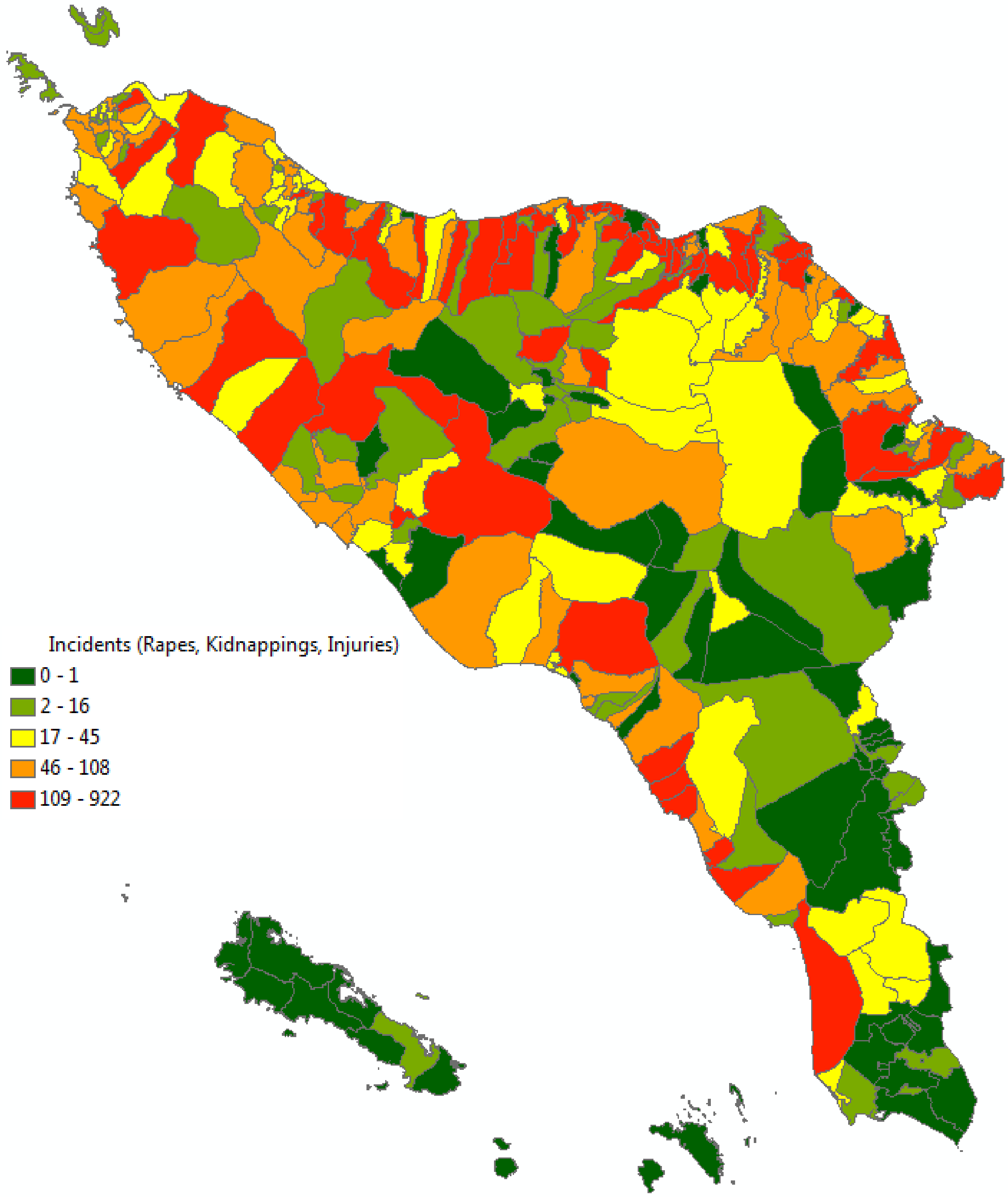
Note: Violent incidents plotted are cumulative from 1999 – 2004 and include injuries, kidnappings and rapes. They are expressed as a share of 1000 persons.
Source: NVMS dataset.

Map A4.2: Casualties in Aceh from 1999 – 2004



Note: Casualties plotted are cumulative from 1999 – 2004.
Source: NVMS dataset.

Map A4.3: Violent incidents in Aceh from 1999 – 2004



Note: Incidents plotted are drawn from the 2004 – 2011 period.
Source: NVMS dataset.

Table A4.1: Conflict regressions on GDP growth

DV: GDP growth Measure of conflict:	High Violence vs No/Low Violence		Deaths (per 1,000 people)		Violent incidents (per 1,000 people)		Damaged buildings (per 1,000 people)	
Wartime conflict (average year)	-0.026 **		-0.011 *		-0.006		-0.006	
	0.010		0.010		0.000		0.000	
Wartime conflict x 2005		-0.085 **		-0.042 *		-0.033 ***		-0.023
		0.030		0.020		0.010		0.020
Wartime conflict x 2006		-0.056		-0.033 *		-0.013 *		-0.023 *
		0.030		0.010		0.010		0.010
Wartime conflict x 2007		-0.003		-0.002		-0.001		0.000
		0.010		0.000		0.000		0.000
Wartime conflict x 2008		-0.038 **		-0.004		-0.004		-0.003
		0.010		0.000		0.000		0.000
Wartime conflict x 2009		-0.005		-0.002		-0.001		-0.008
		0.010		0.000		0.000		0.000
Wartime conflict x 2010		-0.007		-0.001		0.000		0.001
		0.010		0.000		0.000		0.000
Wartime conflict x 2011		-0.006		-0.001		0.000		0.002
		0.010		0.000		0.000		0.000
Wartime conflict x 2012		-0.008		-0.001		0.000		0.000
		0.010		0.000		0.000		0.000
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spatial & Serial corr SEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	264	264	264	264	264	264	264	264
R-sqr	0.64	0.66	0.65	0.71	0.54	0.58	0.54	0.57

Table A4.2: Difference-in-differences regressions: economic legacy effects of conflict on peacetime Night-light Intensity per capita changes

DV: Light Intensity per capita (annua Measure of conflict:	High Violence vs No/Low Violence		Deaths (per 100 people)		Violent incidents (per 100 people)		Damaged houses (per 100 people)	
Wartime conflict (average year)	-0.007		-0.017 ***		-0.011 ***		-0.013	
	0.01		0.000		0.000		0.010	
Wartime conflict x 2005		0.006		-0.023 ***		-0.016 ***		-0.018
		0.01		0.010		0.000		0.010
Wartime conflict x 2006		-0.013		-0.029		-0.017		-0.025
		0.02		0.020		0.010		0.010
Wartime conflict x 2007		-0.019		-0.039 *		-0.024 **		-0.026
		0.02		0.020		0.010		0.020
Wartime conflict x 2008		-0.03		-0.030 ***		-0.021 ***		-0.019
		0.01		0.000		0.000		0.020
Wartime conflict x 2009		-0.001		-0.001		-0.004		0.000
		0.02		0.010		0.010		0.010
Wartime conflict x 2010		-0.005		-0.002		-0.002		-0.007
		0.01		0.010		0.000		0.000
Wartime conflict x 2011		0.015		0.008 **		0.005 **		0.001
		0.01		0.000		0.000		0.010
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4428	4428	4428	4428	4428	4428	4428	4428
R-sqr	0.26	0.26	0.26	0.28	0.26	0.27	0.26	0.26

Note: Night-lights are available for one year less than the GDP data. Buildings destroyed or damaged was not available at the Kecamatan level, which is the reason for the lack of an additional column containing it.

CHAPTER 5

Indigenous crops or non-indigenous cattle?

Soil organic carbon of forest-to-crop versus forest-to-pasture land use changes in Eastern Panama

5.1 Introduction

Forest biomes are major sinks of Carbon (C) and take part in Earth's natural carbon cycle by absorbing carbon dioxide from the atmosphere. Tropical forests are particularly productive in Carbon sequestration and capture and store much of terrestrial C (see e.g. Malhi, Baldocchi, & Jarvis, 1999). The building up of soil C through carbon sequestration from the atmosphere is critical to biomass and crop production, quality of the soil, soil biodiversity, filtering and denaturing of pollutants, and not least mitigating climate change (Lal et al., 2012).

Soil Organic Carbon (SOC)[90] is particularly relevant since it contains more Carbon than both living plant biomass and atmospheric CO_2 together (see Jobbagy & Jackson, 2000 as cited in Laganiere et al., 2009). In fact between 40 percent and 70 percent of total carbon in forests is stored in the soils (see Wei et al 2014; Fonseca et al, 2011, Fonseca et al, 2008; Jandl, 2006; Lagos and Vanegas, 2003, Malhi et al., 1999; and Dixon 1996).

[90] In this article, the terms Soil Organic Carbon (SOC), Soil Organic Matter (SOM), Soil Stored Carbon, Soil Carbon, and Organic Matter are used interchangeably.

This is not only true globally, but also locally in Panama. In an area not far from the study site (around 50km), it was shown that the largest share of measured Carbon was stored in the soil (45-73%), by Tschakert, Coomes and Potvin (2007). Adding to the relative importance of soil stored C vis-à-vis plant stored C is its longevity and timeliness. Stable fractions of SOC remain for more than 1000 years in the soil, which by far surpasses the duration C is stored even in very old trees (see Lutzow et al., 2006 as read in Laganiere et al 2009).

In the Republic of Panama, Central America, deforestation is mostly driven by disorderly and unsanctioned settlements on forested land and the conversion of forests to agricultural systems, for either animal grazing or crop cultivation (Tschakert, Coomes and Potvin (2007). Panama has seen ongoing deforestation, and there has not been a single year so far over the last 40 decades (the entire time for which we have records) where the country has seen no deforestation. At the same time however, the deforestation rates have decreased during the last two decades, from 36,000 ha yr^{-1} in the 1990s to approximately 12,000 ha yr^{-1} in the 2000s (ANAM, 2010).

One reason behind this decrease in deforestation is urbanization, as many subsistence farmers leave their ranches and farms behind, seeking a brighter future in the city. Some argue that these demographic rural-urban shifts have been so strong that they have even resulted in an increase in total forest cover from 1992 – 2000 (Wright and Samaniego, 2008). There is thus a two-directional tendency in Panama, with regards to forest changes. One, where landless peasants and smallholding farmers are pushing the agricultural frontier further and actively contributing to deforestation in search of new means of production by converting the deforested areas to crop or pasture land (see e.g. Perz, 2001; and Carr, 2009). And another, where farmers flock to the cities in search of opportunities, leading to demographic and socioeconomic shifts and ultimately to reforestation through natural regeneration (see e.g. Hecht and Saatchi, 2007; and Wright and Mueller-Landau, 2006).

Land use and Land Cover Change (LULCC) change is a serious concern for global environmental degradation. Aside from reported losses of species richness, land-use change can accelerate soil erosion, increase surface water run-off and cause substantial increases in greenhouse gas (GHG) emissions. Terrestrial C pools have decreased significantly historically due to land use changes, where forested landscapes were turned into agricultural land (see Jandl et al., 2007; Laganiere, Angers, and Pare, 2009). Between 39 and 50 percent of the Earth's land surface has been severely altered by human activity with changes to agricultural systems accounting for the main part of these changes (Uriate, Schneider & Rudel, 2010). Anthropogenic CO_2 emissions from 1750 to 2011 were driven in large parts by LULCC, to the extent of about a third of all anthropogenic CO2 emissions stemming from it (IPCC, 2014). LULCC's contribution to global CO2 emissions has decrease over time so much that from 2000 to 2009 it was only 12 percent (IPCC, 2014).

Land-use change in the tropics is of particular concern; it constitutes between 12 percent and 20 percent of total anthropogenic GHG emissions, making tropical land-use change the second largest source of GHG emissions to the atmosphere after fossil fuel use (IPCC 2007, IPCC 2011, van der Werf et al., 2009, Don et al., 2010). Deforestation converts tropical forests from a potential carbon sink to a substantial source of atmospheric carbon dioxide (Malhi et al., 1999). Tropical soils are estimated to emit 0.2 Gt of Carbon per year due to land use changes, and overall contribute anywhere from 10-30 percent of the total emissions from deforestation (Houghton, 1999, Achard et al., 2004). Land use and land cover change critically effect soil quality through nutrient depletion, erosion and compaction (see e.g. Hillel, 2003).

Ranching cattle is the primary reason for deforestation and LULCC. In fact, 80 percent of current deforestation is because of cattle ranching (Nepstad et al, 2008). Of all deforestation activities, cattle ranching is widely regarded to cause the most environmental damage. The reason for the deleterious impacts of pastoral-based grazing systems in the tropics is a combination of soil compaction, leaching of nutrients, and erosion (Greenwood & McKenzie, 2001; Ledec, 1992).

Indigenous land, indigenous slash-and-burn agriculture, and related soil stored Carbon measures in Eastern Panama are discussed in detail by Tschakert, Coomes, and Potvin (2007) for the Ipetí-Emberá indigenous community. The Emberá are a sister indigenous community to the Wounaan, which is the tribe whose crop cultivation techniques and soil quality impacts are studied in this article. Both tribes were formerly known by the name Chocó, speaking different languages that are both part of the Chocoan language family though. Tschakert et al. (2007) describe Emberá farmers that first clear the forest with machetes and axes and then burning it, so that they can grow crops such as rice, corn, yam, yucca, banana, plantains and beans. They find a cultivation cycle of 2 to 3 years and a subsequent fallow period of 2 to 31 years, during which the farmers shift to another cell within the parcel. They also mention neighboring colonists, and their deforestation for pasture and cattle raising, but do not evaluate these grazing land use strategies, which is the main contribution of this paper. Another additional contribution of this paper is that it looks at the relevance of secondary forests for carbon capture and storage, and verifies whether reforestation / afforestation activities allow for a complete recovery of SOC levels.

Slash and burn agriculture has been practiced in Panama for over 5000 years (see Tschakert et al. (2007). Once regarded as unsustainable, swidden-fallow agriculture, by which name slash-and-burn agriculture is also known, has been accepted as a vital pillar upon which to base developing strategies for the rural poor, in sync with sustainability considerations (see. Tschakert, 2007; Abizaid & Coomes, 2004; Coomes et al. 2000; & Toledo et al. 2003). For more information on shifting agriculture, see Lal et al's book called Recarbonization of the Biosphere (2012).

Kaimowitz (1996) discusses four different types of cattle ranchers, ranging from the agro-industrial large-scale entrepreneur to the small holding pastoralist with only a few animals (anywhere from 10 – 50 cattle). The colonist cattle ranchers studied in this article squarely fall within the last and also smallest category. Similar to the indigenous farmers, colonist cattle ranchers also use slash-and-burn techniques, with the main difference that they convert the sites to cattle ranching pastures, as opposed to crop cultivation sites. Another difference is that they do not allow cleared plots to re-grow, but actively protect against weed incursions.

The sample sites were not selected to be representative of the eastern province of Panama, the country of Panama, let alone the tropics as a whole. This is not an article about generalizing the C concentration results and predicting carbon sink estimations to broader areas. The field observations are not meant to be extrapolated to regional, continental or global scales, by delivering measurements of carbon pools;[91] rather they were picked so as to enable us to compare the impacts of indigenous crop-cultivation relative to encroaching pasture and cattle grazing activity on soil carbon concentration, at sites that are as comparable to one-another as possible.

This article contrasts the ecological implications of Wounaan land use with that of the non-indigenous colonists, in terms of soil quality by measuring and comparing soil organic matter (C). By doing so, it provides an intensive measure of environmental degradation, as opposed to an extensive measure, by looking at areas deforested for example. Land use comparisons related to the expansive nature of this deforestation are discussed in detail in Heger (2009). The average pasture site resulting from deforestation is much larger than the average crop site. While an average Wounaan household used about 1.42 ha for crop cultivation, the average migrating colonist household used an area of about 50 ha for cattle ranching, which is 39 times more. The more spatially expansive nature of pasture cultivation also aggregated up to national level statistics. In Panama, almost 80 percent of agricultural land is under pasture coverage, the rest is under crop cultivation (see Wright and Samaniego 2008).

Whether the colonist forest-to-pasture conversion for the purpose of ranching cattle is legal has been discussed elsewhere (see Heger & McNish, 2010). How the colonist pasture land use compares to indigenous crop land use in terms of income per capita and income per hectare deforested is also discussed elsewhere (see Heger, 2009). It has been shown that crop cultivation indeed yields a higher per hectare gross and net income compared to ranching cattle (see Heger 2009, and Wright and Samaniego 2008).

[91] Bulk density measures were only collected so as to assure that the sites compares are the same in levels, not to produce C per ha measures.

5.2 Objectives and hypotheses

The aim of this study is to compare the relative impacts of indigenous forest-to-crop conversion with non-indigenous colonist[92] forest-to-pasture conversion on soil quality in Eastern Panama. Nutrient levels under different land uses are quantitatively compared, with a particular focus on Soil Organic Carbon (SOC). To the best of my knowledge, no one has directly compared SOC in indigenous crop cultivation sites versus migrating colonist pasture sites before. Indigenous crop cultivation and non-indigenous migrant cattle ranchers' pasture cultivation is compared with Primary Forest (Native Forest) and Secondary Forest (Re-growth Forest). The forested land use serves as the benchmark for assessing the impact of forest-to-crop conversion and forest-to-pasture conversion. The primary and secondary forests together serve as yardsticks of what were the SOC levels before perturbation and the secondary forest sites serve as a guide as to what the cultivated fields could return to once the forest is allowed to re-grow.

The definition adapted in the paper for the four different land-use strategies (primary forest, secondary forest, pastureland and cropland) is the following: Primary forest refers to a forest that has never altered by human activity. These types of forests are very rare and only a few truly primary forests remain (Lugo and Brown (1983), as cited in Don et al. 1993). The forest areas categorized as primary forests in this study have never been deforested according to the memory of the Wounaan indigenous community, which has settled in the area three generations ago. Furthermore, the Amerindians were not aware of any humans that inhabited the area prior to them. Secondary forests refer to forests that develop naturally after a formerly cultivated land is abandoned and has been allowed to re-grow. This does not include plantation forest, which is established by humans on purpose. Pastureland is land used for grazing and cattle-ranching and does not include naturally developed grasslands, where no animals are grazing. Cropland includes land used for cultivation of maize (*zea mays*) and rice

[92] My search for an alternative term to that of 'colonist' was not fruitful. This term is used in the literature; see e.g. Tschakert et al. 2007. Other terms include *Colons* or migrating Latino forest dwellers.

(*oryza Sativa*),[93] both rain-fed. Rice cultivated was upland rice, which is grown on dry soil, as opposed to paddy rice, which is grown in flooded rice paddies.

This article's aim is comparing SOC levels between the four different land uses (non-uses) and can be isolated to five separate yet related research questions:

(a) What happens to SOC concentrations after the forest has been converted to non-indigenous pasture for ranching cattle? Contrasting forest SOC (primary and secondary) with pasture SOC.

(b) What happens to SOC concentrations after indigenous slash and burn agriculture? Contrasting forest SOC (primary and secondary) with crop cultivation SOC.

(c) Is crop cultivation or ranching cattle more detrimental to soil stored nutrients? Contrasting pasture sites with crop sites.

(d) Do pasture sites degrade in SOC levels over time? Comparing a chronosequence of pasture site SOC levels.

(e) Can SOC be restored in a reforestation/afforestation effort? Comparing primary forest with secondary forest data.

Based on the literature presented below, we functionally relate SOC levels from (a) through (c) in the form of the following working hypothesis:

Forest = pasture > crop-cultivation

Based on the literature presented below, we express the soil carbon evolution dynamics (d) with the following functional relationship:

Pasture 2 years > Pasture 10 years > Pasture 20 year

[93] Aside from the rice and maize crops analyzed in this article, other crop types that were also cultivated include yams (*discorea*), pineapples (*ananas comosus*), plantains (*musa paradisica L.*) and banana (*musa sapientum L.*), as well as sugarcane.

To test the merits of reforestation efforts as outlined in (e), we test the following functional relationship of SOC:

Primary forest = Secondary forest

5.3 Literature on land use change effects on soil organic carbon

5.3.1 Forest versus pasture

Forest-to-pasture conversion has important implications for soil physical and chemical characteristics, and the role of Carbon storage in soils (de Moraes, 2002). In principle, substantial changes in SOC are expected because grasses contain a lower concentration of lignin than woody vegetation according to agronomic functional understanding (Parton et al., 1987 as cited in Moraes et al., 2002). Empirical data however show a different trend.

Empirical data show that SOC does not change significantly in converting a forest to pasture, and if they change, they rather tend to increase. The preponderance of papers found that SOC was either higher (albeit not statistically significantly different) or the same after forest-to-pasture conversion then before (see e.g. Huth et al 2012). Powers et al. (2011) conducted the latest meta-analysis of land-use change studies analyzing the impact on SOC in the tropics. For forest-to-pasture conversion, they find an average increase in soil C stock by almost 10 percent. Guo and Gifford (2002) who conducted a previous meta-analysis for the tropics found that overall SOC levels rose by 8 percent.[94] There are however also articles that show the opposite tendency. Neuman-Cosel et al. (2010) for example investigated soil carbon dynamics of secondary forests on converted pasture sites in Panama and even though they did not find significantly different levels of SOC, they found that the SOC levels in most secondary forest sites exceeded those in pasture sites in most instances.

For low activity soils in the tropics, like the Ultisol examined in this field study, the SOC consequences of forest-to-pasture conversion heavily depend on precipitation. The

[94] Guo and Gifford's definition of pastures however also includes grassland.

mechanisms through which precipitation determines the impact of forest-to-pasture conversion on SOC are water erosion, plant production, fluxes of soil C pools, and total soil stocks and residence time (see Amudson, 2001, as cited in Powers et al., 2011). Whether SOC changes were positive, equal, or negative depends on precipitation patters. In high rainfall areas (> 3000 mm per year) and low rainfall areas (< 1000 mm per year) the average impact recorded was negative. It is argued that both higher soil moisture and higher temperature environments enhance the decomposition rates and therefore could speed up SOC losses (Don et al 2011).

For the in-between rainfall studies (1000 – 3000 mm per year), under which group the studied site in this article falls, the effect of forest-to-crop conversion was on average positive, according to Guo and Gifford (2002). Powers et al.'s (2011) meta study showed that while for annual precipitation of 1501 – 2500 mm surveyed studies showed an average increase of SOC of more than 26 percent (ranging from 21 to 32), they showed almost a stand-still of 1 percent (ranging from -14 percent to 19 percent) in the case of 2501 – 3500 mm of precipitation. Based on the average annual precipitation at our field sites of about 2000 mm per annum, we expect the effect of forest-to-pasture conversion to be positive.

Aside from precipitation there are also other mitigating factors at play. The discrepancies between the studies are also due to differences in the type of change, the intensity of land-use, and topography. Grazing intensity for example plays a key role in determining the adverse impact of forest-to-pasture conversion in the tropics (Elmore & Esner 2006). The sustainability of soil quality after forest conversion to pasture depends not only on appropriate management strategies but also on time since conversion (Cerri et al. 2004); previous work has shown that carbon, phosphorus and calcium stocks in tropical pasture soils decrease fairly constantly over time (Asner et al. 2004).

5.3.2 Forest versus crop cultivation

Evidence with regards to forest-to-crop conversion, unlike forest-to-pasture conversion, is not ambiguous and dependent on mitigating factors such as precipitation. Despite the nutrients captured in the soil because of combustion of the vegetation in the slash-and-burn process, soils under crop-cultivation are found to contain significantly less carbon than soils under primary or secondary forest cover. Powers et al. (2011) find that on average forest-to-crop conversion leads to a decrease in SOC of more than 20 percent. Similarly the change to shifting cultivation is found to reduce SOC significantly, and by a substantive margin, albeit by a bit less so than crop cultivation without fallow periods. For comparable mineralogy and precipitation classes to the one investigated by this study, an average decrease of 10 percent (ranging from -23 to +7) is reported.

According to Don, Schumacher and Freibauer (2011), the most severe SOC losses follow a conversion of primary forest to cropland (with a decrease of the magnitude of a forth compared with previous SOC levels) and even more so for conversion to perennial crops (with a decrease of almost a third) compared to all land-use change types. They find that SOC changes are on average -20 percent (+/- 5 percent) and forest-to-perennial crop conversion lead to a -32 percent (+/- 4 percent) change.

5.3.3 Cattle pasture versus crop cultivation

There are very few studies that look at conversion of cropland to pasture or vice-versa. According to Guo and Gifford (2002) land use change from "pasture"[95] to crop leads to the starkest drop in SOC. The three studies that were discussed in Powers et al (2011) show mixed evidence. Nevertheless, this article is more interested in comparing current pasture with crop sites that were both initially under forest cover anyways, than looking at what happens when cropland is converted to pasture sites or vice versa. Don et al. (2011) find that conversion of primary forest to cropland leads to a more than twice as high loss in SOC than a conversion to grassland does, however the grassland definition not only includes pastures, but also other native grassland types of land cover that are not used for ranching cattle, which makes the interpretation harder.

[95] As mentioned previously, their definition of pasture sites includes also natural grasslands that have not been cultivated and anthropocentrically perturbed.

Synergizing the results from sections a. and b. therefore leads me to expect that forest-to-pasture conversion will have lead to a higher SOC levels compared with forest-to-crop conversions.

5.3.4 Primary versus Secondary Forest

Contrasting primary with secondary forests should help us in assessing whether there is hope in reforestation projects of deforested and degraded areas, by looking at how SOC concentrations in secondary forests compare to agricultural land and particularly whether they recover to the levels of primary forests. The ensuing question of whether secondary tropical forest is of secondary importance and the extent to which a forest can recover from anthropogenic disturbance is hotly debated. The answer depends on what area and measure one looks at: biodiversity, biomass[96], or SOC, and the answer based on preponderance of evidence is respectively: yes, no, and no.

In terms of biodiversity value the question has been answered with a decisive yes by a recent meta-analysis (Gibson et al 2011). Early studies have gone as far as to argue that tropical forests were a 'non-renewable resource' calling the deforestation process to be irreversible (see Gomez-Pompa et al. (1972) as read in Letcher and Chazdon (2009)). The few truly undisturbed forests that do exist have biodiversity values that are substantially higher than those of secondary forests, which in Gibson et al's case were mostly more degraded forests.

In terms of biomass accumulation, secondary forest follow a saturation curve in which levels increase with age until they reach the level of an old-growth forest (see e.g. Saldar- riaga et al. 1988, Pena-Claros 2003, Gehring et al. 2005, Howorth & Pendry 2006 as read in Letcher and Chazdon, 2009). Other studies even found higher biomass in secondary forests, passed their intermediate age (see Denslow and Guzman (2000), and Marın-Spiotta et al. (2007), and Letcher and Chazdon, 2009 as read in Letcher and Chazdon, 2009).

[96] Biomass can be conceptually split between above ground biomass and below ground biomass, of which SOC is a part.

Secondary forest SOC pools can recover to levels similar to those in old-growth forests, but it takes time. Fonseca et al. (2011) found a positive correlation, albeit a very low one, with age and SOC in secondary forests, indicating that the recovery process is slow. The slow recovery is attributed to the sluggish uptake of carbon in soils (Gamboa et al., 2008; McGrath et al., 2001; Robert, 2002; Saynes et al., 2005; Singh et al., 2007; Turner et al., 2005 as read in Fonseca et al, 2011). It takes anywhere from 20 to 100 years for full recovery to kick in (Rhoades, Eckert, Coleman, 2000; & Neumann-Cosel, et al., 2010). Secondary forests may even exceed SOC of primary forest (Sayes et al., 2005). Guo and Gifford (2002) find that established pastures that were converted to secondary forests generally showed stagnant SOC levels (but with a definition of pastures that also includes natural grasslands). They also find that croplands reverting to secondary forests showed full recovery in terms of SOC. There is however also evidence indicating the contrary, that SOC does not recover in secondary forests to old-growth forest levels. According to Don, Schumacher and Freibauer (2011), primary forests store more SOC than secondary forests, by almost 10 percent.

Letcher & Chazdon 2009 found that the biomass of secondary forests was not impacted by the amount of time the land was under pasture management before the regeneration took place. Zarin et al. (2001, as read in Letcher and Chazdon, 2009) found that there was no recordable biomass difference in secondary forest sites regardless of whether they were used for crop-cultivation (and fallow) or pasture before. Other studies (e.g., Hughes et al. 1999, Steininger 2000, Kammesheidt 2002, as cited in Letcher and Chazdon (2009)) find that biomass accumulation was impacted by prior land-use.

Letcher and Chazdon (2009) who applied a chronosequence for aboveground biomass by looking at different forest age groups found that biomass continuously increases in secondary forests with age, reaching comparable levels at about 30 years of age, and even surpassing old growth biomass beyond that (at 30 to 42 years of age). Letcher and Chazdon (2009) also show that there is no difference in species decomposition comparing older secondary forests with old-growth forests. There were no apparent impacts of soil characteristics on species composition (Letcher and Chazdon, 2009).

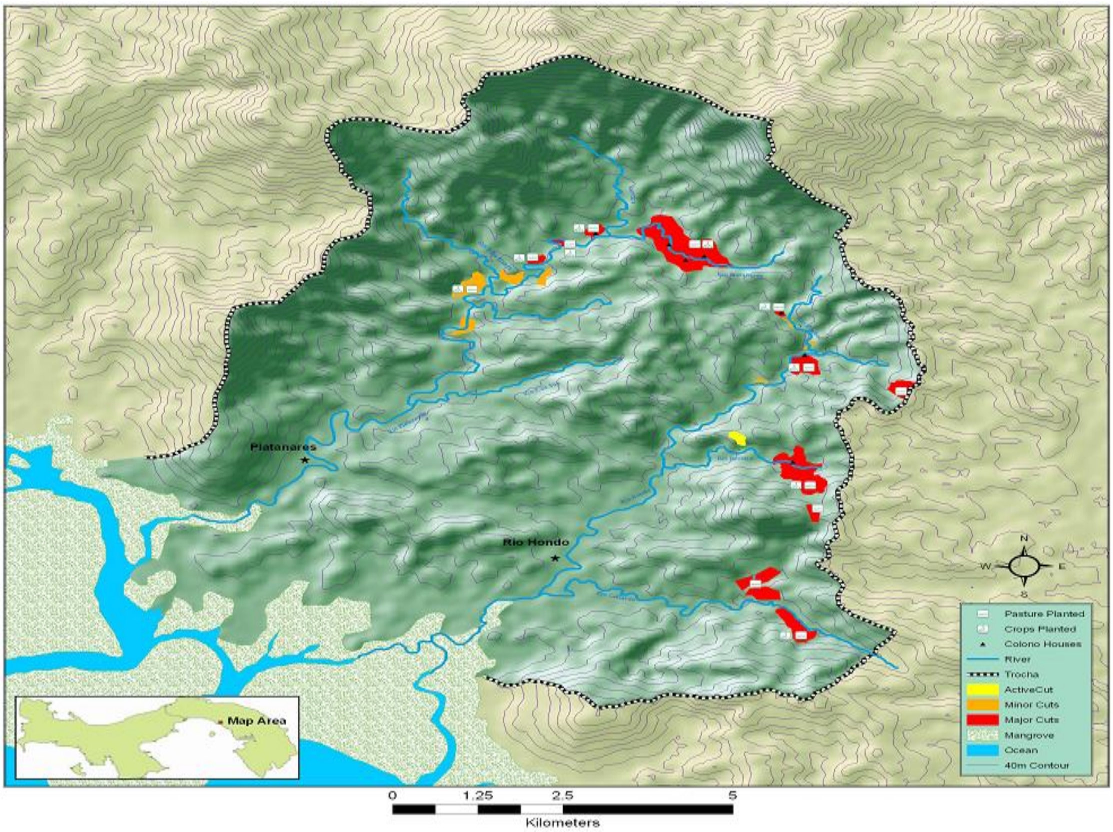
5.4 Study design and methods

5.4.1 Study site and sampling design

The study sites (see Map 5.1) were located in the east of Panama Province in the forests of the districts of Chimán and Chepo (8°43′12″N 78°37′12″W), on hillsides (15-100 m.a.s.l.) near the indigenous communities of Rio Hondo, on the river Rio la Maestra and Platanares, on the river Rio Platanares. The indigenous Wounaan area is demarcated by the dashed frontier. Annual precipitation in the area is about 2100 mm, varying from a minimum of 3mm in March to a maximum of 409 mm in October.[97] Average daily temperatures are about 26 degrees Celsius and vary very little over the months. Generally the dry season goes from January to April and the wet season ranges from May to December with dry-wet- and wet-dry transition periods in between (for a more detailed elaboration on season length, see Wolf et al, 2011). The vegetation type of the area is evergreen wet tropical rainforest, with a seasonal aspect to it (see Tschakert 2007, and Holdridge et al, 1971).

[97] Precipitation and temperature measures for the field sites were calculated with "Worldclim – Global Climate Data" accessed at: http://www.worldclim.org/current.

Map 5.1: Study Site: Forest coverage in indigenous territories and pasture sites



Note: This map was produced by Cameron Ellis, a consultant for the NGO Native Future, who was working on mapping the Wounaan territory.

The Wounaan are practicing shifting agriculture. Shifting agriculture is a rotational form of agriculture with a crop and fallow cycle. Shifting cultivation is carried out with the slash-and-burn practice, as the land-clearing element of the farming cycle, during the dry periods, following the wet season usually in April and May. Plots of land, on average 1 – 2 hectares are deliberately scorched; leaving only stumps and large trees in the field after the remaining vegetation has either been cut or burnt. The ashes from the combusted vegetation provide nutrients for farming, in a low-nutrient low-fertility soil environment (Fujisaka et al, 2000). No fertilizers, neither mineral fertilizers, nor organic ones such as manure, were used by the Wounaan.

In the Wounaan's case, crops alternate with fallow periods such that crops are grown on a particular parcel of land for predominantly one year (sometimes two), after which the forest is allowed to re-grow for, on average, about seven years. Substantial forest re-growth occurs on the fields that have been left idle, and is generally referred to as *rastrojo*, which is Spanish for very young secondary forest. The seven yearlong fallow periods correspond well to what indigenous farmers have considered as necessary for field recovery in a survey (Tschakert, Coomes and Potvin, 2007). This eight yearlong crop-fallow cycle is then consequently repeated.

Four categories of land-use were examined in this study: primary forest (anthropogenically undisturbed), secondary forest (25 - 40 years old), slash-and-burn agriculture with rice and maize cultivated (~ 2-3 months since conversion from mostly secondary forest), and pasture (2-20 years since clearance). For the pasture sites we collected a chronosequence of samples for 2 years, 9 years and 20 years since conversion.

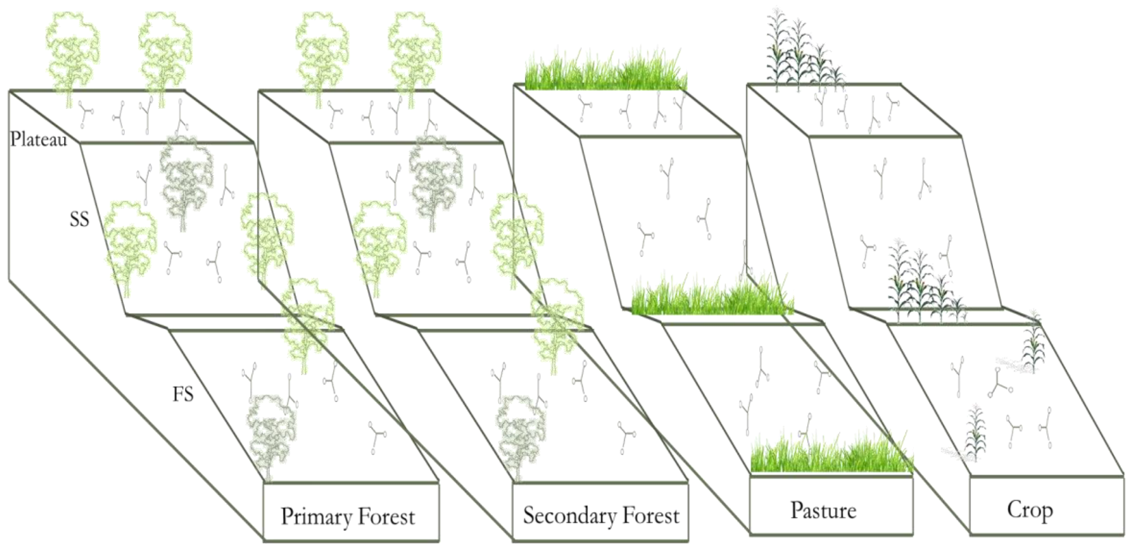
Samples for the fallow period, which was on average seven years, during which the crop sites were allowed to re-grow, were not taken, because it was impossible to establish the steepness of the slopes, and other - for the stratification relevant - features of the sites, due to the thick forest coverage which made the territory factually impenetrable. In other words, there was no way to establish that the fallow sites were similar to the sample sites from the other land-use strategies. Looking at another community of the same tribe, which applies very similar agricultural techniques, living about 70km in direct linear distance from the study sites, Tschakert et al. (2007) found that even though above-ground biomass (herbs, litter, and trees) was significantly larger in fallow vegetation than in crop vegetation, there was no difference in SOC between crops and fallow for the upper layers of the soil.

It is normally very difficult to identify differences between land use types because of high spatial heterogeneity (Yanai et al., 2003), however our sampling strategy was devised so as to control for these spatial factors, and to assure that land use type (land management practice) was the only varying factor between the sites. All sites sampled are located within an 8-km radius thus keeping the microclimate constant, as testified by the same levels of rainfall, and temperature. There is ample evidence that these biophysical factors are relevant and would confound our results if not taken into consideration (Guo and Gifford, 2002; Powers et al 2011). Precipitation and clay mineralogy are the most crucial biophysical drivers in explaining differences in soil C stocks in tropical regions (see Amudson, 2001; deKoenig et al, 2003 and Powers et al 2002 read in Powers et al 2011). We chose a paired-site approach to control for topography and site-characteristics such as slope profile, elevation, size of the field, slope composition, and slope inclination.

After extensive hikes and field appraisals, we picked 12 paired sites representative of four land use changes (LUC). It took several weeks to find sites under different LUCs that were comparable in terms of topography and slope. The finally sampled sites range from 30 – 33 degrees for the shoulder slope, and 21 – 24 degrees for the foot slope; and a flat (0 degree) plateau (see Figure 5.1). No fertilizer addition, guarantees a genuine comparison between the different land-use schemes.

In summary, we sampled the 12 samples per land-use (4 different land uses), as shown in figure 1, with in 3 replications, generating a total of 142 samples. It would have been 144, but two of the secondary forest samples disappeared in the soil laboratory. For the third secondary forest replication, the forth sample of the plateau and the forth sample of the shoulder slope was missing.

Figure 5.1: Schematic of the soil sampling strategy



Note: SS refers to shoulder slope and FS to foot slope.

A random sampling design was used for gathering the soils data. Sampling was conducted, after the initial scouting for comparable sites during a two weeklong period at the beginning of the rainy season in late May/early June 2008 (the wet season usually goes from April to September, and the dry season from January to April).[98] The average monthly rainfall (temperature) during the month of May was 270 mm (26.9 degrees Celsius) and during June 235 mm (26.5 degrees Celcius).[99] Within the topographical position of a site (e.g. foot slope) four composite samples were taken, whereby the centroid for the samples was located at a random position. The three composite samples were taken at a distance of 1m to the centroid, based on 3 random angles (the centroid itself was not sampled). The triangles (w/o the outer sides) in figure 5.1 are supposed to represent the composite sampling design.

The samples were taken from the topsoil (the upper, outermost layer) at each plot at 0-30 cm[100] depth and were then combined, homogenized and treated as a single sample. The litter was removed when sampling and roots were sieved and removed in the lab. The extracted samples were dried in situ. Guo and Gifford (2002) find that while topsoil C stocks are impacted substantially by LUC (up to even halved for forest-to-crop conversion), deeper soil layers are not. Furthermore, Tschakert, Coomes and Potvin (2007) find that most of the Carbon was stored in the upper layers, with more than half already being stored in the upper 10cm.

Prior to collecting our topsoil samples with the random design, we investigated the soil texture and clay mineralogy of the paired sites to make sure that they were all the same soil type. We tested and classified the soils from our study sites and confirmed that they were all Ultisols (USDA classification) or Acrisols (FAO classification) using visual, textual and chemical properties of 20 cm sections from 1 m depth cores, as has been suggested by detailed soil maps from ANAM. It has been shown that soil types substantially determine SOC levels in the soil (see e.g. Lopez-Ulloa, Veldkamp, and

[98] I collected the samples during my Masters of Science in Natural Resources and Environmental Management at the University of Hawaii.
[99] Precipitation and temperature measures for the field sites were calculated with "Worldclim – Global Climate Data" accessed at: http://www.worldclim.org/current.
[100] Most Carbon is stored in this upper layer.

deKoning, 2005 as read in Powers et al 2011). The pH values of the soil samples averaged 4.8 and ranged from 4 to 6.6.

Soil chemical analysis was carried out by the Instituto de Investigación Agropecuaria de Panamá (IDIAP), the Panamanian National Research Institute for Agriculture, where soil organic matter was estimated using the Walkley-Black method, soil phosphorus (P) was measured by Mehlich 1 extraction, trace metals (copper, iron, manganese and zinc) by Mehlich III extraction, calcium (Ca) and magnesium (Mg) were measured by atomic absorption spectrometry and potassium (K) was measured using a photometer. Soil pH was measured in water. The phosphorus concentrations in the soil were below the laboratory's detection limit. The results for the measures other than soil organic carbon are presented in the appendix.

Indigenous and non-indigenous colonist owners of agricultural fields were interviewed about information regarding the agricultural fields and the adjacent forests, including questions about time since conversion, age of adjacent forests, crop and fallow history, land use, and management practices, among other questions. These household and field surveys indicated that the kind of crops grown included rice, maize, yams, yucca, bananas, plantains, sugarcane, and beans. The soils sampled for the agricultural fields include rice and maize only. They were the most prominent crops cultivated.

5.4.2 Statistical analysis

Site means (n = 3) were used for all statistical analyses. The effects of land-use on soil properties were investigated by a one-way Analysis of Variance (ANOVA); topographical position was nested within sites and the interaction between land-use and slope position was included. If the overall ANOVA was significant for a given variable, post-hoc pair-wise comparisons of the land-use types were conducted using Tukey's Honestly Significant Difference Test.

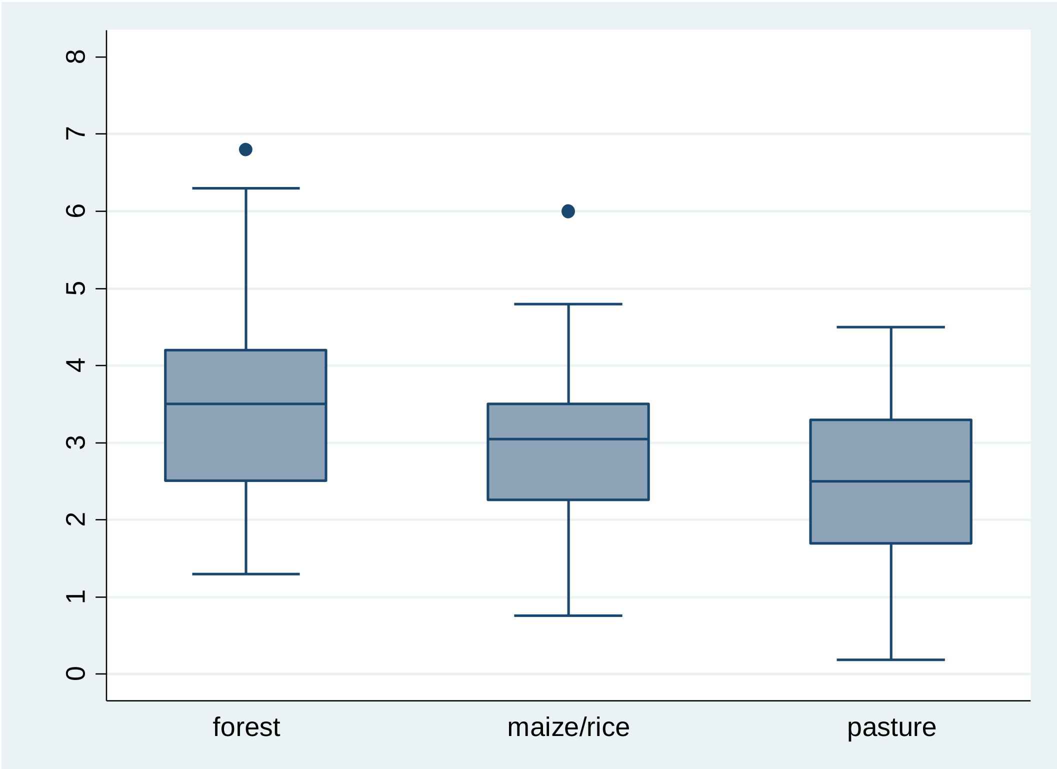
5.5 Results

Land-use clearly affected soil chemical properties. Also, topographical position and slope played an important part in determining soil nutrient levels. Forest sites stored significantly higher levels of SOC in the soil, compared with crop sites and pasture sites. Pasture sites had lower levels of SOC in all topographical positions, but they were not statistically significantly less.

Soil organic matter content was significantly higher in the forest sites than in the pastures (treatment effect: $F_{3,24} = 5.14$, $p = 0.0003$; Fig. 5.2). They were also higher compared with cropland (maize and rice) sites (treatment effect: $F_{3,24} = 2.98$, $p = 0.0151$; Fig. 5.2). Cropland sites were almost significantly different from pasture sites (treatment effect: $F_{3,24} = 1.83$, $p = 0.1192$; Fig. 5.2), but the trend is that they store more SOC. The average of 3.5 mg/kg of soil carbon in forest sites contrasts the 3.1 mg/kg in the maize/rice fields,[101] and the 2.5 mg/kg in the pasture sites. Maize/rice had the smallest variability around the means, and forest and pasture sites had roughly the same degree of dispersion.

[101] There was no difference between rice and maize fields in terms of SOC stored which is why they were pooled together. This may be partly explained by the fact that it was still early in the cropping season, as both crops were only sown 2 months prior to sampling. It is possible that over the subsequent months a divergence would have been observed.

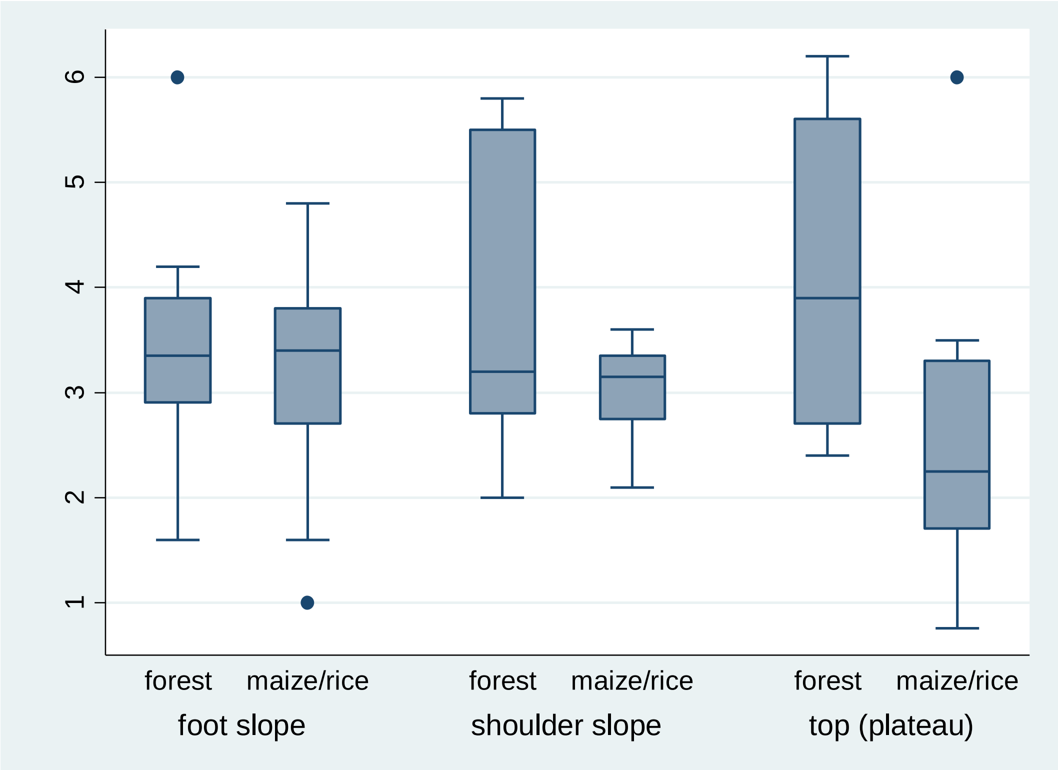
Figure 5.2: Soil Organic Content by vegetation class



Note: The upper hinge of the box depicts the 75th percentile, the middle hinge depicts the median, and the lower hinge depicts the 25th percentile. The whiskers plot upper and lower adjacent values and the solid dots depict outlier values.

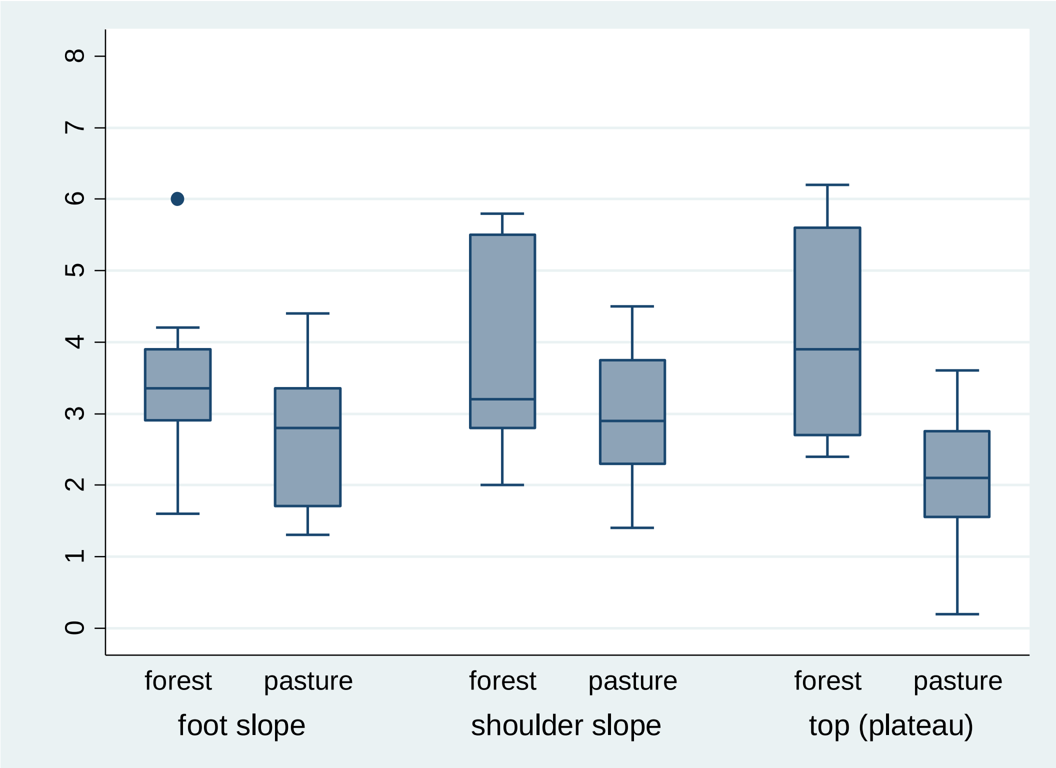
Topographical position is key in determining the significant differences of cropland and pasture SOC levels compared with forest sites. As illustrated in figures 5.3 and 5.4, the significantly higher levels of SOC under the forestland mostly stem from stark differences in the plateau's Carbon levels. Soil carbon levels of almost 4 mg/kg in the forest covered sites compare with levels of about half of that, with just over 2 mg/kg in the cropland and pasture sites. The SOC level gap between forest and agricultural sites at other slope and topographical positions is miniscule. Most of the variation across land uses is therefore driven by the variation of the plateau sites.

Figure 5.3: Forest-to-crop conversion implications for SOC depends on topography



Note: The upper hinge of the box depicts the 75th percentile, the middle hinge depicts the median, and the lower hinge depicts the 25th percentile. The whiskers plot upper and lower adjacent values and the solid dots depict outlier values.

Figure 5.4: Forest-to-pasture conversion implications for SOC depends on topography

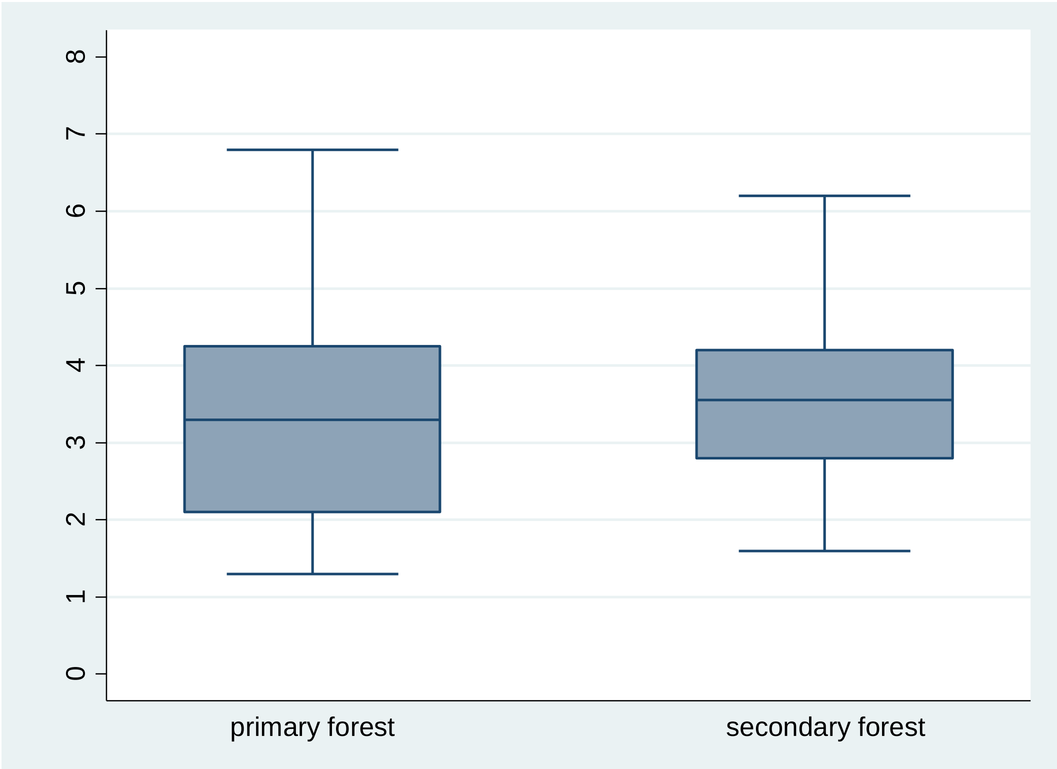


Note: The upper hinge of the box depicts the 75th percentile, the middle hinge depicts the median, and the lower hinge depicts the 25th percentile. The whiskers plot upper and lower adjacent values and the solid dot depicts outside values.

In the forest-to-crop conversion scenario, crop sites had a marginally higher soil carbon concentration at the foot slope positions (3.4 mg/kg vs 3.3 mg/kg), roughly the same mean tendency at the shoulder slope positions (3.2 mg/kg), but were outweighed by almost 2mg/kg (3.9 mg/kg versus 2.3mg / kg) at the plateau. In the forest-to-pasture conversion scenario, pasture sites did not have higher SOC levels in any of the topographical positions. The highest gap was similar to the forest-to-crop conversion in the plateau sites. Forest sites display a higher degree of variance compared with agricultural (both crop and pasture site) samples at the shoulder slope and plateau topographical positions; a similar variance at the foot slope.

SOC levels in secondary forest sites were marginally higher compared with primary forest sites (3.4 mg/kg versus 3.2mg/kg), albeit not statistically significant (see figure 5.5). Secondary forest samples were more homogenous compared with primary forest samples, and displayed a much lower variance around the mean.

Figure 5.5: Soil Organic Content in primary versus secondary forest



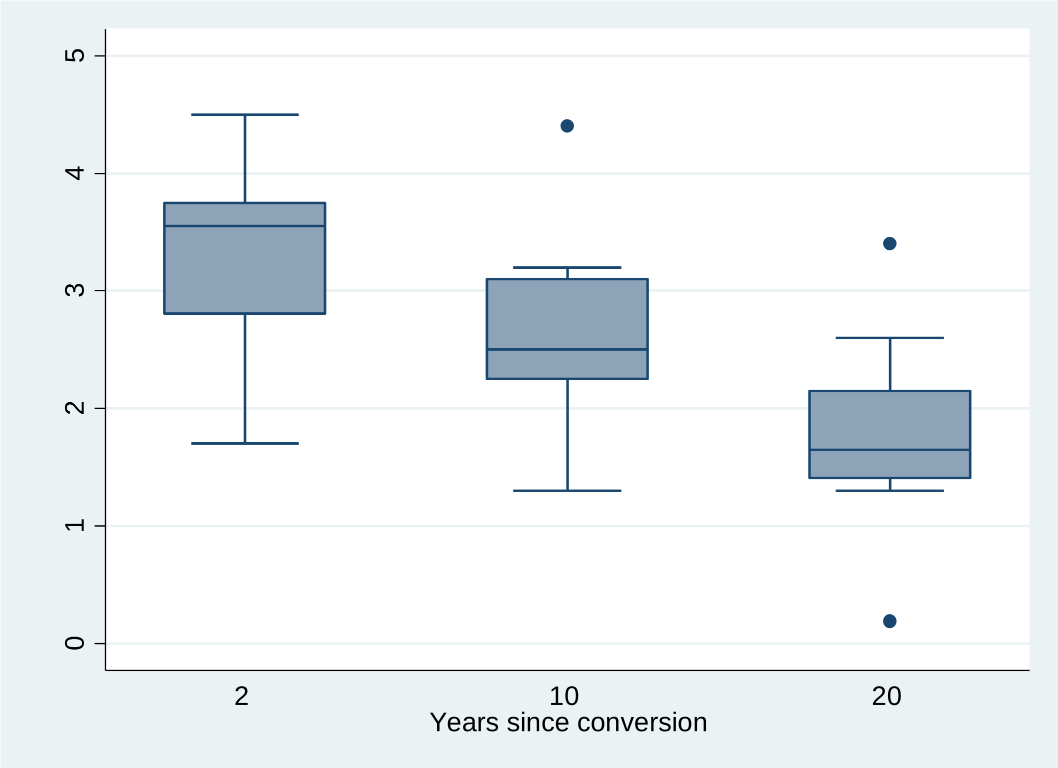
Note: The upper hinge of the box depicts the 75th percentile, the middle hinge depicts the median, and the lower hinge depicts the 25th percentile. The whiskers plot upper and lower adjacent values.

Cronosequential analysis shows that soil organic content drops dramatically over time in pasture sites. Whereas the pasture site have an even higher average of SOC two years after forest-to-pasture conversion with 3.7 mg/kg versus the 3.4 mg/kg in the forest sites, they drop to an average of 2.4 mg/kg 10 years after conversion. By 20 years after forest conversion, pasture sites have reached a low level of 1.6 mg/kg.

Secondary forest sites contain slightly more SOC than their primary forest counterparts, with 3.5 mg/kg compared with 3.2 mg/kg (see figure 5.6). The fact that carbon levels are able to rebound beyond initial levels is a promising sign and shows that there is potential for reforestation/ afforestation projects. Figure 5.7 depicts a chronosequence of a hypothetical scenario spanning from an unperturbed state of primary forestry to a reforested secondary forest, 30 years after.[102]

[102] The reason why this is only a hypothetical scenario is that the secondary forests sampled in this study were previously under crop cultivation and not under pasture cultivation. The logic of figure 6 is thus

Figure 5.6: Soil organic content drops over time since forest-to-pasture conversion



Note: The upper hinge of the box depicts the 75th percentile, the middle hinge depicts the median, and the lower hinge depicts the 25th percentile. The whiskers plot upper and lower adjacent values and the solid dots depict outside values.

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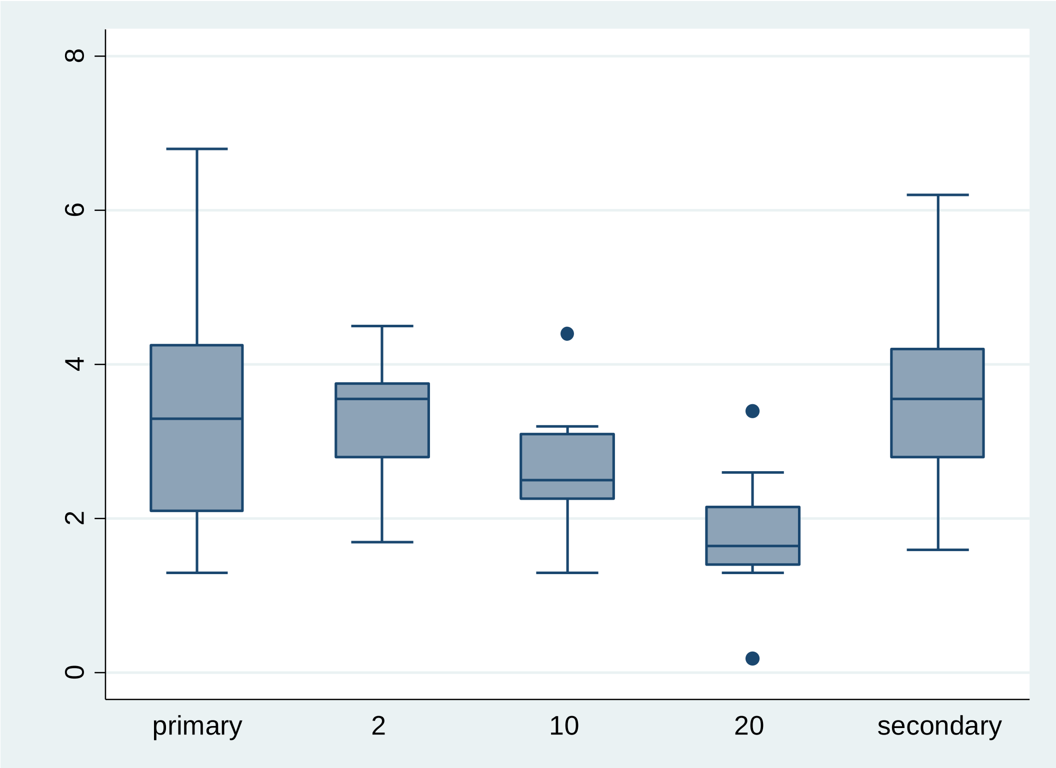
predicated upon the idea that SOC dynamics would behave similarly in the reforestation of pasture sites compared with crop sites.

Figure 5.7: Cronosequence from deforestation to reforestation



Note: The upper hinge of the box depicts the 75th percentile, the middle hinge depicts the median, and the lower hinge depicts the 25th percentile. The whiskers plot upper and lower adjacent values and the solid dots depict outside values. Caveat: The depicted secondary forest site in this graph corresponds to re-growth forest that was cleared for the purposed of crop cultivation, not pasture. Logic of the graph therefore hinges on the notion that soil stored carbon recovery process behaves the same regardless of type of previous land use.

5.6 Discussion

The preponderance of studies in the literature show that forest-to-crop land conversions should not affect soil quality and the amount of soil stored carbon negatively, if anything they should boost SOC levels. The majority of papers furthermore show that forest-to-crop conversion adversely affects soil nutrient amounts stored. By looking at indigenous crop cultivation, and smallholding cattle ranching activities, something that has been overlooked in the literature, this article finds evidence for the opposite. The results from contrasting indigenous crop cultivation with non-indigenous colonist cattle ranching show that forest-to-crop conversion has a smaller negative effect on soil organic carbon (SOC) concentration than forest-to-pasture conversion.

The reasons for why indigenous crop cultivation techniques showed to be less degrading of soil quality have to do with factors relating to the sustainable agricultural practices of the studied indigenous community (no-tillage farming, and ample fallow periods), the unsustainable practices of the colonist cattle ranchers (ranching cattle beyond the carrying capacity of the land, combined with a no-fallow management of pastures), which are exacerbated by the idiosyncrasies of weather conditions in the area (high precipitation and temperature levels). These factors are held responsible for explaining why the agricultural techniques studied in this article showed the contrary to what would have been expected from reading the literature (e.g. Powers et al., 2011 and Don et al., 2003).

The indigenous community studied, did not engage in tillage on its fields. Plowing would have allowed the soil to oxidize, and a heightened exposure to the wind and water elements would have come about by tillage. Both soil erosion and tillage deplete Carbon, because Carbon has a low density, which means that wind and water erosion can easily wash it away. Eroded soils are thus depleted of Carbon. No-tillage farming practices protect soils from biological degradation and maintain soil quality (see e.g. Aslam et al, 1999, Six et al., 2000; Del Galdo et al., 2003).

The indigenous community would cultivate a parcel of land for only one year (maximum of two years in a few cases) until it would let it re-grow (fallow period) for on average seven to ten years, before it would after rotation with other parcels, revert back to the original parcel for cultivation. This constitutes a quite conservative use of fallow periods in rotational cropping and contributes to the sustainable management of soil quality (see e.g Christianty 1986).

By overpopulating pasture sites with cattle beyond the carrying capacity, colonist cattle ranchers caused high rates of soil compaction and soil erosion. The necessary land to raise one cow for beef in the tropics is between one and seven hectares, depending on soil fertility and the rate of decline of grass nutritional value (Shane, 1986). The carrying capacity of pastureland in the lowland tropics of Panama is recommended to be at a Minimum 1 ha per cow (McCorkle, 1968). We observed an average of 0.8 hectares that were available per cow, which exceeds even the minimum land that needs to be available under the most favorable circumstances. The ecological maximum carrying capacity of the land is therefore exceeded. Resulting soil compaction, and soil erosion contribute substantially to significant reductions of SOC levels in pasture soils.[103]

The interaction effect of topography and slopes relating to the impact on SOC levels was contrary to what was expected. The prior was that steeper slopes would demonstrate a wider gap between agricultural sites and forest sites, because it was expected that water erosion would be more effective on steeper less protected slopes. The fact that the flat plateau displayed the widest gap between forest and crop/pasture sites, and the only significant one, might have something to do with more exposure to wind and also to higher exposure to direct sun radiation.

There is limited scope for extrapolation of collected SOC results to other sites, and the representativeness for regional soil pools is limited (low external validity)[104]. However, due to the controlled nature of the study, where the most crucial mitigating factors that have been identified in the literature such as microclimate (precipitation & temperature), soil type, topography, slopes, and elevation are controlled for, the internal validity of the results is high. The compared land sites therefore have a high degree of comparability and the observed differences in SOC between the land uses should be only due to the land uses themselves and nothing else. In summary, while the present article does not serve to extract carbon levels for any meaningful level of regional representation, it does deliver a precise comparison of the consequences of indigenous crop cultivation versus non-indigenous cattle ranching for SOC concentrations.

Timing, and through it soil degradation forces such as erosion, plays a crucial part in damaging soil quality under pastureland management. Young pasture sites do not differ much from crop fields in the first two years, but the older they get, the more SOC they lose, so much so that after 20 years since the time of forest-to-pasture conversion, the

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[103] The decrease in soil C is driven by a decrease in organic matter input to the soils, increased decomposition and erosion (see Six et al., 2000; Murty et al., 2002; Lal, 2005; McLauchlan, 2006 as read in Laganiere, Angers, and Pare, 2009). Eroded soils are therefore depleted of Carbon. Erosion has been shown to be a major SOC loss pathway (see e.g. van Noordwijk et al., 1997; and Berthe et al., 2007 as cited by Don et al., 2011). The importance of erosion of the tropical lowland for the carbon cycle and pasture productivity has also been discussed in Huth et al. (2012) and Hertemik (2006).

[104] Because this study is not about computing Carbon pools, but rather about comparing the impact of indigenous crop cultivation with non-indigenous cattle ranching, assuming similar bulk density measures, I do not report bulk density measures.

soils have almost halved in carbon content. On a positive note however this article finds evidence that these SOC losses are not irreversible and that reforestation can restore soil quality. These results are quite comforting, and indicate that reforestation efforts can undo the damage done by cattle hoofs.

By the same timing token, however, one of the study's caveats is that it does not provide SOC information by months since conversion. The representativeness of the selected months in question is therefore a pressing concern. The samples for this study were taken about two months after the parcel of land has been scorched, during the beginning of the rainy season. From the literature we know that in the post-burning period, there are increased levels of SOC in the soil, due to increased soil inputs (Palm et al, 1996 as read is Tschakert et al., 2007) and in increased soil microaggregates (Garcia-Olivia et al 1999 as read in Tschakert et al., 2007). Turner et al. (2015) for example found that SOC is seasonably variable within a year, dependent on rainfall and temperature in a lowland tropical forest in Panama. For example, they found that SOC decline by about 16 percent between the end of the wet season and the late dry season. Having measures for the months 3 – 12, before the parcel is allowed to revert to secondary forests, would improve the interpretability of the results immensely. Furthermore, I did also not sample the fallow sites that were less than ten years old for reasons of impenetrability of the thick forest and the resulting inability to establish that these sites would have been comparable. The time representativeness of the crop sites is a crucial issue and should be the focus of future studies. The results presently available would need to be adjusted upwards or downwards, depending on how much (if anything) one thinks the surveyed months over-represent the yearly average in SOC.

There might be an issue of underestimation of the true impact of secondary forests. Even though secondary forests turned out to be the largest SOC sink, even compared with primary forests, this may still be an underrepresentation of the true impact of re-growth to secondary forest. The idea put forward in the literature (for a summary see Powers et al., 2011 and Guo and Gifford, 2002) is that it is more likely that unproductive agricultural parcels are allowed to revert back to secondary forests than productive ones. Therefore the underlying soil quality of our secondary forest sites might have been lower than the underlying soil quality of the other sites, thus biasing the SOC results obtained for secondary forests downwards. If this is the case, one would have to adjust the estimated SOC figure for secondary forests upwards by whatever fraction one estimated that the soil originally had less SOC. Semi-structured interviews with the Amerindians however, have not vindicated that there is a difference in fertility of land according.

A reason for why the underlying original soil quality of pasture sites might be underestimated is that they had only a second pick in where to deforest and cultivate. Because the Wounaan have settled in the area first, it is plausible that they picked the land sites that were most productive. Furthermore continuous violent confrontation between the Amerindians and the encroachers (as documented by la Prensa, 2009), may lead the encroachers to rather settle at a suboptimal swath of land in terms of pasture productivity, but that is at a safer distance from the Wounaan, or a relatively better strategic vantage point to them. Semi-structured interviews with the colonist cattle ranchers however, have not confirmed that they felt that the land they settled at and are now cultivating is any less productive than possibly surrounding land. Furthermore, the Wounaan located in, and cultivated the areas they did mostly to issues related to accessibility by the water and vicinity to the village.

Soil quality is crucial in combating the adverse effects of climate change. By sequestering CO_2 from the atmosphere, soils perform a dual service and contribute to both climate change adaptation as well as mitigation. Soil quality contributes to adaptation by reducing the risks of a changing climate by increasing a soil's resilience to extreme events (such as droughts or floods), and by strengthening its buffering capacity. It also contributes to mitigation, by decreasing the severity of the problem; by taking CO_2 from the atmosphere through biomass, and putting it back into soil. Soil under indigenous management therefore performs not only locally a higher environmental service, by guaranteeing a better soil quality for local usage, but also globally, by guaranteeing better climate change adaptation and mitigation practices.

The interpretation of the results of this study with respect to the entire scope of environmental quality and degradation characteristics remains limited to soil quality and carbon sequestration levels. There are other important environmental implications of crop and pasture land uses that extend beyond the scope of this article, such as the impacts of other greenhouse gases (GHG) such as methane, which is produced by cattle bowel movements and considered a much more potent climate gas than CO_2. There is other literature that is dedicated to these broader environmental effects, such as the life-cycle analysis, which has shown that plant-based food production results in substantially lower GHG emissions compared to animal production (see e.g. Carlsson-Kanyama & Gonzalez, 2009; Bellarby et al., 2012 & Berners-Lee et al., 2012).

5.7 Conclusion

This chapter compares the impacts of deforestation on soil quality, by looking at the understudied drivers of indigenous crop-cultivation and smallholding colonist cattle ranching. A focus on indigenous farming practices was a substantial omission in the literature assessing impacts of land use changes on soil organic carbon (SOC), as was a focus on a smallholding pastoralist cattle ranching setting. This chapter is a first attempt to fill this gap.

Despite of what has been suggested in the literature, which is that pasture sites stored an equal amount of SOC to forest sites, this study finds that they stored significantly less, owing mostly to grazing intensity beyond the carrying capacity of the land. Furthermore, this study finds also that indigenous crop cultivation, although worse than forest cover, is better for soil quality than pastoralist cattle ranching, owing mostly to sustainable land management practices including no-tillage and long fallow period crop rotations.

The study finds evidence of how devastating the impacts of erosion are over time on the pasture sites. Whereas the pasture sites start out with roughly similar soil organic carbon levels for the first two years, they drop rapidly in Carbon content over the next decades, reducing SOC to almost half after 20 years. On a positive note, this depletion in soil organic matter is reversible, and this study shows evidence of how reforestation leads to SOC levels that parallel those of unperturbed primary forests, in some instances even outweigh them.

The study finds also that the effects of deforestation depend substantially on topographical position. While slope inclination did not interact significantly with gaps in SOC observed between land uses, topography mattered. I find that the only topography where the gap between land uses was significant was the plateau, alluding to the importance of wind erosion and sun radiation, because this part is most exposed in the tropical lowland geography. For the purposes of soil quality only it is therefore much less detrimental if deforestation occurs on the slopes rather than the plateaus.

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Appendix

Other nutrients, other than SOC were also analysed. Their results are presented below.

Soil pH and soil K concentrations were significantly higher in the forest sites compared to the agricultural land use types (treatment effect: $F_{3,24} = 6.98$, $p = 0.001$ and $F_{3,24} = 11.68$, $p < 0.001$, respectively). Crop cultivation and ranching cattle did not differ significantly in terms of pH and K. Soil Ca concentrations were significantly higher in the old-growth forest compared to pastures and secondary forest but there was no difference between old-growth forest and croplands (treatment effect: $F_{3,24} = 4.77$, $p = 0.01$). Soil Zn was higher in the old-growth forest than in the pastures and secondary forest (treatment effect: $F_{3,24} = 9.99$, $p < 0.001$), whereas soil Fe concentrations were significantly higher in pastures compared to all other land-use types (treatment effect: $F_{3,24} = 11.92$, $p < 0.01$). Soil Cu concentrations were significantly lower in the croplands compared to the old-growth forest sites and there was a trend towards lower soil Cu in the croplands compared to the pasture sites (treatment effect: $F_{3,24} = 3.66$, $p = 0.027$).

There were no effects of land-use type on the concentrations of Al, Mg, or Mn in the soil.

CHAPTER 6

Conclusion

Brief summary of findings

In chapter 2, I find that natural disasters need not lead to a reduction of per capita economic output, neither in the short-term nor in the long-term. The case of Aceh recovering from the Indian Ocean Tsunami, which I examined in this PhD thesis, highlights the cracks of this generality. The largest reconstruction effort in the developing world illustrates that a natural disaster can be a window of opportunity. Reconstruction in Aceh caused per capita economic output to not only be higher in the immediate aftermath years of the Tsunami, but also beyond, once the province had recovered. Higher per capita economic output was not only achieved in the short run, as capital was being replaced, but the upgraded capital was also used more productively in the long run, increasing economic output.

In chapter 3, I investigate some of the channels through which creative destruction operates. There are many causes for why the Indian Ocean Tsunami and the reconstruction effort triggered a creative destruction process of the Acehnese economy. Investments increased substantially, private aggregate consumption was not only smoothed, but also boosted, and the structural transformation process was accelerated, leading to a shift from lower productivity to higher productivity sectors. Labour and value-added moved out of agriculture into more productive sectors such as services.

In chapter 4, I find that there are negative economic legacy effects from armed conflict. The armed conflict, in contrast to the Indian Ocean Tsunami, resulted in a depression of economic output in Aceh. I found that the armed conflict during the Acehnese civil war had a negative economic overhang effect, meaning that the violence during war continued to hold its grip on economic development, even after it was over. The worse the violence, as measured by a suite of indicators of human suffering, such as casualties, injuries, rapes and kidnappings, the more depressed economic output once peace was obtained.

I chapter 5, I find that indigenous crop cultivation in Eastern Panama is low-impact in that it maintains a relatively high concentration of soil organic carbon (SOC). Conventional land use findings in the literature suggest that there is less SOC stored after forest-to-crop conversions than after forest-to-pasture conversions. However, the indigenous low-intensity crop cultivation strategy studied in this PhD thesis shows that indigenous cultivation techniques (for rice and maize) do not store significantly less SOC than forests do. Conversely, pasture sites do store significantly less. I also found that SOC in secondary (re-growth) forest is not statistically different from primary forests, indicating that the SOC concentration drop following the conversion of forests can be reversed.

Discussion and future research

Although I have been able to answer some interesting empirical questions in this PhD thesis – such as can a natural disaster be the catalyst of creative destruction for an economy?; or are there negative economic legacy effects from violence and armed conflict? – my doctoral research process in fact unearthed more additional questions than it gave answers to in the first place.

An area of future inquiry is disentangling the Tsunami flooding effects from the aid flow effects in Aceh. In the absence of having comparable districts that were just treated by aid and others that were just treated by flooding, it is almost impossible to decipher where the effects come from, particularly as interaction effects and countervailing effects may be an issue. Future research into how other countries that were also heavily affected by the Indian Ocean Tsunami floods, but not as much by the "aid floods" should provide insight into the questions of how much of the observed effects came from aid, as opposed to the flooding. Sri Lanka would be the logical next regional area of scrutiny, as parts of the country were also severely inundated by the Indian Ocean Tsunami. The island has a similar economic development level to Aceh, and is also comparable in other human development dimensions such as health and education, but it received much less aid as a result of the government's critical stance towards accepting assistance from the international community. Sri Lanka would be the perfect testing ground for evaluating flooding treatment in the absence of aid.

The reason why I abstained from examining the effects of flood aid closely in this PhD thesis is twofold; I could not get my hands on the final RanD aid dataset (I used a preliminary version for this PhD thesis), and aid was not randomly allocated. On the latter point, even though an as-if random allocation assumption of Tsunami flooding to each district can be defended quite easily, the same cannot be extended to aid disbursements. I showed that the correlation coefficient between regional aid disbursements and intensity of flooding is upwards of 0.8; indicating that they are substantially linked, yet not perfectly so. There remains room for plenty of other factors that could explain why aid does not perfectly follow the flooding intensity, which could in turn confound a causal aid-growth interpretation. Because this PhD thesis primarily focussed on a rigorous and solid causal identification strategy, I did not investigate the effects of aid to any sufficient level of detail. I intend to pursue the link of aid intensity and recovery however in the future.

In future work, I intend to analyse the marginal relationships between disaster recovery aid and economic growth. There are many reasons to believe that the aid-growth relationship is not a linear one. I would like to scrutinize the exact shape of the aid-growth curve in case of Aceh. Looking at the marginal return per added aid dollar in terms of growth would be a great contribution to the literature. As mentioned, such an analysis would no longer follow the framework of a natural experiment, as Tsunami aid was not assigned randomly, which would require an alternative estimation approach such as an instrumental variables regression or a similar method.

Splitting up the aggregate aid flows into several groups, such as the main targeted sector (construction, health, education, agriculture, etc…), or the sources of funding (NGOs, IFIs etc…), should allow providing shades of grey for the aid impact analysis, and allow to assess which programs were the most effective and the most efficient. For example, a disaggregated aid-growth analysis would allow estimating the heterogeneous effects of the types of aid, ranging from reconstruction aid to capacity building aid. In addition, it would also allow estimating whether the so-called soft aid had an additional economic value, or whether it was only hard aid that made a difference in terms of growth promotion.

An extension of the presented analysis in PhD thesis with data beyond 2012 is required to test the persistence of the higher economic output path, and to truly capture “the long run.” There is no agreement in the literature as to what constitutes the “long run,” with lower estimates starting at five years, but expanding the eight-year period in this PhD thesis would certainly be a great contribution. Once more recent data become available, one could investigate how sustainable the findings about a permanently higher economic output per capita are considering even longer periods. This should be the most straightforward extension for future research.

I show the importance of scale for the unit of analysis chosen in this PhD thesis, in that I show that the creative destruction results only emerge in a fine grained level of analysis (using districts and sub-districts), but when using province or even nation level data these results “wash out”. A more systematic assessment of the effects of unit size on the impact evaluation of natural disasters need to be carried out in the future, to understand why exactly the effects disappear when using aggregated figures.

The role of remittances has not been studied in this PhD thesis, as data on remittances was not available, and despite my best efforts, I was unable to obtain data on it for Aceh. It would be interesting to study, in a different context, for which there is data, the different effect of remittances versus aid on growth. Furthermore, it would also be interesting to investigate whether conditionalities on financial assistance have an effect on the nature of economic recovery. In other words, comparing the growth promoting contribution of financial assistance that does not have to be paid back (such as grants) with financial assistance that does have to be paid back (such as loans), and more broadly aid that does come with conditions.