**The Impact of the Indian Ocean tsunami on Aceh’s**

**Long-Term Economic Growth**

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Abstract: Existing studies typically find that natural disasters have negative economic consequences, resulting in, at best, a recovery to trend after initial losses or, at worst, longer term sustained losses. We exploit the unexpected nature of the 2004 Indian Ocean tsunami for carrying out a quasi-experimental difference-in-differences analysis of flooded districts and sub-districts in Aceh. The Indonesian province saw the single largest aid and reconstruction effort of any developing world region ever afflicted by a natural disaster. We show that this effort triggered higher long-term economic output than would have happened in the absence of the tsunami.

JEL classification: O40, O47, Q54

*“… 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, cited in Schonhardt, 2014, para. 4).*

# Introduction

On December 26 2004, an earthquake of magnitude 9.1 on the Richter scale off the west coast of Sumatra triggered a series of devastating tsunamis hitting 14 countries across the Indian Ocean, particularly Indonesia, Sri Lanka and India. The death toll in Indonesia was estimated to be up to 130,000 people (Frankenberg et al, 2011) with an immediate economic cost of up to USD 5 billion (World Bank, 2005 & Masyrafah & McKeon, 2008). Within Indonesia, the only affected large island was Sumatra. Of this easternmost island, only two of its nine provinces were affected and of the two, the province of Nanggroe Aceh Darussalam, or ‘Aceh’ for short, was most severely hit, accounting for approximately 90 percent of damages (BRR, 2006).

In the aftermath of the disaster, Aceh became the location of the single largest reconstruction effort in the developing world. The aid allocated to the region (USD 7.7 billion) by far surpassed the direct monetary damages. 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. Aside from the sheer size of the reconstruction effort, also its quality was to a very high standard, albeit far from perfect (Fengler, Ihsan & Kaiser, 2008). 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 committed 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 and aid volatility, normally a huge problem, was kept under control (Masyrafah & McKeon, 2008). Aceh not only benefitted from aid, but also from increased transfers from central government and remittances. In addition, a historic peace deal was struck in 2006, successfully ending a nearly 30-years-long secessionist war against the central government that had cost approximately 15,000 lives over the course of the conflict.

Did the reconstruction effort succeed in these very favourable conditions? Can human effort turn the impact of a natural disaster that results in devastating human loss hitting a poor region of this world into positive economic consequences after the economy has recovered from the initial shock, lifting it onto a higher output trajectory than it otherwise would have been on? Employing sub-national gross domestic product (GDP) and night-lights data we demonstrate that the districts and sub-districts of the Indonesian province of Aceh that have been hit by the Indian Ocean tsunami of December 2004 experience sustained higher economic growth and night luminosity from 2006 onwards than counterfactual districts and sub-districts that have not been hit. In Authors (2018), which exclusively focuses on the economic legacy effects of armed conflict, we show that the tsunami-triggered growth effects cannot be the consequence of the end of violent conflict since we find that the spatial distribution of the conflict is uncorrelated with the spatial distribution of where the waves made landfall and that districts that benefited more from peace (where conflict had been more intense) grew relatively less than those that were less affected by the violence.

Economic studies overwhelmingly find natural disasters to either have no noticeable impact or negative consequences on the economies of affected countries (e.g. Cavallo et al. 2013). Only few studies find sustained positive economic effects in the aftermath of disasters and typically only under certain circumstances such as high development level of the country, insured losses and, most importantly, only moderately destructive disasters (Loayza et al. 2012; Cavallo & Noy 2011). What explains this pessimistic outlook for developing countries in particular?

Natural disasters destroy productive capital and lead to expenditure reductions and therefore also reduce the consumption component of aggregate GDP (see e.g. Baez et al, 2010; Carter et al, 2007; and Anttila-Hughes & Hsiang, 2011). Most studies find short-term negative effects after which economies rebound and enter onto a “recovery to trend” trajectory: the disaster results in an immediate substantial contraction in output that remains below the non-disaster counterfactual potentially for a few years, but eventually re-bounds and converges to the pre-disaster trend (see e.g. Strobl 2011). By contrast, other studies suggest affected countries are permanently relegated to a lower growth path (e.g. Hsiang and Jina, 2014). In this perspective, the destruction of capital is so severe and long-lasting that affected economies never fully recover. An economy might eventually start to grow again without, however, ever reaching its pre-disaster trajectory (see e.g. Burke et al, 2009; Hsiang, Meng & Cane, 2011; and Hsiang & Jina, 2014). Developing countries, in particular, are expected to suffer economically from natural disasters (Kahn, 2005; Heger, Julca & Paddison, 2009; Loayza et al, 2012; and Fomby, Ikeda & Loayza, 2009) though Gignoux and Menéndez (2016) provide some counter-evidence from long-run effects of earthquakes in rural Indonesia, not covering either Aceh or the 2004 tsunami, however. Developing countries typically lack 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 Noy & Nualsri, 2008), and sufficient savings (Paxson, 1992; and Mechler, 2009) that would cushion the economic blow.

Against this pessimistic outlook, some have argued for positive economic effects via concerted and well-executed reconstruction efforts. Replacing lost capital increases the demand for goods and services, boosting aggregate demand in the wake of the natural disaster, often buttressed by significant foreign aid inflows (Horwich, 2000; Kunreuther et al, 2004). Affected economies might bounce back after initial losses, following a trajectory which could best be described as “recovery to counterfactual trend”. In another scenario, a so-called “recovery beyond counterfactual trend” takes place. This might be temporary, in which case the economy would go back down to the initial trend after some time period, or might be sustainable, in which case the aid-fuelled reconstruction effort propels the economy not only above the counterfactual trend or growth trajectory but there is no relative contraction back down to the counterfactual trend when the aid and reconstruction efforts cease. Note that in either version of “recovery beyond counterfactual trend”, the positive economic shock that follows the negative economic shock of the natural disaster does not change the long-term growth fundamentals and therefore the long-term growth trajectory of the affected economy.

Some argue that an even better post-disaster economic performance is possible, namely a permanently higher long-term growth trajectory. From this perspective, natural disasters can result in ‘creative destruction’. Specifically, if the capital destroyed was old and unproductive a switch to a higher productivity equilibrium is possible if the new capital stock is more productive (Benson & Clay, 2004; Benson & Clay, 1998; Skidmore & Toya, 2002; Hallegate & Dumas, 2009; and Cuaresma et al, 2008).

Figure 1 graphically displays the five principal stylised trajectories for an economy hit by natural disaster relative to the counterfactual that would have occurred in the absence of the disaster. The first one is the most pessimistic one, in which the disaster results in permanently lower economic output. The second trajectory, “recovery to counterfactual trend”, results in a net economic loss, albeit a temporary one, with the counterfactual growth trajectory reached again after some time. The severity of the initial contraction in economic activity and the **Figure 1: Stylized impact trajectories of the disaster relative to the counterfactual path**

length of the time until the old trend line is reached again together determine the size of the temporary economic loss. Whether the third trajectory, “temporary recovery beyond counterfactual trend”, results in a temporary net economic gain or temporary net economic loss depends on the size of the initial contraction, the length of time until recovery propelled the economy beyond trend, the size of the expansion beyond trend and the length of time it remains above trend. By contrast, the fourth trajectory, “sustainable recovery beyond counterfactual trend”, provides a definite economic gain since after the initial contraction the economy is not contracting back to trend but grows at trend value but from the higher starting point above the initial trend line. Finally, the fifth trajectory, “creative destruction”, provides a productivity gain and would predict not only that there is a definite economic gain but that the economy was permanently set on a higher growth trajectory. As we will see below, Aceh experienced the fourth scenario, one of a sustainable recovery beyond the counterfactual trend.

There are three methodological issues with many of the existing empirical studies that are potentially problematic. First, the vast majority of existing studies have to resort to employing national GDP data.[[1]](#footnote-1) However, “… much of the interesting variation in economic growth takes place within, rather than between, countries” (Henderson, Storeygard and Weil, 2012, p. 995). This is particularly true for assessing the growth consequences of natural disasters which typically hit only a sub-set of a nation-state. Using spatially coarse indicators such as national GDP as impact measures to evaluate the effect of localized events such as natural disasters masks spatially heterogeneous effects.[[2]](#footnote-2) Second, with some exceptions (Hsiang & Jina 2014; Strobl 2011; Bertinelli & Strobl 2013; Felbermayr & Groeschl 2014; duPont et al, 2015; and Lynham et al, 2017), researchers have not had access to exogenous measures of the intensity of natural disaster impact, using endogenous measures such as estimates of direct human or economic loss instead. Third, relevant studies that employ causal identification strategies have only recently started to emerge (e.g., Kousky 2013; Hsiang & Jina, 2014; Cavallo et al, 2013; and Lynham et al, 2017).

As section 2 explains, we overcome these problems by employing GDP and night-lights data at the district and sub-district level, by computing exogenous measures of disaster intensity and by employing difference-in-differences as well as synthetic control causal identification techniques that exploit the quasi-natural experiment character of the tsunami. Section 3 reports results from our main estimations, while section 4 explores the robustness of results to various specification issues and discusses five potential threats to their inferential validity. Section 5 goes beyond looking at aggregate growth in economic activity and analyses the causal effect on structural economic change in Aceh. Section 6 concludes.

# The Indian Ocean tsunami: a quasi-natural experiment

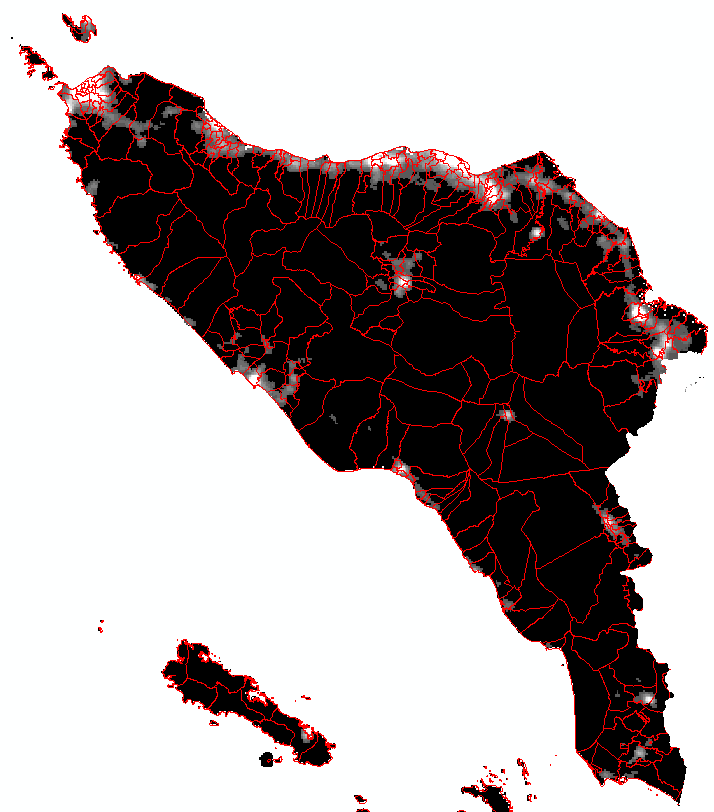
Our empirical strategy of identifying causal economic impacts of the 2004 Indian Ocean tsunami and subsequent reconstruction effort is based on observing differences in economic activity between flooded districts/sub-districts and non-flooded districts/sub-districts, which serve as a plausible counter-factual comparator group to the treated (flooded) units. We exploit the unexpected and unprepared-for nature of the 2004 tsunami. Geographic happenstance dictated why some stretches on Sumatra were hit but others were not. The waves reached far inland (up to 9km), particularly in areas with flat topographies. How far the waves reached inland was again dictated by geographic happenstance, being a function of elevation, vegetation, water depth, and topography (Ramakrishnan et al, 2005; Kohl et al, 2005; Umitsu et al, 2007).

Systematic differences of pre-treatment conditions would violate the comparability of the counterfactuals, and therefore foil the quasi-natural experiment. The most important inferential threats stem from differences in initial growth performance of the treated units versus the control units, as such differences are likely to impact on how each group recovers from the tsunami. We find no systematic pre-treatment differences in our difference-in-differences or synthetic control estimates. Furthermore, differences in preparedness and mitigation efforts between the treatment and control group would be a cause for potential systematic differences. Yet, people were completely unprepared for the tsunami (USAID, 2014). The last time a tsunami struck the shores of Sumatra was during medieval times (Monecke et al, 2008). Also, since the earthquake occurred right off the coast of Indonesia, the tsunami reached Indonesia only about thirty minutes later rendering effective early warning very difficult to achieve even if there had been an early warning system and risk awareness in place.

### District-level GDP and sub-district level night-lights data

We source district-level GDP data from the Indonesia Database for Policy and Economic Research (INDO-DAPOER),[[3]](#footnote-3) which is maintained by the World Bank. DAPOER draws heavily on data collected by the annual National Socio-Economic Survey (SUSENAS). SUSENAS is a national survey, which is representative at the district level, fielded every year and consisting of a sample of about 250,000 households. We exclude the oil and gas sector from the GDP data since the inclusion of this sector would render creating a counter-factual comparator very difficult. None of the affected districts have oil and gas resources, whereas some of the control districts do. Economic activity from oil and gas production is much more volatile than economic output from other sectors. In addition, there are data quality issues resulting in discrepancies of data coming from the Ministry of Energy and Mineral Resources and other governmental agencies (see World Bank, 2009).

Where we account for the intensity of the natural disaster, we require greater variation in the data than is available at the district level and therefore move to the sub-district level for which we have no GDP data. As an alternative, we use night-lights data, which is increasingly used as a proxy for local economic activity (see e.g. Chen and Nordhaus, 2011; Henderson et al, 2012; Bertinelli & Strobl, 2013; Gillespie et al. 2014). Sourced from US Air Force satellite data capturing images of the intensity of lights at night every day, the National Oceanic and Atmospheric Administration (NOAA) provide maps of annual average night-lights, where the highest resolution is a pixel of the size of about 30x30 arcseconds.[[4]](#footnote-4) The lights are recorded based on brightness, which is expressed by way of Digital Numbers (DN) ranging from 0 to 63, where 0 is darkness and 63 is the highest level of luminosity. Map 1 displays night-lights data for the 276 sub-districts (Kecamatans) in Aceh in 2004. Table 1 provides summary descriptive statistics of the average luminosity in flooded and non-flooded sub-districts in 2004. Not surprisingly, given sub-districts at or close to the coast were more likely to be flooded and also tend to be more densely populated, the average luminosity is higher in flooded than in non-flooded districts. Also note that whilst luminosity in each pixel is measured on a scale from 0 to 63 DN, no sub-district contains only pixels of highest luminosity, which is why the maximum average luminosity is 36.4 and 38.8 DN in non-flooded and flooded sub-districts, respectively.

**Map 1: Night-lights in Aceh’s 276 sub-districts (Kecamatans) in 2004**

Note: The demarcations represent the borders of the Kecamatans (sub-districts). Brighter colours show greater night-lights luminosity.

**Table 1: Summary descriptive statistics for average luminosity in Aceh’s 276 sub-districts (Kecamatans) in 2004**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | Obs | Mean | Std. Dev. | Min | Max |
| Flooded | 68 | 5.28 | 8.87 | 0 | 38.8 |
| Non-flooded | 208 | 2.30 | 4.33 | 0 | 36.4 |

To create the night-lights observations per Kecamatan per year for our regressions, to be consistent with our GDP analysis, which is the sum of economic activity within a unit, we sum up the DNs of all pixels within a sub-district’s borders. These data are not normally distributed and show high levels of skewness (4.97) and kurtosis (33.87). We therefore follow Michalopoulos & Papaioannou (2011) and Lowe (2014) and log-transform the data as follows:

Where *c* denotes the Kecamatan, *N* denotes the number of grid-cells within a Kecamatan, and *t* denotes the year. Results are robust if we replace this log-transformation with an alternative inverse hyperbolic sine transformation, which transforms DNs as follows (detailed results not shown):

The use of night-lights data as a proxy for local economic output is not uncontroversial (for a discussion see e.g. Addison and Stewart 2015 and Bluhm and Krause 2018). Even for the purpose of measuring luminosity, the satellite data face problems of measurement error due to deteriorating satellite performance over time, geo-location errors, blooming and top-coding at high luminosity. That said, recent evidence suggests night-lights data serve quite well for predicting local economic outcomes (see Weidman & Schutte 2016). Moreover, the problem of top-coding of night-lights data in particularly densely populated areas identified by Bluhm and Krause (2018) is hardly relevant for Aceh. Also, our use of time and sub-district fixed effects follow the advice in Bluhm and Krause (2018) on how to mitigate the measurement error. All our night-lights data come from one satellite only, so we do not need to worry about heterogeneity and potentially idiosyncratic measurement error that stems from using data from different satellites and which Bluhm and Krause (2018) correct for with dummy variables for each satellite. Gillespie et al. (2014) show that the evidence from night-lights data in Aceh and North Sumatra after the tsunami is consistent with evidence from a large-scale longitudinal household survey. Given these recent findings, we use night-lights data, but only where we have to, namely at the sub-district level for the estimation of a dose-response relationship. Our main analysis and all our robustness tests are at the district level where we use GDP data. Our results will show that the dynamics of the tsunami’s impact are strikingly similar in qualitative terms at both levels of the analysis with the two different measures of economic activity. This is consistent with the findings on night-lights activity reported in Gillespie et al. (2014) though their analysis only extends to 2008 and does not employ causal identification techniques.

### Exogenous impact measures from flooding data

To create exogenous measures of whether a district has been affected and, in a second step, by how much it has been affected, we employ satellite data on inundation from the tsunami. We 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). They were produced in the weeks after the disaster and capture satellite information from 1-5 days after the tsunami struck.[[5]](#footnote-5) The equivalent of about 34 percent of the Acehnese shoreline, in total 600 km, was flooded by the 2004 Indian Ocean tsunami. The total area destroyed was 120,295 ha, where about 1/5th was settlement, and 1/3rd was agricultural land (Shofiyati et al, 2005).

In a first step, we use the flood maps to establish a treatment dummy – a district was flooded or not – see map 2. In a second step, we use two plausibly exogenous measures of the intensity by which an area was impacted upon by the tsunami: (i) the share of the physical area of a sub-district that was flooded; (ii) the population that could have hypothetically been affected by flooding as a share of the total population within a sub-district. We compute the latter by matching the tsunami flood maps with fine-grained population density maps in the year 2000 (any changes to the population distribution between 2000 and 2004 introduce some small measurement error).[[6]](#footnote-6)

The population density grid I used had a resolution of approximately five km2 (CIESIN, Columbia University, 2005)."

**Map 2: Inundation areas of the 2004 Indian Ocean tsunami in the Aceh province**

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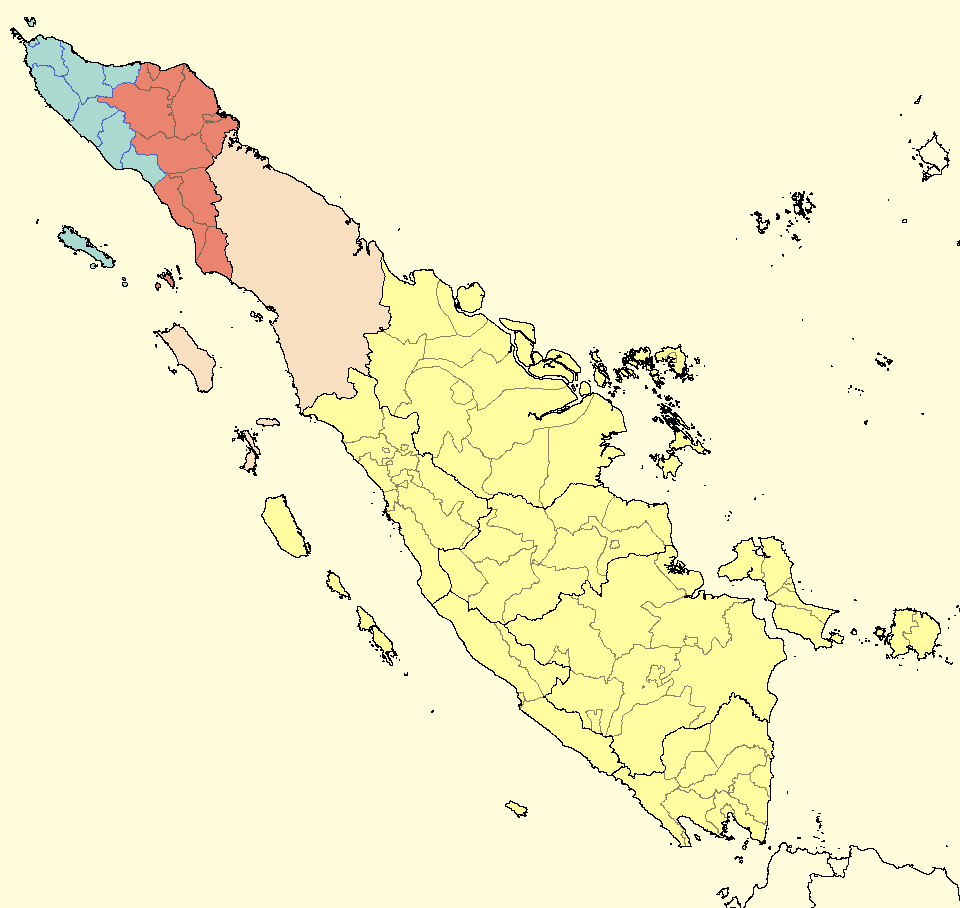
Note: Flooded areas according to maps from German Remote Sensing Data Center & the Dartmouth Flood Observatory. Spectral differences between land area before the tsunami struck (on the same day) and the week after the tsunami had flooded areas, were used to determine the areas that were flooded The Aceh province has 23 districts, of which 10 were flooded and 13 were not. The above map does not show the two island districts of Simeulue and Aceh Singkil that were also flooded.

### Causal identification techniques

For causal identification, we predominantly use difference-in-differences regression. Map 3 shows that 10 districts in Aceh were flooded by the tsunami, whereas the remaining 13 districts of the province were not flooded and can therefore serve as the pool of counterfactual districts. Even though North Sumatra was also affected by the tsunami, for the main analysis we exclude this province that is adjacent to Aceh (province marked in light orange in map 3). The reason is that there were only two districts flooded in North Sumatra, both barrier island districts, which were much more difficult to reach in the reconstruction effort. Nevertheless, in a robustness check, we include North Sumatra.

Using only counterfactual districts from Aceh itself helps in controlling for unobserved heterogeneity since this province is quite different from the rest of Sumatra. Most notably, the province was waging a secessionist war against the central government of Indonesia for 29 years prior to the tsunami, resulting in 15,000 casualties. Moreover, Aceh is more religiously and culturally conservative and has become more so since 2004. Nevertheless, to ensure that our results are not driven by choosing a particular pool of counterfactual control districts, we also employ a second pool of counterfactuals from the remainder of Sumatra’s districts, composed of 76 districts, depicted in yellow in map 3. A third pool of counterfactual districts that we use in our main analysis is the combined set of the first and second pool.

**Map 3: Composition of treatment group and various control groups on the island of Sumatra**

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13

10

76

Note: The 10 blue districts indicate the tsunami flood treated districts of Aceh. The 13 red districts are the counterfactual districts from Aceh. The 76 yellow districts are another set of counterfactual districts from the remainder of the Sumatra Island. North Sumatra districts (light orange area) were not included in the main analysis, but were included in robustness tests.

Formally, there are two groups of districts, those hit by the tsunami (treated districts; D = 1) and those that were not (control districts; D = 0). There are two main periods in our dataset, pre- and post-disaster, with the pre-disaster period ranging from the years 1999 – 2004 and the post-disaster period 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 *Ydi(t)*, where *i* denotes the district, *d* signals whether the district has been treated or not, and *t* is 0 for the pre- and 1 for the post-disaster period. *Y*, our measure of economic activity, is proxied by district level GDP data in a first step and by sub-district level night-lights data in a second step. The estimate of interest is the average treatment effect on the treated (ATET):

The estimate is obtained by difference-in-differences computation, which computes the difference of economic activity between treatment and control groups:

However, in practical terms we disaggregate the treatment period into specific sub-periods, estimating separate treatment effects, and we also estimate a coefficient for the pre-treatment period of 2003 and 2004 as a test for the parallel historic paths assumption. The timeline of aid flows is important for our analysis. Aid totalled USD 7.7 billion. By the end of 2005 about 80 percent of the funds were disbursed (Kweifio-Okai, 2014) and aid was officially completed in early 2009 (Henderson & Lee, 2015; and Masyrafah & McKeon, 2008).[[7]](#footnote-7) We therefore estimate the following equation with district- and year-fixed effects and standard errors adjusted for panel-specific serial correlation within units and for contemporaneous spatial autocorrelation across units up to a distance of 100km (Conley 1999 & 2008; Hsiang 2010):

In estimating equation (1), should not be statistically significant if the parallel historic paths assumption is correct.[[8]](#footnote-8) The coefficientcaptures the direct damaging impact of the tsunami in the year 2005 and should therefore be negative and statistically significant. The aid-fuelled reconstruction period of 2006 to 2008 is captured by the coefficient . Whilst one would expect the coefficient to be positive and statistically significant, its size will determine what kind of recovery there has been. If the cumulative economic benefits over the period 2006 to 2008 are smaller than the economic loss in 2005, then an overall negative impact prevails. By contrast, if the cumulative economic outcome is about the same size as the immediate impact loss, then we see recovery to trend. If the cumulative economic performance of 2006 and 2008 more than compensates for the loss in 2005, then there is evidence of a net positive economic effect in the aftermath of the disaster. With aid flows drying up in 2008, the coefficient tests whether the growth performance collapsed as a consequence, or whether the recovery was sustained.

In a robustness test (as well as for the analysis of structural economic change in a later section), we also employ the synthetic control method for causal inference as an alternative to our difference-in-differences estimation for the estimations with GDP data at the district level, following Abadie and Gardeazabal (2003) and Abadie, Diamond, and Hainmueller (2010, 2014). With this alternative identification technique, one does not choose a discrete set of control group districts. Instead, the synthetic control method is designed to produce a single synthetic comparator, which best mimics the aggregate treated (i.e. flooded) region in its pre-treatment characteristics. The method constructs a weighted combination from districts in the control group, based on pre-specified characteristics, to which the average of the treatment group is then compared. As Kaul et al (2015) and Botosaru & Ferman (2017) show, adding co-variates to the set of pre-specified characteristics on top of the pre-treatment outcome measures is not necessary. We obtain almost the same Root Mean Squared Prediction Error (RMSPE) with and without co-variates,[[9]](#footnote-9) which is why we report results based on using pre-treatment outcomes only, following the parsimony criterion and also the recommendations in Botosaru & Ferman (2017).

# Results

Figure 2 displays the mean GDP dynamics of the treated group with the mean dynamics of two control groups, namely non-flooded districts once within Aceh and once from the rest of Sumatra. The figure is consistent with the parallel historic paths assumption, which allows the inference that the treatment group is indeed comparable to the counterfactuals, as they perform historically similarly in the years leading up to the disaster. Following the natural disaster the parallel historic paths are ruptured and significant deviations occur. The trends in group mean GDP tentatively suggest that, not surprisingly, flooded districts had a lower output in 2005 and, more importantly, a higher output after 2005 than their non-flooded counterfactuals, but this will be tested more formally below together with the parallel historic paths assumption. The vertical black dashed line in figure 2 indicates the year by which most aid had been spent. Figure 2 suggests that Aceh’s stunning economic recovery was sustained and that Aceh reached a higher output path without falling back to the GDP trend of its counter-factual comparison groups.

**Figure 2: GDP dynamics in Aceh’s flooded districts compared to counterfactuals**

tsunami

most aid spent

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Note: Blue line represents average of flooded districts (n=10). Red line represents average of non-flooded counterfactual districts within Aceh (n=13), yellow line depicts counterfactuals from the rest of Sumatra (n=76). GDP measures are normalized to the year 2004. The vertical blue line indicates when the disaster struck and the vertical black line depicts when aid flows dried up.

Table 2 presents three sets of results from estimating equation (1) for the three different sets of counterfactuals. The coefficient for the period of lead years, 2003 and 2004, is statistically insignificant and small suggesting that the parallel historic paths assumption holds and that the two groups – flooded and non-flooded – are indeed comparable. With the tsunami striking the shores of Aceh on 25 December 2004, the negative effect shows in the following year. In 2005, the districts affected by the tsunami displayed an average growth rate that was between, depending on the choice of counterfactuals, 8.1 and 8.6 percentage points lower than it would have been, had the tsunami not occurred. In the recovery period of 2006 to 2008 the GDP in flooded districts of Aceh jumped up by between 3 and 6.3 percentage points per annum compared to the non-flooded counterfactuals, allowing the flooded districts to make up over the course of three years for much in excess of the foregone GDP in the year prior. There is no evidence of a contractionary spiral after aid has stopped. The positive if statistically insignificant and relatively small coefficients for the period covering the years 2009 to 2012 imply that the recovery from the 2006 to 2008 period was sustainable. The total growth advantage over the period 2006 to 2012 amounts to between 9.6 and 23.7 percentage points, depending on the counterfactual, as compared to relative losses of between 8.1 and 8.6 percentage points in 2005. In sum, more so than just making up for lost output, the strong growth of the recovery period propelled the affected local economies onto a higher output path (consistent with what was already tentatively suggested by figure 2). This analysis is relative to a counterfactual of non-affected districts. If we look at growth performance in affected districts in absolute terms, their growth increases from an average of 3.4 percent per annum over the period 2001 to 2004 to on average of 7.3 percent per annum over the period 2006 to 2012.

Reverting back to the growth analysis relative to non-affected districts, the output gain of flooded over non-flooded districts holds no matter what the set of counterfactual non-flooded districts. The advantage is less pronounced when comparing the flooded districts to non-flooded districts within Aceh only, rather than non-flooded districts in the rest of Sumatra. Specifically, while the flooded districts of Aceh grew by 6.3 percentage points faster per annum during the recovery period of 2006 to 2008 compared to the non-flooded districts of the rest of Sumatra, they only grew by 3 percentage points per annum faster compared to the non-flooded districts of Aceh. This discrepancy may be explained by small positive spill-over effects from the reconstruction efforts in flooded districts spilling over into neighbouring non-flooded districts. However, since such spill-over effects work against our central finding and we find positive economic effects of treated units over their counterfactuals despite these spill-over effects, this violation of the stable unit treatment value assumption (SUTVA) does not threaten the inferential validity of our finding. Also, we will demonstrate further below in a robustness test that any positive spill-over effect is not strong enough for non-flooded districts neighbouring flooded districts to experience a statistically significant growth advantage over other, i.e. non-neighbouring, non-flooded districts (see table 8 below).

**Table 2: The effect of the tsunami on district-level GDP over the different phases of the tsunami**

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  |  |  |  |  |  |  |  |  |  |  |
| Treated group: | Tsunami affected districts (blue) in Aceh | | | | | | | | | |
|  | Sumatra control districts (red & yellow) | | |  | Non-Aceh control districts (yellow) | | |  | Aceh non-flooded control districts (red) | |
| Control group: |  |  |
|  |  |  |
| Dep. Var.: Annual GDP growth rate |  |  |  |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |  |  |
| Pre-tsunami dummy (2003-04) | 0.0204 |  |  |  | 0.0205 |  |  |  | 0.0201 |  |
|  | (0.0129) |  |  |  | (0.0134) |  |  |  | (0.0121) |  |
| Tsunami dummy (2005) | -0.0818\*\*\* |  |  |  | -0.0810\*\*\* |  |  |  | -0.0864\*\*\* |  |
|  | (0.0279) |  |  |  | (0.0280) |  |  |  | (0.0285) |  |
| Tsunami dummy (2006-08) | 0.0589\*\* |  |  |  | 0.0634\*\* |  |  |  | 0.0302\*\* |  |
|  | (0.0250) |  |  |  | (0.0267) |  |  |  | (0.0137) |  |
| Tsunami dummy (2009-12) | 0.0101 |  |  |  | 0.0116 |  |  |  | 0.00131 |  |
|  | (0.0100) |  |  |  | (0.0109) |  |  |  | (0.00697) |  |
|  |  |  |  |  |  |  |  |  |  |  |
| Year FE | Yes |  |  |  | Yes |  |  |  | Yes |  |
| District FE | Yes |  |  |  | Yes |  |  |  | Yes |  |
| Observations | 1,283 |  |  |  | 1,118 |  |  |  | 295 |  |
| R-squared | 0.52 |  |  |  | 0.51 |  |  |  | 0.67 |  |

Note: Colour labels refer to map 3. Each column reports results from separate OLS regressions. Standard errors adjusted for panel-specific serial correction, heteroscedasticity and contemporaneous spatial correlation in parentheses. \*, \*\*, \*\*\* statistically significant at the 10, 5 and 1 percent level.

We now turn to accounting for variation in the severity of the tsunami impact (i.e. “the flooding dose”) and estimate *ATET(DOSE)*, the average treatment effect given the level of exposure to the flooding. Since we need more variation than is possible at the district level we go one administrative level further down to the sub-district (Kecamatan) level. The counterfactual comparator group for these sets of estimations are non-flooded sub-districts within Aceh. Because there are no GDP figures available for this level, we use night-lights as a proxy for economic activity. Errors are clustered on sub-districts, which accounts for serial correlation and heteroscedasticity.[[10]](#footnote-10)

Results are presented in table 3. Looking at either measure of tsunami intensity confirms the growth advantage of flooded areas using the simple tsunami dummy, and also the timing associated with the effects. As before, the time placebo test for the parallel historic paths assumption for the period 2003 and 2004 does not suggest a statistically significant difference between the later-on flooded and non-affected districts before the tsunami. In the immediate aftermath of the tsunami, in the year 2005, the flooded Kecamatans’ luminosity decreased relative to non-flooded sub-districts though note that this effect is not statistically significant for the share of flooded area as intensity measure. During the recovery period, luminosity increased statistically significantly more in flooded sub-districts than in their counterfactual comparators and the size of the estimated effect, which is the increase per annum, suggests a recovery well beyond compensating for the immediate loss in 2005. In the post-recovery period, the estimated coefficients are now negative (they were positive for GDP growth) but they are statistically insignificant and substantively small.

**Table 3: The effect of tsunami intensity on sub-district level night-lights over the different phases of the tsunami**

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  |  |  |  |  |  |  |  |  |  |
| Dep. Var.: Annual night-lights growth rate |  | Share of population flooded |  |  |  | Share of area flooded |  |  |  |
|  |  |  |  |  |  |  |  |  |  |
| Pre-tsunami intensity (2003-04) |  | 0.00498 |  |  |  | 0.462 |  |  |  |
|  |  | (0.00398) |  |  |  | (0.377) |  |  |  |
| Tsunami intensity (2005) |  | -0.00765\* |  |  |  | -0.663 |  |  |  |
|  |  | (0.00415) |  |  |  | (0.437) |  |  |  |
| Tsunami intensity (2006-08) |  | 0.0160\*\*\* |  |  |  | 1.752\*\*\* |  |  |  |
|  |  | (0.00261) |  |  |  | (0.228) |  |  |  |
| Tsunami intensity (2009-12) |  | -0.00207 |  |  |  | -0.192 |  |  |  |
|  |  | (0.00159) |  |  |  | (0.159) |  |  |  |
|  |  |  |  |  |  |  |  |  |  |
| Year FE |  | Yes |  |  |  | Yes |  |  |  |
| Sub-district FE |  | Yes |  |  |  | Yes |  |  |  |
| Observations |  | 3,444 |  |  |  | 3,444 |  |  |  |
| R-squared |  | 0.08 |  |  |  | 0.08 |  |  |  |

Note: Standard errors clustered on sub-districts in parentheses. \*, \*\*, \*\*\* statistically significant at the 10, 5 and 1 percent level.

To investigate whether the growth advantage in treated sub-districts holds at all levels of damage, we estimate separate regressions for each quintile of the flooding intensity distribution. For ease of exposition, we aggregate to the entire post-tsunami period, thus giving us an estimate at which quintile of the flooding intensity distribution was there a growth advantage over non-flooded sub-districts over the period 2005 to 2012 as a whole. Table 4 shows that only the most heavily hit sub-districts had a statistically significant growth advantage in the recovery period. The coefficients for the other four quintiles are statistically insignificant with either measure of tsunami intensity. This result suggests that the previously reported average effects are really due to effects in the most heavily hit sub-districts.

**Table 4: The effect of tsunami intensity on sub-district level night-lights at quintiles of intensity**

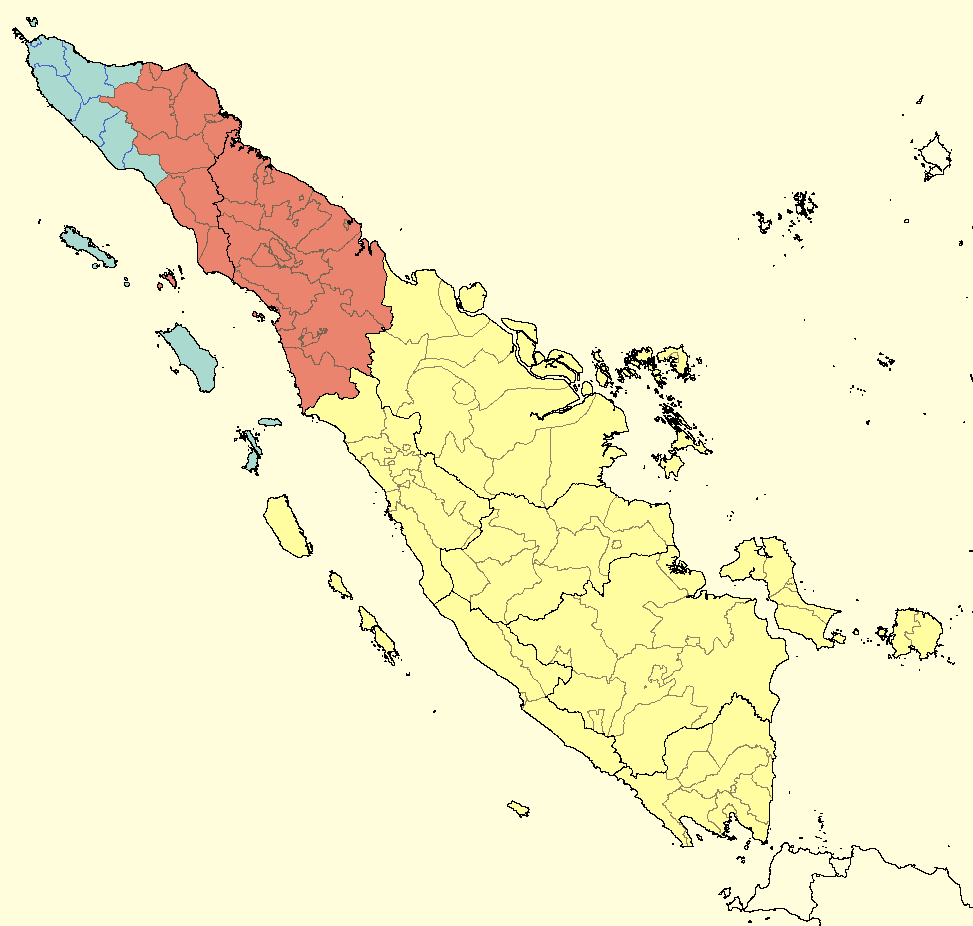
|  |  |  |
| --- | --- | --- |
|  |  |  |
| Dep. Var.: Annual night-lights growth rate | Share of population flooded | Share of area flooded |
|  |  |  |
| Tsunami dummy (2005-12) first quintile | 0.0909 | -0.205 |
|  | (0.304) | (0.302) |
| Tsunami dummy (2005-12) second quintile | 0.140 | 0.0596 |
|  | (0.273) | (0.301) |
| Tsunami dummy (2005-12) third quintile | 0.214 | 0.0812 |
|  | (0.228) | (0.180) |
| Tsunami dummy (2005-12) fourth quintile | -0.305 | -0.0246 |
|  | (0.230) | (0.266) |
| Tsunami dummy (2005-12) fifth quintile | 0.379\*\*\* | 0.349\*\*\* |
|  | (0.0852) | (0.0862) |
|  |  |  |
| Year FE | Yes | Yes |
| Sub-district FE | Yes | Yes |
| Observations | 3,444 | 3,444 |
| R-squared | 0.07 | 0.07 |

Note: Standard errors clustered on sub-districts in parentheses. \*, \*\*, \*\*\* statistically significant at the 10, 5 and 1 percent level.

# Robustness Tests and Threats to Inferential Validity

In this section, we submit our findings to a number of robustness checks. First, we also included the districts of North Sumatra (see map 4). For this analysis there are now 12 (blue) districts flooded by the tsunami in the treatment group and 37 (red) districts in the first control group of non-flooded districts within Aceh and North Sumatra. A second control group is composed of 76 non-affected (yellow) districts consisting of districts from the remainder of unaffected Sumatra districts, excluding the Aceh and North Sumatra provinces. As before, a third control group consists of the combined set of the first two control groups.

**Map 4: Including North Sumatra: Composition of treatment and control group**

******

12

76

37

Note: The two tsunami stricken districts of North Sumatra are the island districts of Pulau Nias and Pulau Tanahbala.

Table 5 demonstrates that our main results are robust to this expanded sample of both treated and non-treated districts.

**Table 5. Robustness test: including North Sumatra**

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  |  |  |  |  | |  | |  |  | |  | |  |  | |  |
| Treated group: |  | Tsunami affected districts (blue) in Aceh & North Sumatra | | | | | | | | | | | | |
|  |  | All Sumatra control districts (red & yellow) | | |  | | Rest of Sumatra control districts (yellow) | | |  | | Aceh & North Sumatra control districts (red) | | |
| Control group: |  |  | |  | |
|  |  |  | |  | |
| Dependent Variable: GDP growth rate |  |  |  |  | |  | |  |  | |  | |  |  | |  |
|  |  |  |  |  | |  | |  |  | |  | |  |  | |  |
| Pre-tsunami dummy (2003-04) |  | 0.0157 |  |  | |  | | 0.0138 |  | |  | |  | 0.0196 | |  |
|  |  | (0.0169) |  |  | |  | | (0.0178) |  | |  | |  | (0.0185) | |  |
| Tsunami dummy (2005) |  | -0.0816\*\*\* |  |  | |  | | -0.0873\*\*\* |  | |  | |  | -0.0698\*\* | |  |
|  |  | (0.0300) |  |  | |  | | (0.0303) |  | |  | |  | (0.0304) | |  |
| Tsunami dummy (2006-08) |  | 0.0493\* |  |  | |  | | 0.0454\* |  | |  | |  | 0.0573\* | |  |
|  |  | (0.0269) |  |  | |  | | (0.0256) |  | |  | |  | (0.0316) | |  |
| Tsunami dummy (2009-12) |  | -0.0209 |  |  | |  | | -0.0259 |  | |  | |  | -0.0108 | |  |
|  |  | (0.0251) |  |  | |  | | (0.0257) |  | |  | |  | (0.0253) | |  |
|  |  |  |  |  | |  | |  |  | |  | |  |  | |  |
| Year FE |  | Yes |  |  | |  | | Yes |  | |  | |  | Yes | |  |
| District FE |  | Yes |  |  | |  | | Yes |  | |  | |  | Yes | |  |
| Observations |  | 1,621 |  |  | |  | | 1,144 |  | |  | |  | 633 | |  |
| R-squared |  | 0.34 |  |  | |  | | 0.41 |  | |  | |  | 0.23 | |  |

Note: District level. Colour labels refer to map 4. Each column reports results from separate OLS regression. Standard errors adjusted for panel-specific serial correction and contemporaneous spatial correlation and heteroscedasticity in parentheses. \*, \*\*, \*\*\* statistically significant at the 10, 5 and 1 percent level.

A potential concern about the inferential validity of our findings is that inland districts do not make appropriate counterfactual candidates for the treated districts, which are exclusively located along the coast. Inland districts are different in many ways from coastal districts (e.g. less likely to be engaged in fishing and less likely to draw tourists). This may introduce unobserved heterogeneity, despite having shown similar parallel historic paths of the flooded and non-flooded districts. In a robustness test we dropped all inland districts from the counterfactual pool. As table 6 shows, results are very similar. The one difference is the recovery effect during the 2006 to 2008 period in the third set of estimations, in which non-flooded coastal districts from Aceh only are the comparator groups. This coefficient is now almost identical to the coefficients for the other control groups, whereas it was lower before. This suggests that any positive spill-over effect from treated to non-treated districts occurred for non-treated inland rather than coastal districts.

**Table 6. Robustness test: dropping inland districts.**

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  |  |  |  |  |  |  |  |  |  |  |
| Treated group: | Tsunami affected districts (blue) in Aceh | | | | | | | | | |
|  | Sumatra control districts (red & yellow) | | |  | Non-Aceh control districts (yellow) | | |  | Aceh non-flooded control districts (red) | |
| Control group: |  |  |
|  |  |  |
| Dep. Var.: Annual GDP growth rate |  |  |  |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |  |  |
| Pre-tsunami dummy (2003-04) | 0.0192 |  |  |  | 0.0201 |  |  |  | 0.0144 |  |
|  | (0.0136) |  |  |  | (0.0147) |  |  |  | (0.0101) |  |
| Tsunami dummy (2005) | -0.0818\*\*\* |  |  |  | -0.0828\*\*\* |  |  |  | -0.0754\*\* |  |
|  | (0.0284) |  |  |  | (0.0284) |  |  |  | (0.0301) |  |
| Tsunami dummy (2006-08) | 0.0599\*\* |  |  |  | 0.0625\*\* |  |  |  | 0.0443\*\*\* |  |
|  | (0.0243) |  |  |  | (0.0252) |  |  |  | (0.0158) |  |
| Tsunami dummy (2009-12) | 0.0108 |  |  |  | 0.0125 |  |  |  | 0.00225 |  |
|  | (0.0108) |  |  |  | (0.0120) |  |  |  | (0.00681) |  |
|  |  |  |  |  |  |  |  |  |  |  |
| Year FE | Yes |  |  |  | Yes |  |  |  | Yes |  |
| District FE | Yes |  |  |  | Yes |  |  |  | Yes |  |
| Observations | 945 |  |  |  | 819 |  |  |  | 256 |  |
| R-squared | 0.50 |  |  |  | 0.48 |  |  |  | 0.68 |  |

Note: District level. Colour labels refer to map 3. Each column reports results from separate OLS regression. Standard errors adjusted for panel-specific serial correction and contemporaneous spatial correlation and heteroscedasticity in parentheses. \*, \*\*, \*\*\* statistically significant at the 10, 5 and 1 percent level.

**Cities versus rural districts**

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 more remote districts were hard to reach because the tsunami destroyed much of the infrastructure. Other cities, if to a lesser extent, similarly benefited from early aid. We therefore tested whether there are differences in how the 2 flooded city districts (the so-called *Kotas*) in Aceh recovered from the tsunami, compared to how the 8 flooded rural districts (*Kabupatens*) in Aceh did.[[11]](#footnote-11) The city district estimations has 3 non-flooded city districts within Aceh and 18 non-flooded city districts in the rest of Sumatra as control groups, whereas the rural district estimations has 10 non-flooded rural districts within Aceh and 58 non-flooded rural districts in the rest of Sumatra as control groups.

Table 7 demonstrates that the average growth trend in affected city districts was indeed quite different from the one in rural districts. To start with, not surprisingly given the damage to the agricultural sector caused by the tsunami, rural districts experienced a much stronger contraction in 2005 than flooded city districts did, namely between -9.8 and -10.1 percentage points as opposed to between -1.4 and -3 percentage points, which is much lower and also statistically insignificant in two out of three estimations, namely for the counterfactual pools that include non-Aceh districts. Flooded city districts have then also taken off much more strongly than flooded rural districts. Flooded city districts saw average annual growth rates between 9.4 and 13.9 percentage points above non-flooded city districts. In contrast, at between 4 and 4.5 percentage points higher average annual growth rates than their non-flooded rural districts over the period 2006 to 2008 (if only Aceh serves as counterfactual, the coefficient is much smaller still and also statistically insignificant), the treatment effect was up to a factor of about 3 lower in flooded rural districts as opposed to flooded city districts. Thus, the effect of tsunami flooding on rural districts was quite different following a more gradual increase in GDP post-tsunami. Depending on the counter-factual pool, at best, rural districts recovered approximately to trend or just a bit above it; at worst, they never fully recovered from the exogenous shock. Note, however, that the estimations for rural districts have to be treated with great caution. For the first time, two out of three estimations suggest a violation of the parallel historic paths assumption, which would invalidate the difference-in-differences estimation. For rural flooded districts, we therefore cannot rule out the possibility that some of the post-tsunami growth advantage over rural non-flooded districts may stem from unaccounted for factors that give flooded rural districts a general growth advantage over non-flooded rural districts entirely independently of the tsunami and the post-tsunami reconstruction efforts.

**Subsamples of the data: dropping one flooded district at a time and stratified samples**

Similar to Hsiang and Jina (2014), we have also tested the robustness of our results toward other subsamples, specifically toward dropping one of the ten flooded districts at a time and toward stratifying the data by per capita income and economic size (control districts from all of Sumatra). We find that the growth loss in the year 2005 is somewhat sensitive to the inclusion of the district of Aceh Bidie, without which it is reduced from 8.2 to 4.1 percentage points. However, the annual growth advantage over the period 2006 to 2008 is very stable across subsamples, ranging from a low of 5.0 percentage points to a high of 6.6 percentage points. If we stratify by per capita income in 2004, we find that the 5 poorest flooded districts saw no statistically significant relative loss in 2005 and at 7.1 percentage points enjoyed a greater growth advantage over non-flooded districts during 2006 to 2008 than the 5 richest flooded districts did at 4.7 percentage points. Stratifying by economic size in 2004, we find that the 5 smallest flooded districts experienced a greater loss in 2005 and also experienced a smaller growth advantage during 2006 to 2008 than the 5 largest flooded districts (4.8 versus 6.9 percentage points). With the exception mentioned above, all relevant coefficients are always statistically significant. (Detailed results not shown for reasons of space.)

**Table 7. Robustness test: City districts versus rural districts**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Treated group: | Tsunami affected districts (blue) in Aceh | | | | |  |
| Type of districts: | City districts | |  | Rural districts | |  |
| Control group: | Sumatra control districts (red & yellow) | Non-Aceh districts (yellow) | Aceh non-flooded control districts (red) | Sumatra control districts (red & yellow) | Non-Aceh districts (yellow) | Aceh non-flooded control districts (red) |
| Dep. Var.: Annual GDP growth rate |  |  |  |  |  |  |
|  |  |  |  |  |  |  |
| Pre-tsunami dummy (2003-04) | 0.00667 | 0.00751 | 0.000770 | 0.0240\* | 0.0240 | 0.0244\* |
|  | (0.00843) | (0.00929) | (0.00815) | (0.0142) | (0.0148) | (0.0136) |
| Tsunami dummy (2005) | -0.0153 | -0.0135 | -0.0298\*\*\* | -0.0984\*\*\* | -0.0979\*\*\* | -0.101\*\*\* |
|  | (0.00955) | (0.0103) | (0.00721) | (0.0293) | (0.0292) | (0.0304) |
| Tsunami dummy (2006-08) | 0.134\* | 0.139\* | 0.0938\* | 0.0399\*\* | 0.0445\*\* | 0.0134 |
|  | (0.0783) | (0.0779) | (0.0486) | (0.0186) | (0.0210) | (0.0103) |
| Tsunami dummy (2009-12) | -0.00171 | -0.000400 | -0.00955 | 0.0134 | 0.0150 | 0.00432 |
|  | (0.00823) | (0.00910) | (0.00732) | (0.00977) | (0.0109) | (0.00616) |
|  |  |  |  |  |  |  |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| District FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 295 | 260 | 61 | 988 | 858 | 234 |
| R-squared | 0.80 | 0.80 | 0.83 | 0.46 | 0.45 | 0.66 |

Note: District level. Colour labels refer to map 3. Each column reports results from separate OLS regression. Standard errors adjusted for panel-specific serial correction and contemporaneous spatial correlation and heteroscedasticity in parentheses. \*, \*\*, \*\*\* statistically significant at the 10, 5 and 1 percent level.

**Synthetic control results**

The results from the difference-in-differences analysis are robust to employing a close methodological alternative, the synthetic control method. We constructed a synthetic twin to the average of flooded districts drawing from the pool of all non-flooded districts from Sumatra. Figure 3 shows that not surprisingly the pre-tsunami growth path of the treated Aceh district average and its synthetic control counterpart are practically identical. This is of course what synthetic control is all about. Importantly, the post-tsunami growth path of the flooded districts rises above the growth path of its synthetic control counterfactual and sustains this growth advantage until the end period.

**Figure 3: Trends in district average GDP: synthetic control method**

most aid spent

tsunami

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Note: Average GDP of 10 affected districts versus synthetic control consisting of weighted average of 72 comparator districts outside of Aceh.

**Threats to inferential validity**

We now discuss five potential threats to the inferential validity of our analysis, namely diversion of economic resources from non-treated to treated units in the form of aid, economic spill-over effects, survival of the fittest individuals, migration between districts, and market pricing of former volunteer work.

Did the treated units gain a growth advantage over non-treated units because economic resources were diverted away from the latter to help the former in the wake of the tsunami in the form of domestic aid? Whilst the clear majority of aid for reconstruction came from abroad, about one third came from the Government of Indonesia (Masyrafah and McKeon 2008: 20). However, there is no evidence that would suggest that the Indonesian government aid was financed by reallocating money away from non-affected districts within the island of Sumatra, let alone non-affected districts within Aceh. We can therefore exclude the possibility that the growth advantage of affected districts within Aceh over non-affected districts within Aceh or non-affected districts within Sumatra was caused by reallocation of financial resources from non-affected to affected districts.

Economic spill-over effects from treated to non-treated units bias the estimation of treatment effects since they violate the stable unit treatment value assumption (SUTVA). In principle, spill-over effects could go in either direction: reconstruction efforts could positively spill-over into neighbouring non-treated units or, conversely, economic activity could be drawn away from non-treated units. We will formally test for statistically significant spill-over effects further below after discussing survival of the fittest individuals and migration.

Could it be that economic activity per capita was boosted because the people that were killed were less productive than those that survived? If the population loss was in turn made up by other people migrating into flooded areas, then this could explain higher GDP growth. As Neumayer and Plümper (2007: 551) point out: “Natural disasters do not affect people equally”, which prompts a careful look into the composition of casualties. Evidence seems to suggest that survival of the economically fittest is unlikely to have been an issue in this particular disaster. For example, there was no difference in survival rates across socio-economic attributes (Frankenberg et al, 2011). In addition, 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 in the sense that richer people were more likely to survive than poorer people. However, not surprisingly, children and the elderly were more likely to die than working-age adults (Frankenberg et al, 2011) and, all other things equal, this boosts GDP per capita. The effect on GDP, rather than GDP per capita, will largely depend on inward migration making up for loss of population, to which we turn next.

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. On the one hand, there is internal displacement, where people escape from the hazard and its repercussions and move away from the affected district. On the other hand, people also move towards the flooded area to seek the job opportunities created there in the wake of reconstruction. Both demographic shifts would also call into question the Stable Unit Treatment Value Assumption.

Internal displacement is unlikely to pose a major inferential threat because most of the approximately 67,000 displaced households from the tsunami moved to different villages within their districts (World Bank, 2007). About two-thirds of them were sheltered by their family and friends (World Bank, 2008) 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. According to one source, 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 had returned to their villages (World Bank, 2007).

By contrast, voluntary labour migration has been much more significant. Aceh lost almost 10 percent of its population from direct disaster casualties but its population grew by roughly the same over the course of the three recovery years after 2005, which is well above the historic population growth in Aceh. There has therefore been some net migration into Aceh and particularly into affected districts of Aceh in the wake of the reconstruction efforts. However, Aceh’s total population was not much higher in 2008 than before the tsunami, excluding the possibility that the growth in GDP was simply due to growth in population.

What about the effect of out-migration from non-affected counterfactual districts? Their GDP performance will be negatively affected by out-migration due to the loss of people. Yet, it is important to note most of the labour migrants came from the province of North Sumatra that borders the province of Aceh. Since our results hold even if our only counterfactuals are from the remainder of Sumatra (without non-flooded districts in either Aceh or North Sumatra), our results are robust to this potential inferential threat.

We offer two tests to explore whether economic and migration spill-over concerns together with changes in population composition threaten the inferential validity of our findings. Firstly, if compositional changes in the population structure in flooded districts due to the disproportionate loss of children and the elderly coupled with inward migration of economically productive people are the main drivers behind the finding that affected districts outperform their counterfactuals in terms of growth in GDP, then one would expect the growth advantage of treated districts over their counterfactuals to be much stronger in GDP per capita terms than in GDP terms. Table 8 replicates the estimations for table 2 but in per capita terms. If all of Sumatra’s non-affected districts serve as counterfactuals, then the growth advantage during the 2006 to 2008 period is 7.8 percent in GDP per capita terms, whereas it was 5.9 percent in GDP terms. With only non-Aceh non-affected districts as counterfactuals, the relevant figures are 8.7 percent in per capita and 6.3 percent in total GDP terms. If only non-flooded districts within Aceh serve as counterfactuals, then there is no statistically significant growth advantage in per capita terms and in any case the point estimate of 2.4 percent in per capita terms is below the statistically significant growth advantage in GDP terms of 3 percent.[[12]](#footnote-12) We infer from these findings that compositional changes in the population of affected districts coupled with inward migration of economically productive individuals from other parts of Sumatra have contributed to the growth advantage of flooded districts in Aceh. However, the differences between the growth advantage in GDP per capita as opposed to GDP terms are too small in absolute terms that these two combined potential confounders can be the only driver behind our main estimation results. The growth advantage point estimates are also not statistically significantly different from each other as running seemingly unrelated regression of growth in both GDP and GDP per capita reveals.

**Table 8: The effect of the tsunami on district-level GDP per capita over the different phases of the tsunami**

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  |  |  |  |  |  |  |  |  |  |  |
| Treated group: | Tsunami affected districts (blue) in Aceh | | | | | | | | | |
|  | Sumatra control districts (red & yellow) | | |  | Non-Aceh control districts (yellow) | | |  | Aceh non-flooded control districts (red) | |
| Control group: |  |  |
|  |  |  |
| Dep. Var.: Annual GDP  per capita growth rate |  |  |  |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |  |  |
| Pre-tsunami dummy (2003-04) | 0.0516 |  |  |  | 0.0618 |  |  |  | -0.0109 |  |
|  | (0.0477) |  |  |  | (0.0513) |  |  |  | (0.0210) |  |
| Tsunami dummy (2005) | 0.0146 |  |  |  | 0.0200 |  |  |  | -0.0185 |  |
|  | (0.0321) |  |  |  | (0.0324) |  |  |  | (0.0325) |  |
| Tsunami dummy (2006-08) | 0.0782\*\*\* |  |  |  | 0.0871\*\*\* |  |  |  | 0.0239 |  |
|  | (0.0298) |  |  |  | (0.0315) |  |  |  | (0.0182) |  |
| Tsunami dummy (2009-12) | 0.0257 |  |  |  | 0.0312 |  |  |  | -0.00630 |  |
|  | (0.0185) |  |  |  | (0.0194) |  |  |  | (0.0148) |  |
|  |  |  |  |  |  |  |  |  |  |  |
| Year FE | Yes |  |  |  | Yes |  |  |  | Yes |  |
| District FE | Yes |  |  |  | Yes |  |  |  | Yes |  |
| Observations | 1,283 |  |  |  | 1,118 |  |  |  | 295 |  |
| R-squared | 0.25 |  |  |  | 0.25 |  |  |  | 0.35 |  |

Note: Colour labels refer to map 3. Each column reports results from separate OLS regressions. Standard errors adjusted for panel-specific serial correction, heteroscedasticity and contemporaneous spatial correlation in parentheses. \*, \*\*, \*\*\* statistically significant at the 10, 5 and 1 percent level.

As a second formal test, we employ a placebo-type difference-in-differences analysis in which we drop the districts that were actually flooded from the analysis and instead make their geographical neighbours the placebo treated units. Table 9 provides the results where non-neighbouring districts only in Aceh and North Sumatra (first column) or in the entire island of Sumatra (second column) function as the counterfactual pool of non-treated districts.[[13]](#footnote-13) Contrary to districts that were actually flooded by the tsunami, we do not find statistically significant growth differences between districts that neighbour flooded districts (the placebo treated units) and the counter-factual pool of non-neighbouring non-flooded districts whether those come from Aceh and North Sumatra only or the entire Sumatra. This suggests that spill-over effects are unlikely to invalidate our findings.

**Table 9. Robustness test: placebo test making districts neighbouring districts affected by the tsunami the placebo treated group**

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  |  |  |  |  | |  | |  |  | |  | |  | |  |  |
| Placebo treated group: |  | Neighbours of tsunami affected districts in Aceh & North Sumatra | | | | | | | | | | | |
|  |  | All Sumatra control districts | | |  | | Only Aceh & North Sumatra control districts | | |  | |  | |
| Control group: |  |  | |  | |
|  |  |  | |  | |
| Dependent Variable: GDP growth rate |  |  |  |  | |  | |  |  | |  | |
|  |  |  |  |  | |  | |  |  | |  | |
| Pre-tsunami dummy (2003-04) |  | -0.00633 |  |  | |  | | -0.00267 |  | |  | |
|  |  | (0.0143) |  |  | |  | | (0.0163) |  | |  | |
| Tsunami dummy (2005) |  | -0.00236 |  |  | |  | | 0.0134 |  | |  | |
|  |  | (0.0101) |  |  | |  | | (0.00895) |  | |  | |
| Tsunami dummy (2006-08) |  | 0.0122 |  |  | |  | | 0.0265 |  | |  | |
|  |  | (0.0270) |  |  | |  | | (0.0264) |  | |  | |
| Tsunami dummy (2009-12) |  | 0.00264 |  |  | |  | | 0.0172 |  | |  | |
|  |  | (0.0120) |  |  | |  | | (0.0131) |  | |  | |
|  |  |  |  |  | |  | |  |  | |  | |
| Year FE |  | Yes |  |  | |  | | Yes |  | |  | |
| District FE |  | Yes |  |  | |  | | Yes |  | |  | |
| Observations |  | 1,465 |  |  | |  | | 477 |  | |  | |
| R-squared |  | 0.37 |  |  | |  | | 0.23 |  | |  | |

Note: District level. Each column reports results from separate OLS regression. Standard errors adjusted for panel-specific serial correction and contemporaneous spatial correlation and heteroscedasticity in parentheses. \*, \*\*, \*\*\* statistically significant at the 10, 5 and 1 percent level.

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, 2017). This public service is not remunerated. The volunteer labour system has its roots in Islamic tradition, dates back to the ancient sultanates and is referred to as “gotong royong.” Lamb (2014) suggests 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”, making people reluctant to help their neighbours unless they received cash in return. Crowding out of altruistic motives through price incentives is a topic that has received considerable attention in behavioural economics (see e.g. Frey and Oberholzer-Gee, 1997). By pricing what was formerly not priced in the market, GDP could also have been boosted, biasing the before and after comparison. However, looking at boat aid, Freire, Henderson and Kuncoro (2017) find the opposite to crowding out. Specifically, the more aid people received the more likely they were willing to give back and work for the community. Granted boat aid is not cash-for-work aid, so it is unclear whether the Freire, Henderson and Kuncora (2017) result holds more generally. But even if there were some crowding-out effects, any plausible effect size is much too small to invalidate our inference that flooded districts grew faster after the tsunami than their counterfactuals.

Axbard (2016) points to another way in which informal economic activity, specifically piracy, can become formalized in that he shows that the extent of piracy is strongly determined by economic opportunities for fishermen. Piracy attacks did indeed decrease after 2005, that is, at the same time as the reconstruction effort starts. However, as Figure 2 of Axbard (2016) shows, the major hot spots of piracy are outside Banda Aceh and almost no piracy attacks happened close to affected districts within this province. We can therefore also exclude the possibility that this particular shift from informal to formal economic activity confounds our results.

# The tsunami’s effect on structural economic change

In this section, we briefly explore the economic transformation and structural change resulting from the tsunami and the ensuing aid and reconstruction effort. Economic development is typically associated with structural change out of agriculture and possibly manufacturing toward services. Hence, one would expect to find evidence of this kind of structural change in Aceh. Using the synthetic control method introduced in section 4 above and employing the same INDO-DAPOER dataset as before, but at the province-level since for GDP sub-components no data exist at the district-level, we demonstrate that the flooded districts in Aceh experienced a faster structural change out of agriculture and, to some extent, out of manufacturing (though from a very low level) and into services than occurred in the synthetic counter-factual. Simultaneously, we find a stronger and sustained increase in capital formation in Aceh compared to its synthetic counter-factual. This is important as economists typically worry that short-run investment booms after disaster are followed by long-run depressed capital formation (Noy 2009; Hsiang and Jina 2014).

Figure 4 exhibits a drastic fall in the agricultural share in GDP in the treated unit, the province of Aceh, relative to its counterfactual, the synthetically created non-treated unit from the remainder of Sumatra. Agricultural value added is almost stationary in both treated and non-treated units before the tsunami. Had Aceh followed its counterfactual comparator post-tsunami, it would have slowly structurally transformed and reduced the agricultural sector share by about 2 percentage points, as indicated by the dashed line, arriving at a share of agriculture of the economy of 43 percent by 2012. Instead, Aceh in fact arrived at 32 percent. The tsunami thus caused an extra-reduction of the share of agriculture of 11 percentage points by 2012. 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.

**Figure 4: Agricultural share of GDP trends: Aceh versus synthetic Aceh**



Manufacturing in Aceh has always been a small sector, accounting for about 6 percent of provincial GDP prior to 2004, which contrasts to the national average of about 22 percent. As figure 5 demonstrates, the tsunami accelerated the slow historical decline in manufacturing value added evolution. Judged by the counterfactual synthetic control unit, Aceh’s manufacturing share of GDP would have been about 5 percent by 2012. Instead, it fell to 3.5 percent.

**Figure 5: Manufacturing share of GDP trends: Aceh versus synthetic Aceh**



Figure 6 demonstrates a sharp increase in the services sector share of the economy in Aceh relative to the synthetic control unit. It rose from about 40 percent of economic activity before the tsunami to almost 55 percent in 2012. In the absence of the tsunami, the services sector would have also grown, but at a much slower pace, to about 42 percent as indicated by the counterfactual synthetic control unit. The tsunami thus triggered an additional increase of 13 percentage points in the services sector share. The services sector absorbed most of the displaced economic activity from agriculture. As with the agricultural share, most of the drastic departure from the counterfactual occurs in the years 2005 to 2008, after which it seems to move again in parallel to the counterfactual trajectory.

**Figure 6: Service share of GDP trends: Aceh versus synthetic Aceh**



As figure 7 demonstrates, Aceh experienced a hike in capital formation rates in 2005 and 2006 relative to the counter-factual synthetic control unit. An investment bonanza followed the tsunami destruction in an effort to rebuild the destroyed capital of the province. The wedge between the solid line (Aceh) and the dashed line (the synthetic control unit) represents the total extra investment per capita in Aceh in the years following the tsunami.[[14]](#footnote-14) Investments 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. After this peak, the gap between the flooded and the counterfactual groups continued to narrow to an extra investment of about USD 30 per person in 2012.

**Figure 7: Capital formation per capita (in current USD) trends in Aceh versus synthetic Aceh**



During the reconstruction and investment bonanza, around 140,000 new houses, 1,700 schools, and 1,000 government buildings were constructed (BRR, 2009). According to the INDO-DAPOER dataset, Aceh had almost 1,500 more schools (an increase of about one quarter) and almost twice as many hospitals than before the tsunami; from less than 30 to almost 60. These improvements in physical infrastructure went hand in hand with eventual improvements in social and human development at the end period of our study, after deterioration during the first few years in the aftermath of the tsunami. For example, the percentage of households with access to electricity went up from 84 to 97 percent, the number of doctors increased from 820 to 1,361, the number of midwives increased from 4,475 to 7,046, which increased the percentage of births attended by a skilled health worker from 82 to 92 percent. As an overall measure, the human development index rose from 69 to 73.

In terms of transport infrastructure, 36 airports and seaports and 3,700 km of roads were built by 2008 (BRR, 2009). Not all of the new roads were asphalted but while before the tsunami, the length of all asphalted roads in Aceh added up to 7,100 km, by 2008 the length had reached 9,500 km. 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.

Importantly, much of the physical capital was not simply re-built as before but built back better, i.e. to a higher standard than before. The rebuilt houses for example have improved standards employing cement, which was formerly dedicated only for richer houses and mosques (Steinberg & Schmidt 2010). The roads were rebuilt employing better asphalt, they are wider and are further away from the coastline (Jha et al., 2010). Granted, however, not all construction was productivity enhancing: some of the reconstruction was into white elephant projects that now stand empty (Lamb, 2014).

# Conclusion

Can a concerted and very large scale aid and reconstruction effort ever turn a devastating natural disaster into an opportunity such that economic output is higher in its aftermath, as compared to a scenario where the disaster did not happen? If there is one case where the odds for this to have happened are high, it is the Indonesian province of Aceh, which experienced the single largest reconstruction effort to ever benefit a region in the developing world hit by natural disaster. The sudden influx of foreign aid was not only of sizeable magnitude but also administered relatively efficiently. Employing sub-national measures of economic activity using difference-in-difference methods, and exploiting a quasi-experiment allowing for causal identification, we have shown that the human intervention following the tsunami triggered higher long-term economic development in afflicted districts and sub-districts than in their non-affected counterfactual counterparts. Note that due to the relatively small share of affected districts’ GDP in relation to Indonesia’s total GDP, had we analysed the impact of the tsunami and reconstruction effort with aggregate national GDP data, as the vast majority of existing studies do, we would have found no statistically significant effects. As discussed in the Introduction, national level data are simply too coarse to tease out the economic effects of localised natural disasters in large countries.

Whilst it cannot compensate for the loss of life or the lasting non-economic damage caused on well-being, particularly that of traumatised people and their children (Cas et al. 2014; Caruso and Miller 2015; Frankenberg et al. 2017), our findings do paint a very positive picture in economic growth terms. The tsunami was only growth depressing in the first year following the disaster. During the subsequent recovery years, growth was considerably boosted by the reconstruction effort. Importantly, economic output did not contract relative to the counterfactual growth path when the aid funds dried up in 2008. The post-disaster experience has therefore been of the “sustainable recovery beyond counterfactual trend” type rather than one of the other four stylized trajectories discussed in the Introduction.

What can be learned from Aceh’s experience and to what extent, if any, can this experience be generalized to other potential natural disaster events with devastating impact in the developing world? One contributing factor was a change in the composition of the population with some of the children and elderly killed during the tsunami being replaced by economically more productive adults who migrated to Aceh and partly replaced the population loss. However, as we discussed in section 5, this cannot have been the only driver of the economic success story. No successful “sustainable recovery beyond counterfactual trend” reconstruction after such a devastating disaster would have been possible without massive amounts of predominantly foreign aid that was well coordinated and dispersed. Whilst we have no direct counterfactual, it seems extremely plausible that without this massive, concerted and well organised aid effort, the havoc from the tsunami could not have been converted into an economic success story. This implies that small amounts of aid or large amounts of aid that are badly dispersed due to uncoordinated donor competition or incompetent and corrupt aid management are unlikely to result in a replication of Aceh’s success story. At the same time, we warn against viewing Aceh’s success as evidence that large-scale aid-fuelled ‘big push’ development ideas (e.g., Sachs 2005) can work. Helping a region to recover and, as was the case for Aceh, more than recover from an exogenous shock that made it very significantly poorer overnight is very different from lifting poor people or a poor region onto a higher economic development path they had never enjoyed before for, presumably, endogenous reasons that are difficult to modify.

Aceh additionally benefited from a violent separatist conflict ceasing abruptly in the wake of the tsunami. Even though, as mentioned in the Introduction, this cannot be the cause of the long-term economic growth advantage enjoyed by the areas hit by the tsunami over their counterfactuals in which the waves did not make landfall, conflict cessation certainly facilitated the reconstruction effort in the region, which would have been rendered very difficult and perhaps impossible had the conflict instead escalated further. There is some evidence that natural disasters tend to raise the risk of violent conflict (Nel and Righarts 2008), which stands in stark contrast to what happened in this region, and a lesson learnt from Aceh’s success story is that reconstruction has the best chances of success if peace is maintained or restored.

In sum, our analysis demonstrates that whether a disaster depresses or stimulates long-term economic development is ultimately subject to human choice, political willingness to bring peace and the effective use of large-scale foreign aid as the contrast between Aceh and Haiti in the wake of the 2010 earthquake demonstrates. Major natural disasters will always wreak havoc in the short run but they need not leave an economic disaster in their aftermath.

# References

Abadie, A. and Gardeazabal, J., 2003. The economic costs of conflict: A case study of the Basque Country. *American economic review*, *93*(1), pp.113-132.

Abadie, A., Diamond, A. and Hainmueller, J., 2010. Synthetic control methods for comparative case studies: Estimating the effect of California’s tobacco control program. *Journal of the American statistical Association*, *105*(490), pp.493-505.

Addison, D. M. & B. P. Stewart (2015). “Nighttime Lights Revisited: The Use of Nighttime Lights Data as a Proxy for Economic Variables.” Policy Research Working Paper 7496. The World Bank, Washington, D. C.

Anttila-Hughes, J. K. & S. M. Hsiang (2011). “Destruction, Disinvestment, and Death: Economic and Human Losses Following Environmental Disaster.” Working paper. Columbia University and Princeton University.

Axbard, S. (2016). “Income Opportunities and Sea Piracy in Indonesia: Evidence from Satellite Data.” *American Economic Journal: Applied Economics*, 8(2): 154-94.

Baez, J., A. de la Fuente & I.V. Santos (2010). “Do Natural Disasters Affect Human Capital? An Assessment Based on Existing Empirical Evidence.” IZA (Institute for the Study of Labor), Discussion Paper No. 5164.

Benson, C. & E. Clay (1998). “Developing Countries and the Economic Impacts of Natural Disasters.” In: *Managing Disaster Risk in Emerging Economies*. Eds. A. Kreimer and M. Arnold, p. 11-21.

Benson, C. & E. Clay (2004). “Understanding the Economic and Financial Impacts of Natural Disasters.” Disaster Risk Management Series, No. 4. IBRD/WB (International Bank for Reconstruction and Development), The World Bank, Washington, D.C.

Bertinelli, L. & E. Strobl (2013). “Quantifying the Local Economic Growth Impact of Hurricane Strikes: An Analysis from Outer Space for the Caribbean.” *Journal of Applied Meteorology and Climatology*, 52: 1688–1697.

Bluhm, R., & M. Krause (2018). “Top Lights. Bright Cities and their Contribution to Economic Development”. Working Paper #2018-041. Maastricht University and UNU-MERIT.

Botosaru, I., & B. Ferman (2017). “On the Role of Covariates in the Synthetic Control Method.” MIPRA Paper No. 81940.

BRR (Reconstruction and Rehabilitation Agency). (2006). “Aceh and Nias: Two Years after the tsunami.” Progress Report.

BRR (Reconstruction and Rehabilitation Agency). (2009). “10 Management Lessons for Host Governments Coordinating Post-Disaster Reconstruction.” <http://www.recoveryplatform.org/assets/publication/BRR%2010%20Management%20Lessons%20for%20Host%20Governments.pdf>

Burke, M. B., E. Miguel, S. Satyanath, J. A. Dykema & D. B. Lobell (2009). “Warming Increases the Risk of Civil War in Africa.” *Proceedings of the National Academy of Sciences*, 106 (49): 20670-20674.

Burton, M.L. and Hicks, M.J., 2005. Hurricane Katrina: preliminary estimates of commercial and public sector damages. *Marshall University: Center for Business and Economic Research*.

Carter, M., P. D. Little, T. Mogues & W. Negatu (2007). “Poverty Traps and Natural Disasters in Ethiopia and Honduras.” [*World Development*](http://econpapers.repec.org/article/eeewdevel/), 35 (5): 835-856.

Caruso, G. and Miller, S. 2015. “Long run effects and intergenerational transmission of natural disasters: A case study on the 1970 Ancash Earthquake.” *Journal of Development Economics*, 117: 134-150.

Cas, A.G., Frankenberg, E., Suriastini, W. and Thomas, D. (2014). “The impact of parental death on child well-being: evidence from the Indian Ocean tsunami.” *Demography*, 51 (2): 437-457.

Cavallo, E. & I. Noy (2011). “Natural Disasters and the Economy — A Survey.” *International Review of Environmental and Resource Economics*, 5 (1): 63-10

Cavallo, E., S. Galiani, I. Noy & J. Pantano (2013). “[Catastrophic Natural Disasters and Economic Growth.](https://sites.google.com/a/eduardocavallo.com/www/SSRN_version.pdf?attredirects=0)” *Review of Economics and Statistics*, [95 (5): 1549-1561](http://www.mitpressjournals.org/doi/abs/10.1162/REST_a_00413).

Chen, X. and Nordhaus, W.D., 2011. Using luminosity data as a proxy for economic statistics. *Proceedings of the National Academy of Sciences*, *108*(21), pp.8589-8594.

Conley, T.G. (1999). “GMM Estimation with Cross Sectional Dependence.” *Journal of Econometrics*, 92 (1): 1–45.

Conley, T.G. (2008). "Spatial Econometrics." *The New Palgrave Dictionary of Economics*. Second Edition. M. Palgrave.

Cuaresma, J.C., J. Hlouskova & M. Obersteiner (2008). “Natural Disasters as Creative Destruction? Evidence from Developing Countries.” *Economic Inquiry*, 46 (2): 214-226.

duPont, W., I. Noy, Y.Okuyama, & Y. Sawada (2015). “The Long-Run Socio-Economioc Consequences of a Large Disaster: The 1995 Earthquake in Kobe.” *PLoS ONE* 10(10)

Fengler, W., A. Ihsan & K. Kaiser (2008). “Managing Post-Disaster Reconstruction Finance – International Experience in Public Financial Management.” The World Bank, Washington, D.C.

Fomby, T., Y. Ikeda & N. Loayza (2009). “The Growth Aftermath of Natural Disasters.” World Bank Policy Research Working Paper 500. Washington, D.C.

Frankenberg, E., Friedman, J., Ingwersen, N. and Thomas, D. (2017). “Linear child growth after a natural disaster: a longitudinal study of the effects of the 2004 Indian Ocean tsunami.” *The Lancet* 389: S21.

Frankenberg, E., T. Gillespie, M. Braughton, A.M. Cooke, T. Armenta & D. Thomas (2009). “Assessment of Natural Hazard Damage and Reconstruction: A Case Study from Banda Aceh, Indonesia.” California Centre for Population Research No. 001-09. University of California, USA.

Frankenberg, E., T. Gillespie, S. Preston, B. Sikoki & D. Thomas (2011). “Mortality, the Family and the Indian Ocean Tsunami.” Economic Journal, 121 (554): F162–182.

Freeman, P. K., L. A. Martin, R. Mechler, K. Warne & P. Hausmann (2002). “Catastrophes and Development. Integrating Natural Catastrophes into Development Planning.” The World Bank, Washington, D.C.

Freire, T., J.V. Henderson & A. Kuncoro (2017). “Volunteerism After the Tsunami: The Effects of Democratization.” *World Bank Economic Review*, 31 (1): 176-195.

Frey, B.S. and Oberholzer-Gee, F., 1997. The cost of price incentives: An empirical analysis of motivation crowding-out. *American economic review*, *87*(4), pp.746-755.

Gignoux, J. and Menéndez, M. (2016). “Benefit in the wake of disaster: Long-run effects of earthquakes on welfare in rural Indonesia.” *Journal of Development Economics*, 118: 26-44.

Gillespie, T.W., Frankenberg, E., Fung Chum, K. and Thomas, D. (2014). “Night-time lights time series of tsunami damage, recovery, and economic metrics in Sumatra, Indonesia.” *Remote Sensing Letters*, 5 (3): 286-294.

Hallegatte, S. & P. Dumas (2009). “Can Natural Disasters have Positive Consequences? Investigating the Role of Embodied Technical Change.” *Ecological Economics*, 68 (3): 777–786.

Heger, M., A. Julca & O. Paddison (2009). “Vulnerability in Small-Island Economies: The Impact of “Natural” Disasters in the Caribbean.” In: *Vulnerability in Developing Countries*. Eds. W. Naude, A. U. Santos-Paulino & M. McGillvray. United Nations University, New York.

Henderson, J. V., A. Storeygard & D. N. Weil (2012). “Measuring Economic Growth from Outer Space.” *American Economic Review*, 102 (2): 994-1028.

Henderson, J.V. & Yong Suk Lee, 2015. "[Organization of Disaster Aid Delivery: Spending Your Donations](https://ideas.repec.org/a/ucp/ecdecc/doi10.1086-681277.html)." [*Economic Development and Cultural Change*](https://ideas.repec.org/s/ucp/ecdecc.html), 63(4): 617-664.

[Hochrainer-Stigler, S](http://www.iiasa.ac.at/search/publication.php?authors=Hochrainer-Stigler,S.)., R. B. Sharma, R., Mechler (2012). “Disaster Microinsurance for Pro-poor Risk Management: Evidence from South Asia.” *Journal of Integrated Disaster Risk Management*, 2 (2): 70-88.

Horwich, G. (2000). “Economic Lessons of the Kobe Earthquake.” *Economic Development and Cultural Change*, 48 (3): 521-54

Hsiang, S. M. & J. A. S. Jina (2014). “The Causal Effect of Environmental Catastrophe on Long run Economic Growth: Evidence from 6,700 Cyclones.” NBER Working Paper No. 2035

Hsiang, S. M. (2010). “Temperatures and Cyclones Strongly Associated with Economic Production in the Caribbean and Central America.” *Proceedings of the National Academy of Sciences*, 107 (35): 15367–1537

Hsiang, S. M., K. C. Meng & M. A. Cane (2011). “Civil Conflicts are Associated with the Global Climate.” *Nature*, 476 (7361): 438–441.

Hugo, G., 2008. *Migration, development and environment*. Geneva: International Organization for Migration.

Jha, A. K., J. D. Barenstein, P. M. Phelps, D. Pittet, S. Sena (2010). *Safer Homes, Stronger Communities A Handbook for Reconstructing after Natural Disasters*. World Bank, Washington D.C.

Kahn, M. (2005). The Death Toll from Natural Disasters: The Role of Income, Geography, and Institutions. [*Review of Economics and Statistics*](http://econpapers.repec.org/article/tprrestat/), 87 (2), 271-284.

Kaul, A., S. Kloessner, G. Pfeifer, and M. Schieler (2015). Synthetic Control Methods: Never Use All Pre-Intervention Outcomes Together With Covariates. Working Paper. University of Saarland.

Kohl, P. A., A. P. O’Rourke, D. L. Schidman, W. A. Dopkin & M. L. Birnbaum (2005). “The Sumatra-Andaman Earthquake and tsunami of 2004: The Hazards, Events and Damage.” *Prehospital and Disaster Medicine*, 20 (6): 357-58; 361.

Kousky, C., Michel-Kerjan, E.O. and Raschky, P. (2013). Does federal disaster assistance crowd out private demand for insurance. Risk Management and Decision Processes Center. The Wharton School, University of Pennsylvania, Working Paper #2013-10.

Kunreuther, H., R. Meyer & C. Van den Bulte (2004). “Risk Analysis for Extreme Events: Economic Incentives for Reducing Future Losses.” NIST GCR 04-871. Gaithersburg, MD: National Institute of Standards and Technology, U.S. Department of Commerce.

Kweifio-Okai, C (2014). “Where did the Indian Ocean Tsunami Aid Go?” The Guardian 25 December 2014. <https://www.theguardian.com/global-development/2014/dec/25/where-did-indian-ocean-tsunami-aid-money-go>

Lamb, K. (2014). “Banda Aceh: where community spirit has gone but peace has lasted.” The Guardian 27 January 2014. <https://www.theguardian.com/cities/2014/jan/27/banda-aceh-community-spirit-peace-indonesia-tsunami>

[Linnerooth-Bayer](http://www.tandfonline.com/author/Linnerooth-Bayer%2C+J), J. & [R. Mechler](http://www.tandfonline.com/author/Mechler%2C+R) (2007). “Disaster Safety Nets for Developing Countries: Extending public—private partnerships.” *Environmental Hazards*, [7](http://www.tandfonline.com/loi/tenh20?open=7#vol_7) ([1](http://www.tandfonline.com/toc/tenh20/7/1)): 54-61.

[Linnerooth-Bayer, J](http://www.iiasa.ac.at/search/publication.php?authors=Linnerooth-Bayer,J.)., R. Mechler & S. Hochrainer-Stiegler (2011). “Insurance Against Losses from Natural Disasters in Developing Countries: Evidence, Gaps and the Way Forward.” *Journal of Integrated Disaster Risk Management*, 1(1): 59-81.

Loayza, N., V. E. Olaberría, J. Rigolini & L. Christiaensen (2012). “[Natural Disasters and Growth: Going Beyond the Averages](https://ideas.repec.org/a/eee/wdevel/v40y2012i7p1317-1336.html).” [*World Development*](https://ideas.repec.org/s/eee/wdevel.html), 40(7): 1317-1336.

Lynham, J., I. Noy, and J. Pager (2017). “The 1960 Tsunami in Hawaii: Long-Term Consequences of a Coastal Disaster.” *World Development*, 94, 106-118.

Masyrafah, H. & J. M. McKeon (2008). “Post-tsunami Aid Effectiveness in Aceh: Proliferation and Coordination in Reconstruction.” Brookings, Wolfensohn Center for Development Working Papers, No.6.

[Mechler, R](http://www.iiasa.ac.at/search/publication.php?authors=Mechler,R.). (2009). “Disasters and Economic Welfare: Can National Savings Explain Post-disaster Changes in Consumption?” Policy Research Working Paper Series No. 4988, The World Bank, Washington, D. C.

Michalopoulos, S. & E. Papaioannou (2011). “Divide and Rule or the Rule of the Divided? Evidence from Africa.” NBER Working Paper No. 17184.

Monecke, K., W. Finger, D. Klarer, W. Kongko, B. G. McAdo, A. L. Moore & S. U. Sudrajat (2008). “A 1000-year Sediment Record of tsunami Recurrence in Northern Sumatra.” *Nature*, 455: 1232–1234.

Nazara, S. and Resosudarmo, B.P., 2007. *Aceh-Nias reconstruction and rehabilitation: Progress and challenges at the end of 2006* (No. 70). ADB Institute Discussion Papers.

Nel, P. & M. Righarts (2008). “Natural disasters and the risk of violent civil conflict.” *International Studies Quarterly*, 52(1): 159-185.

Neumayer, E. & T. Plümper (2007). “The gendered nature of natural disasters: The impact of catastrophic events on the gender gap in life expectancy, 1981–2002.” *Annals of the Association of American Geographers*, 97(3): 551-566.

Noy, I & A Nualsri (2008). “[Fiscal storms: public spending and revenues in the aftermath of natural disasters](https://scholar.google.com/citations?view_op=view_citation&hl=en&user=CYSYIlUAAAAJ&citation_for_view=CYSYIlUAAAAJ:LkGwnXOMwfcC).” *Environment and Development Economics* 16 (1): 113-128.

Noy, I. (2009). “The Macroeconomic Consequences of disasters.” *Journal of Development Economics*, 88: 221–231.

Paxson, C. H. (1992). “Using Weather Variability to Estimate the Response of Savings to Transitory Income in Thailand.” *American Economic Review*, 82 (1): 15-34.

Ramakrishnan D., S. Ghosh, V. Raja, R. Vinuchandran & A. Jeyram (2005). “Trails of the Killer tsunami: A Preliminary Assessment Using Satellite Remote Sensing and GIS Techniques.” *Current Science*, 88(5):709–71

Sachs, J. (2005). *The end of poverty: How we can make it happen in our lifetime*. Penguin UK.

Schonhardt, S. (2014). “What Aceh Got Right Rebuilding from the 2004 tsunami.” The Wall Street Journal 18 December 2014*.* <http://blogs.wsj.com/indonesiarealtime/2014/12/18/what-aceh-got-right-rebuilding-from-the-2004-tsunami/>

Shofiyati, R., R. D. Dimyati, A. Kristijono & Wahyunto (2005). “Tsunami Effect in Nanggroe Aceh Darussalam and North Sumatra Provinces, Indonesia.” *Asian Journal of Geoinformatics*, 5: 100–111.

Skidmore, M. & H. Toya (2002). “Do Natural Disasters Promote Long run Growth?” *Economic Inquiry*, 40 (4): 664-687.

Steinberg, F. & P. Smidt (2010) *Rebuilding Lives and Homes in Aceh and Nias*. Indonesia Urban Development Series. Manila: Asian Development Bank.

Strobl, E. (2011). “The Economic Growth Impact of Hurricanes: Evidence from U.S. Coastal Counties.” *Review of Economics and Statistics*, 93 (2): 575-589.

Strobl, E. (2012). “The economic growth impact of natural disasters in developing countries: Evidence from hurricane strikes in the Central American and Caribbean regions.” *Journal of Development Economics*, 97 (1): 130-141.

Umitsu, M., C. Tanavud & B. Patanakanog (2007). “Effects of Landforms on tsunami Flow in the Plains of Banda Aceh, Indonesia, and Nam Khem, Thailand.” *Marine Geology*, 242: 141-153.

USAID (United States Agency for International Development). (2014). “Lessons Learned a Decade after the Indian Ocean tsunami.” <http://blog.usaid.gov/2014/12/lessons-learned-a-decade-after-the-indian-ocean-tsunami/>.

Weidmann, N.B., and S. Schutte (2016). Using night light emissions for the prediction of local wealth. *Journal of Peace Research*. Vol 54, Issue 2, pp. 125 - 140

World Bank (2005). “Indonesia: Preliminary Damage and Loss Assessment, The December 26, 2004 Natural Disaster.

World Bank (2007). “2006 Village Survey in Aceh: an Assessment of Village Infrastructure and Social Condition.” The World Bank, Washington, D.C., USA.

World Bank (2008). “Understanding Poverty in Aceh.” The World Bank, Washington, D.C., USA.

World Bank (2009). “Aceh Growth Diagnostic: Identifying the Binding Constraints to Growth in a Post-Conflict and Post-Disaster Environment.” The World Bank, Washington, D.C., USA.

1. The first papers to investigate the disaster-growth nexus with sub-national data were Strobl (2011, 2012) and Bertinelli & Strobl (2013) [↑](#footnote-ref-1)
2. 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, which is about 100 percent of the annual GDP of Mississippi and about 150 percent that of Louisiana, the two most affected states. Whilst representing a massive loss for the two affected states, the US national economy as a whole was barely affected (Cashel & Labonte, 2005). [↑](#footnote-ref-2)
3. For a more in-depth documentation of the dataset, see <http://data.worldbank.org/data-catalog/indonesia-database-for-policy-and-economic-research>. We set growth rates in the non-flooded Aceh district of Subulussalam to missing over the period 2003 to 2006. The GDP figures recorded in INDO-DAPOER are evidently unreliable during this period, likely on account of administrative changes. Our findings are, however, robust to including the recorded growth rates in Subulussalam over this period (results not shown). [↑](#footnote-ref-3)
4. 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), Henderson et al (2012) and Addison and Stewart (2015). Arcseconds of 30x30 correspond to roughly an area of 0.86 km2 if squared at the equator. [↑](#footnote-ref-4)
5. 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. [↑](#footnote-ref-5)
6. In the absence of representative survey and census data at the Kecamatan level, which would have allowed the computation of population measures at this level, 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 downscaled to the 1 km resolution level using night-lights (NL) data. We are not concerned that this biases our results since the population estimates only draw on the spatial distribution of NL in pre-treatment times.

    "The population density grid I used had a resolution of approximately five km2 (CIESIN, Columbia University, 2005)."

   "(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 subnational administrative maps, so that I can express the people flooded as a share of those living within each Kecamatan boundary."

   Here with this footnote:

   "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 indicatorThe population density grid I used had a resolution of approximately five km2 (CIESIN, Columbia University, 2005)." [↑](#footnote-ref-6)
7. Unfortunately, we know of no data source that reliably geo-codes the spatial distribution of the aid. [↑](#footnote-ref-7)
8. The choice of two years for the pre-treatment period is somewhat arbitrary. Results are robust to choosing longer periods. [↑](#footnote-ref-8)
9. These additional covariates are the sectoral value added measures, population size, poverty rates, doctors per 1,000 people, as well as water and sanitation access, all measured before the treatment in 2005. [↑](#footnote-ref-9)
10. Unfortunately, we cannot employ standard errors adjusted for contemporaneous spatial correlation following Hsiang (2010) with night-lights data as the dependent variable since not all estimations converge. [↑](#footnote-ref-10)
11. Both the Kota (city), as well as the Kabupaten (regency) are second-level administrative subdivisions in Indonesia. Each have their own local government and legislative body. Population size and density, the economy and other demographic factors determines whether Indonesia regards a district as a Kota or Kabupaten. [↑](#footnote-ref-11)
12. Note that contrary to GDP, there is no statistically significant loss in GDP per capita in 2005 in affected districts. This is of course because the substantial loss in GDP was accompanied by an equally substantial loss in population. [↑](#footnote-ref-12)
13. We cannot restrict the counter-factual pool to non-neighbouring districts in Aceh only as there are too few of these. [↑](#footnote-ref-13)
14. 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 effect. [↑](#footnote-ref-14)