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Abstract

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Keywords: Difference-in-differences, Indian Ocean tsunami, bank lending, Thailand
JEL Classification: G21, G28

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1. Introduction

Bank credit is the predominant source of finance to firms and households in developing countries. Disruptions to the flow of bank credit are likely to affect the ease with which firms and households can access finance, and ultimately lead to detrimental effects on the real economy.

In this paper, we exploit the 2004 Indian Ocean tsunami as a natural setting to examine how negative shocks affect aggregate bank lending in a developing country. The Indian Ocean tsunami provides an interesting laboratory to explore the impact of an exogenous shock on bank credit supply. Unlike many so-called exogenous shocks (such as changes in monetary policy) which take time to affect the financial system and real economy and can be anticipated, the impact of a tsunami on economic and environmental conditions is sudden and unexpected. As such a tsunami represents an exogenous shock such that any subsequent observed changes in bank credit supply are caused by the shock and not coincident changes in other relevant economic variables. Furthermore, unlike other natural disasters (such as hurricanes) which arise from seasonal patterns in weather conditions, tsunamis in the Indian Ocean are extremely rare and strike without warning.

A priori it is not clear how aggregate bank lending might respond in face of a large and significant exogenous weather shock. On the one hand, aggregate bank lending may decline after a shock as the resultant damage caused by the severe weather event exposes banks' balance sheets to unexpected losses arising from a decline in the value of collateral and the economic prospects of households and firms in affected areas. This reduces banks' capacity to assume more risk via increased lending. Aggregate lending may then decline in affected areas as banks move funds to finance projects in geographic areas unaffected by the weather shock, where borrowers' prospects and collateral values are more predictable. On the other hand, aggregate lending may increase after a severe weather event in response to an increase in credit demand by borrowers requiring increased funding for reconstructing and repairing properties (Cortés and Strahan, 2015). Aggregate bank lending in affected areas may then increase as banks strive to support creditworthy borrowers and protect existing bank-borrower relationships. In addition, banks may act as conduits to channel government funds to support firms and households in areas affected by the severe weather event.

The effects of a severe weather event on bank lending may also vary between severely and mildly affected geographic areas. Firms and households in mildly affected areas suffer less following a shock. Bank lending portfolios and risk-taking capacity in these areas are only slightly affected. As a result, aggregate bank lending is likely to decrease by a smaller amount in mildly affected relative to severely affected geographic areas. By contrast, aggregate lending may change dramatically in severely affected areas because of higher credit demand of firms and households or because of the inability of banks to continue lending in the face of increased pressure on balance sheets.

We examine the effects of the Indian Ocean Tsunami on aggregate bank lending using data from the Bank of Thailand. The data comprises monthly information on selected items of commercial bank balance sheets at aggregated level in 75 provinces. From the Office of the Board of Investment, we collect monthly data on the number and value of corporate investment projects (a proxy of credit demand) approved by Thai Board of Investment. We test three main hypotheses. The first hypothesis contends that following the tsunami, aggregate bank lending declines in affected provinces. The second hypothesis contends that following the tsunami, aggregate lending in severely affected provinces declines more significantly than in the mildly affected provinces. Finally, the third hypothesis contends that following the tsunami there is a lasting impact on aggregate bank lending.

In order to test these hypotheses, we use the difference-in-differences estimator. This method does not require data at individual bank level, and is relatively simple to employ using aggregate data. Furthermore, this approach avoids many of the endogeneity issues that are present when comparing heterogeneous entities because unobserved time-constant effects to the outcome have been eliminated through differencing (Bertrand et al., 2004). Therefore, it is valuable for evaluating causal effects. The difference-in-differences estimator is appropriate when a shock produces an immediate effect on the outcome variable of interest. This is the case for the 2004 Indian Ocean tsunami event used in the present study.

The results of the empirical analysis suggest that following the 2004 Indian Ocean Tsunami, aggregate bank lending declines in affected Thai provinces compared to unaffected counterparts. In monetary terms, bank credit supply in the affected provinces declines by more than THB150 million in the 12-month period after the tsunami on average. Within affected provinces, aggregate bank lending in severely affected provinces declines more significantly compared to mildly affected counterparts. The tsunami appears to have a longer term negative effect on aggregate bank lending, with the most severe impact observed three months after the event (when a decline of THB1200 million is observed for the severely affected against the unaffected group). This impact lasts long and dissipates over a 20-month period.

We contribute to two strands of the literature which investigate the impact of exogenous shocks on bank credit supply. First, we provide evidence on the impact of a rare disaster on aggregate bank lending in a setting where banks act as the primary source of financing for firms and households. Previous studies show that shocks to aggregate bank lending have a significant impact on economic growth (Peek et al., 2003) and firm investment (Amiti and Weinstein, 2013; Chava and Purnanandam, 2011). We argue that many shocks to aggregate credit supply explored in the literature thus far are not strictly exogenous since, to some degree, these shocks could be anticipated. We show that a rare natural disaster can have a long lasting effect on aggregate bank lending. In addition, the impact of the shock on aggregate lending differs significantly between severely and mildly affected geographic areas.

Second, we augment the findings of a handful of recent bank-level studies in developed countries that present evidence of the impact of natural disasters on credit supply (Chavaz, 2014; Cortés and Strahan, 2015; Lambert et al., 2015; Garmaise and Moskowitz, 2009; Hosono et al., 2015).[1] In the current context, the results of this study provide evidence of the impact of a severe weather event in a geographic area where insurance protection and government financial support (which can act as mechanisms for risk transfer and augment borrowers' capacity to cope with unexpected events) are limited.[2]

The rest of the paper is structured as followed. Section 2 provides a background to the present study. Section 3 presents the data. In section 4 we present the model and the results. Section 5 presents various robustness tests. Section 6 concludes.

2. Background

Tsunamis occur following large-scale disturbances in the ocean. The most common cause is an undersea earthquake which creates an explosive vertical motion leading to a

[1] Other studies explore the impact of natural disasters on credit demand. For example, Czura and Klonner (2010) investigate the effects of the 2004 Indian Ocean tsunami in South India and find that interest rate of loans offered by chit funds rises substantially because of increased demand for credit from borrowers. Berg and Schrader (2012), on the other hand, use the number of loan applications to proxy demand and find that loan applications to microfinance institutions increase significantly while the probability of a loan being approved decrease, particularly for new borrowers after volcano eruptions in Ecuador.

[2] Chavaz (2014) and Cortés and Strahan (2015) suggest that banks move funds from unaffected areas (where they do not have physical presence) to affected areas in order to meet the increasing demand for funds after disasters. This leads to an increase in lending in disaster affected areas after a shock. Cortés and Strahan (2015) also show that the effects of natural disasters on lending can extend up to 12 months. On the other hand, Garmaise and Moskowitz (2009) find that the decrease in credit supply is only 3 months following an earthquake. All of these aforementioned studies focus on the US, where government intervention and support to affected areas are commonplace following a natural disaster. Furthermore, households are to some extent covered by property and other forms of insurance.

sudden rise and fall of the sea level. Major tsunamis are generated by earthquakes with magnitudes exceeding seven on the Richter scale and which take place less than 30 kilometres beneath the surface of the earth. The resulting tsunami propagates as a series of waves, which involve the movement of water all the way to the sea floor. In the open ocean, a tsunami is barely noticeable. However, as a tsunami approaches the coastline, the wave height and the speed of the current increase dramatically. The resulting waves can reach up to 30 metres high and last for several hours.[3]

On 26th December 2004, a powerful earthquake measuring 9.1 on the Richter scale with its epicentre just off the Northern part of Sumatra, Indonesia created a tsunami that affected 14 countries from Asia to Africa. The unexpectedness of the tsunami and the lack of any prior warning meant that the devastation and fatalities were spread throughout countries around the Indian Ocean. Within two hours, the tsunami claimed over 63,000 lives in Thailand, Sri Lanka and India (Bernard et al., 2006).[4] In Thailand (the geographic focus of the present study), the tsunami killed 8,000 people and caused severe damage to property, fishing vessels, housing, infrastructure and agricultural crops. The tsunami flooded coastal areas two to three kilometres in land. The affected areas (shown in Figure 1) were contaminated with salt water to the detriment of agricultural production and water quality (UNEP, 2005). There were sizeable losses to key parts of the real economy. According to estimates reported by the Asian Disaster Preparedness Centre (2006), the two most affected industries (accounting for over 90% of total recorded losses) were tourism (estimated losses equal to THB71972 million) and fisheries (estimated losses of THB6481 million).

In Thailand, the most affected geographic areas were the six provinces in the south of the country comprising Krabi, Phangnga, Phuket, Ranong, Satun and Trang. These six provinces are classified as affected provinces in the present study. Table 1 provides a summary of the economic impact of the tsunami in these six affected provinces. Overall, the cumulative economic impact accounted for approximately 50% of total economic outputs in affected provinces. However, the effects of the tsunami differed across affected provinces, with most impact concentrated in Phuket, Krabi and Phangnga. Average losses and damage to these provinces exceeded 75% of annual respective outputs. This is far higher than the

[3] See: NOAA at http://wcatwc.arh.noaa.gov/?page=tsunami_science; Australian Bureau of Meteorology at http://www.bom.gov.au/tsunami/info/faq.shtml

[4] The worst hit country was Indonesia with 167,540 listed as dead or missing and damages of $4,451.6 million. The remaining fatalities occurred in Sri Lanka (35,322), India (16,269), Thailand (8,212), Somalia (289), Maldives (108), Malaysia (75), Myanmar (61), Tanzania (13), Bangladesh (2), Seychelles (2), South Africa (2), Yemen (2), and Kenya (1).

losses recorded for the other three affected provinces, estimated at below 10% of annual output.

Insert Figure 1. Tsunami affected provinces in Thailand near here

Insert Table 1. The tsunami economic impact in Thailand by province near here

3. Data

We collect monthly data on bank lending from Bank of Thailand. This data source provides monthly data on selected items of commercial bank balance sheets and the number of bank branches at provincial level in 75 provinces.[5] From the Office of the Board of Investment of Thailand we also collect data on the number and value of investment projects (a proxy of credit demand in the real economy) approved to the corporate sector.

Figure 2 presents a preliminary analysis of the evolution of bank lending (measured as aggregate provincial loans outstanding scaled by total credits) in severely affected, mildly affected and unaffected provinces before and after the tsunami.[6] Affected provinces are classified based on estimated damage and losses (Asian Disaster Preparedness Centre, 2006).

In the year before the tsunami in December 2004, there was a similar growth pattern among severely affected, mildly affected and unaffected provinces in lending. Even though lending in severely affected provinces was significantly higher than that of mildly affected which, in turn, was higher than lending in the unaffected areas, there appears to be a parallel trend in terms of lending growth among these three groups in the year prior to the tsunami. After the tsunami, the aggregate lending ratio in the severely affected provinces falls below the corresponding level in unaffected provinces, but recovers gradually from this significant decline. However, it takes 21 months for lending in severely affected provinces to return to a similar level to that of unaffected provinces. Lending in mildly affected provinces does not show a significant change after the tsunami (remaining at a parallel trend to the unaffected provinces). Overall, our descriptive analysis shows that following the tsunami aggregate

[5] Aggregate data does not allow us to investigate how lending behaviour varies across banks. However, the relatively high frequency of aggregate data allows us to construct a panel at monthly (rather than quarterly or yearly) level. This allows us to capture the effects of the tsunami on our outcome variable of interest in a timely fashion.

[6] 'Total credits' is the term used by Bank of Thailand to describe the sum of loans, overdrafts and securities investments on commercial bank balance sheets. Total credits account for approximately 80% of total bank assets over the period of the study.

lending changes dramatically in the severely affected areas, while remaining stable in the mildly affected and unaffected areas.

Insert Figure 2. Loan-to-total credits ratio of banks in affected and unaffected areas near here

4. Methods and Results

In order to explore the impact of the tsunami on aggregate bank lending, we conduct a more formal analysis as follows. First, we investigate the impact of the tsunami on aggregate bank lending across all affected provinces. This allows us to test formally our first hypothesis, which contends that following the tsunami aggregate lending in affected provinces declines. Second, we split the affected provinces into mildly affected and severely affected areas. This allows us to test directly our second hypothesis which contends that following the tsunami, aggregate lending in severely affected provinces declines more significantly than in mildly affected provinces. Third, we investigate the lasting impact of the tsunami (if any) on bank lending.

Tsunami effects on bank lending

In order to test our first hypothesis, we estimate the following difference-in-differences model:

$$\Delta \mathrm{LOAN}_{i,j,t} = \beta.\left(\mathrm{TSUAFF}_{i,j} \text{ x } \mathrm{TIME}_t\right) + \gamma.\Delta \mathrm{BRANCH}_{i,j,t} + \vartheta.\Delta \mathrm{DEPOSIT}_{i,j,t} + \omega.\mathrm{Trend}_{j,t} + \mathrm{Time}_t + \mathrm{Location}_{i,j} + \varepsilon_{i,j,t} \quad (1a)$$

$\Delta \mathrm{LOAN}_{i,j,t}$ is the change in aggregate outstanding loans (in THB millions) of commercial banks in province i in region j between month t and (t-1). In order to estimate the change in bank lending, a more precise measure would be the monetary value of new loans granted by banks between month t and (t-1). However, due to a lack of available data, loan stock rather than flow is used. The use of loan stock makes it more difficult to draw inferences regarding the change in new loans issued. However, given that non-performing loans are likely to increase following a disaster (leading to reduced loan repayments), a decrease in loans outstanding would imply a decrease in new loans granted.[7]

$\mathrm{TSUAFF}_{i,j} \times \mathrm{TIME}_t$ is an interaction variable which is the product of an indicator variable for tsunami affected areas (which equals one if affected and zero otherwise) and the dummy for months after the tsunami (which equals to one for months following the tsunami and zero otherwise). This variable captures the effects of the tsunami on bank lending. Given that the tsunami occurred on the 26th December 2004, January 2005 is considered as the first month after the event. We estimate the model using a 24-month window around the tsunami as the baseline, such that t runs from 1 (January 2004) to 24 (December 2005). Given that we are testing whether there is a significant difference in terms of bank lending between affected and unaffected provinces after the tsunami, β is the key parameter of interest. $\beta < 0$ implies that bank lending in the affected provinces decreases following the tsunami compared to unaffected areas. $\beta > 0$ implies the opposite.

$\Delta\mathrm{DEPOSIT}_{i,j,t}$ is the change in the aggregate deposits of commercial banks in province i in region j between month t and (t-1) (in THB millions). We control for the changes in deposits given that this is the main source of bank liabilities used to finance assets, particularly in developing countries.[8] We expect that higher aggregate bank deposits are associated with more lending as loans are the major assets held by commercial banks.[9]

$\Delta\mathrm{BRANCH}_{i,j,t}$ is the change in the number of branches of commercial banks in province i in region j between month t and (t-1). The number of branches may impact on the aggregate level of bank loans extended to borrowers within a particular province. Physical

[7] Suppose L_t and L_{t-1} are outstanding loans at month t and month (t-1) respectively; $R_{(t-1,t)}$ are loan repayments and $N_{(t-1,\,t)}$ new loans granted during (t-1) and t monthly period; loans written-off are assumed to be zero because we study a sample of commercial banks without lending direction from the government; the relationship between outstanding loans from one month to the next can be expressed mathematically as: $L_t = L_{t-1} - R_{(t-1,t)} + N_{(t-1,t)}$ (*). As observed $L_t < L_{t-1}$ (**) therefore $R_{(t-1,\,t)} > N_{(t-1,\,t)}$. Given that non-performing loans tend to increase after the disaster, $R_{(t-1,\,t)}$ would be more likely to decrease and consequently, new loans granted, $N_{(t-1,\,t)}$, would fall in order for (*) and (**) to hold.

[8] This is fairly accurate to the fact that within 24-month window around the tsunami, the loan-to-deposit ratio is approximately 90% on average.

[9] The inclusion of total deposits might lead to two potential issues. The tsunami can co-vary with deposits which are correlated with loans as the outcome ('included variables' bias) (Atanasov and Black, 2016) and bank branches (multicollinearity bias). For example, deposits could decrease after the shock because firms and households withdraw cash from banks in order to cope with losses. Deposits might also increase if firms and households cash out insurance and deposit the money into banks while waiting for reconstruction of their fixed assets. The second scenario, however, is less likely the case because of lacking insurance coverage. Branches, on the other hand, tend to help banks to raise more deposits given the importance of physical presence associated with banking businesses in Thailand. In order to check if these can cause biases, we first run a difference-in-differences estimator in which deposits are considered as the outcome (instead of loans), the results suggest no differences in deposits between tsunami affected and unaffected areas. Second, we run a Spearman's rank correlation test and find that correlation coefficients between deposits and branches are relatively low. These findings alleviate our concerns.

branches are used by banks to obtain (soft) information from their borrowers for lending (Agarwal and Hauswald, 2010). This is especially the case in developing countries where soft information on borrowers' prospects and local knowledge play a significant role in loan screening and credit judgments. This may be particularly true in lending to small businesses where hard information and automated credit scoring technologies are limited or absent (Udell, 2015). Extensive empirical evidence suggests that geographic proximity increases the probability of commercial loans being approved (Brevoort and Hannan, 2006) and declines in loan rates (Degryse and Ongena, 2005).

$\text{Trend}_{j,t}$ is the growth rate of loan in region j between month t and (t-1). This variable is included to capture the pre-treatment parallel trend assumption being associated with difference-in-differences estimator (Atanasov and Black, 2016). Time_t and $\text{Location}_{j,t}$ are time- and province-fixed effects. $\varepsilon_{i,j,t}$ is the error term. We estimate equation (1a) using OLS with standard errors clustered at province level.

Even though unobservable fixed effects have been captured through differencing, one major problem with (1a) is that some unobservable, but time-variant variables such as credit demand and quality of borrowers in a province may also affect bank lending. Therefore, in order to isolate the effects of the tsunami on bank lending, we control factors affecting bank lending that are specific to provinces and which may change over time. As we do not have data on the number of loan applications (which provides a useful proxy for credit demand), we use the number and value of investment projects approved to firms (at regional level) to measure credit demand. A higher number and value of projects approved would lead to an increase in the demand for bank loans[10]. The inclusion of these additional control variables leads us to Equation (1b).

$$\Delta\text{LOAN}_{i,j,t} = \beta.\left(\text{TSUAFF}_{i,j} \text{ x } \text{TIME}_t\right) + \gamma.\Delta\text{BRANCH}_{i,j,t} + \vartheta.\Delta\text{DEPOSIT}_{i,j,t} + \mu.\Delta\text{NOP}_{j,t} + \pi.\Delta\text{VAP}_{j,t} + \omega.\text{Trend}_{j,t} + \text{Time}_t + \text{Location}_{i,j} + \varepsilon_{i,j,t} \qquad (1b)$$

$\Delta\text{LOAN}_{i,j,t}$, $\text{TSUAFF}_{i,j} \text{ x } \text{TIME}_t$, $\Delta\text{BRANCH}_{i,j,t}$ and $\Delta\text{DEPOSIT}_{i,j,t}$ are defined as before.

[10] Isolating shocks to loan supply from those to demand has always been an empirical challenge. It would be more informative if we were able to obtain the value and number of projects approved to firms at province level so as to infer about loan demand changes in the affected provinces after the tsunami. As aforementioned, an increase in the value and number of investment projects are likely to be associated with a higher demand for loan, meaning that the decline in lending is from the supply side. Alternatively, if a decrease in the value and number of investment projects is observed, the decline in bank lending is likely a result of a reduction in loan demand rather than supply. Hosono and Miyakawa (2015) provide an excellent discussion on how to tackle this identification problem when data allow.

$\Delta NOP_{j,t}$ is the change in the number of investment projects approved to firms in region j between month t and (t-1). $\Delta VAP_{j,t}$ is the change in the value of investment projects approved to firms in region j between month t and (t-1) (in THB millions).

Table 2 reports the results from the estimation of Equation (1a) (the baseline) and Equation (1b) (the baseline plus other regional control variables). The key estimate, $\hat{\beta}$, is negative and statistically significant (third row of Table 2). These results suggest that following the tsunami bank lending in affected provinces declines more compared to unaffected provinces. As the loan amount is measured in Thai Baht (THB) millions. The magnitude of these coefficients indicates the difference in monetary value of bank lending. These coefficients become larger when time- and province-fixed effects are added to the original model (Model 1 in Table 2). Averaged out across estimations, bank lending in affected provinces declines by over THB150 million (around USD4 million) relative to unaffected provinces.[11]

Turning to the bank control variables, the number of bank branches shows a positive relationship with bank lending. This result is consistent with the evidence that physical distance facilitates banks to collect, soft, information and consequently to increase lending (Agarwal and Hauswald, 2010; Brevoort and Hannan, 2006).

Total bank deposits (where significant) exhibit a positive relation with bank lending. This is unsurprising given that deposits are the predominant source of bank financing in developing countries. Similarly, lending growth in the region is positively related to provincial lending. Regional control variables such as the number and the value of investment projects approved to firms are also expected to be positively related to bank lending. These two variables are used as indirect indicators of credit demand. However, none of these coefficients are significant.

Insert Table 2. DiD in lending between the affected and unaffected provinces near here

Tsunami effects in mildly and severely affected areas

In order to investigate whether the tsunami affects aggregate bank lending across affected provinces differently, the affected provinces are divided into mildly and severely affected provinces (based on the respective ratio of estimated damage and losses to total gross

[11] The mean difference is calculated by averaging the key coefficients (the interaction between the tsunami and post-tsunami months) across four models with credit demand control variables (Model 1b) in Table 2. Exchange rate of THB35: 1USD is used for currency conversion.

economic outputs the year before the tsunami, Table 1). We then examine the impact of the tsunami on aggregate bank lending in severely and mildly affected provinces using Equation (2).

$$\Delta \mathrm{LOAN}_{i,j,t} = \theta.\left(\mathrm{MILD\_TSUAFF}_{i,j} \text{ x } \mathrm{TIME}_t\right) + \epsilon.\left(\mathrm{SEVERE\_TSUAFF}_{i,j} \text{ x } \mathrm{TIME}_t\right) + \gamma.\Delta \mathrm{BRANCH}_{i,j,t} + \vartheta.\Delta \mathrm{DEPOSIT}_{i,j,t} + \mu.\Delta \mathrm{NOP}_{j,t} + \pi.\Delta \mathrm{VAP}_{j,t} + \omega.\mathrm{Trend}_{j,t} + \mathrm{Time}_t + \mathrm{Location}_{i,j} + \varepsilon_{i,j,t} \qquad (2)$$

$\mathrm{MILD\_TSUAFF}_{i,j} \text{ x } \mathrm{TIME}_t$ is the interaction between mildly affected provinces (Ranong, Satun and Trang) and the months after the tsunami. $\mathrm{SEVERE\_TSUAFF}_{i,j} \text{ x } \mathrm{TIME}_t$ is the interaction between severely affected provinces (Krabi, Phangnga and Phuket) and the months after the tsunami. The base category is the interaction between unaffected provinces and the months following the tsunami, which is dropped from the specification.

Table 3 presents the results of testing second hypothesis. The coefficients for the interaction between mildly affected provinces and the post-tsunami period are statistically significant in two (out of four) cases, while those for severely affected counterparts are significant in all cases. Both mildly and severely affected provinces experience a reduction in aggregate bank lending compared to unaffected counterparts. However, when comparing the magnitudes of these coefficients across the mildly and severely affected areas, those of the former group are statistically and significantly higher than those of the latter, suggesting the decline in aggregate bank lending to the severely affected provinces is much more pronounced. Aggregate bank lending decreases in the severely affected areas by a factor exceeding three compared to the decline observed in mildly affected provinces. Other control variables exhibit a similar pattern with those reported in the combined affected group in Table 2.

Insert Table 3. DiD in lending between mildly and severely affected provinces near here

The longer term impact of the tsunami on aggregate bank lending

In this section, we explore the longer term impact of the tsunami on aggregate bank lending. As proposed in our third hypothesis, the tsunami causes a long term impact on aggregate bank lending. In order to test this hypothesis, we specify the models as shown in

(3a) for the overall affected areas and (3b) where affected areas are divided into severely and mildly affected categories.

$$\Delta \mathrm{LOAN}_{i,j,t+m} = \beta_m.\left(\mathrm{TSUAFF}_{i,j} \text{ x } \mathrm{TIME}_{t+m}\right) + \gamma_m.\Delta \mathrm{BRANCH}_{i,j,t+m} + \vartheta_m.\Delta \mathrm{DEPOSIT}_{i,j,t+m} + \mu_m.\Delta \mathrm{NOP}_{j,t+m} + \pi_m.\Delta \mathrm{VAP}_{j,t+m} + \omega.\mathrm{Trend}_{j,t} + \mathrm{Time}_{t+m} + \mathrm{Location}_{i,j} + \varepsilon_{i,j,t+m} \quad \text{(3a)}$$

$$\Delta \mathrm{LOAN}_{i,j,t+m} = \theta_m.\left(\mathrm{MILD\_TSUAFF}_{i,j} \text{ x } \mathrm{TIME}_{t+m}\right) + \epsilon_m.\left(\mathrm{SEVERE\_TSUAFF}_{i,j} \text{ x } \mathrm{TIME}_{t+m}\right) + \gamma_m.\Delta \mathrm{BRANCH}_{i,j,t+m} + \vartheta_m.\Delta \mathrm{DEPOSIT}_{i,j,t+m} + \mu_m.\Delta \mathrm{NOP}_{j,t+m} + \pi_m.\Delta \mathrm{VAP}_{j,t+m} + \omega.\mathrm{Trend}_{j,t} + \mathrm{Time}_{t+m} + \mathrm{Location}_{i,j} + \varepsilon_{i,j,t+m} \quad \text{(3b)}$$

All variables are as defined in Equation (1b) and Equation (2). In Equation (3a) and (3b), t represents the 12-month period prior to the occurrence of the tsunami; m represents each additional month after the tsunami up until the tsunami effects dissipate. We anticipate a diminishing effect of the tsunami. As a result, β_m, θ_m and ϵ_m (m = 1, 2, 3, …, d, where d is the month from which the impact of the tsunami dissipates) are expected to increase over time from a large negative value toward zero. In other words, we expect that the difference in lending between the unaffected and affected provinces will decline over time as the effects of the shock diminish. There are d regressions to be estimated.

Figure 3 depicts the lasting impact of tsunami on bank lending. The effects of the tsunami dissipate over time. The largest decline in aggregate bank lending is recorded three months after the tsunami. Aggregate bank lending is THB500 million (USD14 million) less in affected provinces compared to the unaffected counterparts. This difference narrows over time, before dissipating completely 20 months after the tsunami. The relative coefficients indicating these monetary values are statistically significant with the averaged p-value (across four models in Table 4) of 0.11 in month 20.

A similar examination of the lasting effects of the tsunami across mildly and severely affected provinces reveals that aggregate lending is only affected negatively in provinces where the tsunami caused extensive damage. While the difference between the mildly affected and unaffected provinces is small (THB200 million at peak at three months after the tsunami) and the (positive) coefficients suggest an increase, not a decrease in lending in the first nine months in the mildly affected group. The difference between the severely affected and unaffected provinces is indicated by negative coefficients, suggesting a decline in lending compared to the unaffected group. Three months after the tsunami, aggregate bank lending in the severely affected provinces declines more than twice as much as that of the entire group of affected provinces (THB1200 million). This result is particularly strong when estimated using Model 2 and Model 4 (Table 4).

Taking the mildly affected group separately and comparing the coefficients and p values over time, we find that the coefficients are positive in the first nine months (averaged across four models), but become negative after month 10 (Figure 3) and the relative p value becomes significant (Table 4, Mild, Model 1, Column 10, Row 12). This appears to suggest that because the effects from the tsunami are mild, banks moved funds from severely affected to mildly affected areas (which are geographically close to severely hit provinces) in the first few months after the tsunami. Alternatively, it may take time for these (mild) effects to manifest themselves to bank lending compared to severely affected provinces, which are impacted immediately. However, this result should be treated with caution given the aggregated nature of the data used.[12]

Insert Figure 3. The lasting effects of the tsunami on bank lending – averaged across models near here

Insert Table 4. The lasting impact of the tsunami on lending – individual models near here

Overall, the results of our empirical analysis suggest that the Indian Ocean tsunami significantly reduced aggregate bank lending in affected provinces. Through a 24-month window around the tsunami, aggregate bank lending in the affected provinces is shown to decrease by THB150 million (USD4 million) on average compared to lending in unaffected areas. The results of our investigation within the affected provinces reveal that the tsunami generates a long lasting impact on aggregate lending (20 months). The largest decline in aggregate lending takes place three months after the tsunami. The overall decline in aggregate

[12] From these preliminary results, one could also hypothesize that the effects of the tsunami spread to the mildly affected areas later but last longer because of, perhaps, relatively weaker economic infrastructures of these provinces. The severely affected counterparts, even though being hit harder, would recover faster thanks to their stronger economic conditions and government financial supports as a result of their larger contributions to the national economy. Unfortunately, we could not test these hypotheses due to limited data availability.

lending in affected provinces is driven by changes in aggregate lending in severely affected provinces.

5. Robustness tests

In order to test the robustness of our empirical results, we first check the sensitivity of the impact to the time window used. We narrow the original 24-month time window to 18-month, 12-month and six-months, and then re-estimate Equation (1b). The results (reported in Table 5) are consistent with the main findings above. Noticeably, the key coefficients for longer time windows have smaller magnitudes than those for shorter time windows, reflecting the diminishing effects of the tsunami over time.

Second, we test whether the estimated differential impact on aggregate bank lending between the affected and unaffected provinces is attributable to the impact of the tsunami, or whether in fact this arises from some other causes. We test this via a set of placebo tests. This is executed by changing the date of the tsunami occurrence to the years earlier and later than December 2004. This is to assess whether the key parameters of interest are still significantly (negative) different from zero. If this is the case, the difference in aggregate bank lending has been caused by factors other than the tsunami itself. The tsunami is falsified to occur in December 2003 and then in December 2005. Table 6 presents the results of these estimations. This test provides strong evidence that the tsunami caused the observed changes in aggregate bank lending.

Our modelling approach assumes that there is no serial correlation in the differenced errors. We check if this assumption is supported by applying a fixed-effects estimator. The results from these estimations, reported in Table 7a (time-demeaned), are consistent with those produced by the difference-in-differences estimator.

Another inherent limitation of difference-in-differences method is the inconsistency of the standard error of the key estimate because the outcomes are serially correlated (Bertrand et al., 2004). This could be the case as we use a long time series of 24-month window around the tsunami. In order to address this problem, we ignore the time series by averaging the variables into two periods, the pre- and post-tsunami, and re-estimate Equation (1b). The results, shown in Table 7b (time-collapsed) confirm our earlier results.

Difference-in-differences estimates could be biased if one of the explanatory does not change much over the study period. This type of bias could exist in our study with the number of bank branches in each province. As we use monthly data to capture the timely effects of the tsunami, the number of bank branches does not change from one month to the next in many cases. Therefore, we replace the change in number of bank branches (differences) with the number of branches (levels). We use a lag of one month to allow the delayed effects of branching presence on lending. The results reported in Table 8 show a consistent outcome with those generated previously.

Furthermore, a critical, but factual, assumption underlying the difference-in-differences approach is that the lending outcome in treatment and control group should follow a common trend in the absence of treatment. Even though we have added loan growth in our estimation and visual evidence in Figure 2 lends some support to this assumption, we carry out two additional tests. First, as the tsunami struck six provinces in the South of Thailand, we narrow our control group to those provinces in Southern region which we believe share common characteristic in loan growth with the affected provinces because of their similarities in terms of social and economic developments. The results of this robustness test are shown in Table 9. The main findings are supported.

Second, we employ propensity score matching to match affected with unaffected provinces. In doing so, we first estimate a probit model based on our original sample of 50 provinces in the month immediately before the tsunami. The dependent variable equals one if the province was affected by the tsunami and zero otherwise. The probit model includes province-variant variables similar to our baseline model (Model 1a). However, the loan growth is defined as the average growth of loan over three months preceding the tsunami in order to help satisfy the parallel trend assumption. From the probit estimation, we use the propensity scores predicted and conduct a one-to-one nearest-neighbour matching procedure to match the tsunami affected provinces with those unaffected. The differences in propensity scores are set to be less than 0.01. After matching, we have four matched pairs of provinces. We then re-run our estimations on the matched sample using Equation (2) for different windows as reported in Table 10. The results from this estimation are also consistent with our main findings.[13]

Table 5. DiD in lending between affected and unaffected provinces – different tsunami windows near here

Table 6. DiD in lending between affected and unaffected provinces – artificial tsunami date near here

[13] None of the coefficients in the probit model are statistically significant. This supports the assumption that the tsunami is an exogenous event.

Table 7. The effects of the tsunami on lending between affected and unaffected provinces – fixed effects estimators near here

Table 8. DiD in lending between affected and unaffected provinces – branch levels near here

Table 9. DiD in lending – using neighbour provinces as a control group near here

Table 10. DiD in lending – using the propensity scores matched sample as a control group near here

6. Conclusion

The supply of bank credit is of crucial importance for the health of the economy. This is especially the case in developing countries where bank credit is the predominant source of finance to households and firms. To date, most studies that have investigated the effects of exogenous shocks on bank credit supply are confined to developed economies. The paucity of evidence for developing economies motivates the present study, where exploit the Indian Ocean tsunami in December 2004 as an exogenous shock in order to study its causal effects on aggregate commercial bank lending in Thai provinces.

We test a series of hypotheses. First, we examine whether aggregate lending in affected provinces decreases after a tsunami. Second, we investigate whether following a tsunami, a decline in lending in severely affected provinces is more significant than in mildly affected locations. Finally, we investigate whether a tsunami generates a long term effect on aggregate bank lending.

Employing the difference-in-differences estimator we find that following a tsunami there is a significant decline in the aggregate supply of credit to affected areas. Our analysis of spatial variations among the affected provinces shows that these results are driven by changes taking place in provinces that were severely affected by the tsunami. These results are robust to a variety of sensitivity checks and searches for alternative causes.

As such, the findings of this study are of relevance to government agencies tasked with monitoring the flow of credit to the real economy during settled and unsettled periods. Further research could usefully engage in compiling dis-aggregated data so as to establish the effects of a severe weather shock on the lending and investment decisions of banks in developing countries at micro-level.

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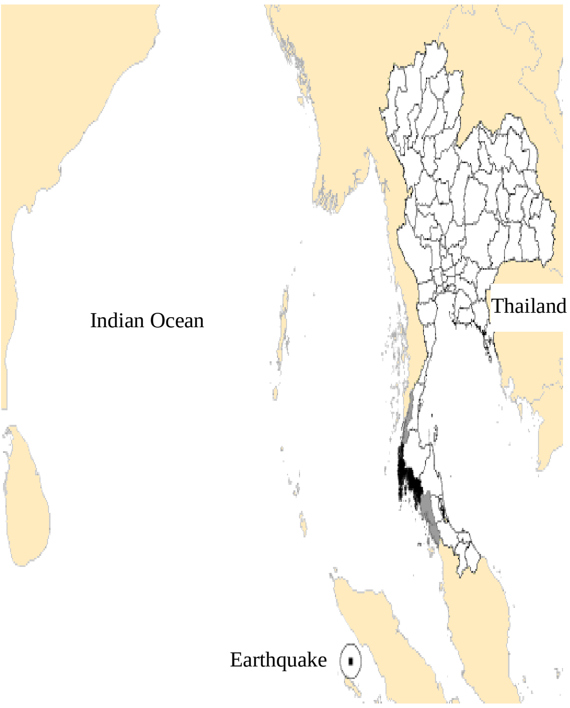
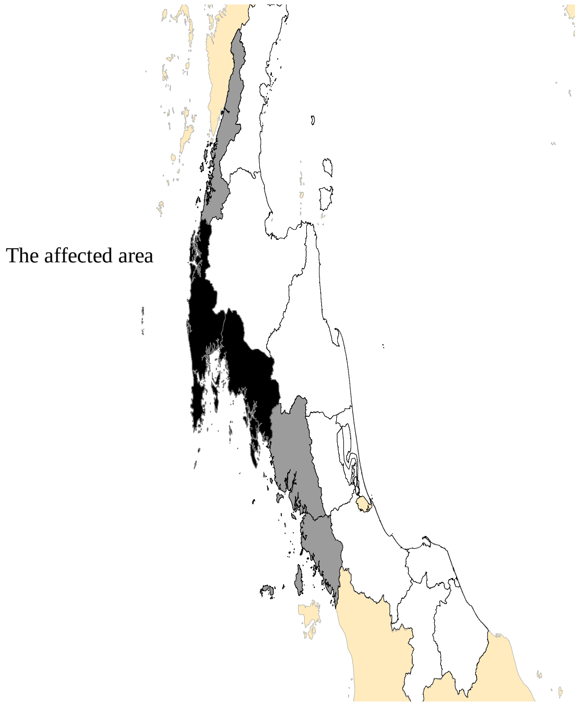
Figure 1. Tsunami affected provinces in Thailand



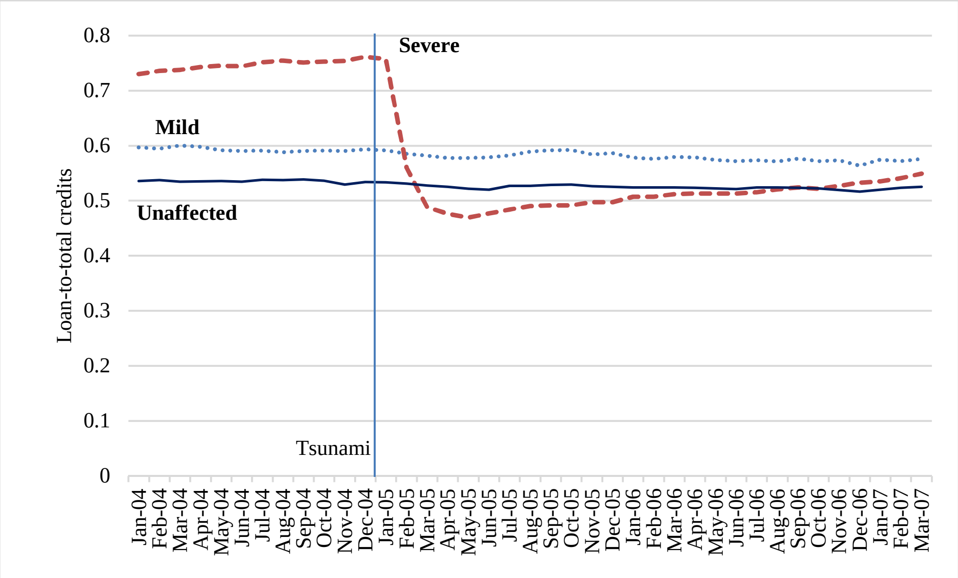
(1a)



(1b)

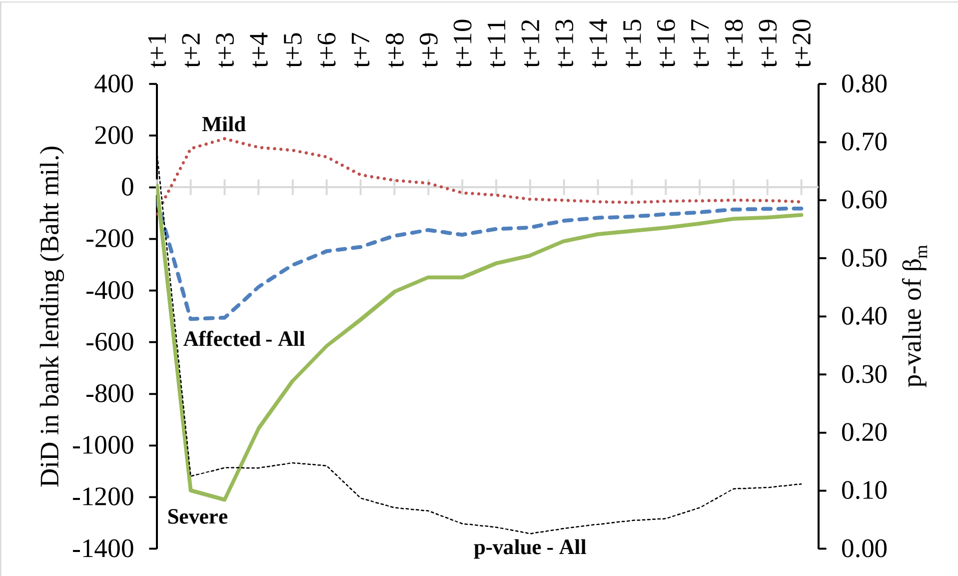
Note:
Figure 1a shows the epicentre of the earthquake that generated the Indian Ocean tsunami in 2004 and the geographic location of Thailand. Figure 1b highlights six provinces affected by the tsunami in the South. The severely affected area is coloured black (Krabi, Phannga and Phuket) while the less affected provinces (Ranong, Satun and Trang) is in (dark) grey. The unaffected locations are in white. The severity is classified based on estimated losses over previous year provincial domestic economic outputs (Asian Disaster Preparedness Centre, 2006).

Figure 2. Loan-to-total-credits ratio of banks in affected and unaffected areas



Note:
This figure graphically compares changes in bank lending among the unaffected, severely affected and mildly affected provinces in Thailand after the Indian Ocean tsunami that occurred on the 26th December 2004. Loan-to-total credits is defined as the ratio of outstanding loans over total credits, a sum of loans, overdrafts and securities investment which accounts for 80% of total bank assets. The loan-to-total-credits ratio is constructed based on monthly aggregate data by provinces on commercial banks from Bank of Thailand. The severely affected group consists of three provinces, Krabi, Phangnga and Phuket and the mildly affected group includes Ranong, Satun and Trang. The provinces hit by the tsunami and severity are based on data from Asian Disaster Preparedness Centre (2006). The unaffected areas include other provinces but exclude Bangkok.

Figure 3. The lasting effects of the tsunami on lending – averaged across models



Note:

The figure shows the difference-in-differences (DiD) in lending between the tsunami affected and unaffected provinces over m months after the tsunami (m = 1, 2, 3,…, 20). The difference is indicated by β_m (Equation 3a) (between all provinces affected and unaffected), θ_m (between mildly affected and unaffected) and ϵ_m (between severely affected and unaffected) (Equation 3b). These parameters are averaged across four models estimated using Equations (3a) and (3b) as shown below.

$$\Delta LOAN_{i,j,t+m} = \beta_m\left(TSUAFF_{i,j} \text{ x } TIME_{t+m}\right) + \gamma_m \Delta BRANCH_{i,j,t+m} + \vartheta_m \Delta DEPOSIT_{i,j,t+m} + \omega.Trend_{j,t+m} + \mu_m \Delta NOP_{j,t+m} + \pi_m \Delta VAP_{j,t+m} + Time_{t+m} + Location_{i,j} + \varepsilon_{i,j,t+m} \quad (3a)$$

$$\Delta LOAN_{i,j,t+m} = \theta_m\left(MILD\_TSUAFF_{i,j} \text{ x } TIME_{t+m}\right) + \epsilon_m\left(SEVERE\_TSUAFF_{i,j} \text{ x } TIME_{t+m}\right) + \gamma_m \Delta BRANCH_{i,j,t+m} + \vartheta_m \Delta DEPOSIT_{i,j,t+m} + \omega.Trend_{j,t+m} + \mu_m \Delta NOP_{j,t+m} + \pi_m \Delta VAP_{j,t+m} + Time_{t+m} + Location_{i,j} + \varepsilon_{i,j,t+m} \quad (3b)$$

The p-values are the average p-values of β_m across four models. The individual coefficients and relevant p-values for each model are reported in Table 4. Model 1 is without time- and province-fixed effects. Model 2 is with province-fixed effects only. Model 3 is with time-fixed effects only. Model 4 is with both time- and province-fixed effects.

Table 1. The tsunami economic impact in Thailand by province

Groups	Provinces (by order of severity)	Damage-to-GPP ratio (%) (1)	Loss-to-GPP ratio (%) (2)	Impact-to-GPP ratio (%) (1) + (2)
Severely affected provinces	Phuket	10.4	79.7	**90.1**
	Krabi	15.4	53.3	**68.7**
	Phangnga	42.0	25.9	**67.9**
Mildly affected provinces	Ranong	4.2	12.0	**16.2**
	Satun	3.4	2.8	**6.2**
	Trang	0.8	5.2	**6.0**
Averages	Severely affected	22.6	53.0	**75.6**
	Mildly affected	2.8	6.7	**9.5**
	All affected	11.5	38.2	**49.7**

Note:
This Table is constructed based on data from Table 5.2 (p.21) in the report on the economic impact of the Indian Ocean tsunami in Thailand by Asian Disaster Preparedness Centre (ADPC) (2006). ADPC collected information from, including interviews with, 11 various governmental bodies in Thailand and three international organisations (World Bank, Food and Agriculture Organisation and World Health Organisation). In order to ensure the validity and accuracy of the results as well as the compatibility with the assessments from other countries, ADPC used the disaster assessment methodology originally developed by the United Nations' Economic Commission for Latin America and the Caribbean which was also used to a varying degree in the national disaster evaluations led by the World Bank. The total impact is the cumulative damage and losses of three sectors: social sector (housing, education and health), production (agriculture, livestock, fisheries, industry, commerce and tourism) and infrastructure (water supply, electricity, transport and communications and others). The affected provinces are ranked in the order of severity which is indicated by the total impact over the provincial economic outputs. GPP denotes Gross Provincial Product.

Table 2. DiD in lending between affected and unaffected provinces

	Model 1		Model 2		Model 3		Model 4	
	Basic (1a)	Control (1b)	Basic (1a)	Control (1b)	Basic (1a)	Control (1b)	Basic (1a)	Control (1b)
Tsunami x time	-164.11***	-140.17***	-159.13*	-159.12*	-169.82***	-146.11***	-180.35**	-175.05**
	(46.34)	(47.84)	(82.53)	(85.90)	(47.61)	(51.97)	(72.75)	(73.90)
No. of branches	129.63***	111.98***	49.71***	71.16***	135.67***	120.72***	51.60***	75.89***
	(26.92)	(15.08)	(15.45)	(17.15)	(29.77)	(17.10)	(16.24)	(19.73)
Total deposits	0.03***	0.05	0.01	-0.07	0.03***	0.05	0.01	-0.11
	(0.01)	(0.06)	(0.01)	(0.05)	(0.01)	(0.09)	(0.01)	(0.09)
Trend	8900.48***	8144.61***	9035.55***	8131.52***	8229.47**	8934.91**	7987.25**	9052.55**
	(2386.36)	(2574.25)	(2498.00)	(2607.80)	(3823.44)	(4398.14)	(4039.31)	(4340.52)
No. of projects		1.06		0.15		-1.66		-0.81
		(1.30)		(1.38)		(1.43)		(1.35)
Value of investment		-0.00013		-0.00058		-0.00011		0.00004
		(0.00160)		(0.00148)		(0.00110)		(0.00126)
Province-fixed effects	No	No	Yes	Yes	No	No	Yes	Yes
Time-fixed effects	No	No	No	No	Yes	Yes	Yes	Yes
No. of provinces	75	50	75	50	75	50	75	50
No. of observations	1,725	1,150	1,725	1,150	1,725	1,150	1,725	1,150
R^2	0.18	0.21	0.37	0.34	0.19	0.22	0.37	0.35

Note:
This Table reports the difference-in-differences in lending between affected and unaffected provinces. The dependent variable is the change in lending of commercial banks at aggregate level in province i at month t as defined in Equation (1a) for basic results; for the control results, see Equation (1b) with control variables of the region. The main independent variable of interest is the interaction between the tsunami affected province and the months following the tsunami. Model 1 is without time- and province-fixed effects. Model 2 is with province-fixed effects only. Model 3 is with time-fixed effects only. Model 4 is with both time- and province-fixed effects. The estimation is based on 24-month window around the tsunami. The number of provinces drops because regional level data for the central region are not available (25 provinces). Robust standard errors clustered at province level are in parentheses. *, ** and *** denote significant level at 10%, 5% and 1%, respectively.

$\Delta\mathrm{LOAN}_{i,j,t} = \beta.\left(\mathrm{TSUAFF}_{i,j}\ \mathrm{x}\ \mathrm{TIME}_t\right) + \gamma.\Delta\mathrm{BRANCH}_{i,j,t} + \vartheta.\Delta\mathrm{DEPOSIT}_{i,j,t} + \omega.\mathrm{Trend}_{j,t} + \mathrm{Time}_t + \mathrm{Location}_{i,j} + \varepsilon_{i,j,t}$ (1a)

$\Delta\mathrm{LOAN}_{i,j,t} = \beta.\left(\mathrm{TSUAFF}_{i,j}\ \mathrm{x}\ \mathrm{TIME}_t\right) + \gamma.\Delta\mathrm{BRANCH}_{i,j,t} + \vartheta.\Delta\mathrm{DEPOSIT}_{i,j,t} + \omega.\mathrm{Trend}_{j,t} + \mu.\Delta\mathrm{NOP}_{j,t} + \pi.\Delta\mathrm{VAP}_{j,t} + \mathrm{Time}_t + \mathrm{Location}_{i,j} + \varepsilon_{i,j,t}$ (1b)

Table 3. DiD in lending between mildly and severely affected provinces

	Model 1	Model 2	Model 3	Model 4
Mildly-affected x time	-78.80***	-4.36	-83.43**	-18.90
	(26.76)	(13.66)	(33.61)	(37.29)
Severely-affected x time	-201.50***	-314.98***	-208.75***	-332.73***
	(64.03)	(101.44)	(72.86)	(96.85)
Difference (Severe – Mild)	-122.7*	-310.62***	-125.32*	-313.84***
	(64.09)	(100.19)	(65.71)	(107.60)
No. of branches	112.59***	69.62***	121.39***	74.14***
	(15.12)	(17.50)	(17.21)	(20.01)
Total deposits	0.05	-0.08	0.05	-0.12
	(0.06)	(0.06)	(0.09)	(0.10)
Trend	8143.55***	8135.40***	8928.01**	9062.52**
	(2573.92)	(2609.93)	(4399.54)	(4347.67)
No. of projects	1.07	0.13	-1.67	-0.78
	(1.30)	(1.38)	(1.43)	(1.35)
Value of investment	-0.00013	-0.00059	-0.00011	0.00005
	(0.00160)	(0.00147)	(0.00110)	(0.00127)
Province-fixed effects	No	Yes	No	Yes
Time-fixed effects	No	No	Yes	Yes
No. of provinces	50	50	50	50
No. of observations	1,150	1,150	1,150	1,150
R^2	0.21	0.35	0.22	0.35

Note:
This Table reports the difference-in-differences in lending between mildly and severely affected provinces. The dependent variable is the change in lending of commercial banks at aggregate level in province i at month t as defined in Equation (2). The main independent variables of interest are the interactions between the provinces mildly affected and those severely affected and the months following the tsunami. The base is the interaction between the unaffected areas and the time after the tsunami. We test the difference of the coefficients between severely and mildly affected areas as indicated by Difference (Severe – Mild). Model 1 is without time- and province-fixed effects. Model 2 is with province-fixed effects only. Model 3 is with time-fixed effects only. Model 4 is with both time- and province-fixed effects. The estimation is based on 24-month window around the tsunami. Robust standard errors clustered at province level are in parentheses. *, ** and *** denote significant level at 10%, 5% and 1%, respectively.

$$\Delta \mathrm{LOAN}_{i,j,t} = \theta.\left(\mathrm{MILD\_TSUAFF}_{i,j} \text{ x } \mathrm{TIME}_t\right) + \epsilon.\left(\mathrm{SEVERE\_TSUAFF}_{i,j} \text{ x } \mathrm{TIME}_t\right) + \gamma.\Delta \mathrm{BRANCH}_{i,j,t} + \vartheta.\Delta \mathrm{DEPOSIT}_{i,j,t} + \omega.\mathrm{Trend}_{j,t} + \mu.\Delta \mathrm{NOP}_{j,t} + \pi.\Delta \mathrm{VAP}_{j,t} + \mathrm{Time}_t + \mathrm{Location}_{i,j} + \varepsilon_{i,j,t} \quad (2)$$

Table 4. The lasting impact of the tsunami on lending – individual models

t+m	Affected - All				Severe				Mild			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
t+1	-26.0	-68.6	-24.6	-74.3	83.8	-67.5	84.6	-73.1	-135.8	-69.6	-133.7	-75.5
	(0.854)	(0.525)	(0.869)	(0.492)	(0.718)	(0.648)	(0.726)	(0.622)	(0.230)	(0.520)	(0.249)	(0.490)
t+2	-473.9	-487.4	-517.5	-559.8	-1091.3	-1199.1	-1133.9	-1269.3	135.3	219.0	94.8	147.1
	(0.112)	(0.173)	(0.084)	(0.129)	(0.015)	(0.030)	(0.012)	(0.025)	(0.080)	(0.025)	(0.269)	(0.129)
t+3	-470.5	-484.2	-515.0	-550.2	-1127.7	-1239.9	-1169.6	-1302.4	171.3	259.6	129.6	194.3
	(0.116)	(0.190)	(0.095)	(0.157)	(0.015)	(0.034)	(0.013)	(0.031)	(0.044)	(0.013)	(0.123)	(0.033)
t+4	-355.7	-372.6	-389.5	-429.0	-850.3	-974.9	-881.7	-1030.9	131.5	221.2	99.5	164.8
	(0.106)	(0.193)	(0.092)	(0.166)	(0.014)	(0.039)	(0.013)	(0.037)	(0.066)	(0.019)	(0.133)	(0.027)
t+5	-274.5	-293.6	-300.5	-336.1	-668.2	-796.3	-693.9	-839.4	116.1	205.3	91.3	162.6
	(0.107)	(0.209)	(0.093)	(0.182)	(0.012)	(0.039)	(0.011)	(0.038)	(0.070)	(0.017)	(0.140)	(0.024)
t+6	-223.5	-246.2	-240.3	-278.1	-533.6	-669.5	-550.8	-703.2	85.8	174.0	69.7	142.2
	(0.094)	(0.208)	(0.084)	(0.185)	(0.008)	(0.038)	(0.007)	(0.037)	(0.100)	(0.019)	(0.180)	(0.026)
t+7	-211.6	-237.4	-223.3	-254.0	-439.1	-572.4	-451.9	-590.0	15.9	92.6	94.8	77.5
	(0.052)	(0.169)	(0.023)	(0.105)	(0.001)	(0.024)	(0.001)	(0.016)	(0.513)	(0.006)	(0.917)	(0.184)
t+8	-168.6	-196.3	-176.2	-210.4	-329.7	-467.5	-337.9	-484.2	-7.4	70.5	-14.4	58.4
	(0.029)	(0.152)	(0.014)	(0.088)	(0.000)	(0.013)	(0.000)	(0.009)	(0.721)	(0.006)	(0.699)	(0.243)
t+9	-147.4	-173.5	-153.4	-188.2	-274.5	-411.3	-281.0	-429.1	-20.2	60.8	-25.7	48.2
	(0.021)	(0.144)	(0.013)	(0.082)	(0.000)	(0.012)	(0.000)	(0.008)	(0.308)	(0.011)	(0.450)	(0.295)
t+10	-169.0	-194.4	-172.5	-200.3	-283.3	-406.9	-287.9	-416.3	-54.7	15.0	-57.2	12.4
	(0.009)	(0.106)	(0.005)	(0.052)	(0.000)	(0.012)	(0.000)	(0.008)	(0.020)	(0.196)	(0.112)	(0.784)
t+11	-144.4	-169.9	-151.9	-180.0	-226.2	-352.6	-235.0	-364.2	-62.5	10.5	-69.0	1.8
	(0.006)	(0.101)	(0.006)	(0.035)	(0.000)	(0.010)	(0.001)	(0.004)	(0.011)	(0.377)	(0.060)	(0.967)
t+12	-140.2	-159.1	-146.1	-175.0	-201.5	-315.0	-208.8	-332.7	-78.8	-4.4	-83.4	-18.9
	(0.005)	(0.070)	(0.007)	(0.022)	(0.003)	(0.003)	(0.006)	(0.001)	(0.005)	(0.751)	(0.017)	(0.615)
t+13	-116.7	-132.1	-124.3	-145.9	-150.7	-256.3	-160.1	-270.5	-82.8	-8.6	-88.6	-22.3
	(0.021)	(0.067)	(0.028)	(0.023)	(0.073)	(0.003)	(0.081)	(0.001)	(0.006)	(0.587)	(0.012)	(0.528)
t+14	-108.2	-119.2	-115.0	-132.6	-127.4	-225.4	-136.6	-238.8	-89.1	-13.5	-93.5	-27.1
	(0.038)	(0.059)	(0.049)	(0.022)	(0.169)	(0.002)	(0.171)	(0.001)	(0.005)	(0.421)	(0.009)	(0.433)
t+15	-105.7	-112.1	-111.8	-125.9	-119.0	-208.6	-128.2	-222.2	-92.4	-16.1	-95.6	-30.2
	(0.049)	(0.060)	(0.061)	(0.024)	(0.226)	(0.003)	(0.221)	(0.002)	(0.004)	(0.379)	(0.007)	(0.380)
t+16	-96.8	-103.8	-103.0	-116.8	-106.4	-195.8	-115.5	-208.4	-87.4	-12.1	-90.5	-25.7
	(0.055)	(0.062)	(0.066)	(0.025)	(0.255)	(0.004)	(0.245)	(0.003)	(0.002)	(0.405)	(0.005)	(0.427)
t+17	-86.6	-96.3	-93.9	-109.9	-88.1	-182.5	-98.4	-195.6	-85.1	-10.7	-89.5	-24.7
	(0.092)	(0.067)	(0.096)	(0.028)	(0.366)	(0.005)	(0.337)	(0.004)	(0.003)	(0.464)	(0.005)	(0.433)
t+18	-76.8	-87.0	-81.3	-99.3	-70.9	-164.0	-78.3	-176.4	-82.6	-10.4	-84.3	-22.7
	(0.143)	(0.074)	(0.158)	(0.038)	(0.483)	(0.010)	(0.459)	(0.010)	(0.003)	(0.466)	(0.006)	(0.469)
t+19	-74.4	-84.4	-80.2	-97.4	-64.9	-157.5	-73.4	-170.9	-83.9	-11.5	-87.1	-24.3
	(0.155)	(0.073)	(0.159)	(0.036)	(0.520)	(0.012)	(0.484)	(0.010)	(0.003)	(0.408)	(0.005)	(0.430)
t+20	-72.2	-81.7	-78.3	-95.9	-55.1	-147.7	-63.8	-162.5	-89.3	-15.9	-92.8	-29.6
	(0.172)	(0.070)	(0.170)	(0.034)	(0.589)	(0.017)	(0.546)	(0.014)	(0.001)	(0.233)	(0.002)	(0.323)

Note:

This Table reports 240 coefficients indicating the difference in commercial bank lending (in THB million) between affected and unaffected provinces (β_m in Equation 3a) and the difference in lending among unaffected, mildly (θ_m in Equation 3b) and severely (ϵ_m in Equation 3b) affected provinces after m month from the tsunami in December 2004. We run 160 OLS regressions (4 models x 20 months x 2 DiD estimators) in total. The p-values are in parentheses.

The difference-in-differences between affected and unaffected areas are estimated using Equation (3a):

$$\Delta \mathrm{LOAN}_{i,j,t+m} = (\mathrm{TSUAFF}_{i,j} \text{ x } \mathrm{TIME}_{t+m}) + \gamma_m \Delta \mathrm{BRANCH}_{i,j,t+m} + \vartheta_m \Delta \mathrm{DEPOSIT}_{i,j,t+m} + \omega.\mathrm{Trend}_{j,t+m} + \mu_m \Delta \mathrm{NOP}_{j,t+m} + \pi_m \Delta \mathrm{VAP}_{j,t+m} + \mathrm{Time}_{t+m} + \mathrm{Location}_{i,j} + \varepsilon_{i,j,t+m} \quad (3a)$$

The difference-in-differences between mildly-, severely-affected and unaffected areas are estimated using the equation (3b):

$$\Delta \mathrm{LOAN}_{i,j,t+m} = \theta_m(\mathrm{MILD\_TSUAFF}_{i,j} \text{ x } \mathrm{TIME}_{t+m}) + \epsilon_m(\mathrm{SEVERE\_TSUAFF}_{i,j} \text{ x } \mathrm{TIME}_{t+m}) + \gamma_m \Delta \mathrm{BRANCH}_{i,j,t+m} + \vartheta_m \Delta \mathrm{DEPOSIT}_{i,j,t+m} + \omega.\mathrm{Trend}_{j,t+m} + \mu_m \Delta \mathrm{NOP}_{j,t+m} + \pi_m \Delta \mathrm{VAP}_{j,t+m} + \mathrm{Time}_{t+m} + \mathrm{Location}_{i,j} + \varepsilon_{i,j,t+m} \quad (3b)$$

The base is the unaffected group in both equations. The original period is 12-month before the tsunami. Model 1 is without time- and province-fixed effects. Model 2 is with province-fixed effects only. Model 3 is with time-fixed effects only. Model 4 is with both time- and province-fixed effects. The standard errors are clustered at province levels. The VIF tests which are conducted for all regressions show no serious multicollinearity. Total number of observations ranges from 600 (m=1, 13 months x 50 provinces) to 1,550 (m=20, 32 months x 50 provinces); we lose 50 observations in each estimate because of the differencing. Mildly-affected provinces are those with damages and losses of less than 20% and severely-affected provinces of more than 60% of the respective provincial GDP a year before the tsunami, for further details, please see Table 1. Other details are not reported to save space and available upon request. The average coefficients and p-values of β_m (Equation 3a) are presented in Figure 3.

Table 5. DiD in lending between affected and unaffected provinces – different tsunami windows

	Model 2			Model 3			Model 4		
	18-month	12-month	6-month	18-month	12-month	6-month	18-month	12-month	6-month
Tsunami x time	-175.04+	-237.62	-467.94	-152.70***	-242.87*	-517.08*	-191.18*	-279.42	-549.48
	(113.70)	(183.05)	(373.56)	(59.06)	(137.08)	(295.02)	(104.15)	(204.16)	(408.18)
No. of branches	60.90***	49.88	65.23	120.47***	66.01**	58.52*	64.62***	51.88	67.43
	(20.76)	(47.74)	(53.81)	(15.69)	(26.94)	(33.11)	(22.15)	(48.81)	(57.41)
Total deposits	-0.13	-0.13	-0.03	-0.05	-0.10	-0.16	-0.17	-0.15	-0.07
	(0.10)	(0.14)	(0.11)	(0.13)	(0.16)	(0.19)	(0.14)	(0.14)	(0.12)
Trend	8372.83***	8499.52**	7692.92**	8948.18**	7673.66**	5193.11**	9122.04**	8225.11**	6697.90**
	(3043.22)	(3717.92)	(3561.95)	(4406.00)	(3542.23)	(2562.96)	(4410.06)	(3713.99)	(3237.71)
No. of projects	0.76	-0.47	2.36	-0.64	0.41	1.99	0.15	0.59	5.54
	(2.54)	(1.62)	(4.25)	(1.70)	(1.71)	(5.13)	(1.65)	(1.88)	(7.87)
Value of investment	-0.0001	0.0002	-0.0033	0.0003	0.0014	0.0116	0.0006	0.0005	-0.0011
	(0.0015)	(0.0036)	(0.0072)	(0.0010)	(0.0043)	(0.0114)	(0.0013)	(0.0042)	(0.0132)
Province-fixed effects	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
Time-fixed effects	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
No. of provinces	50	50	50	50	50	50	50	50	50
No. of observations	900	600	300	900	600	300	900	600	300
R^2	0.27	0.26	0.33	0.19	0.18	0.22	0.28	0.26	0.34

Note:
This Table reports the difference-in-differences in lending between affected and unaffected provinces using different windows around the tsunami. The dependent variable is the change in lending of commercial banks at aggregate level in province i at month t as defined in Equation (1b). The main independent variable of interest is the interaction between the tsunami affected province and the months following the tsunami. Model 1 is without time- and province-fixed effects. Model 2 is with province-fixed effects only. Model 3 is with time-fixed effects only. Model 4 is with both time- and province-fixed effects. Model 1 (without time- and province-fixed effects also produces similar results but not reported to save space. The estimation is based on 18-month, 12-month and six-month windows around the tsunami. The number of provinces drops because regional level data for the central region are not available (25 provinces). Robust standard errors clustered at province level are in parentheses. *, ** and *** denote significant level at 10%, 5% and 1%, respectively. +indicates a significant level at 15%.

$$\Delta LOAN_{i,j,t} = \beta.\left(TSUAFF_{i,j} \text{ x } TIME_t\right) + \gamma.\Delta BRANCH_{i,j,t} + \vartheta.\Delta DEPOSIT_{i,j,t} + \omega.Trend_{j,t} + \mu.\Delta NOP_{j,t} + \pi.\Delta VAP_{j,t} + Time_t + Location_{i,j} + \varepsilon_{i,j,t} \quad (1b)$$

Table 6. DiD in lending between affected and unaffected provinces - artificial tsunami date

	Model 1		Model 2		Model 3		Model 4	
	2003	2005	2003	2005	2003	2005	2003	2005
Tsunami x time	18.54	20.88	5.18	196.16	21.47	7.66	6.31	196.91
	(51.82)	(108.79)	(26.76)	(139.48)	(52.19)	(99.43)	(28.06)	(129.82)
No. of branches	18.88	157.78***	-10.94	74.66***	21.30	164.76***	-11.93	78.42***
	(13.10)	(25.16)	(12.50)	(19.54)	(14.45)	(28.45)	(14.38)	(23.16)
Total deposits	0.16***	0.11**	0.07**	-0.03	0.18***	0.13**	0.08**	-0.06
	(0.04)	(0.05)	(0.03)	(0.05)	(0.04)	(0.06)	(0.04)	(0.06)
Trend	6464.17***	8023.89***	6371.43***	8137.29***	6562.19***	8818.29**	6306.90***	9115.58**
	(1483.92)	(2524.48)	(1681.40)	(2615.73)	(1608.84)	(4235.36)	(2213.13)	(4354.25)
No. of projects	-1.20	2.90**	-0.41	0.99	-1.29	0.30	-0.37	0.28
	(1.27)	(1.31)	(1.13)	(1.33)	(1.52)	(1.99)	(1.27)	(1.87)
Value of investment	0.0006	-0.0005	0.0002	-0.0005	-0.0003	-0.0021	0.0001	0.0001
	(0.0006)	(0.0042)	(0.0005)	(0.0041)	(0.0011)	(0.0059)	(0.0011)	(0.0059)
Province-fixed effects	No	No	Yes	Yes	No	No	Yes	Yes
Time-fixed effects	No	No	No	No	Yes	Yes	Yes	Yes
No. of provinces	50	50	50	50	50	50	50	50
No. of observations	1,150	1,150	1,150	1,150	1,150	1,150	1,150	1,150
R^2	0.20	0.23	0.33	0.43	0.21	0.24	0.37	0.44

Note:

This Table reports the difference-in-differences in lending between affected and unaffected provinces using artificial tsunami dates. The estimation is based on 24-month window around the artificial tsunami date which is falsified to have occurred one year before (in December 2003) and after (in December 2005) the actual tsunami date. The dependent variable is the change in lending of commercial banks at aggregate level in province i at month t as defined in Equation (1b). Model 1 is without time- and province-fixed effects. Model 2 is with province-fixed effects only. Model 3 is with time-fixed effects only. Model 4 is with both time- and province-fixed effects. The number of provinces drops because regional level data for the central region are not available (25 provinces). Robust standard errors clustered at province level are in parentheses. *, ** and *** denote significant level at 10%, 5% and 1%, respectively.

$\Delta \mathrm{LOAN}_{i,j,t} = \beta.\left(\mathrm{TSUAFF}_{i,j} \text{ x } \mathrm{TIME}_t\right) + \gamma.\Delta \mathrm{BRANCH}_{i,j,t} + \vartheta.\Delta \mathrm{DEPOSIT}_{i,j,t} + \omega.\mathrm{Trend}_{j,t} + \mu.\Delta \mathrm{NOP}_{j,t} + \pi.\Delta \mathrm{VAP}_{j,t} + \mathrm{Time}_t + \mathrm{Location}_{i,j} + \varepsilon_{i,j,t}$ (1b)

Table 7. The effects of the tsunami on lending between affected and unaffected provinces – fixed effects estimator

	(7a) Difference in lending (time-demeaned)		(7b) Difference in lending (time-collapsed)
	Model 1	Model 3	Model 1
Tsunami x time	-1858.93**	-1918.97**	-2004.33**
	(785.69)	(801.37)	(1002.64)
No. of branches	185.43***	183.25***	10.10
	(57.53)	(51.96)	(95.22)
Total deposits	0.48***	0.46**	0.84***
	(0.14)	(0.23)	(0.31)
Trend	7338.16**	3675.97	324.17
	(3612.77)	(4572.00)	(4957.98)
No. of projects	7.20	-0.86	-8.39
	(9.12)	(18.53)	(147.30)
Value of investment	0.0084	0.0036	0.0980
	(0.0080)	(0.0142)	(0.3921)
Time-fixed effects	No	Yes	No
No. of provinces	50	50	50
No. of observations	1,150	1,150	100
R^2	0.95	0.95	0.96

Note:
This Table reports the difference-in-differences in lending between affected and unaffected provinces using fixed-effects estimator on time-demeaned and time-collapsed samples. The dependent variable is the lending of commercial banks at aggregate level in province i at month t as shown in Equation (1b').The results of (7a) are produced by applying the fixed effects estimator (time-demeaned data). The time-collapsed data (7b) are the values of relevant variables averaged for the pre- and post-tsunami periods separately. The fixed effects are then applied to the data to generate the result in (7b) (of which the main variable of interest is identical to difference-in-differences as t = 2). The estimation result with time-fixed effects for (7b) is not shown because of multicollinearity due to limited points of time. For further details of these variables, see Equation (1b). Model 1 is without time-fixed effects. Model 3 is with time-fixed effects. The number of provinces drops because regional level data for the central region are not available (25 provinces). Robust standard errors clustered at province level are in parentheses. *, ** and *** denote significant level at 10%, 5% and 1%, respectively.

$\mathrm{LOAN}_{i,j,t} = \beta.\left(\mathrm{TSUAFF}_{i,j} \text{ x } \mathrm{TIME}_t\right) + \gamma.\mathrm{BRANCH}_{i,j,t} + \vartheta.\mathrm{DEPOSIT}_{i,j,t} + \omega.\mathrm{Trend}_{j,t} + \mu.\mathrm{NOP}_{j,t} + \pi.\mathrm{VAP}_{j,t} + \mathrm{Time}_t + \varepsilon_{i,j,t}$ (1b')

Table 8. DiD in lending between affected and unaffected provinces - branch levels

	Model 1	Model 2	Model 3	Model 4
Tsunami x time	-133.02**	-251.51*	-134.26***	-237.65*
	(52.26)	(128.40)	(48.38)	(126.26)
No. of branches	5.16***	27.63**	5.26***	30.17**
	(1.14)	(10.91)	(1.18)	(12.07)
Total deposits	-0.02	-0.07	-0.05	-0.11
	(0.05)	(0.06)	(0.08)	(0.09)
Trend	8568.37***	8049.31***	9494.34**	9284.60**
	(2628.46)	(2670.33)	(4409.20)	(4304.58)
No. of projects	0.24	0.31	0.17	0.66
	(1.69)	(1.67)	(1.24)	(1.32)
Value of investment	0.00001	-0.00004	-0.00007	-0.00014
	(0.00131)	(0.00111)	(0.00116)	(0.00137)
Province-fixed effects	No	Yes	No	Yes
Time-fixed effects	No	No	Yes	Yes
No. of provinces	50	50	50	50
No. of observations	1,150	1,150	1,150	1,150
R^2	0.26	0.34	0.27	0.35

Note:
This Table reports the difference-in-differences in lending between affected and unaffected provinces using number of branches. The results are estimated based on the replacement of the change in (in Equation 1b) with the lagged number of branches (the LEVEL_BRANCH variable as shown in Equation 1b'' below). The dependent variable is the change in lending of commercial banks at aggregate level in province i at month t. Other variables are as defined in Equation (1b). Model 1 is without time- and province-fixed effects. Model 2 is with province-fixed effects only. Model 3 is with time-fixed effects only. Model 4 is with both time- and province-fixed effects. The estimation is based on 24-month window around the tsunami. Robust standard errors clustered at province level are in parentheses. *, ** and *** denote significant level at 10%, 5% and 1%, respectively.

$$\Delta \mathrm{LOAN}_{i,j,t} = \beta.\left(\mathrm{TSUAFF}_{i,j} \text{ x } \mathrm{TIME}_t\right) + \gamma'.\mathrm{LEVEL\_BRANCH}_{i,j,(t-1)} + \vartheta.\Delta \mathrm{DEPOSIT}_{i,j,t} + \omega.\mathrm{Trend}_{j,t} + \mu.\Delta \mathrm{NOP}_{j,t} + \pi.\Delta \mathrm{VAP}_{j,t} + \mathrm{Time}_t + \mathrm{Location}_{i,j} + \varepsilon_{i,j,t} \text{ (1b'')}$$

Table 9. DiD in lending – using neighbour provinces as a control group

	Model 1	Model 2	Model 3	Model 4
Tsunami x time	-185.46**	-164.22*	-263.15*	-299.20*
	(81.20)	(93.94)	(151.05)	(160.96)
No. of branches	106.04***	73.94***	115.65***	79.62***
	(19.22)	(21.50)	(24.20)	(23.75)
Total deposits	0.06	-0.12	0.09	-0.15
	(0.16)	(0.17)	(0.23)	(0.25)
Trend	9010.43**	9370.59**		
	(4028.21)	(4110.60)	--	--
No. of projects	0.05	0.99	-3.47	1.82
	(3.42)	(3.27)	(6.72)	(5.84)
Value of investment	-0.0041	-0.0019	0.0771	0.0772
	(0.0281)	(0.0261)	(0.0673)	(0.0646)
Province-fixed effects	No	Yes	No	Yes
Time-fixed effects	No	No	Yes	Yes
No. of provinces	14	14	14	14
No. of observations	322	322	322	322
R^2	0.22	0.33	0.23	0.34

Note:
This Table reports the difference-in-differences in lending between affected and unaffected provinces using provinces in Southern region as a control group. The estimation is based on 24-month window around the tsunami date using lending data to provinces within Southern region which has 14 provinces. Six out of these 14 provinces are affected by the tsunami. The dependent variable is the change in lending of commercial banks at aggregate level in province i at month t as defined in Equation (1b). Model 1 is without time- and province-fixed effects. Model 2 is with province-fixed effects only. Model 3 is with time-fixed effects only. Model 4 is with both time- and province-fixed effects. The variable indicated 'Trend' is dropped in Model 3 and 4 because of multicollinearity. Robust standard errors clustered at province level are in parentheses. *, ** and *** denote significant level at 10%, 5% and 1%, respectively.
$\Delta \mathrm{LOAN}_{i,t} = \beta.(\mathrm{TSUAFF}_i \times \mathrm{TIME}_t) + \gamma.\Delta \mathrm{BRANCH}_{i,t} + \vartheta.\Delta \mathrm{DEPOSIT}_{i,t} + \omega.\mathrm{Trend}_t + \mu.\Delta \mathrm{NOP}_t + \pi.\Delta \mathrm{VAP}_t + \mathrm{Time}_t + \mathrm{Location}_i + \varepsilon_{i,t}$ (1b)

Table 10. DiD in lending – using the propensity scores matched sample as a control group

	Model 2			Model 3			Model 4		
	12-month	18-month	24-month	12-month	18-month	24-month	12-month	18-month	24-month
Mildly-affected x time	178.3*	52.62*	10.16	127.4	78.33	22.43	141.7	108.3*	63.05
	(90.53)	(27.57)	(15.49)	(73.30)	(46.78)	(30.35)	(90.19)	(48.89)	(33.30)
Severely-affected x time	-282.6**	-277.6**	-228.5*	-210.4**	-157.9*	-133.9*	-309.8**	-215.7*	-168.4*
	(114.1)	(112.4)	(98.09)	(87.74)	(70.54)	(68.74)	(127.8)	(100.1)	(86.09)
No. of branches	49.73	43.38	36.07	90.52	78.41	81.40*	83.81	70.71	75.82*
	(37.91)	(35.07)	(41.19)	(54.89)	(42.49)	(36.45)	(60.04)	(44.67)	(37.21)
Total deposits	-0.460**	-0.213*	-0.100	-0.497**	-0.397**	-0.299*	-0.557**	-0.415**	-0.329**
	(0.167)	(0.104)	(0.0600)	(0.173)	(0.138)	(0.131)	(0.189)	(0.146)	(0.131)
Trend	8,717*	5,191*	4,242	8,552*	8,563*	7,766	8,275*	8,456	7,786
	(3,891)	(2,733)	(2,387)	(4,231)	(4,455)	(4,265)	(4,321)	(4,487)	(4,332)
No. of projects	-0.561	6.657	5.456*	-2.788*	1.278	0.500	-3.010*	1.488	0.369
	(2.328)	(3.614)	(2.625)	(1.279)	(2.777)	(1.370)	(1.504)	(3.070)	(1.543)
Value of investment	0.0118	0.00348	0.00302	0.0122	0.00055	-0.00014	0.0142	0.00068	-0.00003
	(0.0298)	(0.0107)	(0.00974)	(0.0238)	(0.00462)	(0.00359)	(0.0255)	(0.00484)	(0.00364)
Province-fixed effects	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
Time-fixed effects	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
No. of provinces	8	8	8	8	8	8	8	8	8
Observations	96	144	184	96	144	184	96	144	184
R^2	0.411	0.299	0.243	0.428	0.387	0.345	0.448	0.402	0.362

Note:
This table reports the difference-in-differences results of a matched sample between affected and unaffected provinces. We use a propensity score matching algorithm to identify matches between provinces that were hit by the tsunami and those were not. We first run a probit model based on our original sample of 50 provinces in the month immediately before the tsunami (December 2004). The dependent variable equals one if the province was affected by the tsunami and zero otherwise. The probit model includes province-variant variables similar to our baseline model (1a in Table 2). However, the lending trend is defined as the average growth of loan over three months preceding the tsunami in order to capture the pre-treatment parallel trend assumption. The model is as specified in (1a').

$\mathrm{TSUNAMI}_i = \gamma.\mathrm{BRANCH}_{i,j} + \vartheta.\mathrm{DEPOSIT}_{i,j} + \omega.\mathrm{Trend}_{i,j} + \varepsilon_{i,j}$ (1a')

From the probit estimation, we use the propensity scores predicted and conduct a one-to-one nearest-neighbour matching procedure to match the tsunami affected provinces with those unaffected on the outcome (loan). The differences in propensity scores are set to be less than 0.01. After matching, we have four matched pairs of provinces (the affected provinces are Krabi, Phangnga, Trang and Satun). We then apply the Equation (2) as shown below to this matched sample.

$\Delta\mathrm{LOAN}_{i,j,t} = \theta.\left(\mathrm{MILD\_TSUAFF}_{i,j}\ \mathrm{x}\ \mathrm{TIME}_t\right) + \epsilon.\left(\mathrm{SEVERE\_TSUAFF}_{i,j}\ \mathrm{x}\ \mathrm{TIME}_t\right) + \gamma.\Delta\mathrm{BRANCH}_{i,j,t} + \vartheta.\Delta\mathrm{DEPOSIT}_{i,j,t} + \omega.\mathrm{Trend}_{j,t} + \mu.\Delta\mathrm{NOP}_{j,t} + \pi.\Delta\mathrm{VAP}_{j,t} + \mathrm{Time}_t + \mathrm{Location}_{i,j} + \varepsilon_{i,j,t}$ (2)

The dependent variable is the change in lending of commercial banks at aggregate level in province i at month t. The main independent variables of interest are the interactions between the provinces mildly affected and those severely affected and the months following the tsunami. The base is the interaction between the unaffected areas and the time after the tsunami. Model 2 is with province-fixed effects. Model 3 is with time-fixed effects. Model 4 is with both time- and province-fixed effects. Model 1 (without time- and province-fixed effects also produces similar results but not reported to save space. The estimation is based on 12-month, 18-month and 24-month windows around the tsunami. Robust standard errors clustered at province level are in parentheses. *, ** and *** denote significant level at 10%, 5% and 1%, respectively.

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