The impact of natural disasters on bank performance and the moderating role of financial integration: Evidence from East Asia Pacific

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Abstract

We analyse the impact of natural disasters on commercial bank performance. Further, we explore the moderating impact financial integration has on bank performance during natural disasters. We do so for the East Asia Pacific region during 1992-2010. Our empirical evidence shows that the exogenous impact of natural disasters increases bank credit and default risk. In particular, our results indicate that developing countries are more vulnerable to the adverse impact of bank default risk. Furthermore, our results demonstrate a positive association between natural disasters and tighter bank liquidity. Finally, we report evidence that financial integration worsens the impact of natural disasters on bank performance. Our work implies that, banking systems that depend heavily on foreign capital (or foreign banks), need to account for the risk that capital outflows exacerbate the negative effects of natural disasters on bank performance.

JEL classification: G21, Q54, F38

Key words: natural disasters, bank performance, financial integration, East Asia Pacific

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1. Introduction

This paper examines the impact of natural disasters on a broad range of bank performance measures, namely; credit risk, default risk, liquidity and profitability. Further, it explores the moderating effect of financial integration (measured by the ratio of foreign bank presence and the foreign claims of international banks to GDP) has on the relationship between natural disasters and bank performance. The sample consists of commercial banks from eleven countries within East Asia and the Pacific (China, Japan, Korea, Indonesia, Malaysia, the Philippines, Singapore, Thailand, Vietnam, Australia and New Zealand) over the period 1992-2010.

An assessment of the potential impact of natural disasters on bank performance and factors moderating this relationship are important at both country level and bank level. At the country level, banks are better able than markets or insurance to cater for firms' preferences for financial flexibility (Gorbenko and Strebulaev, 2010; Bos and Li, 2017) with outright lending or additional credit commitments. The banking sector plays an important role in supporting the recovery process of firms following natural disasters by providing ex-post disaster risk financing scheme. In developing countries, where insurance coverage is non-existent or deficient, the role of banks in the reconstruction process becomes more important (Nguyen and Wilson, 2016). However, if banks are strongly affected by disasters (perhaps as a result of the magnitude of the disaster or its geographical concentration) or there are factors worsening its impact on the bank (such as withdrawal of international capital), the role of banks in the reconstruction process could be limited. In the event of a disaster, it is important for banks mangers to maintain normal business operations, profitability, and liquidity. It is also equally important to maintain sufficient capital to ensure the bank's long-term stability, even in the case of future shocks. Given the importance of banking to the economy, we assess the impact of disasters on various aspects of bank performance.

The East Asia Pacific region provides a good context to examine the impact of natural disasters on bank performance and the moderating role of financial integration for two main reasons. First, the region has been affected by numerous destructive natural disasters during the last few decades. Examples include the Indian Ocean tsunami in 2004, cyclone Nargis and the Sichuan earthquake in 2008. Such catastrophic events have a large economic and social impact on the affected countries. Specifically, over the past 20 years, Asia has borne almost half of the estimated global economic cost of natural disasters; roughly $53 billion annually (ADB, 2014). Therefore, it is meaningful to study the impact of disasters on banks performance in the region. Second, there has been rapid financial integration in East Asia Pacific over the past few decades. International banking claims on the region is the highest in the world in 2015 and foreign bank penetration proved to be resilient even after the global financial crisis (World Bank, 2018; Nguyen et al., 2017). Hence, the recent increase in integration of the region as measured by the the receipt of foreign capital and the hosting of foreign banks, means that the East Asia Pacific region is a good context to examine the moderating role of financial integration on the impact of natural disasters on bank performance.

Existing empirical studies examining the impact of disasters on bank performance often focus on the response of banks around an event window of a specific disaster in one country.[1] Cross-country analyses are rare in the literature on the impact of natural disasters on bank performance, with one notable exception being Klomp (2014). This paper focuses on the impact of natural disasters on the country-level financial stability (measured by the Z-score of the national banking sector) of 81 countries during the period 1997-2010. Our study augments Klomp (2014) by employing a wider range of performance measures and by utilising bank-specific variables constructed from financial statements of banks. These measures include credit risk, default risk, liquidity and profitability. Moreover, our paper is the first one to examine the impact of disasters on bank liquidity and profitability in a cross-country context. Indeed it is also rare in country specific analyses with Noth and Schumer (2018) for US context being the only discernible prior analysis.

The literature provides opposing predictions on the moderating role of financial integration on the relationship between natural disasters and bank performance. On the one hand, foreign banks and foreign capital could help to ease financial constraints in host economies by providing access to alternative sources of external financing and compensating for the volatility of domestic credit (De Haas and van Lelyveld, 2006; Allen et al., 2011). On the other hand, the likelihood of associated international capital outflows (Yang, 2008; Noy, 2009) or the less active lending behaviour of foreign banks could amplify the impact of disasters on banks. Given the contrasting predictions, establishing which of these effects dominates is an empirical question of general academic interest and of interest to policymakers.

[1] Garmaise and Moskowitz (2009) study the impact of earthquakes in California (US); Nguyen and Wilson (2016) study the 2004 Indian Ocean tsunami in Thailand, Koetter et al. (2016) study the impact of the 2013 Elbe flooding in Germany; Lambert et al. (2015) study banks hit by Hurricane Katrina in 2005; Hosono et al. (2016) study the 1995 Kobe earthquake; and Collier et al. (2013) study the impact of volcanic eruptions in Ecuador.

However, there has not been any empirical paper directly examines the moderating role of financial integration in the relationship between natural disasters and bank performance. Our paper fills in this gap in the literature by using the ratio of foreign bank penetration and foreign claims of international banks to GDP to proxy for the level of financial integration; then creating the interactions between these measures and the proxy for the impact of natural disasters.

With respect to the measure of the impact of natural disasters, we directly obtain an aggregate disaster index for each country and specific measure of intensity for each type of disasters from a new database on the physical intensity of disasters. It is the Ifo Geological and Meteorological Events (Ifo-GAME) which was initially published and applied to examine the impact of natural disasters on economic growth by Felbermayr and Gröschl (Journal of Development Economics, 2014). The database overcomes weaknesses of the most popular source of disaster damage from "Emergency Events Database" (EM-DAT) by providing the full population of all disasters as well as an exogenous measure of disaster magnitude.

Our findings make several contributions to the existing literature. First, disasters adversely affect bank's credit risk and stability, which is consistent with the cross-country and US evidence in Klomp (2014) and Noth and Schumer (2018), respectively. Complementing these papers, we find that bank default vulnerability from natural disasters is more pronounced in developing countries.

Second, we find a consistent evidence of tighter liquidity following natural disasters, regardless of aggregated or disaggregated measures of disasters intensity, or of level of economic development in countries. This highlights the importance of examining the impact of disasters on bank liquidity, which, as noted above, has been largely un-explored by the current empirical literature.

Third, we report the positive but insignificant influence of disasters on bank profitability. The result is contradictory to the empirical evidence in Noth and Schumer (2018) who find a negative and significant association. The conflicting evidence calls for further studies to directly examine whether the benefit from recovery lending growth or the cost of deteriorating loan quality dominate the ultimate impact of natural disasters on banks profitability.

Finally, regardless of the type of indicators employed (foreign claims of international banks to GDP and foreign banks penetration), financial integration worsens the impact of disasters on bank performance. This could result from the withdrawal of international flows. Given this finding, our paper adds to the existing literature on the volatility of international banking flows toward exogenous shocks not only during financial crisis (e.g Levchenko and Mauro, 2007; Eichengreen et al., 2018) but also during natural disasters (e.g Yang, 2008; David, 2011). Furthermore, our finding also indicates the active role of domestic banks (rather than foreign banks) in expanding recovery loans to support the liquidity constraint of customers. Thus, in addition to the US evidence (e.g Chavaz, 2014; Cortes and Strahan, 2015) and German evidence (e.g Koetter et al., 2016), our paper provides the East Asia Pacific evidence to highlight the importance of local banks and relationship lending as an effective mechanism to mitigate disaster shocks in affected regions. Overall, the finding implies that banking systems and countries that are dependent on the foreign capital or foreign banks should account for the aggregate impact of disasters on bank performance itself and the related impact from the capital outflows, which could both slow down the recovery process of the affected regions after disasters.

The rest of this paper is structured as follows. Section 2 reviews the related literature and introduces our hypotheses. The methodology is presented Section 3. Section 4 presents findings and discussion. Section 5 provides conclusion and implications.

2. Literature review and hypotheses

To summarise, this study seeks to answer the following two research questions: (i) How do natural disasters affect various measures of bank performance (such as credit risk, default risk, liquidity and profitability)?; and (ii) How does financial integration moderate the impact of natural disasters on bank performance? Prior to outlining the empirical strategy of the paper, we develop research hypotheses around these research questions that is built on the extant literature.

Related to the first research question, the extant literature generally confirms the negative impact of disasters on bank default risk and credit risk. For instance, using a simulation approach, Collier et al. (2013) indicate that natural catastrophes could become a systemic risk because of declining capital ratios, reductions in equity and decreases in loan origination immediately following a disaster. An empirical cross-country analysis by Klomp (2014) suggests that large-scale natural disasters, especially geophysical and meteorological disasters, increase the likelihood of a bank's default in emerging countries during the examined period 1997–2010. In addition to default risk, natural disasters could also increase bank credit risk due to the deterioration in payment capabilities of affected borrowers (Klomp, 2014). Additionally, damage to a bank headquarter would reduce managerial capacity to process loan applications at the back office while damage to a branch network is associated with declining financial health and risk-taking capacity (Hosono et al., 2016). As empirically proved by Noth and Schumer (2018), the occurrence of natural disasters in the US during 1994-2012 is associated with higher probabilities of bank default and non-performing assets ratio for two years following a natural disaster.

Another potential impact of disasters is on bank liquidity. Klomp (2014) argues that the tighten liquidity is expected in the aftermath of disasters due to the immediate withdrawals of existing deposits to replace lost physical capital or a higher interbank interest rate as the uncertainty of repayment increases. Unfortunately, there has not been any empirical evidence on the impact of disasters on bank liquidity. Based on these evidences, we develop Hypothesis 1 as follows: "**Hypothesis 1: Natural disasters negatively affect bank credit risk, default risk and liquidity".**

Bank profitability greatly depends on its earning assets taking form of loans or investments. As there is mixed empirical evidence on bank credit supply during natural disasters, it is not straightforward to predict the favourable impact of disasters on profitability via the channel of credit growth. On the one hand, some studies confirm an increase in bank lending after disasters, which could help to increase bank profitability. For instance, providing the US evidence, Chavaz (2014) and Cortes and Strahan (2015) indicate that small and local banks in affected regions increase their lending to meet the increased loan demand from their customers. Likewise, Koetter et al. (2016) find that local banks especially savings and cooperative banks increase their lending to borrowers affected by the 2013 Elbe flooding in Germany. These local banks increase not only their lending levels but also the share of lending relative to their total assets.

On the other hand, some papers document a decrease in bank lending, which could not positively contribute to banks' profitability. Garmaise and Moskowitz (2009) and Nguyen and Wilson (2016) confirm the decline in credit supply in the affected areas following earthquakes in California (US) and the Indian Ocean tsunami in Thailand, respectively. Similarly, Hosono et al. (2016), using the matched firm-bank data, conclude that affected banks' lower lending capacity has a significant adverse effect on firm investment after the 1995 Kobe earthquake. This could be explained by the "flight to quality" behaviour of banks. According to Lambert et al. (2015), banks hit by Hurricane Katrina in 2005 substitutes customer lending with government securities. The asset swap helped to stabilize banks but represents a loan supply contraction that might have hindered the recovery of non-financial firms.[2]

Noth and Schumer (2018) provides an empirical evidence on the adverse impact of disasters on bank profitability in US. As also found in the paper, disasters increase credit risk, default risk and lower equity ratio. These adverse impacts could lower bank profitability. However, the paper does not examine the possibility for banks to benefit from recovery loans growth. In short, the existence of the above opposing predictions prevents us from making unambiguous hypothesis on the impact of disasters on profitability. We treat it as an empirical issue and form the second hypothesis as follows: "**Hypothesis 2: Natural disasters affect bank profitability".**

Related to the second research question, there exists contradictory predictions on the moderating role of financial integration (either measured by the level of foreign banks penetration or foreign capital) on the relationship between natural disasters and bank performance. With regard to the former measure, on the one hand, evidence from (pro)cyclicality lending of foreign banks during local financial turmoil predicts that higher penetration ratio of foreign banks could help to alleviate the consequence of natural disasters. Specifically, lending behaviour of foreign banks are more resilient during local financial shocks (De Haas and van Lelyveld, 2006; Arena et al., 2007). This is because foreign banks have access to liquidity and capital injection from their parent banks (Cetorelli and Goldberg, 2012). On the other hand, if local and domestic banks are more active lenders after disasters, the higher ratio of foreign banks could worsen the impact of natural disasters. In general, though foreign banks may have more funding sources or better screening technologies than domestic banks, local banks have better information about the quality of local borrowers, and especially the more informationally opaque ones (Dell'Ariccia and Marquez, 2004). The occurrence of natural disasters may obliterate information on borrowers and collateral values; thereby local banks would have more advantage in accessing and processing tacit information (Chavaz, 2014). Also empirically proved by Chavaz (2014), Cortés and Strahan (2015) and Koetter et

[2] Bos and Li (2017) also prove that this is a long-term rather than an instantaneous bank response; they report that long-run experience of disasters affects bank risk attitudes and resilience to future shock. Specifically, banks that have had more intense earthquake experiences maintain a lower level of real estate loans, boost their equity buffer, and prefer high-income borrowers compared with banks having less intense experiences.

al. (2016), the credit demand in the affected areas is predominantly satisfied by small and local banks whose activities are concentrated in the affected markets.[3] In other words, these findings suggest that lower integration as represented by a higher proportion of local and domestic banks will help mitigate disaster shocks through their relationship lending.

Foreign capital could also serve as the moderating factor in the relationship between natural disasters and bank performance. On the one hand, generally, foreign capital can ease financial constraints in host economies by providing access to alternative sources of external financing and compensating for the volatility of domestic credit (Allen et al., 2011). In the aftermath of natural disasters, at the country level, the availability of foreign funds helps to speed up the replenishment of capital stock, allowing countries to quickly absorb and respond to the shocks (Noy, 2009; Felbernmayr and Groschl, 2014). From a bank perspective, it can increase its international borrowings to meet the increase in the credit demand and disaster relief (for example, bridging loans for periods of lost business). On the other hand, a likelihood of severe outflows of international capital especially banking flows after a disaster can exacerbate the adverse impact of disasters on bank performance. There has been established evidence on the volatile response of international banking flows towards exogenous shocks. For instance, bank lending flows is more volatile than equity and FDI flows during the event of financial shocks (Levchenko and Mauro, 2007; Eichengreen et al., 2018). In the aftermath of natural disasters, Yang (2008) and David (2011) consistently find that private flows (such as bank lending and equity) seem to experience "capital flight" in contrast to the inflows of foreign aid and remittance.

However, there has not been any empirical studies directly examine how foreign capital moderate the impact of disasters on bank performance. In deed there has been only an evidence about the moderating role of capital account openness on the impact of natural disasters on economic growth. Specifically, countries with a less open capital account are better able to endure natural disasters (Noy, 2009). This follows from the fact that countries with capital account restrictions are less vulnerable to "capital flight" following a natural disaster event.

Overall, based on evidences on the lending behaviour of local banks following natural disasters as well as the volatility of banking flows, we develop the third hypothesis as follows:

[3] Cortés and Strahan (2015) further identify two main mechanisms in which small banks can effectively smooth local credit demand shocks caused by natural disasters, even without access to national or global capital markets. These banks move funds from unaffected areas to affected areas and increase loans sales/securitization to circumvent capital constraints and avoid cutting loan originations.

"**Hypothesis 3: Greater financial integration exacerbates the consequences of natural disasters on bank performance".**

3. Methodology

3.1 Empirical models and estimation method

Following the literature on the determinants of bank performance (Berger et al., 2000; Athanasoglou et al., 2008; Goddard et al., 2011; Wu et al., 2017), the impact of disasters on economic growth (McDermott et al., 2013; Noy, 2009) and on the performance of financial institutions (Klomp, 2014, 2018), we develop a dynamic panel model to test Hypothesis 1 and 2 as follows:

$$Y_{ijt} = \theta_i + \mu_t + \gamma_1 Y_{ijt-1} + \gamma_2\, \mathbf{Dis_{jt}} + \beta_k X^k{}_{jt-1} + \varepsilon_{ijt} \quad (1)$$

We retain the model and variables specification in Eq. (1), then include the interaction term between the measures of financial integration and disasters impact to test Hypothesis 3:

$$Y_{ijt} = \theta_i + \mu_t + \gamma_1 Y_{ijt-1} + \gamma_2 \mathbf{Dis_{jt}} + \gamma_3\, \mathbf{INTEG_{jt}} + \gamma_4\, \mathbf{INTEG_{jt}{*}Dis_{jt}} + \beta_k X^k{}_{jt-1} + \varepsilon_{ijt} \quad (2)$$

Where Y_{ijt} is the dependent variable (CRERISK credit risk, ZSCORE distance-to-default, LIQ liquidity and ROA profitability) for bank *i* in country *j* at time *t.* Y_{ijt-1} is the lagged dependent variable, to account for the potential auto-regressive tendency (persistency over time). γ_1 is the speed of adjustment to equilibrium. The value of γ_1 ranges between 0 and 1 implying that Y (banks profit/risks) persists, but eventually returns to its normal (average) level. A value close to 0 means that the industry is fairly competitive (high speed of adjustment), while a value close to 1 implies a less competitive structure (slow speed of adjustment) (Athanasoglou et al., 2008).

Dis_{jt} is the proxy for disasters intensity (either measured by $DISINDEX_{jt}$ – the country index of disasters intensity or specific intensity measures of each type of disasters, see section 3.2). $INTEG_{jt}$ is the proxy for financial integration (either measured by $CLAIM_{jt}$ – the foreign claim of international banks to GDP, FOR_{jt} – the ratio of foreign banks, and $KAOPEN_{jt}$ – the capital account openness index, see section 3.3). $X^k{}_{jt-1}$ is a vector of (lagged) control variables containing *k* elements that control for country-level factors such as market concentration (CON), economic growth (GDP), inflation (IFL), and credit to private sector (PRICRE). Control variables are introduced with a one-period lag to mitigate possible endogeneity issues between bank performance and macro-economic conditions.

In the dynamic setting given by Equations (1) and (2) the coefficients γ_1 to γ_4, and β_k capture the short-term effect on the dependent variables (Y_{ijt}) in response to a change in the explanatory variables (Dis_{jt}, $INTEG_{jt}$ and X^k_{jt-1}).

θ_i is the *bank-specific fixed effect* to control for unobserved factors that don't change over time for each bank. μ_t is the *time-specific fixed effect* to control for year-specific effects such as the occurrence of a financial crisis (for example, the crises that occurred in 1997/1998, 2008/2009) during the sample period. ε_{ijt} is the error term. Detailed description and sources of all variables are presented in Appendix 1.

With regard to the estimator for the dynamic panel data model, due to the correlation between the fixed effects and the lagged dependent variable, the pooled Ordinary Least Squares (OLS) estimator is biased and inconsistent. The fixed effect (FE) method usually provides an upward biased estimator due to the Nickell (1981)'s finite-sample bias. There are two approaches to deal with this bias (Zhou et al., 2014; Dang et al., 2015). The first involves using instruments for the lagged dependent variable notably such as the System or Difference GMM. The second approach relies on estimators to correct for estimation bias such as the bootstrap-based correction procedure of simulation-based indirect inference method. Comparing the performance of these various method, Dang et al. (2015) reports that the frequently-employed GMM estimator is not always the best one. Despite an increasing number of various complex approaches to address the bias in dynamic panel data models, some papers still rely on the OLS-FE. For example, Felbermayr and Gröschl (2014) and Abedifar et al. (2017) argue that the OLS-FE bias decreases when the time dimension T gets large. As T is equal to 19 years in our paper; we use the OLS-FE estimation (and cluster the standard errors at bank-level for consistent standard errors) to obtain the baseline results.

3.2 Database and measures of natural disasters intensity

The Ifo Geological and Meteorological Events (Ifo-GAME) is a comprehensive database of disaster events (including earthquakes, volcanic eruptions, storms, floods, droughts, and extreme temperature) and their physical intensities constructed from primary geophysical and meteorological information during 1979-2010.[4] The database was initially

[4] This dataset builds on various datasets assembled by primary sources. The data for earthquakes are derived from the seismic activity of the *Incorporated Institute for Seismology* (IRIS). The *Global Volcanism Program of the Smithsonian Institution* measures volcanic eruptions and specifies the magnitude by the Volcanic Explosivity Index (VEI). Two primary data sources for wind speed are the *International Best Track Archive for Climate Stewardship* (IBTrACS) and the *Global Surface Summary*

published and applied to examine the impact of natural disasters on economic growth in Felbermayr and Gröschl (Journal of Development Economics, 2014).

We use the weighted country index, which is directly obtained from Felbermayr and Gröschl (2014), as our main measure of the disasters intensity ($DISINDEX_{jt}$) for each country in the sample. To provide more information about the construction of the variable, at the first step, in a given country and a given year, an event with the highest intensity from each type of disaster is selected then summed up to construct the unweighted index (regardless of different units of measure for each type of events). In the next step, to avoid that the movement of one type of disasters could move the whole index, the inverse of standard deviation of each disaster in each country over the whole examined period is used as the precision weights to construct the weighted index. In short, by its construction, the variable acts as an exogenous shock of natural disasters in the model.

Furthermore, we also test the disaggregated impact of each disaster type on bank performance using the specific intensity measure of each disaster type reported in the Ifo-GAME (such as Richter scale for earthquakes, Volcanic Explosivity Index for volcanic eruptions, wind speed for storms, temperature for extreme temperature and millimetre rainfall for floods and droughts).

We employ the Ifo-GAME database to construct our measure of disasters intensity rather than using "Emergency Events Database" (EM-DAT). Though EM-DAT has been the most popular source of data for disaster damage to date in the literature (Noy, 2009), it suffers from selection bias and endogeneity issue. For instance, Felbermayr and Gröschl (2014) point out that EM-DAT tends to report disasters with stronger physical intensity in countries with higher GDP per capita. Therefore, when a variable (taking form of either, the number of affected/killed people relative to the total population, or the economic loss to GDP) is used to to proxy for the damage of disasters on economic growth (again measured by GDP per capital),

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of Day (GSOD) data. The IBTRACS data are provided by the *National Climatic Data Center of the National Oceanic and Atmospheric Administration* (NOAA), which records data of individual hurricane events. Precipitation data to construct the measure for floods and droughts are recorded by the *Goddard Space Flight Center* of the *National Aeronautics and Space Administration* (NASA) in the *Global Precipitation Climatology Project* (GPCP). Temperature data stem from (GSOD, version 7) which includes records of temperature from over 9,000 worldwide stations and are produced by the *National Climatic Data Center* (NCDC). For more information about the dataset, please refer to Felbermayr and Gröschl (2014).

endogeneity issue is a valid concern. To alleviate the endogeneity concern, some papers (such as Klomp, 2014 and Noy, 2009) construct a count variable to proxy for frequency of disasters. However, EM-DAT does not include the full universe of events, so there is no measure of the number of disasters from which to calibrate a frequency score (Felbermayr and Gröschl, 2014).

3.3 Measures of financial integration

Foreign bank penetration and foreign claims of international banks are used as the main variables to measure the level of financial integration. To proxy for the former, the percentage of foreign banks relative to the total number of banks in a country (FOR) is used. This measure has been widely studied as a determinant of bank performance (Claessens et al., 2001; Wu et al, 2017).

The later indicator is defined as the foreign claims of international banks on a country to GDP of that country (CLAIM). The original data of "foreign claims" are sourced from the Consolidated Banking Statistics (CBS) from BIS. Originally, international banks report to BIS about their foreign financial assets including loans, debt securities, and equities, which is claimed on all sectors of a counter-party country. The statistics, then, are aggregated on the basis of counterparty countries. Though not originally designed with the borrower perspective in mind, the statistics are one of the few publicly available sources to provide information on the reliance of a borrower country on foreign bank credit (Cerutti et al., 2012). Therefore, CLAIM is relevant to assess the size of international capital channelled via international banks (debt-type international capital) to the sampled countries.

As our paper is the first one to use FOR and CLAIM in the context of the impact of natural disasters, we add robustness to our results by also employing KAOPEN (Chinn and Ito, 2008) as the third measure of financial integration. Noy (2009) uses KAOPEN index to examine the moderating role of capital account openness on the relationship between natural disasters damage and economic growth. This *de jure* indicator does not exhibit much variability over-time while FOR and CLAIM better reflects the evolvement and divergence in the level of financial integration in Asia (Nguyen et al., 2017).

4. Results and discussion

4.1. Descriptive analysis

A sample of 8,299 bank-year observations from eleven countries throughout the Asia-Pacific region comprising data from China, Japan, Korea, Indonesia, Malaysia, the Philippines, Singapore, Thailand, Vietnam, Australia and New Zealand over the period 1992-2010 is utilised. The detailed number of banks and observations for each country in each year are presented in Appendix 2. Japan, China and Indonesia are the countries with the highest number of banks, while Korea, Australia and New Zealand lie at another extreme.

Financial data are obtained from Bankscope database. The paper starts with all bank specialisations in the database, then excludes non-commercial banks. Further, we exclude banks with three or less years of observations. Consolidated data is used when available, otherwise unconsolidated. Subsidiaries are excluded when parent consolidated data is available to avoid double counting. In order to account for survivorship bias, the sample includes both active and inactive banks. We follow the standard procedure suggested by Duprey and Le (2016) to harmonize the difference in the end of financial year in reporting countries. Finally, all bank-level data are winsorized at the top and bottom 0.5th percentile to account for extreme values and unobservable data errors.

Table 1 provides descriptive statistics of bank-level and country-level variables used in the baseline regression. Table 2 reports the Pearson pairwise correlation coefficients of the variables. There are no concerns regarding multi-collinearity, since none of the correlations exceed 80%.

[INSERT TABLE 1 AND 2 ABOUT HERE]

Figure 1 and Figure 2 depict, respectively, the evolution of financial integration indicators (CLAIM and FOR) and the disaster intensity index ("DISINDEX") for each country in the sample over the period of 1992-2010. Regarding to the level of financial integration, Singapore and New Zealand are the top two countries with the highest level of financial integration while China and Vietnam lie at the another extreme. In terms of disasters intensity, Japan, Indonesia, and China are the top three countries experienced disasters with largest intensity.

[INSERT FIGURE 1 AND 2 ABOUT HERE]

4.2 The impact of natural disasters on bank performance

4.2.1 The impact of country disaster index on bank performance

We start the discussion with the aggregated impact of disasters measured by the country-year index ("DISINDEX"). Columns (1), (3), (5), and (7) of Table 3 present the parsimonious setting of Eq. (1) which includes only the lagged dependent variable and the disaster index. The extended model with other country-level control variables is reported in columns (2), (4), (6), and (8) of Table 3. Both settings deliver comparable results on the impact of disasters on bank performance.[5]

As seen in Column 2, the coefficient of DISINDEX on CRERISK is 0.075 and significant at 5% level; disasters significantly increase bank credit risk. The result is consistent with findings from Collier et al. (2013) and Noth and Schuwer (2018). Natural disasters expose banks to the unexpected losses arising from a decline in the value of collateral. At the same time, disasters also jeopardize the financial solvency of borrowers in the affected areas, which leads to a deteriorating quality of loans.

The adverse effect of natural disasters also materializes in the form of marginally significantly lower distance-to-default; the coefficient of DISINDEX on Z-score is -0.011 and significant at 10% level (as reported in Column 4). Being congruent with findings in Klomp (2014) and Noth and Schuwer (2018), the result implies that natural disasters would decrease bank stability. In the aftermath of natural disasters, the deteriorating quality and write-offs of loans portfolios together with the severe physical damage to bank facilities would ultimately need to be buffered by additional equity. If a bank could not increase its equity accordingly or is low capitalised, its default probability would be higher. This could explain for the coefficient's marginal significance as the ultimate impact of disasters on bank default also depends on whether banks could increase or have adequate equity buffer.

As seen in Column 6, disasters also exert a negative and significant impact on bank liquidity; the coefficient of DISINDEX on LIQ is -0.032 and significant at 1% level. On the liability side of a bank's balance sheet, once the disaster event occurs depositors could cease making deposits and request advances against their savings. On the asset side of the bank's balance sheet, the bank could convert its liquid assets into loans to support the reconstruction lending, resulting in an increase in aggregate lending (as found in Chavaz (2014), Cortés and Strahan (2015), Nguyen and Wilson (2016)). The evidence appears to contrast with the response of some US banks hit by Hurricane Katrina in 2005, who substituted customer lending with government securities (Lambert et al., 2015). In this East Asia Pacific sample, we do not find an evidence of "a flight to safety" by banks such as in the form of larger cash or government security holdings. Overall, though highly intuitive, the negative relationship between DISINDEX and LIQ has not been previously explored in the literature. The size of

[5] To reiterate, in the setting of a dynamic panel model, the estimated coefficients of each explanatory variable should be interpreted as being conditional on all other regressors and particularly the initial level of the dependent variable.

the coefficients and level of significance point to this being a strong effect. Taken together, the above findings from CRERISK, ZSCORE, and LIQ lends strong support to our Hypothesis 1.

As reported in Column 8, the impact of disasters on ROA is positive (with the coefficient being 0.002), but insignificant. On the one hand, bank profitability could directly benefit from the increase in lending business following the post-disaster reconstruction.[6] The increase in aggregate lending after a disaster event in the affected areas has been found in the literature (Chavaz, 2014; Cortés and Strahan 2015; Koetter et al. 2016). Especially, in some developing Asia countries, banks would act as an agent to channel government funds to support firms and households in these affected areas (Nguyen and Wilson, 2016). On the other hand, as previously found, natural disasters negatively affect bank credit risk and liquidity, which could be translated into a decrease in bank profitability. Therefore, the ultimate impact of disasters on profitability depends whether the benefit from additional lending business outweighs the cost of lower loans quality. In short, we conclude that the result of ROA partly supports Hypothesis 2.

The dynamic specification in the model is not rejected given the significant effect of the lagged dependent variable across different models. Among the four indicators of bank performance, credit risk, liquidity and z-scores exhibit higher persistency with coefficients being 0.543, 0.506, and 0.458 respectively. Profitability seems to persist to a moderate extent with a coefficient of 0.241.

Turning to the rest of explanatory variables, higher economic growth (GDP) and higher level of financial development (PRICRE) adversely affects bank performance. The finding is congruent with findings of other literature (such as Goddard et al., 2011; Wu et al. 2018). The availability of plentiful business opportunities stemmed from economic growth or a more developed financial market might tend to strengthen the competition in the banking sector, resulting in a lower profitability and liquidity. Banks may also lower their credit quality in order to pursue high loan growth and fuel economic growth. Higher levels of inflation (IFL) are associated with greater bank liquidity and instability. Bank managers may respond to inflation pressure by maintaining a substantial proportion of liquid assets, resulting a higher liquidity ratio. Finally, market concentration (CON) is associated with a reduction in a bank's distance-to-default. Consistent with the competition-fragility viewpoint (Beck et al., 2013),

[6] As the data for the volume of newly-extended loans are not available from Bankscope, we use loans to total assets ratio to proxy for the loans' growth. We found a positive but insignificant impact of the disasters intensity index ("DISINDEX" on loans to total assets ratio. The result is available upon request.

greater competition (associated with lower market concentration) undermines prudent bank behaviour, increasing risk-taking, and decreasing bank stability.

[INSERT TABLE 3 ABOUT HERE]

4.2.2 The impact of various type of disasters on bank performance

To assess the impact of specific types of disasters on bank performance, we separately include a measure of intensity for earthquakes, volcano eruptions, storms**,** floods, droughts and extreme temperature (rather than the aggregate disaster index "DISINDEX" as in section 4.2.1) in Eq. (1). We retain the previous model and variables specification.

As seen in Table 4, the distance-to-default coefficients for each type of disaster events are generally negative though insignificant. The aggregate impact of several disasters (proxied by the disaster index "DISINDEX") is more relevant in explaining the reduction of banks stability. The evidence provides another angle to the argument advanced by Klomp (2014); namely, banks default risk is not only associated with large-scale disasters but also to the aggregate impact of multiple disasters. The finding is particularly relevant to those banks located in disaster-prone areas and indeed to banks in areas vulnerable to increasing climate change related natural disasters. Besides, among the four aspects of bank performance, bank liquidity is generally and negatively affected by disaster types (except for droughts and extreme temperature). Finally, the impact of disasters on profitability varies with the type of disasters. The coefficients of storms, extreme temperature and droughts are positive and significant, whereas the coefficient of earth quakes is negative and significant. Taken together, the difference in the impact of various types of disasters on bank profitability partly contributes to explain the insignificant coefficient of the aggregated disaster index (DISINDEX) found in section 4.2.1.

Among different types of disasters, earthquake consistently and negatively affect bank profitability, credit risk and liquidity. The sudden and unexpected nature limits earthquake predictability and human preparation, resulting in physical losses to banks and the associated deteriorating economic prospects and financial solvency of borrowers. Storms, a popular phenomenon in some Asian countries such as the Philippines and Indonesia, also exert significant impact on bank profitability and liquidity. There is limited evidence that the gradual and incremental impact of slow onset events such as droughts, floods or extreme temperature events can be explained by either Ifo-GAME or the model.[7] These three events are likely to become more frequent with climate change (IPCC, 2013) so finding appropriate datasets and empirical techniques to measure their 'slow burning' impact are required.

[INSERT TABLE 4 ABOUT HERE]

4.2.3 The impact of disasters on bank performance- by the economic development of a country

To better understand how the level of economic development of a country moderates the impact of disasters on bank performance, the sample is separated into developed and developing countries.[8] Table 5 reports the impact of the disaster intensity index (DISINDEX) on various bank-level measures of performance for the two sub-samples.

Column 1-4 in Table 5 show the differential effect of disasters on bank credit risk and default risk. Specifically, there is a positive association between disasters and credit risk for banks only in developed countries (as seen in Column 1). Melecky and Raddatz (2011) argue that in high-income countries, the major consequences of large-scale natural disasters are usually passed through to the insurance and banking sector. Accordingly, the detrimental impact of disasters is reflected in the deteriorating quality of loans on the banks' balance sheet. In contrast, developing countries rely more on government assistance (Melecky and Raddatz, 2011). The estimated difference may be explained by the presence of governmental intervention schemes that allow banks in developing countries to restructure their non-performing loans. Additionally, bank regulation in developing countries is generally not as stringent as such of developed counterparts (Klomp and De Haan, 2014). Therefore, the lax regulation could affect the recognition of bad debts as a consequence of natural phenomena in developing countries, leading to the differential result with the developed sub-sample.

There is a significant negative association between disasters and bank distance to default for developing countries only (as reported in Column 6). Compared to developed

[7] A drawback of the Ifo-GAME data is the use of precipitation as an indicator for floods. Other factors such as the intensity and duration of rainfall, the geographical location, climate, and land-surface characteristics are more relevant to a flood occurrence (Zhou and Botzen, 2017). Additionally, due to climate change, sea level rise and tides are increasingly important to affect the occurrence of flooding events (IPCC, 2013). These important factors, unfortunately, are not reflected through the measurement and construction of the variable (floods) in Ifo-GAME. For droughts, the data records only one event for all of the sampled countries during the period of 1992-2010.

[8] Developed countries include Australia, Japan, Korea, New Zealand and Singapore. The rests of the sampled countries belong to the developing group.

countries, developing countries face much larger output declines following a disaster (Noy, 2009). Moreover, banking systems in developing countries are smaller (Klomp, 2014) and as such their ability to absorb the shocks from severe disasters are also more limited. These findings help to explain the vulnerability of banks in developing countries in the presence of natural disasters.

The significant negative coefficients reported in Column 5 and 6 point to a deterioration of liquidity following disasters in both developed and developing countries. As found in section 4.2.1 and 4.2.2, both the aggregated and disaggregated measures of disaster intensity (either using "DISINDEX" or intensity measure of each disaster types) negatively affect liquidity. Together with these results, we observe the consistent adverse impact of natural disasters on bank liquidity regardless of the country level of economic development. This reiterates the importance to examine the impact of disasters on bank liquidity, which has been un-explored by the existing literature.

Column 7 and 8 provide additional evidence to support the argument on the positive impact of disasters on bank profitability. The results document a significant, positive association between the disasters intensity index (DISINDEX) and ROA for the two sub-samples suggesting that disasters increase bank profitability. The evidence can be attributed to the recovery lending opportunities following catastrophic events in developing and developed countries.

[INSERT TABLE 5 ABOUT HERE]

4.3 The moderating role of financial integration

To study the moderating role of financial integration when a disaster event occurs, an interaction term is constructed as the product of disaster index ("DISINDEX") and financial integration proxies (CLAIM, FOR, KAOPEN) in Eq. (2). Table 6 presents the result when both the main term and the interaction term is included in the regression. The coefficient for each of the interaction terms is our main interest.[9] Regardless of the proxy used to measure financial

[9] We observe high multi-collinearity in the regression when the interaction terms are included. Following usual econometric approach to deal with multi-collinearity in the regression with interaction term, we try converting the continuous variable "CLAIM" into the indicator variable to proxy for the high and low level of integration based on the cut-off value of the 95th percentile of CLAIM. Regardless of this transformation, the interaction term retains its sign and significance level. These results are reported in Appendix A3.

integration, we consistently report that financial integration worsens the impact of disasters on various measures of bank performance. The finding strongly supports Hypothesis 3.

With regard to the interaction term between DISINDEX and CLAIM, the significant positive (0.012) and negative (-0.001) coefficients in Column 1 and 2 respectively suggest that disasters increase credit risk and fragility to a larger degree in the case of banks operating in higher financially integrated countries. This is the consequence of a withdrawal in international capital funded by international banks following a disaster, as previously confirmed by Yang (2008) and David (2010). The reduction in foreign funds could slow down the replenishment of the capital stock of the countries, tighten the capital constraint of firms regardless of the effort of commercial banks in expanding recovery loans. Due to this capital constraint, the reconstruction process would be slowed down, making the effect of the disaster in its years of occurrence more dramatic. In terms of ROA, the interaction term between DISINDEX and CLAIM is negative (-0.001) and significant at 1% level. Previously in section 4.2.2 and 4.2.3, we observe that disasters increase bank profitability possibly due to more business from recovery lending. Combining with the negative interaction term between “DISINDEX” and CLAIM, we observe that banks operating in more financially integrated countries, the increase in profitability is lower. This could be because banks in those countries are competing fiercely for recovery lending.

Similarly, the interaction term between DISINDEX and FOR shows that the presence of foreign banks significantly worsens the impact of disasters on banks’ risks and performance. Specifically, the coefficients for the interaction terms are (0.007), (-0.001), (-0.002) and (-0.029) for each of CRERISK, ZSCORE, LIQ and ROA, respectively. The result is possibly not driven by the fact that the performance of foreign banks is more negatively influenced by disasters than such of domestic counter-parts.[10] Indeed, our results indicate that domestic and

[10] In Appendix 4, we report the models estimated to measure the impact of disasters on bank performance by bank ownership. The sample is divided according to domestic and foreign ownership. Domestic bank credit risk and default risk is adversely affected by disasters. This result indicates that most of the significance reported in Table 3 can be attributed to the impact of disasters on domestic banks. The core business of domestic banks is concentrated within each country and therefore they are more exposed to the detrimental impact of a natural disaster. Liquidity of foreign banks is adversely and significantly affected by natural disasters. This could result from the withdrawal of funding from their parent banks if foreign branches locate in the affected area hit by a severe natural disaster.

local banks are more active in terms of extending reconstruction loan and in contributing to the recovery process, as previously confirmed for the case of US banks (Chavaz, 2014), German banks (Koetter et al., 2016)). In other words, if domestic banks are playing an important role in plugging the liquidity shortages of firms facing a sudden disaster shock, a higher percentage of foreign banks will hinder the recovery process.

Lastly, in countries with a more open capital account, the adverse impact of disasters on bank performance is greater. In particular, the coefficients for the interaction term between KAOPEN and DISINDEX are (0.477), (-0.031), (-0.532) and (-0.097) for each of CRERISK, ZSCORE, LIQ and ROA, respectively. The magnitude of these coefficients is also greater than such of the coefficients obtained for the interaction terms between CLAIM (or FOR) and DISINDEX. This indicates that in the incidence of severe disasters international banks withdraw their capital from the affected countries. The response is more pronounced in countries with higher capital account openness which allows more flexible movement of international capital across borders. The evidence is consistent with Noy (2009) who finds that countries with less capital account openness appears to experience less output loss due to natural disasters. In short, the evidence of KAOPEN strengthens our results when CLAIM and FOR are used to measure financial integration. Taken together, natural disasters disproportionally affect bank performance in countries with different level of financial integration, which reinforces our support for Hypothesis 3.

[INSERT TABLE 6 ABOUT HERE]

4.4 Robustness tests

To provide robustness to the baseline results, we examine the specification of Eq. (1) and (2) by including other control variables that are commonly found in the bank performance empirical literature. The additional variables include a set of bank-level covariates: SIZE (natural logarithm of total assets), EQUITY (equity to total assets), INDIV (income diversification), COST (overhead cost) and country-level covariates such as LNGDP (natural logarithm of GDP per capital), POLITY (Polity IV index), and INTEREST (annual real interest rate).

The models estimated with the additional control variables are reported in Table 7. The results yield quantitatively similar findings to the baseline results. Bank- level variables do not add much explanatory power and most of the coefficients are insignificant. This is in part expected due to the presence of the lagged dependent variable in the model. The sign and significance level of existing country-level control variables remain robust. However, some newly added variables such as POLITY or INTEREST obtain abnormally high coefficient; this stems from the endogenous relationship among the country-level control variables.

[INSERT TABLE 7 ABOUT HERE]

5. Conclusion and implications

Our paper provides cross-country evidence on the impact of disasters intensity on various measure of bank performance. First, bank credit risk is negatively influenced due to the adverse impact of disasters on economic prospects and the financial solvency of borrowers. Second, natural disasters also increase bank default; the impact is more pronounced in developing countries. Third, we report a consistent evidence of tighter bank liquidity, regardless of the aggregated or disaggregated disasters intensity measures and of the economic development of the sampled countries. This flows from the fact that banks may choose to convert liquid assets into recovery loans or suffer from deposits withdrawal. Finally, we report the positive but insignificant influence of disasters on bank profitability. Bank profits could be enhanced due to the increase in recovery lending business; however, the benefit could be outweighed by the rising cost of dealing with bad debts in the aftermath of natural disasters. Overall, taken the increase in recovery lending business reflected through the increase in profitability and decrease in liquidity, the evidence indirectly demonstrates that banks in East Asia Pacific region play an important role in supporting the liquidity constraints of borrowers in the aftermath of disasters.

Independent of the measure of financial integration employed (foreign claims of international banks, foreign bank penetration or capital account openness), financial integration worsens the impact of disasters on bank performance. This potentially results from the withdrawal of foreign capital channelled by international banks or the active role of domestic banks (rather than foreign banks) in supplying credit for post-disaster reconstruction. Overall, the finding has important implication for the banking system and countries that are dependent on foreign capital or foreign banks. They should account for the aggregate impact of disasters on bank performance and the risk of capital outflows in assessing disaster exposure as both these factors may slow down the recovery process of the affected regions after disasters.

Some words about the limitations of the paper are warranted regarding the interpretation of our results. Due to the unavailability of data, we could not track the specific locations of banks to match with the affected areas by disaster events. Besides, we also rely on a cross-country approach to examine whether bank’s financial condition is significantly different after a disaster occurs. Taken together, the paper provides an assessment of overall condition, i.e., central tendency or “on average”, not of an individual bank. In this sense, the methodology understates the impact of disasters as some banks might be significantly affected but the negative impact will not be detected unless all banks (or a large number of them) are impacted.

Last but not least, there exist some limitations on the measurement of Ifo-GAME for floods and droughts; therefore our paper could not provide the full assessment on the impact of such events on bank performance. This calls for further studies to find appropriate datasets and empirical techniques to measure the impact of these events which become more frequent because of climate change.

Table 1: Descriptive statistics

Panel A: Overall descriptive statistics

	Mean	Std. Dev	Min	Max
Bank-level variables				
CRERISK (credit risk %)	5.87	7.46	0.03	46.66
ZSCORE (natural logarithm of Zscore)	3.48	1.50	-5.26	6.68
LIQ (liquidity ratio %)	27.35	34.52	0.6	258.04
ROA (profitability %)	0.58	1.80	-8.41	7.39
Country-level variables				
DISINDEX (disaster intensity index)	23.79	7.93	6.81	36.09
CLAIM (financial integration %)	26.67	38.88	0.23	287.47
FOR (financial integration %)	16.52	16.97	0.00	78.00
KAOPEN (financial integration %)	0.76	0.77	0.16	4.40
CON (concentration %)	56.01	24.37	27.29	99.98
GDP (GPD growth %)	9.12	6.60	1.36	33.59
IFL (inflation %)	3.61	6.31	-1.72	58.36
PRICRE (private sector's credit %)	119.07	61.49	13.66	221.29

The table reports descriptive statistics for the variables used in the empirical analysis. There are 8,299 bank-year observations from eleven countries in East Asia Pacific region (comprising data from China, Japan, Korea, Indonesia, Malaysia, the Philippines, Singapore, Thailand, Vietnam, Australia and New Zealand) over the period 1992-2010. For the definition and construction of the variables, see Appendix 1.

Panel B: Descriptive statistics of disaster intensity index and financial integration indicators by country

	DISINDEX		CLAIM		FOR		KAOPEN	
	Mean	**Std.**	**Mean**	**Std.**	**Mean**	**Std.**	**Mean**	**Std.**
AUSTRALIA	16.81	1.91	41.26	13.15	40.25	2.70	0.68	0.11
CHINA	23.53	1.50	6.18	1.52	10.88	4.79	0.13	0.03
INDONESIA	28.87	2.09	21.68	9.02	33.69	8.61	0.67	0.11
JAPAN	31.66	2.29	1.32	4.81	0.69	0.58	0.85	0.02
KOREA	11.32	1.66	20.45	7.74	9.94	8.66	0.32	0.10
MALAYSIA	17.29	1.83	43.60	13.03	30.38	4.30	0.45	0.16
NEW ZEALAND	21.96	2.61	96.39	63.86	74.31	4.41	0.86	0.00
PHILIPPINES	21.71	2.24	21.32	6.05	14.44	1.69	0.39	0.07
SINGAPORE	1.73	1.35	176.14	57.86	52.81	5.68	0.84	0.06
THAILAND	15.73	1.69	30.71	9.19	14.19	6.37	0.32	0.08
VIETNAM	8.81	1.13	9.68	4.24	12.63	4.65	0.17	0.09

The table reports the descriptive statistics (mean and standard deviation) for the disaster intensity index (DISINDEX) and financial integration indicators (CLAIM, FOR and KAOPEN) for each country in the sample.

Table 2: Pairwise correlation among variables

	CRERISK	ZSCORE	LIQ	ROA	CON	GDP	IFL	PRICRE	DISINDEX	CLAIM	FOR	KAOPEN
CRERISK	1.00											
ZSCORE	-0.15***	1.00										
LIQ	0.16***	-0.01	1.00									
ROA	-0.29***	0.06***	0.21***	1.00								
CON	-0.03**	-0.08***	0.10***	0.15***	1.00							
GDP	-0.07***	-0.02**	0.02	0.04***	0.10***	1.00						
IFL	0.26***	-0.08***	0.24***	0.00	0.11***	-0.01	1.00					
PRICRE	-0.21***	0.11***	-0.36***	-0.26***	-0.41***	-0.05***	-0.48***	1.00				
DISINDEX	-0.05***	0.07***	-0.17***	-0.17***	-0.23***	-0.05***	-0.08***	0.48***	1.00			
CLAIM	0.09***	0.05***	0.06***	0.06***	0.09***	-0.04***	0.02*	-0.12***	-0.39***	1.00		
FOR	0.02	-0.06***	0.23***	0.25***	0.30***	-0.01	0.25***	-0.55***	-0.40***	0.65***	1.00	
KAOPEN	0.17***	-0.04***	0.19***	0.18***	0.17***	-0.01	0.08***	-0.30***	-0.66***	0.73***	0.55***	1.00

The table reports the Pearson rank correlation coefficients between exogenous variables as determinants of inefficiency term. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table 3: The impact of disasters (disaster intensity index) on bank performance

	CRERISK		ZSCORE		LIQ		ROA	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DISINDEX	0.074**	0.075**	-0.012*	-0.011*	-0.282***	-0.332***	0.003	0.002
	(0.03)	(0.03)	(0.01)	(0.01)	(0.09)	(0.10)	(0.01)	(0.01)
L.Y	0.542***	0.543***	0.493***	0.484***	0.510***	0.506***	0.243***	0.241***
	(0.03)	(0.03)	(0.01)	(0.01)	(0.04)	(0.04)	(0.03)	(0.03)
L.CON		0.003		-0.003***		-0.005		0.002
		(0.01)		(0.00)		(0.02)		(0.00)
L.GDP		0.057***		-0.006***		0.073**		-0.015***
		(0.02)		(0.00)		(0.03)		(0.00)
L.IFL		0.008		-0.014***		0.224***		0.001
		(0.06)		(0.00)		(0.07)		(0.01)
L.PRICRE		0.015*		0.001		-0.059***		-0.004*
		(0.01)		(0.00)		(0.02)		(0.00)
Intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-sq	0.484	0.488	0.372	0.377	0.324	0.328	0.145	0.149
# Banks	578	578	693	693	724	724	737	737
#Obs.	4698	4697	6096	6080	7258	7228	7359	7333

The table presents the empirical result for Equation (1) using Fixed Effect- OLS regression with robust standard errors clustering around banks. Dependent variables (Y) are ROA (bank's profitability), CRERISK (credit risk), LIQ (liquidity) and ZSCORE (natural logarithm of z-scores to proxy for default risk). A one-year lagged dependent variable is included in the model. Control variables including CON (market concentration), GDP (GDP growth rate), IFL (inflation) and PRICRE (credit to private sector to GDP) are introduced with one-year lag. The country-year aggregated disaster index (DISINDEX) is sourced from Ifo-GAME dataset. Notes: ***,**,* denote significance level at the 1%, 5% and 10%.

Table 4: The impact of various types of disasters on bank performance

	CRERISK (1)	ZSCORE (2)	LIQ (3)	ROA (4)
Disaster types				
Earthquake	0.244**	-0.016	-0.393*	-0.039*
	(0.099)	(0.013)	(0.222)	(0.022)
Volcanos	-0.099	-0.012	-0.123	0.018
	(0.179)	(0.023)	(0.394)	(0.032)
Storm	-0.013	-0.001	-0.083***	0.007***
	(0.009)	(0.001)	(-0.309)	(0.002)
Extreme temperature	-0.023	-0.001	0.045	0.0167***
	(0.011)	(0.002)	(0.051)	(0.002)
Flood	0.445	0.023	-1.394*	-0.028
	(0.277)	(0.05)	(0.693)	(0.067)
Drought	0.843	0.026	0.745	0.870**
	(1.727)	(0.203)	(2.178)	(0.382)
Intercept	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

The table presents the empirical result for Equation (1) using Fixed Effect- OLS regression with robust standard errors clustering around banks. The model specification and variables are retained from Table 3. The specific intensity measures for each type of disasters are sourced from Ifo-GAME dataset; specifically, Richter scale for earthquakes, Volcanic Explosivity Index VEI for volcanic eruptions, wind speed for storms, temperature for extreme temperature, millimetre rainfall for floods and an indicator variable for droughts. See details in Felbermayr and Groschl (2014). Notes: ***,**,* denote significance level at the 1%, 5% and 10%.

Table 5: The impact of disasters on bank performance- by the level of economic development

	CRERISK		ZSCORE		LIQ		ROA	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	developed	developing	developed	developing	developed	developing	developed	developing
DISINDEX	0.192***	-0.064	0.020	-0.038***	-0.318**	-0.706***	0.050***	0.041**
	(0.06)	(0.07)	(0.01)	(0.01)	(0.15)	(0.23)	(0.02)	(0.02)
L.Y	0.573***	0.521***	0.473***	0.490***	0.357***	0.541***	0.255***	0.203***
	(0.08)	(0.04)	(0.02)	(0.02)	(0.13)	(0.04)	(0.06)	(0.04)
L.CON	-0.039***	-0.008	-0.003	0.005***	0.021	-0.001	0.006**	0.005*
	(0.01)	(0.02)	(0.00)	(0.00)	(0.05)	(0.03)	(0.00)	(0.00)
L.GDP	0.044*	0.091***	0.016***	-0.004	0.093*	0.075	0.006	-0.012***
	(0.02)	(0.02)	(0.00)	(0.00)	(0.05)	(0.05)	(0.01)	(0.00)
L.IFL	0.630***	0.003	0.058**	-0.013***	0.385	0.243***	-0.012	0.007
	(0.21)	(0.07)	(0.03)	(0.00)	(0.40)	(0.08)	(0.03)	(0.01)
L.PRICRE	-0.024*	0.052***	0.004***	-0.001	-0.001	-0.115***	0.009***	-0.013***
	(0.01)	(0.01)	(0.00)	(0.00)	(0.03)	(0.03)	(0.00)	(0.00)
Intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-sq	0.593	0.485	0.409	0.398	0.179	0.379	0.139	0.205
# Banks	238	342	286	409	288	438	298	441
#Obs.	2851	1846	3108	2972	3531	3697	3616	3717

The table presents the empirical result for Eq.1 using Fixed Effect- OLS regression with robust standard errors clustering around banks. The full sample is broken on the development level of countries. Developed countries include Australia, Japan, Korea, New Zealand and Singapore. The rests of countries belong to the developing group. The model specification and variables definition are retained from Table 3. Notes: ***, **, * denote significance level at the 1%, 5% and 10%.

Table 6: The moderating role of financial integration

	CRERISK (1)	ZSCORE (2)	LIQ (3)	ROA (4)
DISINDEX	-0.133**	-0.009	-0.360***	0.021*
	(0.06)	(0.01)	(0.12)	(0.01)
CLAIM	-0.194***	0.006**	-0.083	0.009
	(0.07)	(0.00)	(0.08)	(0.01)
DISINDEX#CLAIM	0.012***	-0.001***	0.004	-0.001***
	(0.00)	(0.00)	(0.00)	(0.00)
DISINDEX	-0.021	-0.032***	0.146	0.038***
	(0.04)	(0.01)	(0.10)	(0.01)
FOR	-0.246***	0.009	0.692***	0.095***
	(0.06)	(0.01)	(0.15)	(0.01)
DISINDEX #FOR	0.007***	-0.001**	-0.029***	-0.002***
	(0.00)	(0.00)	(0.01)	(0.00)
DISINDEX	-0.191***	0.008	0.000	0.063***
	(0.06)	(0.01)	(0.14)	(0.01)
KAOPEN	-3.535**	0.525**	10.878***	1.372***
	(1.77)	(0.21)	(3.94)	(0.36)
DISINDEX #KAOPEN	0.477***	-0.031***	-0.532**	-0.097***
	(0.09)	(0.01)	(0.21)	(0.02)
Intercept	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

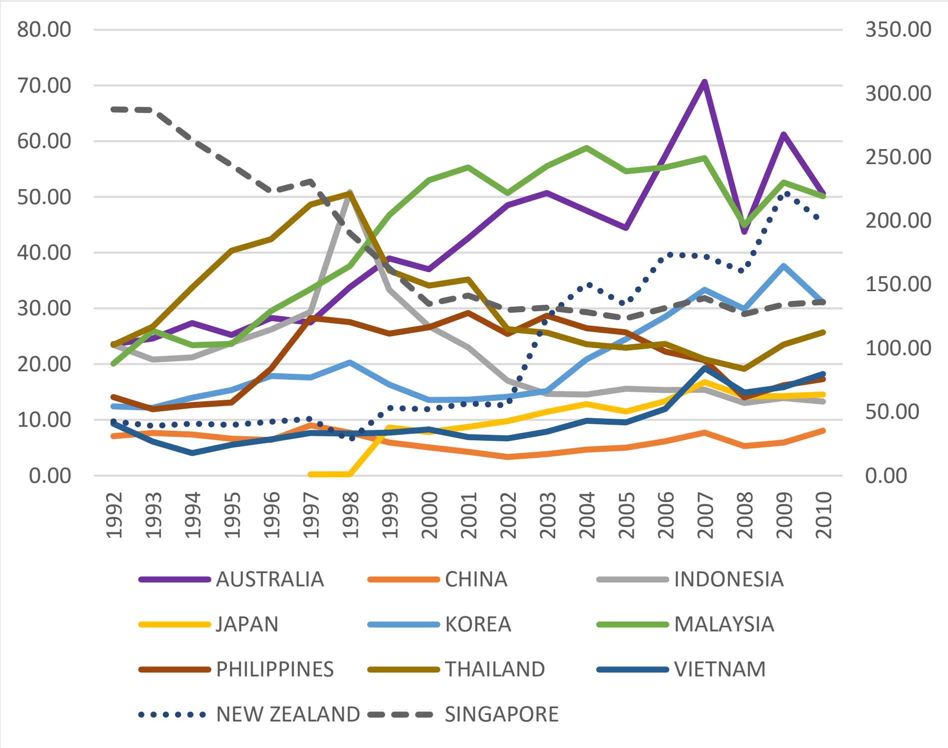
The table presents the empirical result for Eq.2 using Fixed Effect- OLS regression with robust standard errors clustering around banks. DISINDEX is the disaster intensity index. Financial integration is measured by CLAIM (the foreign claims of international banks to GDP), FOR (the ratio of foreign banks to total number of banks), KAOPEN (capital account openness index). The interaction terms between DISINDEX and various indicators of financial integration (CLAIM, FOR, KAOPEN) are created, then included in the model separately. Other control variables and model specification are retained from Table 3. Notes: ***,**,* denote significance level at the 1%, 5% and 10%.

Table 7: Robustness test (Adding additional bank- and country- control variables)

	ROA		CRERISK		LIQ		ZSCORE	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DISINDEX	0.004	0.043***	0.089**	-0.101*	-0.281***	-0.194*	-0.013*	-0.006
	(0.01)	(0.01)	(0.04)	(0.06)	(0.09)	(0.11)	(0.01)	(0.01)
CLAIM		0.023***		-0.147***		0.048		0.006**
		(0.01)		(0.05)		(0.05)		(0.00)
DISINDEX#CLAIM		-0.002***		0.010***		-0.001		-0.001***
		(0.00)		(0.00)		(0.00)		(0.00)
L.Y	0.251***	0.246***	0.527***	0.507***	0.494***	0.493***	0.479***	0.468***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.01)	(0.01)
L.SIZE	-0.144***	-0.167***	-0.414*	-0.135	-0.259	-0.373	0.006	-0.025
	(0.04)	(0.04)	(0.24)	(0.25)	(0.45)	(0.49)	(0.03)	(0.03)
L.EQUITY	-0.006	-0.006	0.017	0.027	0.006	0.009	0.001	-0.000
	(0.01)	(0.01)	(0.04)	(0.04)	(0.17)	(0.17)	(0.00)	(0.00)
L.INDIV	-0.004	-0.004	-0.003	-0.001	-0.025	-0.021	0.001	0.002
	(0.00)	(0.01)	(0.01)	(0.01)	(0.04)	(0.04)	(0.00)	(0.00)
L.COST	0.045	0.041	-0.142	-0.005	-0.242	-0.279	-0.035*	-0.038*
	(0.04)	(0.04)	(0.26)	(0.25)	(0.38)	(0.39)	(0.02)	(0.02)
L.CON	-0.001	-0.001	-0.019**	-0.014*	-0.009	-0.009	-0.002*	-0.004***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.02)	(0.02)	(0.00)	(0.00)
L.GDP	-0.015***	-0.015***	0.060***	0.065***	0.067*	0.072**	-0.006***	-0.005**
	(0.00)	(0.00)	(0.02)	(0.02)	(0.03)	(0.04)	(0.00)	(0.00)
L.IFL	0.006	0.012	-0.044	-0.045	0.193**	0.187**	-0.023***	-0.023***
	(0.01)	(0.01)	(0.06)	(0.06)	(0.08)	(0.08)	(0.00)	(0.00)
L.PRICRE	-0.002	-0.002	0.018**	0.020**	-0.063***	-0.068***	0.000	0.001
	(0.00)	(0.00)	(0.01)	(0.01)	(0.02)	(0.02)	(0.00)	(0.00)
L.LNGDP	-0.068	0.077	-2.983*	-1.819	1.536	1.236	0.155	-0.136
	(0.20)	(0.21)	(1.71)	(1.74)	(3.73)	(3.97)	(0.18)	(0.20)
L.POLITY	0.909***	0.341	-8.827***	-6.113***	-0.930	-1.576	-0.026	-0.166
	(0.31)	(0.28)	(2.97)	(2.33)	(3.01)	(2.85)	(0.15)	(0.15)
L.INTEREST	3.980	13.347	5.827	-43.714	12.177	8.654	-16.740***	-13.444***
	(10.94)	(11.07)	(43.95)	(43.13)	(104.39)	(105.44)	(4.94)	(4.80)
R-sqr	0.164	0.187	0.497	0.471	0.320	0.318	0.379	0.338
#Banks	730	726	572	570	717	713	686	678
#Obs.	7084	6482	4632	4050	6979	6377	5918	5399

The table presents the empirical result for Eq.1 and 2 using Fixed Effect- OLS regression with robust standard errors clustering around banks. Additional bank-level variables are included such as SIZE (natural logarithm of total assets), EQUITY (equity to total assets), INDIV (income diversification), COST (overhead cost). The country-level covariates such as LNGDP (natural logarithm of GDP per capital), POLITY (Polity IV index), INTEREST (annual real interest rate). Notes: ***,**,* denote significance level at the 1%, 5% and 10%.

Panel A: CLAIM



Panel B: FOR

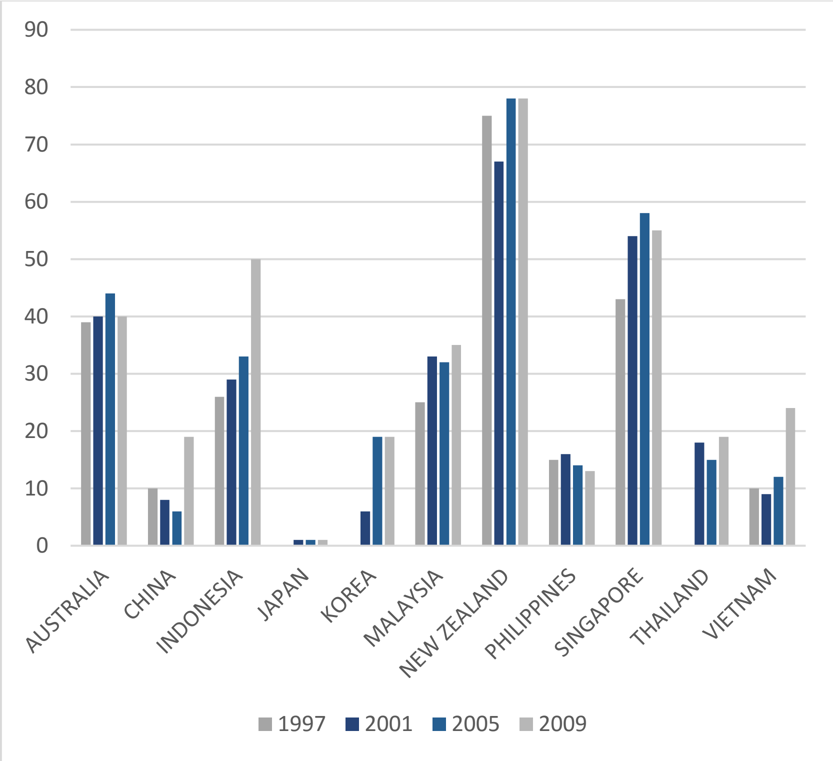


Figure 1: Financial integration (CLAIM and FOR) for each country in the sample during the period of 1992-2010

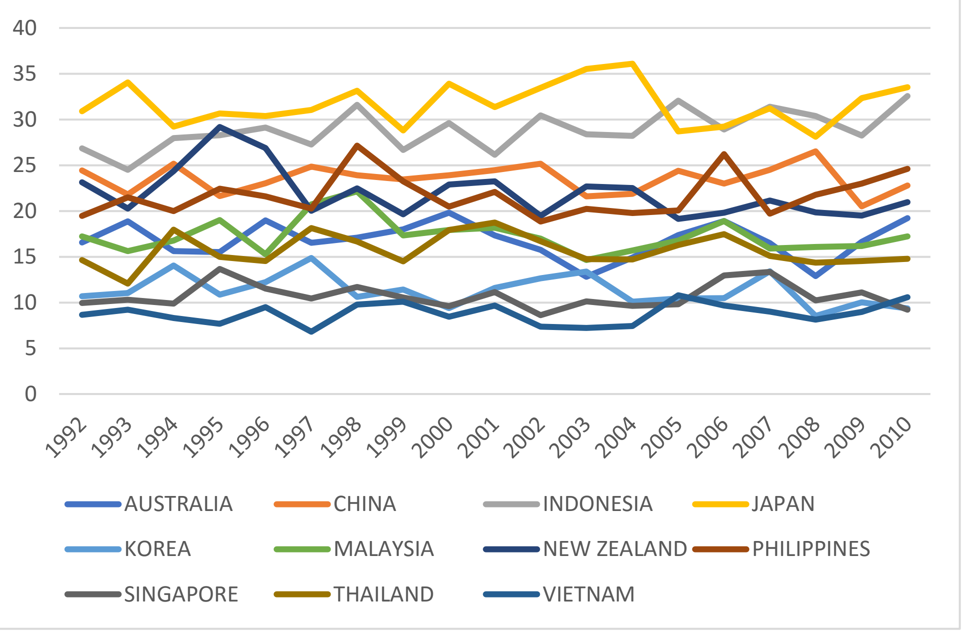


Figure 2: The disaster index (“DISINDEX”) for each country in the sample during the period of 1992-2010

APPENDIX 1: Definition and specification of variables

Variables	Definition	Data Source
1. Dependent Variable		
ROA	Net Income/ Total assets (%)	Bankscope
CRERISK	Non-Performing loans/ Gross loans (%)	Bankscope
LIQ	Liquid assets/deposits and short-term funding (%)	Bankscope
ZSCORE	Natural logarithm of bank Z-SCORE. Z-SCORE is equal to [ROA+ (Total Equity/Total assets)]/ [Std. (ROA)]. The Std. (ROA) is calculated over a three-year rolling window.	Bankscope
2. Variables of interest		
DISINDEX	"DISINDEX"- the weighted annual index for disasters' intensity in each country	Ifo-Game
Earthquake	"mag"- the maximum Richter scale experienced	Ifo-Game
Storm	"combi"- the maximum wind speed experienced	Ifo-Game
Volcanos	"maxvei"- the maximum Volcanic Explosivity Index (VEI) experienced	Ifo-Game
Extreme temperature	"dif_temp"- the percentage difference between the maximum temperature in one month from the corresponding long-run (1979-2010) monthly mean	Ifo-Game
Flood	"flood"- the positive difference between total monthly precipitation and the average monthly rainfall of the (1979-2010) period	Ifo-Game
Drought	"drought" equal 1 if at least 3 subsequent months (or 5 months within year) have rainfall below 50% of the long-run average monthly rainfall mean, 0 otherwise.	Ifo-Game
CLAIM	Foreign claims of international banks to GDP of a country (%)	BIS-CBS
OPEN	The Chinn-Ito index of capital account openness	Chinn and Ito (2008)
FOR	Numbers of foreign banks to Total number of banks (%)	Claessens and Horen (2015)
3. Control variables		
CON	Market concentration = top 3 largest banks assets/ total banks assets (%)	Bankscope
IFL	Inflation rate = $(CPI_t - CPI_{t-1})/ CPI_t$ (%)	GFD- WB
GDP	GDP growth rate = $(GDP_t - GDP_{t-1})/ GDP_{t-1}$ (%)	GFD- WB
PRICRE	Private credit to GDP =Bank credit to private sector/ GDP (%)	GFD- WB
LNGDP	Natural logarithm of GDP per capital	GFD- WB
POLITY	Political index	Polity IV
INTEREST	Real interest rate	WDI- WB
SIZE	Size= natural logarithm of total assets	Bankscope

EQUITY	Equity ratio = total equity/ total assets (%)	Bankscope
INDIV	Income diversification = (share of non-interest income/ total income) (%)	Bankscope
COST	Overhead cost = Total non-interest operating expense/total assets (%)	Bankscope
OWN	Equal 1 for a foreign bank, equal 0 for domestic banks	Bankscope

APPENDIX 2: Number of banks and observations for each country and year

Year	Australia	China	Indonesia	Japan	Korea	Malaysia	New Zealand	Philippines	Singapore	Thailand	Vietnam	Total
1992	21	15	47	150	21	1	3	19	14	18	7	316
1993	23	20	64	151	28	4	6	23	15	19	10	363
1994	24	22	72	152	28	30	6	26	15	21	12	408
1995	25	26	74	153	29	41	7	28	20	21	14	438
1996	27	28	76	151	30	43	7	29	20	22	15	448
1997	22	33	63	150	31	42	7	32	21	23	15	439
1998	23	36	64	148	21	40	7	31	18	22	18	428
1999	21	40	64	145	19	38	7	29	18	22	20	423
2000	17	44	56	143	18	31	8	26	20	22	21	406
2001	20	41	49	145	18	28	7	24	17	22	22	393
2002	18	53	47	144	17	33	7	30	14	22	26	411
2003	16	61	50	142	18	33	7	31	16	22	26	422
2004	13	72	49	143	18	36	6	27	14	20	30	428
2005	15	90	54	140	18	37	6	29	16	22	31	458
2006	15	109	53	138	17	34	7	29	17	22	35	476
2007	16	128	54	140	16	34	7	24	18	23	35	495
2008	16	123	53	138	16	34	8	24	17	24	36	489
2009	13	133	58	141	18	34	8	24	18	24	45	516
2010	10	146	60	150	18	38	8	25	17	25	45	542
Total	355	1,220	1,107	2,764	399	611	129	510	325	416	463	8,299

APPENDIX 3: The moderating role of financial integration- An interaction term between DISINDEX and an indicator variable of CLAIM

	CRERISK (1)	ZSCORE (2)	LIQ (3)	ROA (4)
DISINDEX	0.083**	-0.015**	-0.327***	0.006
	(0.04)	(0.01)	(0.09)	(0.01)
HIGH	-7.621***	-0.972***	1.782	0.791*
	(2.38)	(0.25)	(4.72)	(0.48)
DISINDEX#HIGH	0.394***	0.030***	-0.019	-0.053***
	(0.13)	(0.01)	(0.17)	(0.02)
Intercept	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
R-sqr	0.496	0.380	0.328	0.162
#Banks	578	693	724	737
#Obs.	4697	6080	7228	7333

The table presents the empirical result for Eq.2 using Fixed Effect- OLS regression with robust standard errors clustering around banks. In this table, the continuous financial integration variable (CLAIM) is transformed to be an indicator variable. HIGH stands for the level of integration of a country being above the 95th percentile of CLAIM's value (being equivalent to the level of financial integration in Singapore and New Zealand). Then an interaction term between DISINDEX and HIGH is created. Model specification and other control variables are retained from Table 6. Notes: ***, **, * denote significance level at the 1%, 5% and 10%.

APPENDIX 4: The impact of disasters on bank performance- by type of bank ownership

	CRERISK		ZSCORE		LIQ		ROA	
	Foreign	Domestic	Foreign	Domestic	Foreign	Domestic	Foreign	Domestic
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DISINDEX	-0.013	0.067^{*}	0.017	-0.019^{***}	-1.176^{***}	-0.134	-0.028	0.006
	(0.12)	(0.04)	(0.02)	(0.01)	(0.41)	(0.09)	(0.03)	(0.01)
L.Y	0.462^{***}	0.535^{***}	0.504^{***}	0.473^{***}	0.494^{***}	0.501^{***}	0.192^{***}	0.259^{***}
	(0.06)	(0.04)	(0.03)	(0.01)	(0.06)	(0.07)	(0.07)	(0.03)
L.CON	-0.083^{**}	0.012	0.008^{***}	-0.004^{***}	-0.059	0.003	0.009	0.001
	(0.03)	(0.01)	(0.00)	(0.00)	(0.10)	(0.02)	(0.01)	(0.00)
L.GDP	0.029	0.050^{***}	-0.001	-0.005^{**}	0.196	0.042	-0.019^{**}	-0.016^{***}
	(0.05)	(0.02)	(0.01)	(0.00)	(0.13)	(0.03)	(0.01)	(0.00)
L.IFL	0.070	-0.043	-0.006	-0.014^{***}	0.191^{*}	0.224^{***}	0.015	-0.008
	(0.12)	(0.07)	(0.01)	(0.00)	(0.11)	(0.08)	(0.02)	(0.01)
L.PRICRE	0.043	0.015^{**}	-0.001	0.001	-0.113^{**}	-0.048^{***}	-0.002	-0.004^{*}
	(0.03)	(0.01)	(0.00)	(0.00)	(0.05)	(0.01)	(0.01)	(0.00)
R-sq	0.528	0.496	0.428	0.372	0.350	0.309	0.135	0.168
# Banks	108	475	142	561	152	584	156	593
#Obs.	632	4054	1029	5032	1259	5940	1290	6014

The table presents the empirical result for Equation (1) using Fixed Effect-OLS regression with robust standard errors clustering around banks. The full sample is broken on the ownership basis of banks. Model specification and other control variables are retained from Table 3. Notes: ***,**,* denote significance level at the 1%, 5% and 10%.

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