Economic uncertainty and bank risk: Evidence from emerging economies

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Abstract

This paper examines the impact of economic uncertainty on the risk of banks in emerging markets. Using the data of approximately 1500 banks in 34 emerging economies during the period of 2000-2016, we find consistent evidence that bank risk increases with the level of uncertainty. Economic uncertainty mainly exerts its impact by affecting banks' return and its volatility, and the effect of nominal uncertainty is seemingly more conspicuous relative to that of real uncertainty. We also find that the effect of uncertainty on bank risk is conditional on banks' characteristics such as size and efficiency. Moreover, macroprudential policies can play a stabilizing force by mitigating bank risk as economic uncertainty surges.

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1. Introduction

While uncertainty has been a ubiquitous concern of economists and policy makers, its economic implication captures rapidly increasing attention in the aftermath of the global financial crisis (Bloom, 2009; Stock and Watson, 2012; Baker and Bloom, 2013; Christiano et al., 2014). In spite of a marked decline of the global uncertainty since its culmination in 2008-09, country-specific uncertainty surges from time to time in recent years (Ozturk and Sheng, 2018).[1] In particular, the uncertainty in developing and emerging economies has been documented notably higher than their more developed counterparts (Bloom, 2014).[2] A comparison of uncertainty in emerging and advanced countries (Appendix Table 1), using our indicator of uncertainty based on the conditional variance of innovation in key macroeconomic variables, also exhibits greater uncertainty overall in emerging economies than in advanced ones in most years during the period of 2000-2016.[3]

There has been a vastly growing body of research that addresses the effects of uncertainty on real economic activities such as production, investment, consumption and international trade. Extant results commonly find a counter-productive force of economic uncertainty to dampen entrepreneurs' incentive to investment, delay their hiring decisions, increase households' precautionary saving and reduce the volume of international trade, all suggesting economic uncertainty as one of the main causes to the depth and length of economic slump (e.g., Hahm and Steigerwald, 1999; Loayza et al., 2000; Bloom et al., 2007, 2018; Grier and Smallwood, 2007; Bachmann et al., 2013; Leduc and Liu, 2016). However, in stark contrast to the abundant literature on the impact of uncertainty on the real economy, whether and how uncertainty affects the fragility of financial intermediaries, in particular banks, remains a question that is only understudied.

Competing arguments lead to theoretically ambiguous conclusions on the impact of uncertainty on bank risk. On one side, the "real option" theory hints that, as the odds of making wrong decisions increase due to the incomplete information in uncertain times, banks likely adopt a "wait and see" strategy and postpone their loan provision until uncertainty vanishes. If this strategy reduces banks' chances to lend to less creditworthy borrowers, their

[1] For example, uncertainty arises in Switzerland in 2015 after an unexpected removal of the peg of Swiss franc against the euro, in Ukraine 2014 amid political turmoil, in Brazil 2014-15 with rocketed inflation, and in China 2015 when it devalued its currency surprisingly.

[2] Bloom (2014) records that developing countries have 50 percent higher volatility of growth rates, 12 percent higher stock-market volatility, and 35 percent higher bond-market volatility, so overall developing countries experience about one-third higher macro uncertainty.

[3] During our sample period, developed countries exhibit significantly higher uncertainty than emerging economies only in 2001, 2008-09 and 2011. The group of developed countries includes Australia, Canada, France, Germany, Italy, Japan, the Netherlands, Norway, Spain, Sweden, Switzerland, the U.K. and the U.S. The emerging economies include Argentina, Belarus, Bosnia & Herzegovina, Brazil, Bulgaria, Chile, China, Colombia, Croatia, Czech Republic, Estonia, Hong Kong SAR, Hungary, India, Indonesia, Korea, Latvia, Lithuania, Malaysia, Mexico, Pakistan, Paraguay, Peru, Philippines, Poland, Romania, Serbia, Singapore, Slovakia, Slovenia, Thailand, Ukraine, Uruguay and Vietnam.

financial soundness would be bolstered in the periods of uncertainty. Nevertheless, on the other side, uncertainty may drive up the overall probability of borrowers' default, particularly for the firms with severe financial constraints, thus likely converting the distress of firms to higher bank risk. Worsened information problems that are caused by uncertainty may also induce more "herding behaviors" in banks' lending decisions, which may exacerbate their risk if banks' lending decisions deviate from their own fundamental. In addition, the narrowed interest spreads, resulted from reduced financing demand by firms and increased funding cost of banks, may encourage the incentive to "search for yield" when banks' return target is rigid and hence prompt their lending to the "high-risk, high-return" projects. If these adverse effects of uncertainty were more prominent and outweighed its favorable effects, bank risk would increase with uncertainty.

This paper contributes to the extant literature by empirically investigating the nexus between economic uncertainty and bank risk. Our results are summarized as threefold: First, we find consistent evidence for a significantly negative relationship between our indicators of bank stability and the extent of economic uncertainty. Our finding suggests uncertainty as a risk-increasing force in the financial sector of emerging economies. We confirm that this finding is robust against a series of alternative indicators of bank risk and economic uncertainty and different econometric methodologies. Uncertainty mainly exerts its impact by affecting banks' return and its volatility, and the effect of nominal uncertainty is seemingly more conspicuous than that of real uncertainty. Second, we investigate whether the economic uncertainty-bank risk association is conditional on the characteristics of individual banks, and find that the detrimental impact of economic uncertainty is more pronounced in banks with larger size and lower efficiency. Third, as macroprudential policies are increasingly employed by financial regulators and policy makers in the recent decade, we examine if macroprudential policies can effectively stabilize the financial sector by counteracting the adverse effects of economic uncertainty in the emerging economies and find favorable evidence.

Our paper differs from earlier works in several dimensions. First, distinct from most of the extant research that identify the response of macroeconomic variables to the changes in uncertainty, we ask whether economic uncertainty leads to any impact in the financial sector, in particular the banking market. Some existing works only studied the effect of uncertainty on the *quantity* of bank credit,[4] but seldom on its *quality*. Despite the well documented evidence that financial condition tightens amid increased uncertainty, whether such a credit crunch secures a bolstered stability of banks is still a question to be answered. With consistent evidence in this research that bank risk deteriorates with uncertainty, we suggest that there are dual adverse effects associated with uncertainty: not only a recessionary impact on real

[4] See, for example, Buch et al. (2015), Bordo et al. (2016) and Valencia (2017).

economic activities as many prior works have revealed, uncertainty also weakens the soundness of financial markets. We also investigate the heterogeneity of the economic uncertainty-bank risk nexus, which is conditional on the features of banks, such as size and efficiency, and the policy environment, specifically the increasingly exercised macroprudential policies. Our results could shed some light on the potential policy suggestions to neutralize the adverse impact of economic uncertainty.

Second, in this paper, we are interested in investigating the effect of a country's own uncertainty on the riskiness of its banks, other than the spillover effect of uncertainty originated from abroad. Many existing works examine the contagion effects of uncertainty from advanced economies,[5] probably due to the shortage of data on the uncertainty in developing and emerging countries.[6] In this work, based on the information in key macroeconomic variables such as output growth, inflation and exchange rate depreciation, we use the GARCH-in-mean generated conditional variance of innovation to build our time-varying indicator of economic uncertainty for 34 emerging economies. This constructed barometer of economic uncertainty allows us not only to identify the impact of uncertainty on bank risk by better exploiting the heterogeneous variation of uncertainty within and across countries, but also to use the variable-specific uncertainties in our estimation to detect whether real or nominal uncertainties may yield more pronounced impact.

Third, we focus on emerging economies as the context of our economic uncertainty-bank risk investigation, a bloc of countries that have been surprisingly overlooked in earlier related studies. Owing to the deficiency of sophisticated financial instruments to absorb potential risks, the adverse impact of uncertainty is likely more fully exposed in emerging economies. Understanding the underlying financial risk of economic uncertainty also has important policy implications for emerging countries. Although having experienced rapid growth of economic might and significant liberalization of financial sectors in recent decades, emerging countries are haunted by more frequent financial disorders with costly output and welfare loss (Laeven and Valencia, 2018), which makes the stability of financial sectors among the foremost priorities of their decision makers. Moreover, banks are still the predominant part of the financial system and serve as the major funding source in most emerging economies (Cihák et al., 2013). These bank-dependent financing practices in emerging economies imply that the exacerbation of bank risk may have more devastating outcomes than in the countries that are less bank reliant (Kroszner et al., 2007).

The rest of the paper proceeds as follows: Section 2 provides a brief review of related

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[5] For example, Carrière-Swallow and Céspedes (2013), Gauvin et al. (2014), Choi (2018) and Bhattarai et al. (2019).

[6] The seminal work of Baker et al. (2016) constructs the indicator of economic policy uncertainty (EPU) for 24 economies, but mostly developed countries. Jurado et al. (2015) measure the uncertainty in the United States. Multinational data of uncertainty are only published by the recent works of Ozturk and Sheng (2018) and Ahir et al. (2019).

literature, followed by the description of our data and main variables in Section 3. Section 4 introduces our model and econometric methodology. Section 5 presents the estimates of our baseline framework and those of a series of robustness checks. We extend our research by exploring the heterogeneity of the uncertainty-risk nexus across banks' characteristics in Section 6, and the impact of macroprudential policies on the stability of banks amid increased uncertainty in Section 7. Section 8 concludes.

2. Related literature

The majority of prior literature related to uncertainty concentrates on its impact on real economic activities, commonly based on the framework of irreversible investment (Bernanke, 1983; Abel and Eberly, 1994, 1996; Bloom, 2009; Bachmann and Bayer, 2013). A decrease in output is usually attributed to firms' suspended investment and employment until uncertainty disappears. Some more recent works extend the earlier literature by considering financial frictions as a pivotal mechanism that transmits and even amplifies the impact of uncertainty on real economic activities. Gilchrist et al. (2014) find that uncertainty worsens the financial constraints faced by firms and thus compels down their debt-financed investment. Caldera et al. (2016) and Popp and Zhang (2016) suggest that uncertainty shocks have more remarkable economic impact when they elicit a consequential financial tightening. Alessandri and Mumtaz (2019) argue that the vulnerability of economy to increased uncertainty is conditional on the strength of financial institutions. Nevertheless, these works barely address whether economic uncertainty exerts any effects on the riskiness of financial institutions, in particular banks.

The impact of economic uncertainty on the riskiness of banks is only theoretically inconclusive, owing to the debate of competing views. On one side, the "real option" theory developed by McDonald and Siegel (1986), Pindyck (1988), Dixit (1989) and many others implies that the stability of banks might be strengthened in the periods of increased uncertainty. Analogous to producers, banks also face problems of irreversible investment (lending) and hence may take a "wait and see" strategy when uncertainty is elevated.[7] As the "option value of waiting" increases with uncertainty, banks may find that the odds of making a better, more-informed decision increase until uncertainty diminishes, thus reducing the likelihood of making wrong decisions due to incomplete information, and the risk-taking of banks is then expected to be ameliorated. In comparison to the "real option" theory that implies greater financial stability amid higher uncertainty, some works in line with the "volatility paradox" of Brunnermeier and Sannikov (2014) investigate whether financial instability is brewed in a low-uncertainty environment. Danielsson et al. (2018) warn that, the

[7] Aastveit et al. (2017) find that, in line with the "real option" theory, the potency of monetary policy to influence the lending of banks is considerably weaker when uncertainty is high.

prevailing over-optimism in a period of low volatility induces banks to build up their credit and indebtedness excessively, which in turn leads to devastating outcomes. Fostel and Geanakoplos (2014) also suggest that leverage rises when lenders feel more complacent in an extended period of low volatility. Given the above lines of argument, *ceteris paribus*, bank stability could be positively associated with the level of economic uncertainty.

On the other side, at least three forces associated with uncertainty likely inflict higher fragility to banks. First, the recessionary effect of uncertainty on aggregate demand directly increases the default probability of borrowers, which is most likely translated into a deterioration of banks' risk profile. Baum and Wang (2010), finding a positive connection between the extent of economic uncertainty and the credit default swap (CDS) spreads of firms, suggest that greater macroeconomic uncertainty may increase firms' default risk. Tang and Yan (2010) also find similar evidence that CDS spreads increase with the volatility of GDP growth.

Second, economic uncertainty likely worsens the information asymmetry faced by banks as it is harder to accurately forecast their invested projects' future returns, hence leading to more homogeneous lending behaviors, i.e. "herding behaviors", in banks' credit decisions (Baum, et al., 2005; Quagliariello, 2009; Calmès and Théoret, 2014). As information problems are exasperated by uncertainty, bank managers with reputational concerns may be prompted to imitate other banks' lending decisions, because shareholders/funders would be more likely to blame the systematic factors other than managers' own competence when banks collectively fail in lending credit in the same area (Scharfstein and Stein, 1990; Rajan, 1994; Acharya and Yorulmazer, 2008). Meanwhile, uncertain about the profitability of the projects that they consider to finance, banks may look at the lending decisions made by previous decision makers because the initial decisions of the first banks can provide important information for the rest. As implied by Banerjee (1992), Bikhchandani et al. (1998) and Avery and Zemsky (1998), banks' decisions in this context would be characterized by herd behavior, that is, banks do what others are doing rather than collect their own private information. The lending decisions based on "herding behavior" may lead to higher risk if they deviate from the bank's fundamental. Some bank-specific expertise may be required if the bank tends to lend credit into a business that the first movers financed, thus making portfolio replication less suitable for the followers who lack that expertise. As argued by Calmès and Théoret (2014), the homogeneous behaviors of banks could weaken the resilience of the financial system to negative shocks.

Additionally, uncertainty may encourage banks' incentive to take higher risk via its impact on interest rates. Hartzmark (2016) finds supportive evidence that precautionary saving amid uncertainty induces a decrease of the risk-free interest rate, which could impose a downward pressure on the loan interest rate that banks can charge on their borrowers. As firms reduce their investment and employ less labor in the periods of high uncertainty, the lowered demand for credit also tends to depress the interest rate of bank lending. Meanwhile, the higher likelihood that banks are exposed to large adverse shocks in uncertain times causes funders to demand a higher funding premium from banks, driving up their funding costs (Valencia, 2017).[8] These two forces jointly narrow banks' interest rate spreads and thus erode their main source of profit. However, the return target required by shareholders may not change immediately when banks' profits decline, probably because of lagged adjustments of shareholders' expectation, thus driving banks to allocate their assets toward "high-risk, high-return" projects (Dell'Ariccia et al., 2014). The incentive of banks to "search for yield" amid economic uncertainty is in line with the argument of Rajan (2006) and Borio and Zhu (2012) that banks keep or increase their holding of risky assets when facing profit-decreasing environments and sticky rate-of-return targets.[9] As there is no clear clue if the risk-increasing effects of uncertainty would be more overwhelming than the risk-decreasing ones, whether and how bank risk varies with economic uncertainty is left as an empirical question.

A rapidly growing body of literature explores the linkage between economic uncertainty and the lending behavior of banks. Buch et al. (2015) find significant evidence that increased uncertainty leads to a lower proportion of loans within the portfolio of banks, albeit conditional on banks' balance-of-sheet strength. Valencia (2017) reaches a similar conclusion that banks contract credit supply when facing higher uncertainty, in particular for those with higher leverage. Raunig et al. (2017) also document heterogeneous credit reduction across banks with varied size and liquidity in the wake of uncertainty shocks.[10] Different from the works on the impact of general uncertainty, some others study the response of bank lending to specific types of uncertainty. For example, Francis et al. (2014) investigate how political uncertainty affects the cost of bank loans. Gissler et al. (2016) detect a significant reduction of mortgage loans by banks that perceived higher regulatory uncertainty, while general uncertainty did not discourage such loans. Bordo et al. (2016) find adverse effects of economic policy uncertainty on bank credit growth in the U.S.[11] However, most of these

[8] Caldara et al. (2016) find that an increase in uncertainty leads to an increase in the excess bond premium. Bansal and Shaliastovich (2013) find that the risk premium on bonds declines with uncertainty on output growth but increases with uncertainty on expected inflation.

[9] As lowered interest rates reduce the opportunity cost of economic agents to hold non-interest-bearing assets, increased precautionary saving amid higher uncertainty may likely drive up the price of assets if this force outweighs the direct adverse price-decreasing effect of uncertainty (Nakamura et al., 2017). The increased value of assets, in particular the assets served as the collateral of credit, may increase the tolerance of banks to underlying risk and thus lead to a relaxed vigilance (Borio and Zhu, 2012). A number of prior literatures such as Maddaloni and Peydró (2011) and Dell'Ariccia et al. (2012) find that banks loosen their lending standards and increase credit to more risky clients when interest rate is lowered.

[10] A related research by Delis et al. (2014) investigates the variation of bank loans in anxious periods, defined as the times when the perceptions and expectations about economic conditions worsen for economic agents. As reasonably presumed, anxious periods could be also characterized by escalated uncertainty. The authors find significant drops of bank lending during periods of anxiety, similar to the results of many ones in the uncertainty-bank lending literature.

[11] The effect of economic policy uncertainty (EPU) has been deeply explored by a long list of works that include

works focus on the variation of credit volume of banks without assessing the risk impact of uncertainty explicitly.

A small number of others implicitly connect economic uncertainty to the soundness of banks by examining how uncertainty influences banks' lending standards, capital holding and behavior homogeneity. For instance, Alessandri and Bottero (2017), using the data of Italian banks during the years of 2003-2012, suggest that uncertainty reduces banks' likelihood to accept new credit applications, lengthens the waiting time for loans to be released and weakens banks' responsiveness to short-term interest rate changes. In contrast, Bassett et al. (2014) observe only a mild effect of uncertainty on the tightening of bank lending standards in the U.S. Valencia (2016) finds a self-insurance mechanism that leads banks to maintain a higher capital-to-assets ratio when they face higher uncertainty. Baum et al. (2005), Quagliariello (2009) and Calmès and Théoret (2014), exploring the relationship between economic uncertainty and the homogeneity of banks' lending decisions, find a narrowed cross-sectional dispersion of loan-to-assets ratios as uncertainty is heightened, which is interpreted as evidence of inefficient asset allocation that could contribute to a buildup of bank risk.

Only a scarcity of works address the effects of uncertainty in emerging economies, but commonly focus on the spillover impact of global/foreign uncertainty, other than the local uncertainty in emerging economies *per se*. Carrière-Swallow and Céspedes (2013) find that, in comparison to advanced countries, emerging economies suffer more severe falls in investment and private consumption following exogenous global uncertainty shocks, take significantly longer to recover, and do not experience a subsequent overshoot in activity. The authors suggest that the greater severity of outcomes in emerging economies are accounted for by the decline in credit, as the less developed financial sectors in emerging economies are more vulnerable to uncertainty shocks. Choi (2018) documents a significant recessionary impact on the output in emerging economies caused by the financial uncertainty shocks from the U.S., due to the pull of funds by international investors. Bhattarai et al. (2019) study the cross-border effect of uncertainty shocks from the U.S., and note lowered output and price level, depreciated exchange rate, drained capital inflows and falling stock prices in 15 emerging economies. As one of the few exceptions, Fernández-Villaverde et al. (2011) show that a surge of real interest rate volatility in four emerging economies in Latin America triggers a fall in output, consumption, investment, working hours and debt. However, the research on the effect of uncertainty on banking risk in emerging economies is still a void to our best knowledge.

3. Data and variables

Mumtaz and Zanetti (2013), Baker et al. (2016), Gulen and Ion (2016) and many others.

We use unbalanced bank-level panel data of approximately 1500 banks in 34 emerging economies in Central and Eastern Europe, Latin America and Asia with annual observations during the period of 2000-2016.[12] Only commercial banks are selected in our sample, to minimize any possible bias due to the different nature and business scope among banks. In order to avoid the potential problems of selection bias, we include in our dataset not only existing banks but also those that have ceased business operations. We collect the data used to measure banks' risk and their characteristics from Bureau van Dijk's *Bankscope* database, and then construct the needed variables with our own calculation.[13]

3.1 Economic uncertainty

Adopting the common notion in prior literature (e.g., Cukierman and Meltzer, 1986; Grier and Perry, 2000), we define economic uncertainty in this paper as the conditional volatility of a disturbance that is unpredictable from the perspective of economic agents.[14] We construct our index of economic uncertainty by exploiting the information of three widely concerned macroeconomic variables in emerging economies, namely, output growth, inflation and exchange rate depreciation.[15] In line with many earlier practices, for each of the above three variables, we estimate the GARCH (1, 1)-in-mean system of Engle et al. (1987) separately for each country in our sample. The GARCH-in-mean method allows a simultaneous estimation of their mean equation that includes the conditional variance of the residual as a regressor and their conditional variance equation that is presumed to follow an ARMA (1, 1) process (Bollerslev, 1986).

To be more specific, our model is as follows:

$$y_t = \beta_0 + \sum_{i=1}^{N} \beta_i y_{t-i} + \delta_1 h_t^{1/2} + \varepsilon_t \tag{1}$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1} \tag{2}$$

where y_t denotes the growth rate of output, inflation rate and foreign exchange depreciation

[12] To be specific, the selected economies include: Belarus, Bosnia & Herzegovina, Bulgaria, Croatia, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Serbia, Slovakia, Slovenia, Ukraine (Central and Eastern Europe); Argentina, Brazil, Chile, Colombia, Mexico, Paraguay, Peru, Uruguay (Latin America); China, Hong Kong SAR, India, Indonesia, Korea, Malaysia, Pakistan, Philippines, Singapore, Thailand, Vietnam (Asia).

[13] *Bankscope* database has been rebranded as *Orbis Bank Focus* since the end of 2016.

[14] As commented by Jurado et al. (2015), there is no consensus on the measurement of uncertainty yet. The extant literature has documented various uncertainty indicators, including the volatility of stock market returns (Aastveit et al., 2017), the cross-sectional dispersion of firm profits, stock returns or productivity (Buch et al., 2015), the cross-sectional dispersion of subjective forecasts (Diether et al., 2002), or the appearance of certain "uncertainty-related" key words in publications (Baker et al., 2016). All these gauges have their own pros and cons. Other than suggesting an indicator that could be superior to some others, we focus our interest in this paper on the nexus between our uncertainty indicator and bank risk. We employ a series of alternative uncertainty measurements to check the robustness of our conclusion.

[15] Numerous works have addressed the economic relevance of the uncertainty on output growth, inflation and exchange rate (e.g., Cukierman and Meltzer (1986), Grier and Perry (2000), Fountas and Karanasos (2007), Caporale et al. (2015) and many others).

rate, respectively.[16] ε_t represents the residual in the mean equation, while h_t is the conditional variance of the residual. When we use output growth as example, Eq. (1) describes the mean of output growth rate as a function of lagged output growth rate and the variance of its disturbances.[17] Eq. (2) models the error variance of output growth with one lag of the squared error and one lag of the variance. We use the estimated time-varying variances h_t as our time series measure of variable-specific uncertainty, as it well responds to the common notion of uncertainty as the volatility of forecast errors.

Using seasonally adjusted data, we measure output growth as the monthly difference of the logarithm of industrial production index, inflation rate as that of the logarithm of consumer price index, and currency depreciation rate as that of the logarithm of the domestic currencies' foreign exchange rate against the U.S. dollar. All these variations are annualized.[18] In order to make the uncertainty level comparable across countries, we separately normalize our measure of uncertainty for each variable in each country over years:

$$Uncertainty_t = \frac{h_t - \min(h)}{\max(h) - \min(h)} \tag{3}$$

where min(h) and max(h) represent the minimum and maximum value of the error variance of each variable, respectively. A high reading in this indicator is interpreted as a relatively high uncertainty level associated with the variable during the sample period in the specific country.

Perceiving economic uncertainty as the overall uncertainty across economic series, we convert our variable-specific uncertainty indices into a composite index by obtaining equally-weighted averages. We next calculate the annual average of the monthly composite index of uncertainty and present the results in Appendix Table 2. In order to check the robustness of our results, we also employ several other measurements for the uncertainty level across countries. These alternative indicators differ from the above-introduced indicator in terms of construction techniques or conceptual grounding.

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[16] We ensure the stationarity of the three series by using the Augmented Dickey-Fuller test.

[17] Following the common practice in prior literature (e.g., Engle (1982)), we conduct a series of experiments on a *per country* basis to determine the optimal lags, *N*, for each variable's mean equation. We first refer to the Akaike Information Criterion (AIC) and the Schwarz Criterion (SC), and then adjust the lags to secure clean residuals that pass various diagnostic checks for model adequacy. We also experiment fitting our models with the same specification for all three series in each country but only yield less valid results.

[18] We perform a series of diagnostic tests to secure our GARCH-in-mean models are properly specified. First, we conduct the Lagrange Multiplier (LM) test proposed by Engle (1982) for the presence of conditional volatility in each of interested variables in each sample economy and find favorable results overall, suggesting the GARCH model as a reasonable choice for these series. Second, we check if there is evidence for any remaining patterns in the residuals by calculating the Ljung-Box Q-statistics for up to 6 and 12 lags of the levels of the standardized residuals in the estimated GARCH-in-mean systems for each variable in each country. Insignificant $Q(6)$ and $Q(12)$ statistics, as we find generally, suggest that adequate number of lags are included in our specifications such that the standardized residuals are not serially correlated. Third, we compute the Ljung-Box $Q^2(6)$ and $Q^2(12)$ statistics, which test for the sixth- and twelfth-order serial correlation in the squares of standardized residuals. We find again that these statistics are insignificant in almost all cases, which is interpreted as that our models adequately capture the conditional heteroskedasticity in the process of output growth, inflation and exchange rate depreciation. The specific results are available upon request.

3.2 Bank risk

We gauge bank risk by using three Z-score based indices, which are commonly employed in a vast number of literatures.[19] We compute the Z-score (*Z*) as our first proxy of bank risk, which is defined as:

$$Z_{ijt} = \frac{ROA_{ijt} + EA_{ijt}}{\sigma(ROA)_{ijt}} \tag{4}$$

where *ROA* denotes the return on assets, *EA* the ratio of equity to assets, and *σ(ROA)* the standard deviation of return on assets. Similar to the practice of Beck et al. (2013), we adopt a three-year rolling time window to calculate *σ(ROA)*, other than using the full sample period.[20] The subscripts of each variable, *i*, *j* and *t*, refer to bank, country and year respectively. The Z-score is directly interpreted as the number of standard deviations by which bank returns would have to fall to wipe out all of their equity, and is generally viewed as the inversed probability of bank failure. A higher value is suggestive of a higher level of stability in the bank, or alternatively speaking, a lower exposure to insolvency risk. In order to better understand how uncertainty may affect bank risk, we later use the three components of the Z-score, i.e., *ROA*, *EA* and *σ*(*ROA*), which are perceived, respectively, as the indicator of banks' profitability, (inverse of) leverage risk and asset portfolio risk, as our alternative dependent variables. We view the Z-score as a measure of the "absolute" risk of banks because it is calculated by only using banks' own return on assets and equity-assets ratio.

However, a simple comparison based on the values of Z-score may cause biased conclusions, since the identical Z-scores of banks across countries may conceal their relative riskiness in their own market. Assuming a certain level of Z-score in two different countries, in the first country, the stability of a bank with such a Z-score may excel its counterparts if this Z-score is higher than that of most others, whereas in the second country a bank with an equal Z-score might be outperformed in terms of stability if this Z-score is instead lower than that of most others. Put differently, a higher Z-score figure at Bank A in country 1 compared to Bank B in country 2 may not necessarily mean that the former has a relatively less risky position than the latter. In order to overcome this problem, we normalize banks' Z-scores for each country by using the approach in the same fashion of Eq. (3) and denote the outcome as *Z_n*:

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[19] See, for example, Laeven and Levine (2009) and Demirgüç-Kunt and Huizinga (2010).

[20] We alternatively calculate *σ(ROA)* and then the Z-score by using a five-year rolling time window and find the results are qualitatively consistent. However, to use a longer rolling window leads to a considerable reduction in the number of our observations. Because the Z-score is highly skewed, we apply the natural logarithm to (1+ Z-score) to smooth higher values (Beck et al., 2013). Using 1+ Z-score instead of using simply Z-scores is to avoid the truncation of the Z-score at zero. We denote ln(1+ Z-score) as the Z-score in the latter part of the paper for brevity. Prior to our calculation of the Z-score, we removed the outliers of *ROA*，*EA* and *σ*(*ROA*) above the 99th percentile and below the 1st percentile of the sample distribution to rule out abnormality or probable measurement errors.

$$Z\_n_{ijt} = \frac{Z_{ijt} - min(Z_j)}{max(Z_j) - min(Z_j)} \tag{5}$$

where $min(Z_j)$ and $max(Z_j)$, respectively, represent the minimum and maximum value of Z-scores for all banks in country *j* over the sample period. Lying in the range of [0, 1], the results allow for a comparison of relative riskiness that banks are exposed to in their markets, whereby a higher reading in *Z_n* indicates that the bank has a relatively greater stability/lower risk in contrast to its counterparts across countries. We interpret this indicator as reflecting the "relative" riskiness of banks.

Our third risk indicator is based on the concept of "X-efficiency of stability" from Fang et al. (2014) and Tabak et al. (2012) . It can be argued that the banks' current stability may be deviated, to different degrees, from the potential maximum stability that they can achieve, given the different asset portfolios that banks choose to "produce". The "X-efficiency of stability" assumes the Z-score as the outcome of banks' production choice under the trade-off of return and risk, and suggests that identical Z-scores may be associated with banks' varied extents of deviation from their implicit greatest financial stability. We estimate the X-efficiency of banks' financial stability by applying the stochastic frontier approach (SFA) to the following production function:

$$\begin{aligned} Z_{ijt} &= c + \sum_{h=1}^{3}\alpha_h(\ln y_h)_{ijt} + \frac{1}{2}\sum_{h=1}^{3}\sum_{k=1}^{3}\alpha_{hk}\ln(y_h)_{ijt}\ln(y_k)_{ijt} + \sum_{m=1}^{2}\beta_m\ln(w_m)_{ijt} \\ &+ \frac{1}{2}\sum_{m=1}^{2}\sum_{n=1}^{2}\beta_{mn}\ln(w_m)_{ijt}\ln(w_n)_{ijt} + \frac{1}{2}\sum_{h=1}^{3}\sum_{m=1}^{2}\phi_{hm}\ln(y_h)_{ijt}\ln(w_m)_{ijt} + \sum_{g=1}^{2}\delta_g\ln(NP_g)_{ijt} \\ &+ \frac{1}{2}\sum_{g=1}^{2}\delta_{gg}(\ln(NP_g)_{ijt})^2 + \sum_{h=1}^{3}\sum_{g=1}^{2}\kappa_{hg}\ln(NP_g)_{ijt}\ln(y_h)_{ijt} + \sum_{m=1}^{2}\sum_{g=1}^{2}\rho_{mg}\ln(NP_g)_{ijt}\ln(w_m)_{ijt} \\ &+ \pi t + \sum_{h=1}^{3}\theta_h t\ln(y_h)_{ijt} + \sum_{m=1}^{2}\gamma_m t\ln(w_m)_{ijt} + \sum_{g=1}^{2}\pi_g t\ln(NP_g)_{ijt} + f_i + \varepsilon_{ijt} \end{aligned} \tag{6}$$

$$\varepsilon_{it} = u_{it} - v_{it} \tag{7}$$

where y_h (h = 1, 2, 3) represents the quantity of three kinds of bank outputs, namely, loans, securities and off-balance sheet activities. w_m (m = 1, 2) denotes two prices of inputs, which are the price of funds, measured by the ratio of interest expenses over total liabilities, and the average price of other inputs, proxied by the ratio of non-interest operational expenses to total assets, respectively.[21] We also include equity and fixed assets of banks as two netputs (*NP*) in

[21] We experimented by alternatively assuming that there are three inputs, i.e., funds, labor and fixed assets, in banks' operation and calculated their respective prices. The price of labor is measured by personnel expenses divided by total assets, and the price of fixed assets is calculated as the ratio of overhead cost, after ruling out personnel expenses, over fixed assets. Correspondingly, we use equity as the only netput. Although our estimation is consistent with the result when using two input prices, the number of our observations is reduced considerably due to the limitation of data.

the production process. t denotes a time trend. Finally, f_i represents the time-invariant bank-specific effect.

The error term in Eq. (6), ε_{ijt}, is composed of two parts. The first part, u_{ijt}, which is assumed normally distributed, represents measurement errors and the idiosyncratic innovation. The second part, v_{ijt}, captures the banks' inefficiency to perform a production that can render an optimal financial stability, which is assumed to be an exponential function of a bank-specific effect v_i and time t, i.e. $v_{ijt} = v_i \cdot exp(\varpi t)$. v_i is assumed truncated-normal distributed, and ϖ represents the time effect.[22] As recommended by Tabak et al. (2012), estimating a single frontier for all banks across countries allows for the comparison of the X-efficiency item, v_{ijt}, against the same benchmark. We use the method of Greene (2005a, b) to estimate Eq. (6)-(7) and then follow the approach of Battese and Coelli (1988) to convert v_{it} into $Z\_v_{ijt} = E(\exp(-v_{ijt}|\varepsilon)$, a term with a similar pattern to Z and Z_n, where a higher value in the range (0, 1) denotes a closer distance to the implicit optimal stability. Given banks' different asset portfolio and input prices, a high value in Z may or may not be associated with a high Z_v. We perceive Z_v as the barometer of "excessive" risk of banks.[23]

3.3 Bank characteristics

In order to assess the impact of uncertainty on bank risk, we control for four categories of potential risk determinants, namely, bank characteristics, macroeconomic conditions, financial regulations and some other factors. Among bank characteristics, we first control for the size of individual banks, gauged by banks' assets as a share of the aggregate banking sector assets. Banks with a larger scale, on one hand, likely take on more risk owing to the presumption that they are "too big to fail". On the other hand, large banks may have more sophisticated corporate governance and/or reputational cost that discourage them from taking on risk aggressively. We next control for the impact of bank liquidity on banks' risk, including the ratio of liquid assets to total assets as a regressor in our estimation. Cornett et al. (2011) argue that a richer amount of liquid assets may play a stabilizing role on bank credit, whereas Acharya and Naqvi (2012) warn that a redundancy in bank liquidity can be portentous to an approaching financial crisis. The third factor that we control for is banks' operational inefficiency, proxied by the ratio of banks' operating cost to their operating income. A higher value in this ratio is suggestive of lower efficiency in banks' management. Berger and DeYoung (1997), Fiordelisi et al. (2011) and many others have documented a positive relationship between banks' inefficiency and their riskiness.

Fourth, as suggested by Demirgüç-Kunt and Huizinga (2010), the diversity of banks'

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[22] Assuming v_i is half-normal distributed only affects our results very mildly.

[23] We lose a large number of observations when estimating Z_v because of the limited data for some variables. We also experiment estimating Z_v in each country separately but unfortunately it fails to be implemented in many countries due to the deficiency of observations.

business can also influence their financial soundness. We take the diversification of banks' income and funding as control variables. They are measured, respectively, by the ratio of non-interest income to the sum of interest income and non-interest income and the non-deposit funding as a share of the total liabilities. Traditional wisdom elicits the expectation that a higher level of diversification may translate into lower bank risk and stabilized returns, but many empirical works find conflicting evidence (e.g., Stiroh, 2004). At last, we control for banks' ownership status by introducing two dummy variables, indicating if a bank is foreign-owned or domestically state-owned other than domestically private owned.[24] Foreign banks may have both pros and cons when operating in host markets. On one side, foreign banks may own state-of-the-art risk management skills and easier access to international capital markets, but on the other side, they may confront more severe information disadvantages, agency problems and disparity between home and host markets (Chen et al., 2017a). Therefore, whether foreign ownership bolsters the strength of banks might be ambiguous. It is also generally posited that state-owned banks are likely to be riskier in comparison to their privately owned peers, due to either political interference or implicit government protection (Brandao Marques et al., 2013; Iannotta et al., 2013). [25]

3.4 Macroeconomic conditions

The impact of various macroeconomic conditions on bank stability has been recorded in prior literature. We first include in our model the logarithm of GDP per capita in thousands of constant U.S. dollars in respective economies, as the measure of their overall economic development level. A higher GDP per capita may be associated with more mature market regimes and business-friendly environments, which likely foster better financial performance. We next adopt two variables to control for the risk effect of business cycles, namely, the growth rate of real GDP and the inflation rate. Real GDP is calculated by using nominal GDP adjusted by the GDP deflator, and the inflation rate is the percentage change in the consumer price index. Since some of the countries exhibit chronically higher/lower GDP growth rates or inflation rates than other countries, we apply the Hodrick-Prescott filter to these two macroeconomic series and use the cyclical parts as the proxies of business cycles. Interpreted

[24] In line with the common practice of related works, we define a bank as foreign owned if more than 50% of its capital is held by foreign banks, firms, individuals or organizations. We track the year-by-year domestic/foreign ownership status for each bank in our sample by taking the following steps. We first check *Bankscope* for banks' ownership status in the last reporting year. Second, we identify the historical evolution of bank ownership by reading the profile on banks' website, where the changes on ownership are usually documented. We also use the database of *SDC Platinum*, which records both within- and cross-border mergers and acquisitions in banking markets, to distinguish the year when a bank's ownership is changed. If we are still unable to identify banks' ownership status, we resort to various sources such as banks' annual reports, the archives of central banks and the Internet. We follow similar steps to identify domestic government-owned banks, defined as banks with 50% or more of capital owned by government, public institutions or state-owned enterprises.

[25] The capitalization of banks is not included in our estimation as a regressor, since the ratio of equity over assets, a common proxy of capitalization, is a component of Z-score. However, we experiment by including the one-year lagged level of equity-to-assets ratio in our regressions and find our results do not change qualitatively.

as the extent by which a variable in a specific year is discrepant from its long-term trend, a positively higher value suggests that the variable is relatively higher than its typical reading, and vice versa.

We also control for the potential impact of monetary policy on banks' risk. The quickly-growing literature on the "risk-taking channel of monetary policy" suggests that the innovation of central banks' monetary stance can be a significant determinant of bank risk (e.g., Borio and Zhu (2012) and many others). As is a common practice in the literature, we use the first-order difference of short-term interest rates as a measurement of changes in monetary policy. This indicator suggests a tightened (eased) monetary policy stance when its reading is positive (negative).[26] Moreover, we include in our estimations a binary variable for the episodes of banking crisis, exchange rate crisis and sovereign debt crisis in emerging economies over our sample period of 2000-2016 We identify the crisis episodes from Leaven and Valencia (2018).

3.5 Financial regulations and others

How the level of banks' riskiness is affected by the scope and extent of financial regulatory rules has been studied in many earlier research (e.g., Laeven and Levine (2009) and Agoraki et al. (2011)). Our estimation controls for the regulatory stringency on four different aspects: the restriction on banks' activity mix (*Activity mix*), the strictness of regulations on capital adequacy (*Capital adequacy*), the authorities owned by supervisory agencies to intervene banks' structure and operation (*Supervisory power*) and the extent to which banks are exposed to private monitoring and public supervision (*Market discipline*). Using the survey data provided by Barth et al. (2004, 2008, 2013) and following the methodology suggested by Barth et al.(2004), we build country-level time-series indices for each of the above four regulatory dimensions for each emerging economy in our sample.[27] A higher score in these indices represents more stringent regulations.

In spite of the ongoing debate between the "concentration-stability" and "concentration-fragility" views (e.g., Boyd and De Nicoló, 2005; Beck et al., 2013), market structure is taken into account as a possible factor to influence the performance of banks. We compute the assets owned by the three largest banks in a country as a share of the aggregate banking sector assets (*CR3*) and use it as a proxy of the overall market structure. A higher value of *CR3* indicates that the banking market approaches higher consolidation.

A rich body of prior research has analyzed the efficacy of deposit insurance systems on the stability of banking sector (for example, Keeley, 1990; Demirgüç-Kunt and Huizinga,

[26] The data needed for the macroeconomic variables are drawn from IMF's *International Financial Statistics* Database.

[27] Because the regulatory and supervisory statuses are not surveyed every year by Barth et al. (2004, 2008, 2013), we assume that the regulation strength is constant during the period between the previous and current survey.

2005). Deposit insurance may help reduce the funding cost of banks, but has been also cautioned against as a source of moral hazard, which likely facilitates more bank loans toward risky projects. Using the data compiled by Demirgüç-Kunt et al. (2013) and following Barth et al. (2004),[28] we construct a composite index to measure the strength of the deposit insurance coverage, by summing up various design features of deposit insurance schemes, such as the coverage limit as a share of GDP per capita, the source of funding, the compulsoriness of membership, and others.

We also control for *Financial depth*, measured by the credit to private sectors as a share of GDP, as a potential determinant of the risk of banks. A greater value in this variable may be indicative of a higher sophistication of the banking sector, which may shelter banks from negative shocks, but meanwhile may also reflect greater bank-dependence of borrowers to obtain financing, which likely induces higher imprudence of bankers. The degree of financial depth thus may have an ambiguous impact on the stability of banking markets.

Finally, as the literature of "law and finance" has argued, institutional environments, including the effectiveness of contract enforcement and the legal protection on creditors, also influence financial development significantly (e.g., La Porta et al. (1998)). We include *Rule of law* as the proxy for the quality of institutions in our regressions. We obtain the data of the rule of law index from the World Bank's Worldwide Governance Indicators (Kaufmann et al., 2010).

3.6 Descriptive statistics

We present the definition of our main variables and their main descriptive statistics, including the mean, standard deviation and median, in Table 1.[29] The mean value of the Z-score (*Z*) of banks in emerging economies is at 3.339 and the median at 3.381. Within the interval of [-4.108, 7.335], the range of *Z*, along with its standard deviation at 1.136, indicates a relatively wide variation in the financial stability across banks. *Z_n* is centered on its mean value at .562, with standard deviation at .168, also indicating a notable dispersion of banks, even in terms of their relative risk positions. The mean value of the gauge of banks' "excessive" risk, *Z_v*, is .669, which implies that typically a bank's stability deviates from its implicit optimum level by approximately one third.[30] However, as we examine our data for any evidence of regional heterogeneity in the risk of banks, differed indicators provide only mixed results.[31]

[28] We extend the data of Demirgüç-Kunt et al. (2013) by including the economies that introduced their deposit insurance system after 2013, for example, China.

[29] For the Z-score and bank characteristics, except the two ownership dummy variables, we exclude the observations that lie beyond the 99th percentile and below the 1st percentile of their distributions in order to rule out the impact of outliers.

[30] Although not reported, the pairwise correlation between *Z* and *Z_n* is .832 and that between *Z* and *Z_v* is .649.

[31] The indicators of *Z* and *Z_v* point to the highest stability in banks of emerging Asia, while banks in Central and

[Table 1]

The mean level of economic uncertainty, which ranges between [.005, .551] in our sampled economies, is .090, with the standard deviation at .068. Since our indicator of uncertainty is constructed by the equally-weighted average of multiple normalized series of conditional variance of innovation and then a conversion of monthly data to yearly ones, the fairly high level for the mean of uncertainty implies that uncertainty, either arising from the aspect of output growth, inflation or currency depreciation, could be persistent in emerging economies. A closer examination on the standard deviation suggests not only a notable variation of uncertainty between countries, but also within countries.[32] Although not reported, there are seemingly some regional patterns of uncertainty in different areas. The overall uncertainty level in Central and Eastern European countries is observed higher than that in the other two regions.

We also report the pairwise correlation coefficients between the key variables in Appendix Table 3. The correlation coefficient between the Z-score and uncertainty is negative and statistically significant, which indicates a negative co-movement between these two series. The Z-score is also significantly correlated with most of our variables with respect to banks' characteristics, macroeconomic conditions, financial regulations and the others. This result, consistent with many prior works that have suggested these factors as relevant risk determinants, justifies the inclusion of them as covariates in our estimations. We also find that the level of uncertainty is negatively correlated with the variables that proxy business cycles, such as the Hodrick-Prescott filtered real GDP growth rate and inflation rate. Uncertainty may also be heightened amid an expansionary monetary policy, which is conventionally conducted as an economic stimulus instrument, and in the episodes of financial crises. These results are in line with the argument for a counter-cyclical pattern of uncertainty, i.e., uncertainty may surge more likely in the periods of economic slump (Bloom, 2014; Bloom et al., 2018). The characteristics of banks, and the different dimensions of financial regulations, are found only mildly correlated with each other, thus a joint inclusion of these variables are less likely to cause serious problems of multicollinearity.

4. Model

Our baseline econometric model is specified as follows:

$$\begin{aligned} Risk_{ijt} = c + \beta \cdot Uncertainty_{jt} + \lambda \cdot Char_{ijt} + \sigma \cdot Macro_{jt} + \zeta \cdot Regu_{jt} + \eta \cdot Others_{jt} \\ + Years_t + f_i + \varepsilon_{ijt} \end{aligned} \tag{8}$$

Eastern Europe are witnessed with the greatest *Z_n*. According to the indicators of *Z* and *Z_n*, banks in Latin America are seemingly exposed to higher risk than those in the other two regions, whereas *Z_v* suggests that banks in Central and Eastern Europe take more excessive risk than their counterparts.

[32] The standard deviation of uncertainty between countries is .046 while that within countries is .057.

where the dependent variable, $Risk_{ijt}$, is the indicator of banks' risk, i.e., Z, Z_n and Z_v, respectively. $Uncertainty_{jt}$ is our time-series measurement of economic uncertainty in each economy. $Char_{ijt}$, $Macro_{jt}$, $Regu_{jt}$ and $Others_{jt}$ denote, respectively, the vector of bank characteristics, macroeconomic conditions, financial regulations and various other potential determinants of bank risk. $Years_t$ is a series of year dummies that controls for the year-specific shocks. f_i is the time-invariant bank-specific effect and ε_{ijt} is the idiosyncratic error. β, λ, σ, ζ and η are the coefficients to be estimated. To mitigate the problems of endogeneity, we use the one-year lagged observations for our uncertainty indicator and the bank characteristic variables.[33]

We estimate our baseline model by using the fixed-effects estimator, which allows for correlations between the time-invariant bank-specific variable and the other regressors. The Hausman test also suggests that the fixed-effects estimator is preferable to the random-effects estimator. We use heteroskedasticity and within-panel serial correlation robust standard errors, and cluster standard errors at the country-level in estimations.[34] To check the robustness of our main results, we also employ various alternative econometric methodologies later.

5. Empirical results

5.1 Baseline results

We present the estimation results of our baseline model in Table 2, using Z, Z_n and Z_v as the dependent variable, respectively. In column (1), (3) and (5), we include only economic uncertainty, the characteristics of banks, macroeconomic conditions and year dummies as the regressors, and in column (2), (4) and (6) we expand our specifications by adding financial regulations and other determinants of bank risk.

[Table 2]

We find that the estimated coefficients on economic uncertainty in all regressions are negative and statistically significant, suggesting a negative association between economic uncertainty and our indicators of bank stability. As a higher Z-score (Z) indicates a lower insolvency risk exposed to banks, the negative coefficient estimates are interpreted as a decrease of bank stability, or differently speaking, an increase of bank risk with the elevation of economic uncertainty. An increased fragility in banks is also evidenced by the decline of their relative stability position as uncertainty increases, when using Z_n as the dependent

[33] Using one-year lagged uncertainty in our regressions also implicitly assumes that the impact of uncertainty takes some time to be translated into bank risk. We experiment including the contemporaneous uncertainty in our estimations but find that its risk impact is statistically insignificant, either when it is included alone in regressions or when it is included with its one-year lagged level.

[34] Alternatively, we use the number of observations for each bank as the weight of our data and find that our results are not changed qualitatively, and their statistical significance remains. The results are available upon request.

variable. The results based on *Z_v* seemingly imply an increased excess of bank risk when economic outlook is blurred, whereby their stability is more deviated from their implicit maximum stability. Our results add supportive evidence to the hypothesis that the "second moment shocks" matter (Bloom et al., 2009). Beyond the conventional view that uncertainty generates a recessionary impact on the real economy, our finding implies that it also distorts the efficiency of resource allocation in the financial sector. The detrimental impact associated with economic uncertainty is probably attributable to increased borrower distress, the herding behavior on banks' credit decisions and the incentive to "search for yield", which outweigh the potentially beneficial effects of uncertainty. Although many works have documented a "wait and see" strategy adopted by banks when uncertainty emerges (Quagliariello, 2009; Bordo et al., 2016; Alessandri and Bottero, 2017), along with tightened lending standards, prolonged decision processes and curtailed credit provision, our finding suggests that this strategy does not necessarily secure a bolstered stability in the banking sector. Quantitatively, the impact of economic uncertainty on bank risk is also salient. Use the estimation result reported in column (2) of Table 2 as example. As uncertainty surges by one standard deviation (.070), the riskiness of banks which is gauged by the Z-score tends to be correspondingly deteriorated by nearly 8% ($-1.132 \times .070 \approx -.079$). [35]

We also find some other factors that exert significant influence on the variation of bank risk. The abundance of banks' liquid assets helps shelter banks from adverse shocks to their stability, in line with the argument of Cornett et al. (2011). Inefficiency of banks, however, as Berger and DeYoung (1997) and many others have warned, significantly increases their fragility. There are only some weak, at best, evidence on any impact of banks' operational diversification on their risk, as the negative coefficients on income diversification are only statistically significant in a few regressions, while those on funding diversification are only significant when *Z_v* is used as the dependent variable. Nevertheless, we find highly significant evidence that the riskiness of banks varies with their ownership types. Consistent with Iannotta et al. (2013) and Chen et al. (2017a), foreign banks and domestically state-owned banks are found characterized by higher risk than their domestically privately-owned peers.

The riskiness of banks exhibits a counter-cyclical variation, as the negative and statistically significant coefficients on the real GDP growth rate imply. As the GDP growth rate is deviated more negatively from its long-term regularity, the risk of banks tends to increase. The coefficients on our monetary policy indicator are statistically significantly positive, in line with the common conclusions in the flourishing literature of the "risk-taking channel of monetary policy" that bank risk increases with expansionary monetary policy

[35] As uncertainty surged considerably in the period of global financial crisis, we also conduct our estimations by excluding the observations in 2007-2009. We find that our results withstand and remain statistically significant.

(Borio and Zhu, 2012; Chen et al., 2017b). The estimates of the coefficient on the dummy variable *crises* are negative but only statistically significant in two estimations.[36] We detect only limited evidence for the potency of financial regulations on bank stability in emerging economies, although the coefficients on *activity mix*, *capital adequacy* and *market discipline* are commonly positive in all cases.[37,38] Deposit insurance, however, is found playing a counter-productive role on the stability of banks, suggested by the negative coefficients on our indicator of the deposit insurance strength. This finding is consistent with the arguments that more generous deposit protection may exacerbate moral hazard problems in the banking business and fuel the incentive of banks to take more risky bets (Keeley, 1990; Demirgüç-Kunt and Huizinga, 2005).

5.2 Robustness test

5.2.1 Alternative indicators of bank risk

In this section we conduct a series of tests to check the robustness of our estimation results. First of all, we replace our dependent variable by using a number of alternative indicators of bank risk, which are commonly employed in many prior literatures. We first use net charge-offs as a share of gross loans and the ratio of loan loss provisions to gross loans, respectively, as the alternative proxies of bank risk.[39] An increased net charge-offs, which are the operational losses that are acknowledged and written down by banks, as a proportion of gross loans directly reflects an *ex post* deterioration of the riskiness of banks. In contrast, the ratio of loan loss provisions to gross loans is traditionally viewed as an *ex ante* gauge of banks' vulnerability. As presented by column (1) and (2) in Table 3, we find the estimated coefficients on economic uncertainty have positive signs for both risk indicators, and are statistically significant when the loan loss provision ratio is used as the dependent variable and only marginally insignificant when the net charge-off ratio is the dependent variable.

[36] We alternatively experiment by including the dummies for banking crises, currency crises and sovereign debt crises separately in our estimations. The results indicate a significantly negative impact of the episodes of banking crises on the stability of banks, but only insignificant effect of the other two types of crises.

[37] The lack of statistical significance on the estimates of financial regulations is probably attributable to the inclusion of GDP per capita as a regressor since economies with a higher GDP per capita may more likely own a higher level of financial regulatory sophistication. We experiment by ruling GDP per capita out of our estimations and find that the estimates of the coefficient on *capital adequacy* turn to be significantly positive while the coefficients on other regulatory variables are not greatly affected.

[38] The estimated coefficients on *supervisory authority* are negative and statistically significant in one regression and marginally not in the others. This result is seemingly consistent with the "private interest" view (also known as the "public choice" theory) in the literature. Barth et al. (2008, 2009) find that greater official supervisory power, other than promoting higher bank stability, instead leads to more severe corruption in lending. This evidence is explained as that, powerful supervisors may induce banks to provide credit favorably to politically connected firms, in particular in countries with weak institutional environment, thus aggravating banks' riskiness. Beck et al. (2006) also find analogous result that strengthening the power of supervisory agency reduces the integrity of bank lending and results in negative impact on the efficiency of credit allocation.

[39] We also experiment using non-performing loans as a proportion of gross loans as the indicator of bank risk. Although we find that the coefficient estimate for uncertainty is positive, consistent with our baseline results, it is statistically insignificant.

These results provide additional evidence that bank risk tends to increase with economic uncertainty. Next, we employ the Sharpe ratio, which is defined as the return on equity (ROE) divided by the standard deviation of ROE, as our dependent variable.[40] The Sharpe ratio is commonly perceived as an indication of risk-adjusted returns of banks, with higher values being interpreted as greater stability of banks (e.g., Demirgüç-Kunt and Huizinga (2010)). As reported at column (3) in Table 3, the coefficient on uncertainty is negative and highly statistically significant, lending favorable evidence for reduced risk-adjusted returns in banks with increased economic uncertainty.

[Table 3]

Our indicators of bank stability are all based on accounting data so far. We next resort to market data to construct some alternative measurements of bank risk. We first build Merton (1974)'s "distance to default" such that a higher value is indicative of a farther distance to default, or put differently, a higher level of stability.[41] Because many banks in emerging economies are not listed on stock markets, the number of banks that are used in our estimation decreases considerably in this test using Merton's risk index. Nevertheless, as reported at column (4) in Table 3, we find our result is qualitatively consistent, as economic uncertainty significantly shortens banks' distance to default. However, as Bharath and Shumway (2008) argue, Merton's measure of "distance to default" may underperform in out-of-sample forecasts, in comparison with a proposed "naïve distance to default". We alternatively compute the latter indicator for the listed banks in our sample by following Bharath and

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[40] As similar to the construction of the Z-score, we use a 3-year rolling time window to calculate the standard deviation of ROE.

[41] To be more specific, the distance to default (DD) is computed as:

$$DD = \frac{\ln(\frac{V}{F}) + (\mu - 0.5\sigma_V^2)T}{\sigma_V \sqrt{T}}$$

where *V* is the current bank value, *F* is the face value of the bank's debt, μ is the expected return of bank assets and σ_V the volatility of the bank's assets. *T* is the forecast horizon. *V* and σ_V are estimated using the following two equations, as they are not observable. The first one is the call option pricing formula by Merton (1974):

$$E = VN(d_1) - e^{-rT} FN(d_2)$$

where *E* is the equity of the bank, *r* is the risk-free interest rate and *N* is the cumulative density function of the standard normal distribution. d_1 and d_2 are defined as below respectively:

$$d_1 = \frac{\ln(\frac{V}{F}) + (r + 0.5\sigma_V^2)T}{\sigma_V \sqrt{T}} \quad \text{and} \quad d_2 = d_1 - \sigma_V \sqrt{T}$$

The second equation is the volatilities of firms' assets to equity using Ito's formula:

$$\sigma_E = (\frac{V}{F}) N(d_1) \sigma_V$$

We measure *F* by using the total liabilities of the bank. The expected return of assets μ is gauged by one-year lagged ROA of the bank. The forecast horizon *T* is set at 1 as a common practice. The risk-free interest rate *r* is proxied by the money market rate. Equity value *E* is measured as the number of shares outstanding times daily stock price. The data of banks' number of shares and stock prices are from the *Bloomberg* database. We use the iterative procedure described in Bharath and Shumway (2008) to calculate the values of the monthly DD for each bank and then convert them into yearly data by taking a simple average of the monthly DD values.

Shumway (2008) and regress it on uncertainty and other regressors.[42] The result, as reported at column (5) in Table 3, indicating an increased likelihood of bank defaults with higher economic uncertainty, is still qualitatively consistent with our prior findings. We at last use the volatility of banks' stock returns as the proxy of their riskiness, where more volatile returns may underline greater fragility in banks. The result is presented at column (6) in Table 3. Although marginally insignificant, the coefficient on uncertainty with a positive sign seemingly implies increased bank risk with uncertainty, in line with our benchmark findings again.

5.2.2 Alternative indicators of economic uncertainty

We next examine if our findings would vary when economic uncertainty is measured by differed means. We replace our index of economic uncertainty with some alternative measures, which are constructed by different methodologies or have different conceptual grounding. At first, our annualized indicator of uncertainty, which is based on the average of its monthly counterpart, may capture the overall extent to which uncertainty surges, but not the frequency by which uncertainty shocks occur in a country within a year. Hence, for each sample economy, we alternatively construct our annual index of economic uncertainty by counting how many times per year our monthly uncertainty indicator (i.e., the averaged conditional variance of innovation of key macroeconomic variables) exceeds the 75th percentile of its distribution. A greater value in this uncertainty measure is interpreted as that uncertainty arises more often in that year. We regress our dependent variable, i.e., *Z*, *Z_n* and *Z_v*, respectively, on this alternative uncertainty indicator, along with other covariates. We report the estimation results in Panel A of Table 4. The coefficients on this frequency-based uncertainty index are negative and statistically significant in all estimations, implying that bank risk tends to be worsened when economic uncertainty shocks occur more frequently.

[Table 4]

[42] Specifically, the naïve distance to default, which is proposed by Bharath and Shumway (2008), is computed as follows:

We first approximate the volatility of each bank's debt (σ_D) as a simple linear function of the volatility of its equity (σ_E):

$$\sigma_D = 0.05 + 0.25\sigma_E$$

The total volatility of the bank value (σ_V) is then calculated as:

$$\sigma_V = \frac{E}{E+D}\sigma_E + \frac{D}{E+D}\sigma_D$$

where *E* denotes the market value of the bank's equity and *D* is the market value of the bank's debt, which is approximated to its face value (*F*).

Naïve distance to default (naïve DD) is computed as:

$$\text{naïve}\quad DD = \frac{\ln[(E+F)/F] + (r - 0.5\sigma_V^2)T}{\sigma_V\sqrt{T}}$$

where *r* represents the expected return of the bank's assets, which is set to the stock return over the previous year. *T* is set at 1 as before.

Second, we re-estimate our uncertainty indicator by using the multivariate GARCH-in-mean approach, which differs from the univariate GARCH models by allowing a variable's conditional mean to be affected by the conditional variance of innovation in other variables. For example, as we estimate the mean equation of output growth, we assume the mean of output growth to be a linear function of not only the conditional variance of its own innovation, but also that of innovation in inflation and foreign exchange depreciation. That is, output production can be affected by not only its own uncertainty, but also the uncertainties on the price level and exchange rate changes. Analogous specification is also applied to the mean equation of inflation and currency depreciation, respectively.[43] Like our practice before, we construct a composite index of economic uncertainty by averaging the conditional variances of innovation in the above-mentioned macroeconomic variables. The monthly series of uncertainty is then converted to an annual index by another round of averaging. We report our estimation results in Panel B of Table 4. The coefficients on this alternative uncertainty measure have negative signs, and are statistically significant in all but one of the regressions .

Third, we borrow the index of "idiosyncratic" uncertainty from Ozturk and Sheng (2018), which differs from the volatility-based uncertainty indicators by defining uncertainty as the disagreement among professional forecasters with respect to important economic variables. In comparison with the measures of uncertainty which exploit the information contained in objective data, the "idiosyncratic" measurement of uncertainty by Ozturk and Sheng (2018) is based on the surveys to forecasters and more likely captures the dispersion of subjective judgments. The results based on the indicator of "idiosyncratic" uncertainty are presented in Panel C of Table 4. Consistent with our findings before, the estimated coefficients on "idiosyncratic" uncertainty are still negative and highly statistically significant, suggesting that our conclusion withstands our substitution of an uncertainty indicator with different conceptual grounding.

Moreover, we experiment adopting the uncertainty indicator proposed by Buch et al. (2015), which is built by using the bank-level information, other than macroeconomic

[43] To be specific, our multivariate GARCH-in-mean framework, which applies the symmetric BEEK specification of Engle and Kroner (1995) in estimation, is as follows:

$$y_t = \mu + \sum_{i=1}^{p} \Phi_i y_{t-i} + \Psi h_t + \varepsilon_t$$

$$\varepsilon_t \sim N(0, H_t)$$

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B$$

where y_t is a 3×1 vector $[y_{1,t}, y_{2,t}, y_{3,t}]'$, where y_1, y_2 and y_3 represents, respectively, the growth rate of output, inflation rate and foreign exchange depreciation rate. $\varepsilon_t=[\varepsilon_{1,t}, \varepsilon_{2,t}, \varepsilon_{3,t}]'$ is a vector of error terms in each mean equation. $h_t=[h_{11,t}, h_{22,t}, h_{33,t}]'$ is a vector of conditional variance of error terms. The innovation vector ε_t is assumed to be normally distributed, $\varepsilon_t \sim N(0, H_t)$, with its conditional variance-covariance matrix given by H_t. C is constrained to be a lower triangular matrix. A and B are respectively ARCH and GARCH parameter matrices. The number of lags in the mean equation (p) is determined by a series of experiments on a *per country* basis. We first refer to the Akaike Information Criterion (*AIC*) and the Schwarz Criterion (*SC*), and adjust the number of lags, which is limited up to 12 months, to pass various diagnostic checks for model adequacy.

information. Based on the dispersion of cross-sectional shocks to important bank-level variables, this alternative indicator is suggested to be a gauge of the banking-market-specific uncertainty.[44] Following the argument of Bloom et al. (2018) that increased uncertainty will be translated into variations in productivity, we estimate the "productivity shocks" in banks by conducting the procedure described by Buch et al. (2015) and use its cross-sectional dispersion to measure uncertainty.[45] A higher value in this indicator is perceived as reflecting a greater uncertainty prevailing in the banking sector. We re-estimate our baseline model by using this Buch et al. (2015)'s uncertainty index and find that the coefficients on uncertainty are consistently negative in all regressions (Panel D, Table 4). This result suggests that our core findings on the negative economic uncertainty-bank risk nexus are qualitatively intact even when uncertainty is defined as a dispersion of productivity shocks.

5.2.3 Alternative econometric methodologies

In this part, we employ alternative econometric methodologies for estimation to investigate the association between economic uncertainty and bank risk. First, we use the quantile regression estimator proposed by Parente and Santos Silva (2016). Estimating the median, instead of the mean, of the dependent variable conditional on the values of independent variables, the quantile regression estimator provides estimates that are robust to non-normal errors and outliers, and also helps overcome the "Moulton problem" that arises when estimating the impact of aggregate variables on micro units (Moulton, 1990).[46] As reported in Panel A of Table 5, the coefficients on uncertainty, when using *Z*, *Z_n* and *Z_v* as the dependent variable respectively, are still negative and statistically significant in all regressions, lending consistent evidence to our baseline results. Although not reported for brevity, we additionally experiment by replacing the median with the 25th, 75th and 90th

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[44] Buch et al. (2015) also measure the dispersion of the cross-sectional bank-level shocks to some other key variables, such as ROA, asset growth and the short-term funding growth.

[45] To be more specific, we estimate the bank-level productivity by applying the techniques of Levinsohn and Petrin (2003) to the production function described by Buch et al. (2015):

$$\ln y_{ijt} = \beta_0 + \beta_1 x_{ijt} + \beta_2 k_{ijt} + \beta_3 m_{ijt} + \omega_{ijt} + \eta_{ijt}$$

where y denotes bank output, x, k and m represent the free input variables, the fixed input and the intermediate input, respectively. The error term is assumed to be composed of two parts, where ω denotes the unobservable productivity of banks, and η is the random error. i, j, t refers to bank i, country j and year t, respectively. We define banks' output by their total operating income. We choose total liabilities and overhead costs as two free input variables, and fixed assets as the fixed input variable. Total equity is used as the intermediate input. See Nakane and Weintraub (2005) for some similar practices in earlier literature.

We next derive bank-year-specific shocks to productivity by using the residual of the following regression:

$$\Delta \ln(\omega_{ijt}) = f_i + \lambda c_{jt} + \varepsilon_{ijt}$$

where $\Delta\ln(\omega_{ijt})$ is the first-order difference of natural logarithm of the proxy of productivity, f_i is the bank-specific time-invariant effects, and c_{jt} is the country-year dummy variables which control for the time-varying country fixed effects. The error term ε_{ijt} is interpreted as the "productivity shocks" and is used to calculate its cross-sectional dispersion.

[46] Moreover, this estimator allows for the correlation of the error terms within countries, which is detected by the Parente-Santos Silva test.

percentile, respectively, to allow for the parameter heterogeneity across high- and low-risk banks. We still find consistent negative impact of uncertainty on banks with different levels of risk, but the coefficients of uncertainty are only statistically significant in banks with higher stability (the 75th and 90th percentile).[47] Our results seemingly suggest that uncertainty creates devastating financial impact by deteriorating the stability of less-risky banks.

[Table 5]

Next, we employ the fixed effects logit estimation by altering our dependent variable to a binary one which is equal to 1 if the value of our stability indicator is located in its lowest quartile and 0 otherwise. The estimated coefficient on uncertainty in this framework is then interpreted as the impact of uncertainty that may lead the stability of banks to fall into the lowest zone. We find that the estimated coefficients are positive and highly significant in all three cases, as presented in Panel B of Table 5. These results imply that surged uncertainty significantly increases the likelihood of greater riskiness of banks.

Third, we conduct the Fama-MacBeth two-step procedure (Fama and MacBeth, 1973), which first performs a cross-sectional regression for each single period, and then obtains final coefficient estimates as the average of the first step estimates. Our results are reported in Panel C of Table 5. In line with our benchmark finding again, we find the sign on the coefficient of uncertainty is negative and statistically significant in all but one of the estimations. That is, the cross-sectional regressions, which are repeated for each year in our sample period, suggest an overall negative relationship between economic uncertainty and bank stability.

At last, although having used one-year lagged observations of the uncertainty indicator to mitigate the endogeneity problems, we still take into consideration the likelihood that economic uncertainty might be spurred by the underlying fragility in the banking sector, and re-estimate our baseline model by using the 2SLS instrumental variable approach. We employ a number of instrumental variables for economic uncertainty. First, for each sample economy, we use uncertainties in both its largest export market and its largest FDI source country.[48] The implicit assumption is that, the surge of uncertainty in its major trade partner and foreign investment source country may engender a contagious effect and result in an increase of the country's own uncertainty. However, it is less likely that the riskiness of banks in a country would be, at least directly, affected by the prevailing uncertainty in foreign countries. Second, similar to Baker and Bloom (2013), we use two proxies of political shocks, which are presumed to blur the outlook of macroeconomy but not directly affect the risk of banks, as the instrumental variables. The first series is the binary variable which is equal to 1 if there is a

[47] The results are available upon request.

[48] The data of major export markets for respective countries are selected from Bureau van Dijk's *EIU Countrydata* database and the data of major sources of FDI are from the *UNCTAD Statistics*.

close electoral campaign for the government head in a specific country and year. A close election is defined as the gap between the received votes for the (first) two candidates is narrower than 10 percentage points.[49] The second series is the dummy variable which is equal to 1 if there are (successful or unsuccessful) military coups or intrastate armed conflicts with casualty of more than 25 deaths in a specific country and year.[50] Finally, we add the lagged first-order difference of uncertainty as the instrumental variable. The results are reported in Panel D of Table 5. As before, the coefficient estimates in the second stage still yield a negative sign on economic uncertainty, in line with our earlier results, and the estimates are statistically significant in two cases. Although not reported due to the purpose of brevity, we find that, in the first stage regressions, the estimated coefficients on our instrumental variables are in general consistent with our expectation and statistically significant. The Kleibergen-Paap (2006) LM tests on the under-identification of our model suggest that our selected instruments are jointly relevant to economic uncertainty. The Hansen J statistics for the tests of over-identifying restrictions are not statistically significant in all cases, implying an overall validity of our instruments. However, the statistics of the Durbin-Wu-Hausman tests indicate a failure to reject the hypothesis that our specified endogenous variable can be treated as exogenous, which casts doubt on the argument that economic uncertainty could be triggered by vulnerability in the banking sector.

5.3 The impact of uncertainty on the components of the Z-score

In this section we examine the impact of uncertainty on the three components of the Z-score, namely, return on assets (*ROA*), the ratio of equity to assets (*EA*) and the standard deviation of ROA ($\sigma(ROA)$), respectively. This investigation helps provide a better understanding of how uncertainty shocks are translated into greater bank risk, specifically channeled by their effects on the profitability, leverage and portfolio risk of banks.

We first replace the Z-score with the above three variables as the dependent variable in our regressions and report the estimation results in Table 6.

[Table 6]

We find that, for the ROA equation estimation, the coefficient on uncertainty is negative and statistically significant (Panel A). This result is indicative of a dented profitability with surged uncertainty, probably driven by narrowed interest spreads of banks. On one side, the lower demand for credit by firms when they pause their investment and

[49] The data for the votes of election candidates are from the *ElectionGuide* database provided by the International Foundation for Electoral Systems (IFES). If the government head is served by the leader of winning party in parliamentary elections, we let the binary variable be equal to 1 if the gap between the votes received by the top two parties is narrower than 10 percentage points. We also experiment defining a close election as that the gap of received votes is lower than 5 percentage points and find the result holds.

[50] The data for military coups are borrowed from the *Coups d'Etat* database constructed by the Center for Systemic Peace. The data for intrastate armed conflicts are selected from Pettersson et al. (2019).

hiring imposes a downward pressure on banks' loan interest rates, whereas on the other side, the increased likelihood of distress in uncertain times may increase funders' demand for a higher premium from banks. This consequence of eroded profitability of banks amid higher uncertainty is in line with the conjecture that banks may have a stronger incentive to "search for yield" and thus allocate their lending toward more risky projects to gamble for higher returns.

When the equity-to-asset ratio is used as the dependent variable, the estimated coefficient on uncertainty is found to have a positive sign (Panel B), which seemingly implies that there is a tendency of banks to increase their equity and capital holding in the periods of uncertainty. Valencia (2016) argues that the uncertainty-induced financial frictions in raising external finance can lead banks to self-insure against future shocks by maintaining more capital. However, the reduction of banks' leverage with higher uncertainty is statistically insignificant, lending only weak evidence for any potential beneficial impact of uncertainty on the capital sufficiency of banks.

Uncertainty likely exacerbates the portfolio risk of banks as a positive and statistically significant effect of uncertainty on the volatility of bank return indicates (Panel C). This result is likely attributable to augmented imprudence of banks in allocating their resources when uncertainty arises, which prompts either more herding behaviors of banks or more speculative bets on the projects with great variation in returns. Overall, our results suggest that the adverse impact of uncertainty affects the stability of banks mainly through lowering banks' return and lifting the volatility of their return. This adverse impact of uncertainty dominates the seemingly modest beneficial impact of uncertainty on banks' efforts for capital adequacy.

Next, we convert the three components of the Z-score to their relative terms by following the same normalization method as Eq. (5). We denote these terms as *ROA_n*, *EA_n* and σ(*ROA*)*_n*, which measure the extent of banks' return/indebtedness/volatility of return relative to their counterparts across countries. Using these terms as the dependent variable, respectively, we find consistent results that the stability-decreasing impact of uncertainty is more remarkable on banks' return and the volatility of return, but less on their equity-to-assets ratio. We also use the same SFA approach as Eq. (6)-(7) to measure the extent to which the three components of the Z-score deviate from their implicit optimal levels, and represent the results as *ROA_v*, *EA_v* and σ(*ROA*)*_v*. Our estimation results, when using the above three SFA-created terms as the dependent variable, respectively, are qualitatively unchanged, but only statistically significant in the regression of the volatility of bank return.

5.4 The impact of variable-specific uncertainties

We next ask whether the risk impact would differ with variable-specific uncertainties, that is, whether the uncertainty on production, inflation and exchange rate depreciation generate heterogeneous effects on the stability of banks. This question is closely related to the line of research on the potentially distinct impacts of real and nominal uncertainties on various economic areas. For example, Grier and Perry (2000) distinguish the effects of real (i.e. output growth) uncertainty and nominal (i.e. inflation) uncertainty on the GDP growth rate and inflation rate, Beaudry et al. (2001) investigate the impact of nominal uncertainty, specifically the inflation uncertainty, on firms' investment, and Caporale et al. (2015) study the effects of exchange rate uncertainty on international portfolio flows. However, the research on whether and how real and nominal uncertainties might affect the fragility of banks differently is still scarce in existing literature.

We replace our measure of aggregate economic uncertainty with the variable-specific uncertainties, first separately and then jointly, in our estimations. We report the estimation results in Table 7.

[Table 7]

We find that, the coefficient estimates on all variable-specific uncertainties have negative signs, which points to an adverse effect of uncertainty on the risk of banks, common to all the economic aspects where uncertainty emerges. However, when including the three variable-specific uncertainty measures separately in our regressions, only the estimates on the uncertainty of inflation and exchange rate depreciation are shown to be statistically significant in all cases, whereas in comparison the devastating effect of output growth uncertainty only appears statistically insignificant. This finding is suggestive of more conspicuous impact when the variation of inflation and currency depreciation becomes harder to be predicted. Seemingly consistent with the insight of Friedman (1977) that the uncertainty on price level could make it more difficult to extract information from the price system and thus undermine economic efficiency, our results indicate that the riskiness of banks is more sensitive to the variation of nominal uncertainty, but only relatively less to real uncertainty.

Since it is possible that a surged uncertainty on output production may also spur the uncertainty on inflation or exchange rates, we experiment by including jointly all the three variable-specific uncertainty measures in our estimations, even though there are expected problems of multicollinearity which might cause underestimated statistical significance. The results still indicate that all variable-specific uncertainties tend to have the risk-increasing impact, evidenced by a negative sign on all estimated coefficients on uncertainties. However, the effect of inflation uncertainty is still found either statistically significant or only marginally not, while that of the exchange rate uncertainty is only significant in one estimation. We still find no evidence that bank risk may vary significantly in response to uncertainty shocks on output production, even though the effects of inflation and currency depreciation uncertainty have been isolated. Overall, our estimation results indicate that nominal uncertainty, in particular the inflation-specific uncertainty, seemingly has more notable impact on the soundness of banking sectors.

6. What banks are more affected by economic uncertainty?

In this section, we investigate whether the economic uncertainty-bank risk nexus is heterogeneous across different types of banks or not. This investigation, although far from conclusive, helps shed some light on the question whether the adverse impact of economic uncertainty on the banking stability is attributable to the loan demand effect (i.e., increased borrower risk due to higher odds of default) or banks' loan supply effect (i.e., herding behavior and/or search for yield).[51] Under the premise that, increased risk due to generally exacerbated borrower distress could be comparably similar across all types of banks, we, by following Bordo et al. (2016), explore if the risk impact of uncertainty varies significantly with some of the bank-specific characteristics.

In order to analyze the potential heterogeneity of economic uncertainty-bank risk nexus with banks' characteristics, we add the interactive terms of the uncertainty indicator and a number of bank characteristics into our regressions. A significant estimate of the coefficient on the interactive term is interpreted as evidence for a varied risk impact of uncertainty on banks with different features. We report the estimation results in Table 8.

[Table 8]

We first examine the influence of bank size on the association between economic uncertainty and bank risk. We construct the interaction of economic uncertainty with bank size, i.e., *economic uncertainty*×*size*, and include it in our regressions. The estimated coefficients on this interactive term have a negative sign and are statistically significant in all cases, which indicates an increasingly adverse impact of uncertainty on the stability of banks with bank size (Part A, Panel A). Alternatively, we build a dummy variable, which is equal to 1 (0) if the bank size is allocated above (below) the median of its distribution, and then interact this binary variable with our indicator of uncertainty. We find consistent results that the average effect of uncertainty is significantly more pronounced within the group of large banks, relative to their smaller counterparts (Part B, Panel A). An explanation for the greater impact of economic uncertainty with bank size might lie on the potentially stronger incentive of large banks to take risk when uncertainty sours, due to their "too-big-to-fail" status and the presumption of government bailout when they fall into distress (Afonso et al., 2015).[52] In a related research, Chen and Gawande (2017) find that politically connected banks take more risk when government policies are more uncertain. This finding probably sheds some light on

[51] Similar questions are also asked in related research on the credit crunch in periods of uncertainty (for example, Bordo et al. (2016)).

[52] Alessandri and Bottero (2017) also find that the lending of smaller banks is less responsive to uncertainty, which is attributed to the conjectural reason that smaller banks may prefer allocating their loans to local borrowers because of the relative ease or lower cost to gather their information.

our result since large banks are more likely to own political connections than smaller banks.

We also examine liquidity as another possible factor that may influence the economic uncertainty-bank risk nexus. A greater holding of liquid assets, likely a substitute of risky loans, may imply that the bank chooses to “wait and see” until uncertainty diminishes, as the hypothesis of “option value of waiting” argues. We interact economic uncertainty and banks’ liquidity, i.e., *economic uncertainty×liquidity*, and place it into our estimation. There are some evidence that richer liquid assets might buffer the effect of uncertainty on bank risk, as the estimated coefficients on *economic uncertainty×liquidity* have a positive sign and are statistically significant when *Z* and *Z_n* are used as the proxies of bank stability (Part A, Panel B). However, as we alternatively use a dummy variable for the abundance of banks’ liquid assets, which is equal to 1 if the level of liquidity exceeds the median of its distribution and otherwise 0, and include its interaction with uncertainty into estimation, we find no statistically significant results in all cases, although the sign of the estimated coefficients remain positive (Part B, Panel B). We view these results as, at best, some weak evidence that the underlying “option value of waiting” might lead banks to increase their holding of liquid assets, but this strategy seemingly has only a modest effect to shield bank stability from the adverse impact of economic uncertainty.

We next test whether there are any heterogeneous effects of uncertainty when uncertainty is interacted with banks’ inefficiency. Banks with lower operational efficiency might be more likely to exhibit herding behaviors, should their information costs to identify good borrowers increase more significantly when uncertainty blurs the creditworthiness of potential clients. Meanwhile, as their interest margin is eroded with elevated uncertainty, inefficient banks may also find it more difficult to reach their profit target and thus may resort to more risky bets in order to compensate for their lower return. Similar to our earlier practices, we construct an interactive term between economic uncertainty and bank inefficiency, that is, *economic uncertainty×inefficiency*, and add it into our regressions. The estimation results, as expected, yield a significantly negative signed coefficient on this interaction term in all estimations (Part A, Panel C), implying an increasingly detrimental effect of economic uncertainty as the level of banks’ inefficiency increases. We also alternatively use a dummy variable to classify inefficient banks and their efficient peers by letting this variable be equal to 1(0) when our inefficiency indicator of a bank is distributed in the area above (below) its median value. We find that our results are qualitatively the same, although statistically significant in one case and only marginally not in the others (Part B, Panel C).

As the variations of banks’ characteristics are likely correlated with each other, it likely causes misleading results with respect to their roles in affecting the force of economic uncertainty on bank risk, without isolating the effects of other bank characteristics. We hence experiment including all three interactive terms jointly in our estimations and find our results are not qualitatively changed. The estimated coefficients on *economic uncertainty*×*size* remain significantly negative, suggesting that the stability of large banks is more greatly undermined by increased uncertainty than that of smaller banks. Having controlled for the modifying effect of bank size and liquidity on the uncertainty-risk association, the estimation results on *economic uncertainty*×*inefficiency* become strengthened as they turn to be statistically significant in all estimations when banks are distinguished by using dummy variables for their characteristics (Part A and B, Panel D).[53]

7. Do macroprudential policies affect the risk impact of economic uncertainty?

With macroprudential policies being more widely and intensively implemented across countries, in particular in the wake of the 2007-08 global financial turbulence, their efficacy to restrain potential financial risks has attracted increasing attention of financial regulators. As shown by prior works, macroprudential policies can effectively stabilize credit cycles and volatility of the aggregate economy (e.g. Hahm et al. 2012; Boar et al., 2017; Akinci and Olmstead-Rumsey, 2018). However, whether macroprudential policies may curb the uncertainty-induced bank risk is still a question to be answered, in particular for emerging economies where macroprudential actions are conducted more frequently than advanced countries (Cerutti et al. 2017b; Altunbas et al., 2018; Alam et al., 2019). In this section, we briefly investigate the interactive effect of macroprudential policies on the economic uncertainty-bank risk linkage.

Drawing the measures of macroprudential policies from some existing works, we first construct an interactive term of economic uncertainty and the index of macroprudential policies. We then place the stand-alone term of macroprudential policies and its interaction with uncertainty into our model and re-conduct regressions. A statistically significant coefficient estimate on the interactive term is viewed as supportive evidence that macroprudential policies play a force to the nexus between economic uncertainty and bank risk. We report our estimation results in Table 9.

[Table 9]

We first use the index of macroprudential policies compiled by Cerutti et al. (2017a). Their measures of macroprudential policies are based on five categories of instruments, such as capital buffers, interbank exposure limits, concentration limits, loan-to-value ratio limits and reserve requirements.[54] Having identified the direction of policy changes, i.e. tightening

[53] Although not reported, we have examined whether the impact of uncertainty on bank risk is conditional on banks' income and funding diversification and their ownership. We find no significant evidence that the uncertainty-risk association varies with these bank features.

[54] The distinction between microprudential and macroprudential policies is acknowledged blurry (Cerutti et al., 2017a). Meanwhile, some instruments, for example reserve requirements, may have both monetary and prudential

or loosening, Cerutti et al. (2017a) propose a dummy-type indicator for overall macroprudential policies by setting its value at 1 (-1) if the number of tightening policy adjustments is more (less) than loosening ones, and 0 otherwise.[55] We transfer this Cerutti et al. (2017a) series, which is recorded at a quarterly frequency, to yearly data by taking the average for the four quarters per year. A more positive (negative) value suggests that the year-specific macroprudential practices in the country have a more tightening (loosening) trait.

Although not reported, we first experiment by including only the stand-alone term of macroprudential policies in our model, without considering its interactive effect with economic uncertainty. We find that the coefficient estimates on this stand-alone term of macroprudential policies are not statistically significant in any regressions, which suggests no plausible evidence for a direct impact of these policies on the riskiness of banks. We next add the interactive term of uncertainty and macroprudential policies in our regressions. As reported at Panel A in Table 9, the estimated coefficients on economic uncertainty are still negative and highly statistically significant in all estimations, reflecting again an adverse impact of uncertainty on bank stability. However, the coefficient estimates on the interaction term between economic uncertainty and the index of macroprudential policies are found significantly positive. This result is perceived as supportive evidence that the financially devastating impact of uncertainty is ameliorated when tightened macroprudential policy adjustments are implemented, or alternatively speaking, macroprudential policies may exhibit their risk-decreasing efficacy more markedly when uncertainty surges.

We alternatively resort to Cerutti et al. (2017b) for another set of series that measures the uses of macroprudential policies across countries. Different from the index constructed by Cerutti et al. (2017a), this series counts the number of times by which macroprudential tools are used for each country per year, but does not capture the direction of policy changes. Hence, a higher (lower) value in this index tells us that macroprudential practices are more (less) frequently exercised. Analogous to our earlier conduct, we include the stand-alone and the interactive term of this macroprudential policy indicator and economic uncertainty into our model and report the estimation results at Panel B in Table 9. We find that, the coefficient estimates on this interested interaction term are positive, seemingly reflecting some mitigating effects of macroprudential policies on the fragility of banks, but these results are only statistically insignificant. We interpret this finding as that, without considering whether the macroprudential innovations are tightening or loosening, using the frequency of changes to measure the intensity of macroprudential policies yields no significant evidence on the

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objectives.

[55] Cerutti et al. (2017a) also constructed some other instrument-specific or category-specific measures of macroprudential policy changes.

effectiveness of macroprudential policies to reduce the uncertainty-induced bank risk.

Finally, we select the data provided by the recent research of Alam et al. (2019), which covers a more comprehensive set of macroprudential tools than previous data sources. Similar to Cerutti et al. (2017a), the authors record the innovations of macroprudential policies by using the dummy-type variables, i.e., 1 for a tightening action, -1 for a loosening action, and 0 otherwise. The aggregation of these macroprudential innovations across all instruments may, at least to some extent, reveal the intensity of policy adjustments toward an overall tightening/loosening direction. We convert the monthly series of macroprudential policies into annual data by summing up the monthly records for each year. Having added the stand-alone and interactive term of the Alam et al. (2019) indicator for macroprudential policies with economic uncertainty into our estimations, we report the estimation results at Panel C in Table 9. We find consistent evidence that the coefficient estimates on the interactive term are positive and statistically significant in all cases, indicating again that macroprudential policies, in particular the tightening innovations tend to counteract the increase of bank risk when uncertainty surges.

In a short summary, our findings in this section make a supplementary contribution to the previous research concerning the effectiveness of macroprudential policies. Distinct from the investigations for a direct impact of macroprudential policies on banks' behavior, we provide new evidence for an indirectly beneficial force of these policies through mitigating the bank risk which tends to deteriorate amid economic uncertainty.

8. Conclusion

In this paper, we investigate whether the presence of greater economic uncertainty leads to higher bank risk. Using the bank-level data from around 1500 commercial banks in 34 emerging economies, we find significant evidence for a negative association between economic uncertainty and our indicators of bank stability, which implies that bank risk tends to increase with elevated economic uncertainty. Using various alternative proxies of bank risk and economic uncertainty, along with different econometric techniques, we show that our results are qualitatively consistent. Uncertainty exerts its impact mainly by affecting banks' return and the volatility of return, and the effect of nominal uncertainty seems to be more conspicuous than real uncertainty. We also explore what types of banks are more susceptible to the risk induced by uncertainty and find evidence that the impact of uncertainty is conditional on banks' characteristics such as size and inefficiency. Finally, as macroprudential policies have widely been adopted by financial policy makers and regulators as stabilizing instruments, we assess their potency and find favorable evidence that macroprudential policies effectively ameliorate the risk effect of economic uncertainty for banks.

Our research makes contributions to extant literature by searching for the potentially devastating impact of uncertainty beyond the conventionally concerned real economic activities. Many prior works find rich evidence that economic uncertainty causes delayed consumption, investment and employment, which thus lead to recessionary outcomes. In comparison, our findings suggest that, undesired effects of economic uncertainty also emerge in the financial sector, in particular the banking market, as uncertainty may hinder the efficiency of credit allocation and thus the vulnerability of banks likely builds up as a result. Moreover, financial policy makers are traditionally vigilant to the severity of business cycles, usually gauged by the growth rate of real output and the level of inflation, as they are closely linked to the variation of financial stability. However, our results underscore the relevance of the commonly overlooked “second moment shocks” that the volatility of unpredictable innovations in economic conditions also significantly contributes to the increase of financial risks.

Our results bear important policy implications. A greater transparency on economic information and policies, in particular in emerging economies which are still characterized by severe opaqueness on credible economic data and the decision process of important polices, may be essential to mitigate the uncertainty-induced risk in the banking market. As the effects of uncertainty may vary quantitatively across countries, conditional on the typical features, such as size and efficiency, of operating banks, financial regulators need to customize their policy on a per-country basis to neutralize the detrimental impact of economic uncertainty on bank risk. Moreover, macroprudential policies can be included into the toolkit of policy makers to stabilize bank risk when uncertainty sours.

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Table 1. Variable definitions and descriptive statistics

This table summarizes the description of main variables and the source of data. More details of the variables are provided in Section 3. Meanwhile, this table also presents the major descriptive statistics, including the mean, standard deviation and median.

Variable	Definition	Sources	Mean	Std. dev.	Median
Bank risk					
Z	Natural logarithm of Z-scores, i.e., ln [1+(*ROA*+*EA*)/σ(*ROA*)]. *ROA* represents return on assets, *EA* the equity-to-assets ratio, and σ(*ROA*) the standard deviation of return on assets. A higher score suggests a lower probability of bank insolvency, or alternatively speaking, a higher degree of financial stability.	Bankscope and authors' own calculation	3.339	1.136	3.381
Z_n	Normalized Z-scores by using [Z – min(*Z*)]/[max(*Z*) – min(*Z*)], where min and max represent respectively the minimum and the maximum of Z-scores in each market over sample period. A higher score denotes a higher stability/lower risk of the bank relative to its counterparts across countries.	Bankscope and authors' own calculation	.562	.168	.570
Z_v	The X-efficiency of Z-scores. Following Fang et al. (2014) and Tabak et al. (2012), we adopt a stochastic frontier approach (SFA) to estimate the extent to which a bank's stability is deviated from its implicitly optimal level. A higher score suggests a closer distance between the actual Z-score to its potential highest value, that is, a higher stability/lower risk of the bank.	Bankscope and authors' own calculation	.669	.140	.699
Economic uncertainty					
Economic uncertainty	The conditional variance of innovation in GARCH(1, 1)-in-mean models, estimated separately for output production, inflation and exchange rate depreciation in each sample economy and then normalized. The three variable-specific uncertainties are converted into a composite index by equally weighted averaging. A higher value implies a higher level of economic uncertainty.	International Financial Statistics and authors' own calculation	.091	.070	.077
Bank characteristics					
Size	Banks' assets as a share of the aggregate banking sector assets.	Bankscope and authors' own calculation	.033	.063	.008
Liquidity	The ratio of banks' liquid assets to total assets.	Bankscope and authors' own calculation	.268	.189	.221
Inefficiency	The operating cost as a share of total operating revenue.	Bankscope and authors' own calculation	.638	.317	.588
Income diversification	Non-interest income as a share of interest income plus non-interest operating income.	Bankscope and authors' own calculation	.217	.176	.175
Funding diversification	Non-deposit liability as a share of total liability.	Bankscope and authors' own calculation	.126	.170	.065
Foreign	A dummy variable that is equal to 1 if more than 50% of capital is owned by foreign banks, individuals, corporations or other organizations.	Author's own collection	.427	.494	0

State	A dummy variable that is equal to 1 if more than 50% of capital is owned by domestic governments, public institutions or state-owned enterprises.	Author's own collection	.119	.324	0
Macroeconomic conditions					
GDP per capita	Natural logarithm of GDP per capita in thousands of constant US dollars.	International Financial Statistics and authors' own calculation	1.767	.878	1.919
GDP growth rate	The cyclical part in Hodrick-Prescott filtered real GDP growth rate (%). A higher (lower) value suggests a greater positive (negative) deviation from the regularity of GDP growth rate.	International Financial Statistics and authors' own calculation	.079	2.102	.050
Inflation	The cyclical part in Hodrick-Prescott filtered inflation rate (%). A higher (lower) value indicates a greater positive (negative) deviation from the regularity of inflation.	International Financial Statistics and authors' own calculation	-.049	3.878	-.055
Monetary policy	The first-order difference of short-term interest rates (%). A positive (negative) value implies a contractionary (expansionary) policy innovation.	International Financial Statistics and authors' own calculation	-.409	5.829	-.121
Crises	A dummy variable equal to 1 for the periods of banking crisis, exchange rate crisis or sovereign debt crisis in a sampled country, 0 for other periods.	Laeven and Valencia (2018)	.097	.297	0
Financial regulations					
Activity mix	Index of activity regulatory stringency. A higher score suggests more stringent regulations on the scope of banks' business operation.	Barth et al. (2004 , 2008, 2013)	7.555	2.309	7
Capital adequacy	Index of capital regulatory stringency. A higher score suggests more stringent regulations on banks' overall and initial capital.	Barth et al. (2004 , 2008, 2013)	6.819	2.154	7
Supervisory power	Index of supervisory power. The score in this index is higher when supervisory agencies are authorized more oversight power.	Barth et al. (2004 , 2008, 2013)	11.722	1.764	11.85
Market discipline	Index of the private monitor strength. A higher value denotes a higher private monitoring force.	Barth et al. (2004 , 2008, 2013)	8.339	1.341	8
Others					
CR3	The assets owned by the largest three banks as a share of total banking sector assets (%).	Bankscope and authors' own calculation	52.648	15.015	49.731
Deposit insurance	A composite index to reflect the strength of deposit insurance schemes.	Demirgüç-Kunt et al., (2013) and authors' own calculation	6.650	4.162	6.500
Financial depth	Domestic credit to private sectors as a share of GDP (%).	International Financial Statistics	59.475	42.057	46.604
Rule of law	The Rule of Law sub-index in World Bank's Worldwide Governance Indicators (WGI).	World Bank's WGI	-.135	.691	-.339

Table 2. The impact of economic uncertainty on bank risk

This table reports the impact of economic uncertainty on bank risk. The dependent variables are the indicators of bank stability, i.e., *Z*, *Z_n* and *Z_v*, which are defined, respectively, in Section 3.2. The measurement of *economic uncertainty* is based on the conditional variance of innovation in the GARCH-in-mean models for the series of output growth, inflation and foreign exchange depreciation rate. Among the bank characteristics, *size* is measured by the bank assets as a share of the banking sector's aggregate asserts. *Liquidity* is the ratio of liquid assets to total assets. *Inefficiency* is measured by the cost-to-income ratio of banks. *Income diversification* is the non-interest income as a share of total operating income, and *funding diversification* is the non-deposit liabilities divided by total liabilities. *Foreign* is a dummy variable, which is equal to 1 if a bank is owned by foreign individuals, banks, enterprises or organizations. *State* is a dummy variable that is equal to 1 if the bank is domestically state-owned. *GDP per capita* is the natural logarithm of GDP per capita in thousands of constant US dollars. *GDP growth rate* is the Hodrick-Prescott filtered real GDP growth rate, and *inflation* is the Hodrick-Prescott filtered inflation rate. *Monetary policy* is measured by the first order difference of short-term interest rate. *Crises* is the dummy variable that denotes the episodes of banking, exchange rate and sovereign debt crises. Among the indicators of financial regulations, *activity mix* represents the stringency of banks' activity mix, *capital adequacy* reflects the strictness of capital regulatory rules, *supervisory power* captures the authority of financial supervisors to affect the operations of banks, and *market discipline* proxies the extent of private monitoring. *CR3* is the assets owned by the largest three banks in the banking sector. *Deposit insurance* is a composite index that represents the strength of the deposit insurance coverage. *Financial depth* is the credit to private sectors as a share of GDP. *Rule of law* is the rule of law index from the World Bank's Worldwide Governance Indicators. We also include year dummies as regressors in our model. We estimate all regressions by using the fixed-effects estimator. We use heteroskedasticity and within-panel serial correlation robust standard errors, and also allow for intragroup correlations by clustering observations at the country-level. The *p*-value of estimates is in parentheses. ***, ** and * denotes the statistical significance at the 1%, 5% and 10% level, respectively.

Dependent variable	(1) *Z*	(2) *Z*	(3) *Z_n*	(4) *Z_n*	(5) *Z_v*	(6) *Z_v*
Economic uncertainty	-1.309***	-1.132**	-.197***	-.168**	-.223**	-.205**
	(.006)	(.016)	(.005)	(.017)	(.015)	(.024)
Bank characteristics						
Size	.802	.817	.105	.105	-.536**	-.486*
	(.497)	(.470)	(.559)	(.542)	(.044)	(.063)
Liquidity	.227*	.297**	.038*	.049**	.040*	.054**
	(.076)	(.030)	(.067)	(.025)	(.085)	(.024)
Inefficiency	-.528***	-.532***	-.078***	-.078***	-.103***	-.102***
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Income diversification	-.330*	-.267	-.050*	-.040	-.015	-.007
	(.077)	(.146)	(.091)	(.163)	(.689)	(.850)
Funding diversification	-.049	-.059	-.010	-.013	-.062**	-.057**
	(.787)	(.724)	(.681)	(.591)	(.027)	(.018)
Foreign	-.307**	-.366***	-.036**	-.046***	-.044**	-.043**
	(.022)	(.005)	(.027)	(.004)	(.018)	(.016)
State	-.580***	-.554***	-.086***	-.080***	-.053*	-.055*
	(.005)	(.007)	(.003)	(.005)	(.087)	(.082)
Macroeconomic condition						
GDP per capita	.783**	.664	.112**	.085	.025	.025
	(.038)	(.157)	(.033)	(.214)	(.717)	(.771)
GDP growth rate	.010**	.010*	.001*	.001	.009***	.009***
	(.046)	(.067)	(.092)	(.109)	(.000)	(.000)
Inflation	-.009***	-.007*	-.001*	-.001	.000	.000
	(.009)	(.052)	(.081)	(.260)	(.955)	(.578)
Monetary policy	.010***	.008**	.001***	.001*	.002***	.002***
	(.003)	(.017)	(.007)	(.065)	(.001)	(.000)
Crises	-.174	-.212	-.014	-.020	-.107***	-.104***
	(.207)	(.132)	(.369)	(.213)	(.001)	(.001)
Financial regulations						
Activity mix		.007		.002		.005
		(.787)		(.642)		(.257)
Capital adequacy		.014		.002		.001
		(.561)		(.465)		(.719)
Supervisory power		-.064		-.009		-.012**
		(.105)		(.114)		(.046)
Market discipline		.041		.005		.006

		(.346)		(.427)		(.399)
Others						
CR3		-.001		-.000		-.000
		(.578)		(.365)		(.614)
Deposit insurance		-.021		-.003*		-.003*
		(.120)		(.097)		(.067)
Financial depth		.003		.001		.000
		(.262)		(.200)		(.770)
Rule of law		.248		.044		.069
		(.450)		(.368)		(.230)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations (banks)	13044	12614	13044	12614	9375	9095
	(1563)	(1501)	(1563)	(1501)	(1249)	(1205)
R^2	.077	.082	.080	.086	.149	.165

Table 3. Robustness tests: Alternative risk indicators

This table reports the impact of economic uncertainty on bank risk when we use alternative indicators of risk. In column (1), the dependent variable is the amount of net charge-off as a share of gross loans. In column (2), we replace the dependent variable by using the ratio of loan loss provisions to gross loans. The Sharpe ratio, defined as return on equity (ROE) divided by the 3-year rolling-over standard deviation of ROE, is used as the indicator of bank risk in column (3). Our dependent variable is Merton's distance to default, proposed by Merton (1974), in column (4), and a naïve alternative of the distance to default, suggested by Bharath and Shumway (2008), in column (5). We use the volatility of stock returns of listed banks as the dependent variable in column (6). For brevity, we only report the estimates on the coefficient of economic uncertainty. All other regressors in the baseline model are also controlled for. The *p*-value of estimates is in parentheses. ***, ** and * denotes the statistical significance level at the 1%, 5% and 10% level, respectively.

Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)
	Net Charge-off	*Loan loss provision*	*Sharpe*	*Merton's distance to default*	*Naïve distance to default*	*σ(market return)*
Economic uncertainty	1.551 (.144)	1.916** (.016)	-6.150*** (.004)	-2.200* (.070)	-5.156** (.048)	.418 (.102)
Other variables	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations (banks)	6318 (1121)	11522 (1442)	12788 (1522)	1867 (224)	1918 (221)	2675 (240)
R^2	.058	.084	.050	.240	.170	.064

Table 4. Robustness tests: Alternative indicators of economic uncertainty

This table reports the impact of economic uncertainty on bank risk, using some alternative indicators of economic uncertainty. The dependent variables are the indicators of bank stability, i.e., *Z*, *Z_n* and *Z_v*, respectively. In Panel A, the alternative indicator of economic uncertainty is based on the number of uncertainty shocks, when the scale of uncertainty exceeds the 75th percentile of its distribution, in each sample economy in each year. In Panel B, we measure our index of uncertainty by alternatively using the multivariate GARCH-in-mean method. Panel C borrows the "idiosyncratic uncertainty" indicator in Ozturk and Sheng (2018), which reflects the dispersion of forecast with respect to a series of economic variables. In Panel D, we estimate the indicator of uncertainty by following Buch et al. (2015), which is suggested to reflect the dispersion of banks' productivity shocks. For brevity, we only report the estimates on the coefficient of economic uncertainty. All other regressors in the baseline model are also controlled for. The *p*-value of estimates is in parentheses. ***, ** and * denotes the statistical significance at the 1%, 5% and 10% level, respectively.

Dependent variable	(1)	(2)	(3)
	Z	*Z_n*	*Z_v*
Panel A: Uncertainty indicator based on the frequency of uncertainty shocks			
Economic uncertainty	-.015**	-.002**	-.003**
	(.033)	(.045)	(.020)
Other variables	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
Observations	12614	12614	9095
(banks)	(1501)	(1501)	(1205)
R^2	.082	.085	.164
Panel B: Uncertainty indicator based on multivariate GARCH-in-mean models			
Economic uncertainty	-.851**	-.126*	-.132
	(.048)	(.061)	(.105)
Other variables	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
Observations	12842	12842	9215
(banks)	(1513)	(1513)	(1209)
R^2	.080	.082	.166
Panel C: Uncertainty indicator by Ozturka and Sheng（2018）			
Economic uncertainty	-1.704***	-.248***	-.191**
	(.002)	(.002)	(.017)
Other variables	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
Observations	9706	9706	6908
(banks)	(1313)	(1313)	(1042)
R^2	.107	.117	.138
Panel D: Uncertainty indicator by Buch et al. (2015)			
Economic uncertainty	-1.072***	-.144***	-.127**
	(.002)	(.004)	(.016)
Other variables	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
Observations	12614	12614	9095
(banks)	(1501)	(1501)	(1205)
R^2	.085	.088	.163

Table 5. Robustness tests: Alternative econometric methodologies

This table reports the impact of economic uncertainty on bank risk when we employ various different econometric methodologies. The dependent variables are the indicators of bank stability, i.e., *Z*, *Z_n* and *Z_v*, respectively. In Panel A, we report the results of quantile regressions. In Panel B, we build a binary variable, which is equal to 1 (0) when the indicator of bank stability, i.e., *Z*, *Z_n* and *Z_v*, is located in the area below (above) the lowest quartile of its distribution. We then adopt the panel logit methodology to estimate the risk impact of uncertainty by using the constructed binary variables as the dependent variables. Panel C reports the results of the Fama-MacBeth two-step estimation, which performs a cross-sectional regression for each time period and then yields the final coefficient estimates by averaging the first-step coefficient estimates. *Averaged* R^2 is the average value of the R-squares from the cross-sectional regressions in the first step. In Panel D, we assume that economic uncertainty is endogenous and estimate our model by using the 2SLS instrumental variable approach. *Kleibergen-Paap rk LM* reports the *p*-value of the Kleibergen-Paap rank LM statistic for the under-identification test. *Hansen J* reports the *p*-value of the Hansen J test for the over-identifying restrictions. *Durbin-Wu-Hausman* is the *p*-value of the Durbin-Wu-Hausman statistic which tests the endogeneity of economic uncertainty. For brevity, we only report the estimates on the coefficient of economic uncertainty. All other regressors in the baseline model are also controlled for. The *p*-value of estimates is in parentheses. ***, ** and * denotes the statistical significance at the 1%, 5% and 10% level, respectively.

Dependent variable	(1)	(2)	(3)
	Z	*Z_n*	*Z_v*
Panel A: Quantile regression			
Economic uncertainty	-.995*	-.147*	-.147*
	(.052)	(.059)	(.079)
Other variables	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
Observations	12614	12614	9095
(banks)	(1501)	(1501)	(1205)
R^2	.216	.246	.207
Panel B: Panel logit			
Economic uncertainty	2.129***	2.824***	2.359***
	(.002)	(.000)	(.000)
Other variables	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
Observations	12508	12332	9095
(banks)	(1486)	(1464)	(1205)
Panel C: Fama-MacBeth two-step procedure			
Economic uncertainty	-1.050*	-.206	-.262**
	(.071)	(.228)	(.019)
Other variables	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
Observations	12614	12614	9095
	(1501)	(1501)	(1205)
Averaged R^2	.237	.211	.246
Panel D: 2SLS			
Economic uncertainty	-1.047*	-.161**	-.122
	(.056)	(.044)	(.180)
Other variables	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
Observations	10534	10534	7750
	(1277)	(1277)	(1071)
R^2	.072	.075	.152
Kleibergen-Paap rk LM	.000	.000	.000
Hansen J	.305	.234	.427
Durbin-Wu-Hausman	.881	.946	.536

Table 6. The impact of economic uncertainty on the components of the Z-score

This table reports the impact of economic uncertainty as we use the three components of the Z-score, i.e., return on assets (*ROA*), the equity-to-assets ratio (*EA*) and the standard deviation of ROA (σ(*ROA*)), as the dependent variable. In Panel A, *ROA* is used as the dependent variable. In Panel B, *EA* is regressed on the covariates. σ(*ROA*) is employed as the dependent variable in Panel C. We construct *ROA*, *EA* and σ(*ROA*) in relative terms, which are denoted as *ROA_n*, *EA_n* and σ(*ROA*)*_n*, respectively, by using the similar method as Eq. (5). The extents by which *ROA*, *EA* and σ(*ROA*) are deviated from their implicitly optimal level, denoted as *ROA_v*, *EA_v* and σ(*ROA*)*_v*, are also estimated by using the method analogous to Eq. (6) and (7). For brevity, we only report the estimates on the coefficient of economic uncertainty. All other regressors in the baseline model are also controlled for. The *p*-value of estimates is in parentheses. ***, ** and * denotes the statistical significance at the 1%, 5% and 10% level, respectively.

Dependent variable	(1)	(2)	(3)
Panel A: Return on assets			
	ROA	*ROA_n*	*ROA_v*
Economic uncertainty	-1.913**	-.084**	-.075
	(.034)	(.029)	（.476）
Other variables	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
Observations	13855	13855	9715
(banks)	(1556)	(1556)	(1239)
R^2	.095	.099	.087
Panel B: Equity-to-assets ratio			
	EA	*EA_n*	*EA_v*
Economic uncertainty	1.900	.020	.023
	(.299)	(.400)	(.727)
Other variables	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
Observations	13903	13903	9776
(banks)	(1546)	(1546)	(1247)
R^2	.030	.030	.059
Panel C: Standard deviation of ROA			
	σ(ROA)	*σ(ROA)_n*	*σ(ROA)_v*
Economic uncertainty	1.562**	.139**	.311**
	(.021)	(.032)	(.030)
Other variables	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
Observations	12806	12806	9300
(banks)	(1516)	(1516)	(1200)
R^2	.076	.075	.057

Table 7. The impact of variable-specific uncertainties on bank risk

This table reports the impact of variable-specific uncertainties on bank risk. The dependent variables are the indicators of bank stability, i.e., *Z*, *Z_n* and *Z_v*, respectively. In Panel A, we use the GARCH-created conditional variance of innovation in the series of output growth, in Panel B the GARCH-created conditional variance of innovation in inflation, and in Panel C the GARCH-created conditional variance of innovation in currency depreciation rate as the indicators of variable-specific uncertainties in estimations. We first include them separately and then jointly in Panel D. For brevity, we only report the estimates on the coefficient of variable-specific uncertainties. All other regressors in the baseline model are also controlled for. The *p*-value of estimates is in parentheses. ***, ** and * denotes the statistical significance at the 1%, 5% and 10% level, respectively.

Dependent variable	(1)	(2)	(3)
	Z	*Z_n*	*Z_v*
Panel A: Uncertainty on output			
Uncertainty_output	-.485	-.072	-.031
	(.121)	(.129)	(.564)
Other variables	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
Observations	12715	12715	9156
(banks)	(1502)	(1502)	(1206)
R^2	.079	.083	.161
Panel B: Uncertainty on inflation			
Uncertainty_inflation	-.436***	-.056**	-.084***
	(.006)	(.026)	(.005)
Other variables	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
Observations	13178	13178	9436
(banks)	(1532)	(1532)	(1220)
R^2	.086	.086	.161
Panel C: Uncertainty on currency depreciation			
Uncertainty_depreciation	-.590*	-.092*	-.125**
	(.064)	(.051)	(.025)
Other variables	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
Observations	13418	13418	9580
(banks)	(1542)	(1542)	(1227)
R^2	.084	.085	.163
Panel D: All three types of uncertainty			
Uncertainty_output	-.475	-.070	-.026
	(.126)	(.140)	(.609)
Uncertainty_inflation	-.302**	-.036	-.070***
	(.042)	(.123)	(.007)
Uncertainty_depreciation	-.376	-.067	-.102*
	(.257)	(.167)	(.058)
Other variables	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
Observations	12614	12614	9095
(banks)	(1501)	(1501)	(1205)
R^2	.082	.086	.166

Table 8. What banks are more affected by economic uncertainty?

This table reports the heterogeneous effects of economic uncertainty on bank risk across a number of bank-specific characteristics. The dependent variables are the indicators of bank stability, i.e., *Z*, *Z_n* and *Z_v*, respectively. In Part A, we construct the interaction of our uncertainty indicator with banks' size (Panel A), liquidity (Panel B) and inefficiency (Panel C). We first include these interactive terms separately, and then jointly in our estimations (Panel D). In Part B, we alternatively build a dummy variable first, which is equal to 1 as the value of size/liquidity/inefficiency is above its median value, and 0 otherwise. We next construct the interaction of uncertainty with these dummy variables. We re-estimate our models by including these interactive terms separately (Panel A, B and C) and then jointly (Panel D). For brevity, we only report the estimates of the coefficient on uncertainty and those of its interaction with bank characteristics. All other regressors in the baseline model are also controlled for. The *p*-value of estimates is in parentheses. ***, ** and * denotes the statistical significance level at the 1%, 5% and 10% level, respectively.

Dependent variable	Part A			Part B		
	(1)	(2)	(3)	(4)	(5)	(6)
	Z	*Z_n*	*Z_v*	*Z*	*Z_n*	*Z_v*
Panel A: Size						
Economic uncertainty	-.632	-.088	-.126	-.414	-.059	-.079
	(.142)	(.156)	(.135)	(.293)	(.314)	(.303)
Economic uncertainty	-11.677***	-1.869***	-1.789**	-1.136***	-.173***	-.190***
× size	(.007)	(.005)	(.048)	(.006)	(.006)	(.004)
Other variables	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12614	12614	9095	12614	12614	9095
(banks)	(1501)	(1501)	(1205)	(1501)	(1501)	(1205)
R^2	.085	.089	.167	.084	.087	.167
Panel B: Liquidity						
Economic uncertainty	-1.710**	-.264**	-.249*	-1.389**	-.210**	-.234**
	(.019)	(.013)	(.061)	(.021)	(.018)	(.045)
Economic uncertainty	2.647*	.437*	.215	.638	.102	.076
× liquidity	(.092)	(.062)	(.453)	(.238)	(.180)	(.360)
Other variables	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12614	12614	9095	12614	12614	9095
(banks)	(1501)	(1501)	(1205)	(1501)	(1501)	(1205)
R^2	.083	.087	.165	.083	.087	.165
Panel C: Inefficiency						
Economic uncertainty	-.448	-.078	-.056	-.833	-.133*	-.152
	(.458)	(.391)	(.640)	(.109)	(.087)	(.126)
Economic uncertainty	-1.111**	-.146**	-.246**	-.668	-.079	-.128*
× inefficiency	(.033)	(.050)	(.036)	(.128)	(.181)	(.072)
Other variables	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12614	12614	9095	12614	12614	9095
(banks)	(1501)	(1501)	(1205)	(1501)	(1501)	(1205)
R^2	.083	.086	.166	.083	.086	.166
Panel D: All interactions						
Economic uncertainty	-.084	-.023	.045	-.150	-.033	-.019
	(.909)	(.827)	(.750)	(.755)	(.633)	(.841)
Economic uncertainty	-12.692***	-2.001***	-2.108**	-1.293***	-.191***	-.221***
× size	(.004)	(.003)	(.022)	(.001)	(.001)	(.000)
Economic uncertainty	2.607*	.425*	.273	.687	.107	.095
× liquidity	(.071)	(.054)	(.304)	(.169)	(.136)	(.217)
Economic uncertainty	-1.745***	-.247***	-.353***	-1.004***	-.129**	-.181***
× inefficiency	(.001)	(.001)	(.006)	(.009)	(.012)	(.006)
Other variables	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12614	12614	9095	12614	12614	9095
(banks)	(1501)	(1501)	(1205)	(1501)	(1501)	(1205)
R^2	.086	.091	.170	.086	.089	.169

Table 9: The impact of macroprudential policies on the uncertainty-risk nexus

This table reports the impact of macroprudential policies on the economic uncertainty-bank risk association. The dependent variables are the indicators of bank stability, i.e., *Z*, *Z_n* and *Z_v*, respectively. In Panel A, we use the macroprudential policy index, which is constructed by Cerutti et al. (2017a), and build an interactive term of it and uncertainty. In Panel B, we alternatively adopt the indicator of macroprudential policies in Cerutti et al. (2017b) and include its interaction with uncertainty in our estimations. In Panel C, we borrow the macroprudential policy index from the recent research of Alam et al. (2019) and use its interactive term with uncertainty as a regressor in our estimations. For brevity, we only report the estimates on the coefficient of uncertainty and those of its interaction with macroprudential policy index. All other regressors in the baseline model are also controlled for. The *p*-value of estimates is in parentheses. ***, ** and * denotes the statistical significance at the 1%, 5% and 10% level, respectively.

Dependent variable	(1)	(2)	(3)
	Z	*Z_n*	*Z_v*
Panel A: Macroprudential policy by Cerutti et al. (2017a)			
Economic uncertainty	-.902**	-.148***	-.159**
	(.017)	(.007)	(.019)
Economic uncertainty ×	1.692 ***	.238***	.280***
MPI_Cerutti et al. (2017a)	(.000)	(.002)	(.009)
Other variables	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
Observations	10078	10078	7228
(banks)	(1319)	(1319)	(1037)
R^2	.100	.102	.204
Panel B: Macroprudential policy by Cerutti et al. (2017b)			
Economic uncertainty	-.968	-.156	-.274**
	(.107)	(.101)	(.023)
Economic uncertainty ×	.071	.010	.044
MPI_Cerutti et al. (2017b)	(.659)	(.695)	(.167)
Other variables	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
Observations	10078	10078	7228
(banks)	(1319)	(1319)	(1037)
R^2	.099	.101	.204
Panel C: Macroprudential policy by Alam et al. (2019)			
Economic uncertainty	-1.154**	-.173**	-.205**
	(.015)	(.014)	(.026)
Economic uncertainty ×	.178*	.023*	.045***
MPI_Alam et al. (2019)	(.074)	(.100)	(.002)
Other variables	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
Observations	12614	12614	9095
(banks)	(1501)	(1501)	(1205)
R^2	.083	.087	.168

Appendix Table 1. The comparison of uncertainty in emerging and advanced economies

This table presents the average level of uncertainty in the world, in a group of emerging economies and in a group of advanced countries in each year during the period of 2000-2016. It also reports the *p*-value of the statistics of the t-tests, where the null hypothesis (H_0) is that the uncertainty level in emerging economies (E) is equal to that in advanced economies (A) and the alternative hypothesis (H_a) is that E is larger than/unequal to/smaller than A.

Year	Global uncertainty	Uncertainty in emerging economies (E)	Uncertainty in advanced economies (A)	t-test (H_0: E=A)		
				H_a: E > A	H_a: E ≠ A	H_a: E < A
2000	.122	.118	.130	.891	.219	.109
2001	.115	.109	.128	.965	.070	.035
2002	.096	.102	.082	.013	.026	.987
2003	.112	.117	.100	.028	.056	.972
2004	.089	.097	.070	.000	.000	1.000
2005	.096	.098	.091	.141	.282	.859
2006	.092	.097	.076	.000	.000	1.000
2007	.089	.094	.075	.002	.004	.998
2008	.167	.161	.185	.943	.114	.057
2009	.197	.189	.222	.985	.031	.015
2010	.114	.115	.111	.328	.657	.672
2011	.108	.104	.118	.917	.166	.083
2012	.099	.106	.078	.000	.000	1.000
2013	.078	.084	.060	.000	.000	1.000
2014	.057	.061	.042	.000	.000	1.000
2015	.082	.084	.075	.074	.149	.926
2016	.076	.076	.074	.360	.720	.640

Appendix Table 2. The economic uncertainty index in emerging economies

This table reports our measure of economic uncertainty across 34 emerging economies during the period of 2000-2016. A higher value denotes a higher level of economic uncertainty.

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Central and Eastern Europe																	
Belarus				.129	.147	.112	.121	.101	.105	.147	.140	.244	.236	.149	.114	.144	.108
Bosnia and Herzegovina								.035	.087	.160	.067	.046	.051	.027	.040	.041	.042
Bulgaria				.191	.161	.141	.238	.256	.315	.296	.192	.105	.123	.111	.047	.067	.056
Croatia					.099	.156	.086	.088	.246	.275	.147	.099	.270	.136	.077	.129	.094
Czech	.172	.110	.144	.180	.107	.146	.123	.088	.221	.242	.177	.154	.110	.109	.132	.162	.108
Estonia							.124	.098	.230	.245	.139	.133	.085	.063	.073	.111	.109
Hungary	.048	.055	.034	.063	.068	.038	.124	.060	.107	.302	.188	.118	.117	.061	.037	.052	.027
Latvia			.112	.087	.089	.185	.182	.246	.290	.551	.303	.204	.254	.166	.136	.221	.229
Lithuania	.160	.080	.080	.143	.193	.109	.096	.103	.135	.301	.143	.134	.114	.087	.048	.115	.069
Poland	.213	.155	.087	.085	.144	.101	.160	.110	.190	.154	.128	.245	.095	.126	.103	.090	.135
Romania	.223	.122	.071	.067	.071	.115	.082	.070	.119	.178	.143	.085	.087	.121	.054	.101	.072
Serbia				.034	.027	.030	.026	.035	.069	.140	.053	.029	.040	.026	.025	.027	.015
Slovakia	.250	.152	.101	.184	.139	.172	.135	.130	.245	.161	.099	.073	.058	.059	.043	.079	.076
Slovenia	.184	.192	.203	.158	.080	.199	.260	.197	.198	.319	.153	.188	.162	.163	.104	.081	.048
Ukraine					.008	.013	.017	.024	.069	.022	.015	.008	.009	.012	.045	.162	.031
Latin America																	
Argentina	.036	.037	.197	.112	.021	.029	.020	.022	.107	.022	.038	.008	.026	.033	.026	.006	.065
Brazil	.056	.052	.113	.094	.042	.054	.039	.047	.100	.083	.043	.045	.048	.052	.050	.086	.051
Chile	.033	.083	.058	.124	.092	.072	.037	.073	.305	.395	.279	.087	.087	.059	.041	.059	.042
Colombia	.169	.066	.110	.165	.111	.078	.116	.147	.245	.293	.104	.086	.074	.099	.079	.169	.251
Mexico	.048	.120	.128	.041	.043	.103	.054	.034	.115	.092	.050	.038	.050	.061	.030	.045	.051
Paraguay												.153	.158	.087	.046	.057	.095
Peru							.121	.058	.191	.117	.034	.067	.081	.102	.059	.098	.094
Uruguay					.138	.062	.030	.086	.081	.082	.026	.022	.085	.061	.027	.016	.027
Asia																	
China	.053	.041	.074	.097	.104	.091	.057	.135	.087	.133	.077	.053	.077	.046	.032	.080	.075
Hong Kong, SAR	.030	.037	.055	.087	.056	.077	.066	.095	.091	.038	.064	.056	.060	.037	.059	.041	.067
India	.095	.049	.023	.047	.063	.084	.108	.099	.172	.273	.253	.280	.310	.199	.155	.102	.058
Indonesia	.071	.096	.040	.038	.034	.069	.119	.013	.036	.054	.011	.005	.006	.019	.014	.024	.009
Korea	.208	.124	.088	.093	.082	.066	.041	.054	.190	.161	.059	.085	.077	.058	.024	.052	.077
Malaysia	.044	.046	.046	.057	.047	.057	.066	.053	.117	.112	.072	.065	.087	.077	.045	.150	.080
Pakistan				.312	.247	.134	.090	.206	.322	.314	.178	.099	.100	.126	.119	.091	.106
Philippines	.175	.208	.164	.145	.133	.115	.135	.137	.279	.209	.157	.158	.192	.156	.167	.134	.146
Singapore	.060	.165	.094	.096	.106	.149	.134	.168	.188	.284	.267	.287	.121	.107	.027	.057	.105
Thailand		.164	.117	.087	.125	.106	.110	.082	.149	.155	.055	.112	.219	.102	.049	.083	.028
Vietnam											.090	.050	.096	.060	.058	.032	.026

Appendix Table 3. Correlation matrix

This table reports the pairwise correlation of the main variables. The figures in the bold font denote the correlation coefficients with the statistical significance level lower than 10%.

	Z	Uncertainty	Size	Liquidity	Inefficiency	Income diversification	Funding diversification	Foreign	State	GDP per capita	GDP growth rate	Inflation	Monetary policy	Crises	Activity mix	Capital adequacy	Supervisory power	Market discipline	CR3	Deposit insurance	Financial depth	Rule of law
Z	.																					
Uncertainty	**-.043**	.																				
Size	**.037**	**.133**	.																			
Liquidity	**-.059**	**-.100**	**-.065**	.																		
Inefficiency	**-.284**	-.001	**-.104**	**.091**	.																	
Income diversification	**-.135**	.006	**.042**	**.209**	**.125**	.																
Funding diversification	**-.059**	**-.041**	**-.056**	-.010	-.006	**.084**	.															
Foreign	**-.100**	**.050**	**.055**	**.121**	**.095**	**.118**	**.099**	.														
State	- 005	**.022**	**.109**	**-.078**	**-.044**	**-.056**	.007	**-.318**	.													
GDP per capita	**-.043**	.013	**.068**	**.127**	**.030**	**.142**	**.150**	**.259**	**-.155**	.												
GDP growth rate	**.020**	**-.019**	-.004	**.018**	.003	**.015**	**-.007**	-.011	-.012	**.012**	.											
Inflation	-.004	**-.035**	.010	.003	-.004	**.041**	**-.019**	**.012**	.004	-.005	**-.144**	.										
Monetary policy	**.059**	**-.170**	**-.024**	**-.035**	-.006	.001	-.002	-.006	.004	**.026**	**-.184**	**.225**	.									
Crises	**-.144**	**.016**	**-.031**	-.001	**.082**	**.054**	.006	-.003	**-.030**	-.007	**-.048**	**.031**	**.068**	.								
Activity mix	**.073**	**.067**	**-.015**	**-.060**	**-.135**	**-.121**	**-.176**	**-.147**	**.134**	**-.324**	-.000	**-.012**	**-.034**	**-.141**	.							
Capital adequacy	**.111**	**.053**	**-.085**	**-.099**	**-.080**	**-.153**	**-.126**	**.099**	**.064**	**-.259**	**-.035**	.007	**.035**	**.092**	**.076**	.						
Supervisory power	**-.043**	**-.035**	**.028**	**.078**	-.007	**-.101**	**.077**	**.038**	**-.055**	**.016**	.008	**-.015**	**-.052**	**-.053**	**.130**	**.027**	.					
Market discipline	**.069**	**-.124**	**-.118**	**-.083**	**-.110**	**-.148**	**.026**	**-.113**	**.104**	**-.057**	-.007	**-.015**	**.043**	**-.084**	**.274**	**.134**	**.101**	.				
CR3	**-.038**	**.130**	**.226**	**.137**	.003	**.083**	**.018**	**.169**	**-.132**	**.276**	-.009	**.052**	**-.113**	**-.067**	**-.173**	**-.326**	**.117**	**-.096**	.			
Deposit insurance	**.038**	**-.064**	**-.020**	**-.047**	**.029**	-.011	**.118**	**.013**	**.025**	**.018**	-.010	-.004	-.009	**-.068**	**-.081**	**-.057**	**.061**	**-.027**	**-.119**	.		
Financial depth	**.248**	**-.061**	**-.059**	**-.063**	**-.250**	**-.206**	**-.076**	**-.051**	**-.018**	**.194**	**-.013**	-.005	**.063**	**-.070**	**.065**	**.168**	**-.070**	**.248**	**.018**	**-.218**	.	
Rule of law	**.074**	**.245**	**.118**	.007	**-.058**	**.018**	**.015**	**.236**	**-.056**	**.575**	**-.012**	.003	**.022**	**-.130**	**-.176**	**-.152**	**-.070**	**.089**	**.265**	**-.048**	**.367**	.