A Bayesian panel stochastic volatility measure of financial stability.

Mamatzakis[a] E. C. and M. G. Tsionas[b]

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Abstract

We propose to model financial stability, opting for an alternative bank profit function whose volatility is measured within a framework of panel stochastic volatility. Within this model financial stability and volatility are latent variables. To observe financial stability and volatility we employ Bayesian inference procedures organized around Sequential Monte Carlo (SMC) technique and particle filtering. We do so in a single stage that controls also for non-linearities, whilst we also allow for some key bank and country specific variables to impact upon financial stability and volatility. Thus, we provide a new measure of financial stability by country, over time and also at a global level. In an empirical application, we derive financial stability indexes for a plethora of countries, as well as the global financial stability index that acts an early warning index. Our results suggest that the financial cycle is subject to non-linearities. We argue that the global financial system should closely monitor large, systemic, banks as key to support financial stability.

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[a]Department of Management, Birkbeck College, University of London, London WC1E 7HX, UK. E-mail: e.mamatzakis@bbk.ac.uk. [b]Lancaster University Management School, Bailrigg, Lancaster, LA1 4YX, UK. E-mail: m.tsionas@lancaster.ac.uk.

1. Introduction

To come up with a cohesive measure of financial stability is by no means an easy task due to the complexities involved within financial systems. If one's aim is to define financial stability in simple terms, then it could be easily said that a stable financial system is '*crisis free*'. The complication emerges when one would attempt to elaborate at what is '*crisis free*'. Predominantly, the literature (Demirguc-Kunt and Detragiache, 1998, Kaminsky and Reinhardt, 1999, Kaminsky, et al. 1998, Bordo and Schwartz, 2000, Gerdrup, 2003, Chan, 2017) focuses on confining volatility as the key to reduce uncertainty and forecast with some accuracy so as keep the economy '*crisis free*'.[1] Alas, the reality is that financial systems are intricate to such an extent that a simple definition of financial stability would imply compromising in terms of inference and meaningful analysis. After all, volatility and thereby financial stability are not observable within highly complex financial systems. Schinasi (2004) proposes an alternative definition of financial crisis by responding to some interesting question about what defines financial stability. He argues that financial crisis is defined by the soundness of institutions, the stability of markets, the absence of turbulence, the low volatility.[2] There are two main issues that emerge from Schinasi (2004) analysis: first the role of the resilience of the financial sector to financial crisis; and second, the factual observation of financial cycles. As such it would be rather a chimera to have financial markets without fluctuations. An emphasis therefore, it should be also placed on the fluctuations of the financial industry. Chinasi (2004) identifies the role of

[1] For example Chan (2017) provides a model of stochastic volatility for inflation forecasting with time-varying parameters. The author finds evidence that inflation should modelled so as to consider a time varying volatility.

[2] Schinasi (2004) provides the following definition for financial stability: '*A financial system is in a range of stability whenever it is capable of facilitating (rather than impeding) the performance of an economy, and of dissipating financial imbalances that arise endogenously or as a result of significant adverse and unanticipated events.*'

volatility for financial stability. This paper follows from the role of volatility and provides a model that considers and controls for volatility in financial stability.

In some detail, we argue that it is unambiguous the importance of measuring and thereby monitoring financial stability while controlling for volatility, in particular in the aftermath of the financial meltdown late in 2000s. As the financial crisis unfolded, during the second half of 2009, it became evident that financial markets had seriously underestimated credit risks (Allen and Carletti, 2010; Brunnermeier, 2009; Covitz et al., 2013; Li and Zinna, 2014), in particular in segments such as sub-prime mortgages. It was by then too late to make an assessment of the seriousness of the situation and subsequently to react in an attempt to confine the catastrophic implications. The lack of adequately measuring financial stability, so as to act as an early warning prior to the burst of a financial crisis, was identified as a critical failure of the banking industry. To some extent, this inadequacy of financial systems to proceed with an accurate financial stability assessment, at the time, was not a surprise given that for most part of the 2000s there was a general euphoria and thereby optimism, stemming out of a rapid financial globalization based on liberalization, financial innovation, and integration. Vigilance, prior to the financial crisis was clearly not a priority. This general attitude of being complacent towards the underlying risks of financial systems proved to have dire consequences that are still felt across the world to this date.

It is no surprise that central banks have shown strong interest on the subject, as keeping financial systems stable has become one of their prime priorities in recent years (ECB, 2005). In particular, central banks (ECB, 2005, Bank of England, 2008, Sveriges Riksbank, 2008) have enhanced their alertness on whether financial systems, if left unattended, would cope on their own to weather out shocks, and in particular erratic volatility. At the core of this alertness is accurately measuring financial stability. Alas, to date no silver bullets have yet to be found, primarily because volatility and thereby financial stability are notoriously difficult to model and observe (Goodhart et al. 2006). Yet, central banks around the world appear to recognize that a sound banking industry is the corner stone of financial stability. It is not coming as a surprise that there is a strong term in recent years for central banks to act as supervisors and thus regulators of the banking industry.

Earlier studies in the literature focuses on the role of banks (see Li and Zinna, 2014; Eichengreen and Rose, 1999; Demirguc-Kunt, and Detragiache, 1998). The findings show that banks are key in the transmission of the financial crisis to the economy. In addition, Kaminsky and Reinhardt, (1999) Bordo and Schwartz, (2000), and Gerdrup, (2003) that such transmission is through the credit and liquidity channel. Typically, those studies employ data from bank balance-sheets to model financial stability.

Another strand of the literature has primarily focused on market data so as to estimate bank distance to default as key to identify financial risks.[3] Lepetit et al. (2008) opt for bank distance to default to examine the underlying association with product diversification in the European banking industry. The authors further provide evidence that banks' diversification to non-interest income and trading activities could undermine financial stability.[4] In a recent paper, Li and Zinna (2014) opt for multivariate credit risk model based on bank CDS in the US and the UK to count for joint defaults of banks so as to disentangle systemic risk. The authors argue that systemic credit risk differs across countries and prompts high risk premia.

Other empirical studies focused on building financial indicators to measure financial stability. Nelson and Perli (2005) and Van den End (2006) demonstrate that general financial market indicators are valuable inputs to measure financial stability due to the complexity of financial intermediation.[5] Along these lines, Hawkins and Klau (2000), Nelson and Perli (2005), Gray et al (2007), Illing and Liu (2003) and Van den End (2006) propose an aggregate financial stability indicator based on a

[3] Some focus has been directed towards default probabilities to predict bank failures and thereby financial crisis (Helmut et al. 2006). For example, Gropp et al. (2006) analyzed the ability of the distance-to-default and bond spreads to signal bank fragility, whereas Chan-Lau and Sy (2007) introduce the concept of distance-to-capital, an extension of distance-to-default.

[4] It is worth mentioning a strand of literature that proposes network models for identifying bank risk (see Elsinger et al. 2006). Elsinger et al. 2006 demonstrates for the interbank markets that risk could be contained with the necessary injections of capital by the lender of last resort.

[5]Kaminsky and Reinhardt (1999) focus on bank and balance of payment crises to provide a list of early warning indicators for financial stability, i.e. credit and equity prices. Building on this research Borio and Lowe (2002) and Borio and Drehmann (2009) demonstrate that there are threshold values for such early warning the indicators that could be considered over many time periods ahead.

plethora of relevant variables of financial systems.[6] It follows from this literature that the quest of the holy grail of financial stability indicators has led policy-making institutions such as Central Banks (see Bank of England, 2008, Sveriges Riksbank, 2008) but also IMF to define composite financial stability indicators (see IMF, 2006). The main characteristic of all the composite financial stability indicators is their reliance on a weighted average contraction methodology.[7] This is a rather strong assumption that we propose to relax with our modeling.

Moreover, stemming from some strong assumptions in previous financial stability modeling, this paper proposes a novel approach, aiming to correctly identify risks in financial systems early on while we control for non-linearities. It builds on the theoretical doctrines of Goodhart et al. (2006) who argue that financial stability is closely linked to the banking industry within a general equilibrium framework. Goodhart et al. (2006) show that, in fact, understanding bank failure is key to financial stability. Moreover, Goodhart et al. (2006) further develop the theoretical foundations of monitoring financial stability based on some bank specific variables such as profitability and credit risk. In some detail, our methodology is based on building a Bayesian model with dynamic latent variables to describe volatility and financial stability in the banking sector. This methodology explicitly models financial stability, opting for an alternative bank profit function whose volatility is measured within a framework of panel stochastic volatility. Within this model financial stability and

[6]The list of potential variables is long, and to this end not easily exhausted. To name a few, bank profitability, asset quality, capital adequacy, credit growth and risk exposure. In terms of macro finance, it could include inflation, business cycle and monetary aggregates. For example, Bordo et al. (2000) provide a historical analysis of financial instability based on price shocks. Financial market indicators also are detrimental, such as securities prices, bid-ask spreads, historical and implied volatilities, yield curve, and term premia. Illing and Liu (2003) who provide an aggregate composite financial distress index for Canada, mainly based on macro-financial data. In an extension of aggregate composite indexes, Hanschel and Monnin (2005) focus on the banking sector for signs of financial distress. Based on similar approach a plethora of composite indexes have emerged, such as Van den End (2006) for the Netherlands. The key characteristic of these studies is that they model financial stability as a composite, aggregate index of financial stability where the banking industry plays a prominent role. Alas, whether the plethora of indexes has brought new light is debatable, as it is still pending to come with a unified measure of financial stability. This paper provides a new approach of unified measure of financial stability that is flexible enough that could be easily extended to incorporate all sectors of financial systems.

[7] In our modelling we relax the reliance on weights.

volatility are latent variables, not observable. To observe financial stability and volatility we apply Bayesian inference procedures organized around Sequential Monte Carlo (SMC) techniques, also known as particle filtering. Thus, Bayesian inference is facilitated by using SMC particle-filtering techniques to explore the posterior distribution of the model, which is quite complicated. The dynamic unobserved latent variables, namely financial stability and volatility, are integrated out using particle filtering. We do so in a single stage, whilst we also allow for some key bank and country specific variables to impact upon financial stability and volatility. Thus, we provide a new measure of financial stability by country, over time and also at a global level. By doing so, we fill a gap in the literature, departing from the constraints of weighted average composite indicators. In addition, the global sample allows us to examine whether there is a shift of financial stability uncertainties away from advance economies and towards emerging and developing economies as it is reported in the recent IMF's Global Financial Stability Report (2015).

The empirical estimation of our new measure of financial stability is challenging for several reasons, but mainly due to the plethora of determinants of financial stability (see for a review Gadanecz and Jayaram 2009; Acharya et al. 2017). From a policy point of view, the creation of the Single Supervisory Mechanism (SSM) in the euro area and the supervisory role attributed to the European Central Bank are worth noting as the Euro-area is stepping up efforts towards the direction of a unified financial supervisory system (see Hellwig, 2014). Most Central Banks employ weighted averages of banking indicators (i.e. capital adequacy, profitability, liquidity, asset quality) to compose a financial stability indicator. Moreover, the ECB and BoE focus comprehensively on liquidity to extract financial stability indicator of the BoE. Liquidity is decomposed into various layers across markets and dimensions. On the other hand, IMF builds on the idea that the banking industry could be modeled in similar way to a portfolio, and thereby derive a market-based probability of default of each individual bank it estimates the joint default probabilities, i.e. the expected number of bank defaults in the system, given that at least one bank defaults (see IMF, 2008).

From an academic point of view, there is a plethora of papers that propose interesting empirical modelling of financial stability (see Jordá et al. 2017; Brunnermeier at al. 2009; Hellwig 2014; and Acharya et al. 2017). Other seminal papers on financial stability literature are Aikman et al. (2017) and Hollo et al. (2012). We build on this literature and opt to employ a comprehensive list of variables from a rich set of information set in previous studies (see Jordá et al. 2017; Brunnermeier at al. 2009; Hellwig 2014; and Acharya et al. 2017) at a global data set while we control for bank volatility (an unobservable at bank level), given its importance for financial stability (see Schinasi 2004) that we model as a latent variable. We follow from Schinasi (2004) who emphasize the role of low volatility for financial stability. From this perspective, we employ a flexible and well specified bank profit function (see Berger and DeYoung, 1997, Berger and Mester, 1997, Mester, 1996 and Maudos et al., 2002; Brunnermeier at al. 2009; Acharya et al. 2017) so as to model volatility. This allows us to measure the new financial stability index across heterogenous countries of our global data set while we control for bank and country specific variables, and underlying non-linearities. So, the key variable of our model is volatility that is derived from the alternative bank profit function. The estimation of financial stability and volatility is cumbersome, also in light of non-linearities, and to simplify we use Bayesian inference procedures organized around Sequential Monte Carlo (SMC) technique and particle filtering. In addition, we do so in a single stage that allows for some key bank and country specific variables to impact upon financial stability and volatility. Results are of interest as they are robust across different empirical models and provide useful policy implications.

In some detail, the present paper's contribution is fourfold: first, it models financial stability based on Bayesian latent variable modeling, which relaxes previous strong assumptions in the literature. Secondly, we use a large global dataset that covers the vast majority of listed banks in the world, and that was compiled by combining three different databases. Thirdly, we perform sensitivity analysis and examine the association between financial stability and some key bank and country specific variables, whilst we also consider the impact of shocks and the corresponding responses for three groups of countries: advanced, emerging and developing. Lastly, our empirical results are of some significance as they suggest that there are underlying non-linearities and the global financial system should closely monitor large, systemic, banks as key to sustain financial stability.

The rest of the paper is structured as follows: Section 2 presents our model. The data employed is provided in Section 3. Section 4 provides the empirical estimations and discusses our results. Finally, section 5 offers some concluding remarks and policy implications.

2. The econometric model: a return-to-dollar approach

2.1. The return-to-dollar function

Our specification is motivated by the alternative profit function of Humphrey and Pulley (1997) (see also Berger and Mester, 1997, Mester, 1996 and Maudos et al., 2002). To this end, we build on a return-to-dollar function, for the first time in the literature that overcomes a standard problem in the estimation of profit functions, viz. that profits are often negative so logs are not defined.[8]

Specifically, we consider the return-to-dollar function:

$$ret_{i,c,t} = a_{i,c} x_{i,c,t} + v_{i,c,t} \quad (1)$$

where $i=1,\dots n$ denotes a bank, $c=1,\dots m$ a country and $t=1,\dots T$ is time. The $kx1$ vector of regressors x_{ict} includes logs of outputs and input prices, log equity, a time trend and their squares and interactions. Here, $x_{i,c,t} = \frac{TR_{i,c,t}}{TC_{i,c,t-1}} \equiv 1 + \pi_{i,c,t}$ represents return where *TR* and *TC* stand for total revenues and total costs, while $\pi_{i,c,t}$ is profit. In this profit function we opt for two outputs and three inputs as in Sealey and Lindley **(**1977), Casu and Molyneux (2003), and Koutsomanoli-Filippaki and Mamatzakis (2009) in line with the intermediation approach.[9] In some detail, output one is loans while output two is other earning assets, given that banks would not only produce

[8] Some authors (Berger and Mester, 1997) propose to add an arbitrary constant so that all profits are positive and then take logs but that would filter out important information.

[9] It is worth noting, simply put, that bank's role in the economy is that of an intermediate between the ones who have excess in funds (savers) and the ones who have shortage of funds (investors, consumers). In order the bank to fulfil its role it would employ physical capital, labor and financial capital (funds) that is line with previous studies (Berger and Humphrey (1997)Koutsomanoli-Filippaki et al. 2009; Mamatzakis et al. 2015; Sealey and Lindley 1977; Casu and Molyneux 2003).

loans but also other assets for which they would raise revenues. To produce those outputs, the typical bank within a profit function would employ three inputs of production: financial capital (referring to funds that a bank has to raise to produce), physical capital (referring to bank's operation, i.e. buildings and equipment) and labor (number of employees necessary to provide bank services). Note that as this is a profit function we employ the prices of those inputs in the empirical estimation: the price of financial capital that is the total interest expenses over total interest bearing borrowed funds; the price of physical capital that is other operating expenses over fixed assets; and lastly the price of labour which is personnel expenses divided by total assets. Thus, the alternative "*return-to-dollar*" function is a standard translog in logs of input prices, outputs and time trend. Standard country fixed effects are included to capture heterogeneity. In addition, we also include bank-specific effects.

2.2. The volatility modeling

We assume $\upsilon_{i,c,t} \sim N(0, \sigma^2_{i,c,t})$, with the following volatility specification:

$$\sigma^2_{i,c,t} = \beta'_0 + \beta'_1 \sigma^2_{i,c,t-1} + \beta_2 Z'_{i,c,t} + \varepsilon_{i,c,t} \quad (2)$$

where the vector $Z'_{i,c,t}$ contains variables relevant to explain profit rate volatility and also contains a variable $FS_{i,c,t}$ which represents financial stability.[10] Among the variables we include an adjusted z-score for technical efficiency:

$$z - score_{i,c,t} = \frac{CAP_{i,c,t} + (x_{i,c,t} a_{i,c} - 1)}{\sigma_{i,c,t-1}} \quad (3)$$

where CAP_{ict} is the capital-assets ratio.

This Z-score depends on unknown parameters as well as the unknown return-to-dollar inefficiency and volatility and is bank-specific, country-specific and time varying. This is the first time, to our knowledge, that Z-score is modeled in parallel with volatility, as the latter is unobservable and thus agnostic. Previous literature imposes

[10] In the data section and empirical section, we discuss in detail variables in $Z'_{i,c,t}$. Such variables are bank and country specific, such as non-performing loans; equity; total assets; capital ratio; liquidity ratio; GDP per capita.

strong assumption about the measurement of volatility (Laeven and Levine, 2009; Lepetit et al. 2008; Barry et al., 2011; Delis and Staikouras, 2011; among others). Moreover, previous literature group observations to determine the variance and use it as a measure of risk. Our model provides a way of overcoming this reliance on an agnostic measurement of variance rather than opting to provide an appropriate modeling as we propose.

2.3. Financial stability measure

Financial stability at the country level is defined as

$$FS_{i,c,t} = \beta_0 + \beta_1 FS_{i,c,t-1} + \beta_2 Z'_{i,c,t} + \sum_{i=1}^{n} \kappa_{i,c,t} z - score_{i,c,t} + \varepsilon_{i,c,t} \qquad (4)$$

where $Z'_{i,c,t}$ is a vector of variables (macro and bank specific) that contribute to the country-specific financial stability indicator and $\kappa_{i,c,t}$ represents loadings of the z-score which are aggregated across banks in a given country to contribute to the country-specific financial stability indicator. The indicator is a latent, unobserved variable, which affects the volatility of each bank and is determined at the country level by the variables in $Z'_{i,c,t}$.

For the weights, we assume $\kappa_{i,c,t} = \vartheta_{i,c,0} + \vartheta_{1,i,c}\kappa_{i,c,t-1} + \varepsilon_{i,c,t}$ subject to the restrictions $\kappa_{i,c,t} \geq 0$, $\sum_{i=1}^{n} \kappa_{i,c,t} = 1$.

Overall, the aggregate financial stability across countries is:

$$FS^*_{c,t} = \delta_0 + \delta_1 FS^*_{c,t-1} + \delta_2 G_{c,t} + \sum_{i=1}^{n} FS^*_{c,t}\omega_{c,t} + \varepsilon_{c,t} \qquad (5)$$

where $G_{c,t}$ is a vector of bank and country specific variables and $\omega_{c,t}$ represents loadings of country-specific financial stability indicators on the aggregate indicators. Note that in the Appendix we present further detail of aggregate financial stability index.

3. The global data set.

We opt for a global data set over the period from 2000 to 2015 and has annual frequency. The global sample ensures variability across countries and banks. It also provides a rich set of information where our new measure of financial stability can be applied, essentially providing a global financial stability indicator.

Balance-sheet and income statement data where obtained from the Bankscope database, while data on macroeconomic and banking variables were collected from the World Development Indicators Database and from European Central Bank reports. For the estimation of bank default financial stability, stock price data were obtained from Datastream, Bloomberg and Bankscope databases.

We start the construction of our sample by including all the banks in the Bankscope database.[11] Our final sample is an unbalanced dataset that includes 17399 observations for 31 advanced countries, 7130 observations for 35 emerging countries, and 2471 observations for 40 developing countries. The classification of country-groups is based on IMF World Economic Outlook April 2014. All the bank-specific financial variables are obtained from Bankscope database, in thousand Euros. Data for country-level variables are collected from the World Bank Indicators database.

Firstly, for the alternative profit function we opt for two outputs and three inputs as in Sealey and Lindley **(**1977), Casu and Molyneux (2003), and Koutsomanoli-Filippaki and Mamatzakis (2009). Moreover, this intermediation approach employs net loans (y_1) and other earning assets (y_2) as outputs, whilst for the three inputs considers the price of fund (w_1), the ratio of total interest expenses to total customer deposits, the price of physical capital (w_2), other operating expenses over fixed assets, and the price of labour (w_3), personnel expenses divided by total assets.

In addition, a netput is added in the form of equity (E) as in Berger and Mester, (1997), whilst nonperforming loans (*NPL*) is a negative quasi-fixed input. Total cost is defined as the sum of overheads (personnel and administrative expenses), interest, fee, and commission expenses, while profit is defined as profit before tax.

The summary statistics of these variables are provided in Table 1 for each country-group. Interestingly, we notice that the average amount of nonperforming loans in advanced economies' banking industries is almost twice that in emerging

[11]We exclude banks: (i) we had less than three observations over time; (ii) we have no information of the country-level control variables; (iii) we have no information of nonperforming loans.

economies and eight times that in developing economies.

[Insert Table 1 about here]

Prior empirical research in banking (Lozano-Vivas et al. 2002, Delis and Staikouras, 2011) underlines the importance of bank specific control variables. To this end, we employ bank specific total assets (in logs) to control for the size of banks and thereby controlling for heterogeneity across small, medium and large banks. We also opt for the non-interest income ratio, estimated by the sum of the net fees and commissions over total assets, to capture diversification in bank services. In addition, as a proxy for the non-lending activities of banks we consider securities over total assets ratio. To capture competition and concentration, we employ the interest rate spread the C3 ratio, which captures assets of the three largest banks over all country specific banking industry assets. The ratio of bank liquid assets to total assets at the country level controls measures liquidity. We also employ: the loan loss provisions to control for portfolio quality and also credit risk; the funding ratio (deposits to total assets) as well as its broader definition (deposits plus other funding to total assets) to control for the source of bank funds; the off-balance sheet items, as well as its square, measuring the diversity of bank activities; the cash ratio defined as cash and due from banks to assets; and the capital ratio as equity over total assets. Lastly, the ratio of non-performing loans to total loans captures heterogeneity across banks in terms of loan quality.

Country level variables could also assert an impact. To this end, we control for the macroeconomy in line with Barth et al., (2004), Demirguc-Kunt et al., (2003,) Fries and Taci, (2005), Delis and Staikouras, (2011) that also captures heterogeneity across countries in terms of the underlying structure of the economy. To control for the general level of economic development we use real GDP per capita. GDP per capita provides also a measure of aggregate wealth.

Also, given the heterogeneity across countries in our global sample we consider the underlying institutional and regulation at country level by opting for the '*Doing Business'* indexes of the World Bank. In some detail, we employ four indexes: the enforcing contracts index that counts as a measure of bureaucracy in general; the index of resolving insolvency that bankruptcy captures legislation; the index of credit, which encompasses creditor rights and credit information; business index that measures how easy is to start a business. All these indexes could affect financial stability as they measure the institutional economic foundations upon which financial systems operate.[12]

4. Empirical results.

The estimation of our model is not by any means a small feat. For simplicity purposes, we shall provide a summary of the main estimation procedure (while in Appendix we have more details). The estimation takes 120,000 MCMC iterations and we employ 20,000 particle filters. This estimation is proven to be robust while it converges as tested by Geweke's (1992) diagnostics. Note that to ensure robustness, we also perform sensitivity analysis using 50,000 and 100,000 particles per dynamic latent unobserved variable. Our main results stand as any differences are within the bounds predicted by numerical standard errors (NSE).

4.1. The global financial stability index.

Figure 1 shows the Financial Stability Index (FSI) over time, computed from Equation (6) for all countries in the sample. The index is normalized in 2001 to facilitate the exposition of the variability across the world, and accounts fully for parameter uncertainty as we average it over MCMC draws for the parameters and underlying latent variables. As expected there is some variability, in particular in the second half of the last decade, as the global financial crisis takes its toll, whereas there is recovery in recent years.

[Insert Figure 1 about here]

[12]The impact of regulation on financial stability could be of some significance as the credit crunch exposed significant shortcomings in the former that had a detrimental effect on the latter, in particular in the banking industry (Acharya et al., 2011). Acharya et al., (2011) show that improving creditor rights regulation assists risk management of financial systems as lowers the overall risk. Prior to the crises, there are certain components of regulation such as credit information and creditor rights that have attracted attention (Pagano and Jappelli, 1993). The authors show that the availability of credit information, in particular, is assisting financial systems to combat moral hazard and adverse selection in loans. Regarding credit rights Qian and Strahan (2007) show that the former is associated with loans of low interest rates and long maturity, thereby could assist the stability of financial systems. Business regulation could also affect financial stability (Klapper et al. 2006), as such regulation if set right could encourage entrepreneurship and thereby enhance competition and financial stability, whereas on the other hand if it is cumbersome through bureaucratic procedures for new business could have the opposite results.

As depicted by Figure 1 one could identify three distinct periods; from 2000 to 2006, from 2006 to 2010, and from 2010 onwards. During the first period, financial stability index clearly shows strengthening of financial systems across the world, with emerging economies outperforming both advanced and developing economies. This is evidence of the sound dynamism of financial systems in emerging economies early in 2000s. Alas, this was not to last, as the advanced economies registered a dramatic drop in the index as early as in 2006, which the other economies followed with some lags.

It is worth noting that the financial stability index warns for the global financial crisis of the last decade two years earlier that it took place. It might be, therefore, an early warning index, also in light that the last global financial crisis exposed the low degree of alertness of financial markets prior to the crisis (Allen and Carletti, 2010, Brunnermeier, 2009, Covitz et al., 2013). Following our modeling, our results show that signs of the crisis could have been identified well in advance and thereby allowing a better response to.

In terms of emerging and developing economies financial stability indexes, both appear also to experience a dive, but with some lags compared to the index of advanced economies. Once those economies experienced sharp deterioration though, they undershoot the index of advance economies by some significant margin in 2008, whilst they never succeeded to fully recover ever since to the levels prior to the global financial crisis. In contrast, financial stability in advanced economies appear to recover since the all-time low in 2009.

4.2. The financial stability index for advanced economies.

Note that we derive financial stability and volatility at country level as our sample is bank specific for every country. This ensures that the heterogeneity across countries is fully modelled within our framework. For presentation purposes only, we report results in to three groups of countries based on the grouping provided by World Bank and IMF. The allocation of countries might be questionable, but this is not affecting our estimations; it only serves the purpose of presenting of plethora of results. Note that based on our estimations we estimate the financial stability and volatility per country over time. Again to facilitate the presentation as the number of countries is large, we report results for selected groups, otherwise we would have to report 106 different tables or figures as the number of countries.

In this study, we employ a comprehensive data set based on IBCA Bankscope and Orbis Bank Focus that contains all commercial, cooperative, savings, and investment banks that include foreign banks operating within the countries.

To focus on one country is beyond the scope of the current paper which applies the model of financial stability at global level that allows interlinkages between financial markets to be explored. This allows us to model that shocks to financial stability in one country within a group are not independent from shocks in another country. This is crucial as our model is not constrained, i.e. we are able to examine how a shock in financial stability of advanced economies, say, impacts intertemporally on financial stability of emerging or developing economies, and vice versa.

Note that based on our estimations we estimate the financial stability and volatility per country over time. Again to facilitate the presentation as the number of countries is large, we report results for selected groups, otherwise we would have to report 106 different tables or figures as the number of countries.

We turn, now, on financial stability scores for each group in our sample. First, the financial stability scores for advanced economies are reported in Table 2.

[Insert Table 2 about here]

Unsurprisingly, the highest index is reported for US, close to 0.6, whereas the one for Germany, France, UK and Switzerland is not far off from it. Also, unsurprisingly the weakest financial stability at -0.71 and -0.64 is reported for Greece and Cyprus respectively, as both countries are subjected to strong conditionality due to their bail out by IMF, EU and ECB. Portugal and Ireland, two countries that also received financial assistance, show weak financial stability. Strong concerns are raised for Spain and Italy, demonstrating that the Euro Area shows strong financial vulnerabilities. Latvia and Malta also demonstrate negative values for the financial stability index, insinuating their weak financial systems.

Japan reports a low financial stability (0.12), but positive. The result is not striking as Japan has underwent a prolonged financial crisis early in 2000s accompanied by deflation and very low growth which explains the low financial stability score. In a similar range, lower than 0.2 but higher than 0.1, of financial stability index to Japan is Israel, Netherlands, Singapore, Sweden and Taiwan. Regarding the most financially stable group, higher than 0.2, there are several countries, namely Australia, Austria, Canada, France, Germany, Hong Kong, Norway, Switzerland, UK and USA.

From (4) it is possible to determine the contribution of each bank to the country-level financial stability indicator since we have the latent variables.[13] Therefore we have a large number of $\kappa_{i,c,t}$. As these have a natural interpretation as weights, each bank will have a different contribution to the country-level FSI. As such the bank size could be of economic and statistical significance in line with Laeven et al. (2014). Therefore, we disaggregate the contribution from large, medium and small banks, which can be determined from the $\kappa_{i,c,t}$. Large banks are those whose total assets exceed the 75% quantile, and small banks are defined as having total assets less than the 25% quantile at the country-level. In each group we take the posterior median of FSI. In Figure 2 we report the Financial Stability Index (FSI), computed from (4) for advanced financial systems for three sub-groups based on bank-size; large, medium and small.

[Insert Figure 2 about here]

The figure depicts some variability and a drop around the period of global financial crisis. It is, however, astonishing that although the financial stability index for advance economies dived in 2006, for large banks in advanced countries it appears that the dive started earlier, in 2005, showing that the signs of the storm ahead had been visible much earlier than the burst of the crisis in September 2009. However, the financial stability index for large banks appears to remain above the indexes of the

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[13] Please note in addition that equation (4) includes variables other than Z_{ict} , which vary at the bank level.

other two groups. In particular, small and medium banks were hit particularly harsher than large banks, whilst their recovery since the crisis has been lagging behind. The hypothesis '*too big to fail'* might be valid therefore.

4.3. The financial stability index for emerging economies.

Table 3 reports financial stability index for emerging economies. The disparity of financial stability indexes across emerging economies is larger than that in advanced economies.

[Insert Table 3 about here]

The lowest score of bank financial stability in emerging economies is reported for Argentina at -0.5. It is not surprising as Argentina was the center of a currency crisis in 2002 and defaulted. It appears that Argentina's financial system has never recovered since. On the positive side, the fastest growing emerging economies, such as China, Brazil and India, have stronger financial stability indexes than that of countries under stress, such as Argentina, Bolivia, Bulgaria, Russia, Romania, Nigeria. The former group of countries also include Oman, Qatar, Saudi Arabia, South Africa, Turkey, United Arab Emirates. It might worth noting that a positive financial stability score does not imply that financial stability is warranted. For example, Turkey has a positive, though low financial stability score, of 0.25. Turkey has been in somewhat financial dire straits for some years as it has faced successive devaluations of its currency and chronical current account deficit that have undermined confidence of a stable financial system.

Fujii et al. (2014) provide some evidence similar to ours. The authors disaggregate the Luenberger productivity indicator into technical change and efficiency change. The components of financial stability are obtained from the weighted Russell directional distance model.

Figure 3 reports the financial stability index (FSI), computed from (4), for emerging economics according the bank size.

[Insert Figure 3 about here]

As previously, we determine the contribution of each bank to the country-level financial stability indicator for emerging economies based on the bank size. We consider that large banks are those whose total assets exceed the 75% quantile, and small banks are defined as having total assets less than the 25% quantile at the country-level. In each group we take the posterior median of financial stability index (see Figure 3).

A common pattern is again observed in the case of emerging economies as Figure 3 reports the dramatic drop during the global financial crisis. Large banks weathered out the crisis much better than medium and small banks, and they appear to sustain a higher level of financial stability over the whole period. Yet, although large banks recover only partly since the crisis as they are still lagging behind in terms of the level of financial stability prior to the crisis.

Figure 3 shows that the global financial crisis has somewhat equally damaged both small and medium banks in emerging economies, with the former registering a lower level of financial stability overall.

4.4. The financial stability index for developing economies.

Table 4 shows financial stability index for developing economies. This is the first time that such index is reported for this group of countries.

[Insert Table 4 about here]

Results clearly highlight that there is striking homogeneity across most of those countries as they suffer from highly unstable financial systems. To this end, there is not much disparity between financial stability indexes of banks in developing countries as reported for the other two groups of countries. Moreover, financial systems in Andorra, Bermuda, Jordan, Kenya, Mauritius, Tanzania, Uruguay, Vietnam, and Zambia are exemptions as they register positive financial stability indexes, with the index for Andorra and Jordan being reported as quite high. All the rest of developing economies have financial systems that are unstable.

In Figure 4 we report the Financial Stability Index, computed from (4) for developing economies.

[Insert Figure 4 about here]

Again, note that Figure 4 depicts the contribution of each bank to the country-level financial stability indicator for emerging economies, including for three sub-groups: large banks with total assets that exceed the 75% quantile, small banks with total assets less than the 25% quantile at the country-level, and medium sized banks capturing the middle ground. In each group we take the posterior median of financial stability index (see Figure 4).

As in the case of emerging countries we observe the drop in financial stability index of developing economies because of the global financial crisis but note that this took place later for the latter countries than for the former countries. Moreover, financial stability index for developing economies appears to dive in late 2008, reaching its lowest level in 2009. It seems that the global financial crisis took its toll later for the developing economies. Again, however, large banks exhibit much stronger financial index than that of medium and small banks, and appear to sustain a higher level all along, despite of course the dive in 2008. Alas, also in the case of large banks the crisis has been detrimental as financial distress has been only partially recovered, whereas for large banks a further drop in the index for large banks is reported since then.

Overall, financial systems in developing economies remain particularly vulnerable and exhibit a steeper slope compared to advanced economies. This enhances risks globally, as our results identify that although financial stability has been improving in advanced economies, it is not fully recovered, whilst risks have shifted with lags in developing economies (see IMF, 2015).

4.5. Intertemporal posterior-mean filtered volatility

Volatility of the return-to-dollar function in (1) is central in our discussion. It is modeled explicitly in (2) as a dynamic latent variable and is part of our z-score in (3). We believe that, given the specification of the model, it is a natural measure of risk in our setting. In computing z-scores, previous work has used grouped observations to determine the variance and use it as a measure of risk (Lepetit et al. 2008). This approach has its drawbacks, notably that volatility is treated as ‘necessary evil’ to estimate rather than as an essential part of the model.

In Figure 5 we report the intertemporal posterior-mean filtered volatility from (2) for advanced, emerging, and developing economies. This figure reports sensitivity of volatility to 10,000 different priors. Given a new prior, we compute the new posterior using sampling-importance-resampling. The posterior means of the volatility are recomputed and their deviations from the baseline-prior-based posterior means are reported, using kernel densities.

[Insert Figure 5 about here]

It is striking that volatility for advanced economies registered a sharp increase as early as in 2005, while it picked in 2009 and dropped thereafter. However, since 2009 the volatility has remained at higher levels than the levels prior to the crisis. This is a common feature that we also observe on the financial stability index. Advanced economies were warned with signs of financial instability earlier than 2008, whereas emerging and developing economies followed with lags. In particular, stochastic volatility for emerging economies picked later than both advanced and developing economies and reached higher levels before descending later in 2011.

In addition, in Figure 6 we report filtered volatility to different priors for the three groups of countries categorized according to bank size into: large, medium and small banks. The results are remarkably robust to the prior.

[Insert Figure 6 about here]

It is worth noticing that although across all three groups of countries volatility for medium and small banks is reported to exhibit variability, in particular around the years of global financial crisis, large banks demonstrate higher levels of volatility. This would imply that largely large banks drive financial stability, though the latter recover faster than small and medium banks. Moreover, volatility for advanced economies and large banks shows a sharp increase as early as in 2004, with some bounce back reported in 2006, before a picking up again in 2008 and 2009, correcting somewhat since 2011. Stochastic volatility for large banks in emerging economies follows similar trajectory to the one of advanced economies large banks, whilst, interestingly, for large banks in developing economies the volatility dropped in 2006 but picked thereafter and remained high up till 2011.

The above results closely resemble of a roller-coaster type of stochastic volatility movement, casting doubts on whether financial stability has been fully restored since the global financial crisis. It is particularly worrying finding as it implies that risks have never been subdued and could reemerge.

4.6. Regression analysis of volatility and financial stability.

Having derived volatility and financial stability at country and global level would be of interest to examine their underlying association with key bank and country specific covariates.[14] Table 5 presents regression results for volatility **(** $\log \sigma_{ict}^{2}$ **)**. As expected there exists a positive relationship between return-to-dollar volatility and loan loss provision that is in line with '*bad management hypothesis'* (Berger and DeYoung, 1997, Koutsomanoli and Mamatzakis, 2009). The reported in Table 5 positive sign of NIM is compatible with the contestability theory (Berger and DeYoung, 1997). Funding ratio is negative across all models, whether simple or broader measure, indicating that a higher ratio of customer deposits, which are considered a more stable source of funding for banks, lower funding uncertainty and thereby lower return-to-dollar volatility. The sign of OBS ratio is negative suggesting that higher degree of investment diversification infuses volatility. However, note that the coefficient of OBS squared is positive, but significant only in model 2, suggesting the existence of non-linearities. Note also that parameter estimates for total assets (TA) capturing the bank size are positive and significant across different models, insinuating that the larger the bank the larger the volatility (see also Laeven et al., 2014). It is also worth noting that the square of total assets is significant across

[14] To capture bank specific variables and thereby heterogeneity across banks in our sample we include: the loan loss provisions (LLP) to control for portfolio quality and also credit risk; the net interest margin (NIM) to control for competition and profit margin; the funding ratio (deposits to total assets) as well as its broader definition (deposits plus other funding to total assets) to control for the source of bank funds; the off-balance sheet items (OBS), as well as its square, measuring the diversity of bank activities; the size is captured by the logarithm of total assets (TA) as well as its square to test for the *'too big to fail hypothesis'*; the liquidity ratio as liquid assets over total assets (Liquid) to control for liquidity risk; the cash ratio defined as cash and due from banks to assets (Cash ratio); and last the capital ratio as equity over total assets (Eq./TA).

specifications (while its sign is switching from negative to positive for some models) showing the existence of non-linearities in the banking industry.

This result is of interest as one of the main empirical lessons learned from the last recent global financial crisis refers to the significance of understanding that financial cycles are non-linear models. Linear models could interpret business cycle as an approximation, but they are not meaningful when it comes to financial cycle (Gadanecz and Jayaram 2009; Acharya et al. 2017; Aikman et al. 2017 and Hollo et al. 2012). However, non-linearities have not been the main stream modeling approach in financial stability modelling as estimating a non-linear model is not without challenges and, indeed, it could quite cumbersome. This paper proposes model and Bayesian estimation that can efficiently provide estimation of non-linearities.

[Insert Table 5 about here]

Table 6 presents regression results for financial stability (F_{ct}^{*}) at country level. As expected financial stability at country level is significantly and negatively associated with volatility (see models 5 and 6), whereas the remaining results are broadly in line with the one above for volatility.

[Insert Table 6 about here]

Moreover, there exists a negative relationship between financial stability and loan loss provision in line with '*bad management hypothesis'* (Koutsomanoli and Mamatzakis, 2009). Along these lines, the coefficient of NIM is negative, whilst the one for funding ratio (also for broader funding ratio) is positive. The sign of OBS ratio and OBS squared is positive and negative respectively, suggesting non-linearities as in Table 5. Note also that bank specific risk, as measured by bank z-score, appears to assert a positive and significant affect at country level financial stability.

One result that it is worth emphasizing is the size variable, ln of TA, is highly significant and positive suggesting that large banks positively contribute to financial stability (Koutsomanoli and Mamatzakis, 2009; Laeven et al., 2014), while the squared term of the size is negative suggesting non-linearities. Table 5 that presented results for financial volatility also reports non-linearities, though the coefficient of lnTA is positive and significant. These results are of interest as they imply that despite large banks are responsible for much of the bank specific volatility, they are also the ones that enhance financial stability, suggesting that policy makers ought to pay particular attention to large institutions in line with the hypothesis '*too large to fail'* (Koutsomanoli and Mamatzakis, 2009; Laeven et al., 2014; Aikman et al. 2017 and Hollo et al. 2012). To this end, we show herein that large banks contribute to financial cycles by asserting a positive effect on volatility. But, they are also part of the solution, so to speak, as they are also the ones that would contribute to financial stability. Our results emphasize the importance of large banks and the necessity to strengthen their balance sheets also in light of weak profitability given high operating costs. From a policy point of view, it does not come as a surprise that in recent years we have witnessed the Financial Stability Board (FSB) that provides recommendations for the global financial system and the Basel Committee on Banking Supervision (BCBS) that coordinates the identification of global systemically important banks (G-SIBs). In Europe Union, along similar lines, implemented Capital Requirements Directive aiming to enhance capitalisation of large banks, while the European Banking Authority advised the national macroprudential authorities to identify systemically important banks. The SSM and the ECB have also the power to set higher capital requirements for the large systemic banks identified by national authorities in SSM countries.

Lastly, Table 7 presents regression results for global financial stability **(** F_t^* **)**.

[Insert Table 7 about here]

The results in Table 7 are of interest as they show the impact of key economic and financial variables on a composite global index of financial. Moreover, the coefficients of NIM and credit to deposits are negative as well as the coefficient of non-performing loans. In particular, non-performing loans appear to assert a large in magnitude negative effect on global financial stability. The coefficient of ln of TA is highly significant and positive suggesting that large banks positively contribute to financial stability at a global level. It is worth mentioning that our evidence in Table 7 suggests that by improving regulation and institutions, in particular regarding insolvency regulation, the global financial stability is enhanced.[15]

5. Conclusions

This paper proposes a new way of modeling financial stability, a hard to estimate measure, as a dynamic latent variable. As a dynamic latent variable financial stability is unobserved though is modeled explicitly by using an alternative profit function whose variance is measured in the framework of panel stochastic volatility. This allows estimating financial stability as at country level with certain covariates. In the empirical application we use Bayesian inference techniques and opt for a global sample to derive global financial stability indicators. Our new index of financial stability effectively captures the global financial crisis well before it burst, in particular for the developed economies. Overall, our results suggest that financial stability in emerging economies grew more rapidly than that in advanced economies.

These findings have significant implications for regulators and supervisors, whose task is to establish a secure as well as financially stable financial system. In some detail, we present results that demonstrate that there are underlying non-linearities and thereby any modelling of financial stability should consider such non-linearities. Interestingly, our results also show that while large banks contribute to volatility they are also enhance financial stability, providing evidence in favor of '*too large to afford to fail*'. These results are of some significance as they suggest that the global financial system should closely monitor large, systemic, banks as key to sustain financial stability. The Financial Stability Board (FSB), the Basel Committee on Banking Supervision (BCBS), the SSM and the ECB have all identified the importance of large systemic banks and the necessity to ensure adequate capital requirements for those banks that could be set above the capital threshold set by national authorities so as to safeguard financial stability.

Our measure of financial stability may also act as an early warning mechanism. Therefore, monitoring the financial stability using the new index could not only enhance financial systems' ability to better deal with crises, but also could

[15]These results are compatible with previous research (Aikman et al. 2017; Hollo et al. 2012; Acharya et al., 2011; Pagano and Jappelli, 1993; Qian and Strahan, 2007; Klapper et al. 2006), though it is for the first time that the association of global financial stability with regulation is examined.

improve prevention. It appears that our results show that the alarm bell might be ringing, as financial instability is a real threat in emerging, and in particular developing economies, compared to the advanced economies. In addition, we show that policy maker should aim at improving insolvency regulation as a priority so as to enhance global financial stability.

Appendix

Particle Filtering

The particle filter methodology can be applied to state space models of the general form

$$y_T \sim p(y_t \mid x_t),\, s_t \sim p(s_t \mid s_{t-1})\,, \qquad \text{(A1)}$$

where s_t is a state variable.

For general introduction see Gordon et al. (1993), Doucet et al (2001) and Ristic et al. (2001).

Given the data Y_t the posterior distribution $p(s_t \mid Y_t)$ can be approximated by a set of (auxiliary) particles $\left\{s_t^{(i)}, i = 1,...,.N\right\}$ with probability weights $\left\{w_t^{(i)}, i = 1,...,N\right\}$ where $\sum_{i=1}^{N} w_t^{(i)} = 1$. The predictive density can be approximated by

$$p(s_{t+1} \mid Y_t) = \int p(s_{t+1} \mid s_t)\, p(s_t \mid Y_t) ds_t \approx \sum_{i=1}^{N} p(s_{t+1} \mid s_t^{(i)}) w_t^{(i)} \qquad \text{(A2)}$$

and the final approximation for the filtering density is

$$p(s_{t+1} \mid Y_t) \propto p(y_{t+1} \mid s_{t+1})\, p(s_{t+1} \mid Y_t) \approx p(y_{t+1} \mid s_{t+1}) \sum_{i=1}^{N} p(s_{t+1} \mid s_t^{(i)}) w_t^{(i)} \qquad \text{(A3)}$$

Andrieu and Roberts (2009), Flury and Shephard (2011) and Pitt et al. (2012) provide the Particle Metropolis-Hastings technique (PMCMC thereafter) which uses an unbiased estimator of the likelihood function $\widehat{P(s_{t+1}/Y_t)}$ as $P(s_{t+1}/Y_t)$ is often not available in closed form.

Particle Metropolis Adjusted Langevin Filters

Nemeth, Sherlock and Fearnhead (2014) provide a particle version of a Metropolis adjusted Langevin algorithm (MALA). In Sequential Monte Carlo, we are interested in approximating $p(s_t \mid Y_{1:t}, \theta)$. Given that

$$p(s_t \mid Y_{1:t}, \theta) \propto g(y_t \mid x_t, \theta) \int f(s_t \mid s_{t-1}, \theta) p(s_{t-1} \mid y_{1:t-1}, \theta) ds_{t-1}, \quad \text{(A4)}$$

where $p(s_{t-1} \mid y_{1:t-1}, \theta)$ is the posterior as of time $t-1$. If at time $t-1$ we have a set of particles $\left\{ s_{t-1}^i, i = 1, \ldots, N \right\}$ and weights $\left\{ w_{t-1}^i, i = 1, \ldots. N \right\}$, which form a discrete approximation for $p(s_{t-1} \mid y_{1:t-1}, \theta)$ then we have the approximation:

$$\hat{p}(s_{t-1} \mid y_{1:t-1}, \theta) \propto \sum_{i=1}^{N} w_{t-1}^i f(s_t \mid s_{t-1}^i, \theta) \quad \text{(A5)}$$

Global Financial Stability

In the empirical application we are interested also in a financial stability for a global sample. There are three main groups that we report for: advanced, emerging and developing countries, denoted by A, E, D respectively. As such we could modify (5) so as to capture financial stability at the group level as follows:

$$FS^{*}_{c,t} = \delta_0 + \delta_1 FS^{*}_{c,t-1} + \delta_2 G_{c,t} + \sum_{i=1}^{n} FS^{*}_{c,t}\omega_{c,t} + \varepsilon_{c,t}\,, G \subset \{A, E, D\} \quad \text{(A6)}$$

where δs are random coefficients specific to the group G. We use this approach instead of taking a weighted average of $FS^{*}_{c,t}$ for $c \in G$ as weights would have been arbitrary (i.e. based on relative total assets, relative GDP).

Note that the residuals from A1 follow:

$$\varepsilon_{c,t} \sim N\left(0, \sigma^2_{c,t}\right), \forall\ c = \{A, E, D\} \qquad \text{(A7)}$$

This allows us to model that shocks to financial stability in one country within a group are not independent from shocks in another country. This is crucial as our model is not constrained, i.e. we are able to examine how a shock in financial stability of one advanced economy i.e. U.S. , say, impacts intertemporally on financial stability of other countries, for example in emerging or developing economies, and vice versa.

We also control for endogeneity. Thus, the weights $\omega_{c,t}$ are endogenously estimated at country level:

$$\omega_{ct} = \xi_{co} + \xi_{c1}\omega_{c,t-1} + \sum_{l=1}^{L} \frac{TA_{c,t-l}}{TA_{t-l}} \varphi_{cl} + \varepsilon_{ct} \qquad \text{(A8)}$$

To enhance flexibility no restrictions the sign or magnitude of $\omega_{c,t}$s is imposed.

Note that it is feasible to to define G_t as

$$\mathbf{G}_t = \sum_{c=1}^{C} \mathbf{G}_{ct} w_{ct}, \qquad \text{(A9)}$$

where the weights w_{ct} are, again, endogenously determined as:

$$w_{ct} = \eta_{co} + \eta_{c1} w_{c,t-1} + \sum_{l=1}^{L} \frac{GDP_{c,t-l}}{GDP_{t-l}} \varphi_{cl} + \varepsilon_{ct}, \qquad \text{(A10)}$$

subject to $w_{ct} \geq 0$ and $\sum_{c=1}^{C} w_{ct} = 1$.

In the estimation stage, we apply Bayesian inference procedures organized around Sequential Monte Carlo (SMC) techniques also known as particle filtering (PF). Dynamic unobserved latent variables as in (2), (3)-(5) are integrated out using a PF algorithm. The resulting posterior distribution, which includes only "*structural*" parameters, is then explored using the Girolami and Calderhead (2011) that is the MCMC approach. All priors are as diffuse as possible, normal and chi-square.

References

Acharya, V., Amihud, Y., and Litov, L. (2011). Creditor rights and corporate risk-taking, Journal of Financial Economics 102,150–166.
Acharya, Viral V., Lasse H. Pedersen, Thomas Philippon, and Matthew Richardson, (2017). Measuring Systemic Risk, Review of Financial Studies, Volume 30, Issue 1, pages 2–47.
Aikman, David, Michael Kiley, Seung Jung Lee, Michael G. Palumbo, and Missaka Warusawitharana, (2017). Mapping heat in the U.S. financial system, Journal of Banking & Finance, vol. 81(C), pages 36-64.
Andrieu, C. and Roberts G. O. (2009). The pseudo-marginal approach for efficient Monte Carlo computations, Annals of Statistics, 37, 697–725.
Allen, F., and Carletti, E. (2010). An Overview of the Crisis: Causes, Consequences, and Solutions, International Review of Finance, 10, pages 1-26.
Bank of England (2008). Financial Stability Report, No 23, April.
Barry, T. A., Lepetit, L., and Tarazi, A. (2011). Ownership structure and risk in publicly held and privately-owned banks, Journal of Banking & Finance, 35(5), 1327-1340.
Berger, A. and Mester, L., (1997). Inside the black box: What explains differences in the efficiencies of financial institutions, Journal of Banking and Finance 21, 895-947.
Berger, A. and DeYoung, R., (1997). Problem loans and cost efficiency in commercial banking, Journal of Banking & Finance 21, 849-870.
Berger, Allen N., Robert DeYoung, Hesna Genay, and Gregory F. Udell (2000). The Globalization of Financial Institutions: Evidence from Cross-Border Banking Performance, Brookings-Wharton Papers on Financial Services, 3, 23–158.
Bordo, M. and A. Schwartz (2000). Measuring real economic effects of bailouts: historical perspectives on how countries in financial stress have fared with and without bailouts, NBER Working Paper, no 7701.
Bordo, M., M. J. Dueker and D. C. Wheelock (2000). Aggregate price shocks and financial instability: an historical analysis, NBER Working Paper, no 7652.
Borio, C. and M. Drehmann (2009). Assessing the financial stability of banking crises

– revisited, BIS Quarterly Review, March.
Borio, C. and P. Lowe (2002). Asset prices, financial and monetary stability: exploring the nexus, BIS Working Papers, no 114, July.
Boyd, J. H. and G. De Nicolo. 2005. The Theory of Bank Financial Stability Taking and Competition Revisited, Journal of Finance 60 (3), 1329-1343.
Brunnermeier, M. K., (2009) Deciphering the liquidity and credit crunch 2007-2008. Journal of Economic Perspectives, 23, 77–100.
Brunnermeier, M., A. Crockett, C. Goodhart, A. D. Persaud, and Hyun Song Shin, (2009). The Fundamental Principles of Financial Regulation, Geneva Reports on the World Economy 11.
Cappe, O., Godsill, S. and Moulines, E. (2007). An overview of existing methods and recent advances in sequential Monte Carlo, Proceedings of the IEEE, 95(5): 899–924.
Casarin R. and Jean-Michel Marin, (2007). Online data processing: comparison of Bayesian regularized particle filters, Working Papers 0703, University of Brescia, Department of Economics.
Casu B. and Molyneux, P. (2003). A comparative study of efficiency in European banking, Applied Economics 35(17), 1865-1876.
Chan, J. (2017). The Stochastic Volatility in Mean Model with Time-Varying Parameters: An Application to Inflation Modeling, Journal of Business and Economic Statistics, 35(1), 17-28.
Chan-Lau, J.A. and Sy, A., 2007. Distance-to-default in banking: A bridge too far?, Journal of Banking Regulation 9(1), 14–24.
Covitz, D., Liang, N., Suarez, G., (2013). The evolution of a financial crisis: Collapse of the asset-backed commercial paper market, Journal of Finance, 68, 815–848.
Delis, M. D. and Staikouras, P. K. (2011). Supervisory effectiveness and bank risk, Review of Finance, 15, 511-543.
Demirguc-Kunt, A. and E. Detragiache (1998). The Determinants of Banking Crises in Developing and Developed Countries, International Monetary Fund Staff Papers, no 45, vol. 1, pp 81–109.
Doucet, A., Freitas, N., and N. Gordon, E. (2001). Sequential Monte Carlo Methods in Practice, New York: Springer.
Doucet, A. and Johansen, A. M. (2011). A tutorial on particle filtering and smoothing: Fifteen years later. In Oxford Handbook of Nonlinear Filtering.
Eichengreen, B., A. Rose and C. Wyplosz (1996). Contagious currency crises, NBER Working papers, no 5681.
Eichengreen, B. and A. K. Rose (1999). The empirics of currency and banking crises, a non-theoretical study of financial crises, NBER Reporter, December.
Elsinger H., A. Lehar, M. Summer, (2006). Risk Assessment for Banking Systems, Management Science, 52(9): 1301-1314.
European Central Bank (2005). Measurement challenges in assessing financial stability, ECB Financial Stability Review, December.
Fearnhead, P., O. Papaspiliopoulos, G.O. Roberts and A.M. Stuart, (2010). Random weight particle filtering of continuous time stochastic processes, Journal of the Royal Statistical Society B. 72(4), 497-512.
Frankel, J. and A. Rose (1996). Currency crashes in emerging markets: empirical indicators, Journal of International Economics, vol 41, pp 351-66.

Flury, T. and Shephard, N. (2011). Bayesian inference based only on simulated likelihood: particle filter analysis of dynamic economic models, Econometric Theory, 27, 933–956.
Fries, S., Taci, A., (2005). Cost efficiency of banks in transition: Evidence from 289 banks in 15 post-communist countries, Journal of Banking and Finance 29, 55-81.
Gadanecz B. and K. Jayaram (2009). Measures of financial stability - a review Proceedings of the IFC Conference on 'Measuring financial innovation and its impact', Basel, 26-27 August, 2009, vol. 31, pp 365-380, Bank for International Settlements.
Gerdrup, K.R. (2003). Three episodes of financial fragility in Norway since the 1890s, BIS Working Papers, no 142, October.
Geweke, J. (1992). Evaluating the Accuracy of Sampling-Based Approaches to the Calculation of Posterior Moments. In Bayesian Statistics 4 (eds. J.M. Bernardo, Girolami M. and Calderhead B., (2011). Riemann manifold Langevin and Hamiltonian Monte Carlo methods, Journal of the Royal Statistical Society Series b-statistical methodology, Vol: 73, Pages: 123-214, ISSN: 1369-7412.
Girolami M. and B. Calderhead, (2011). Riemann manifold Langevin and Hamiltonian Monte Carlo methods, Journal of the Royal Statistical Society Series b-statistical methodology, Vol: 73, Pages: 123-214, ISSN: 1369-7412.
Goodhart, C., O. Aspachs, M. Segoviano, D. Tsomocos and L. Zicchino (2006). Searching for a metric for financial stability, LSE Financial Markets Group Special Paper Series, Special Paper no 167, May.
Gordon, N., Salmond, D., and Smith, A. (1993). A novel approach to nonlinear/non-Gaussian Bayesian state estimation. IEE Proc. Radar & Signal Proc., 40:107, 113.
Gray, D.F., R.C. Merton and Z. Bodie (2007). New framework for measuring and managing macro financial l stability and financial stability, NBER Working Paper no 13607, November.
Gropp, R., Vesala, J. and Vulpes, G. (2006). Equity and bond market signals as leading indicators of bank fragility, Journal of Money, Credit and Banking, Vol. 38, pp. 399–428.
Illing M. and Y. Liu (2003). An index of financial stress for Canada, Bank of Canada Working Paper no 2003–14, June.
Hall, J. Michael K. Pitt, R. t Kohn, (2014). Bayesian inference for nonlinear structural time series models, Journal of Econometrics, Volume 179, Issue 2, April, Pages 99-111.
Hanschel, E. and P. Monnin (2005). Measuring and Forecasting Stress in the Banking Sector: Evidence from Switzerland, Bank for International Settlements Working Paper, No 22.
Hellwig, M., (2014). Financial Stability, Monetary Policy, Banking Supervision, and Central Banking, Max Planck Institute for Research on Collective Goods Bonn 2014/9.
Hollo, D., M. Kremer and Marco Lo Duca, (2012). CISS – A Composite Indicator of Systemic Stress in the Financial System. ECB Working Paper Series No 1426.
Humphrey, D. B. and Pulley, L. B. (1997). Bank's responses to deregulation: profits, technology, and efficiency, Journal of Money, Credit and Banking, 29, 73–93.

Hawkins, J. and M. Klau (2000). Measuring potential vulnerabilities in emerging market economies, BIS Working Papers, no 91, October.
Kaminsky, G., S. Lizondo and C. Reinhart (1998). Leading indicators of currency crises, IMF Staff Papers 45 (1), pp 1–48.
International Monetary Fund (2006): Financial Soundness Indicators: Compilation Guide, March.
International Monetary Fund (2008): Global Financial Stability Report, April.
International Monetary Fund (2015): Global Financial Stability, October.
Jordà, Ò., B. Richter, M. Schularick, and A. M. Taylor, (2017). Bank Capital Redux: Solvency, Liquidity, and Crisis, NBER Working Paper No. 23287.
Kaminsky, G.L. and C.M. Reinhart (1999). The twin crises: the causes of banking and balance-of-payments problems, The American Economic Review, vol 89, no 3, pp 473–500, June.
Klapper, L., Laevan, L. and Rajan, R. (2006) Business environment and firm entry: evidence from international data, Journal of Financial Economics, 82, 591–629.
Koutsomanoli-Filippaki, A. and Mamatzakis, E., (2009). Performance and Merton-type default risk of listed banks in the EU: A panel VAR approach, Journal of Banking & Finance, Elsevier, vol. 33(11), pages 2050-2061, November.
Laeven, L. and Levine, R. (2009). Bank governance, regulation, and risk taking, Journal of Financial Economics, 93, 259–275.
Laeven, L., Lev Ratnovski and Hui Tong, (2014). Bank Size and Systemic Risk, IMF Staff Discussion Notes 14/4, International Monetary Fund.
Lepetit L., Em. Nys, P. Rous, and Tarazi A. (2008). Bank income structure and financial stability: An empirical analysis of European banks. Journal of Banking and Finance, 32(8), 1452-1467.
Li, J. and Zinna, G., (2014). On Bank Credit Risk: Systemic or Bank-Specific? Evidence from the US and UK. Journal of Financial and Quantitative Analysis 49, 1403-1442
Liu, J. and West, M. (2001). Combined parameter and state estimation in simulation-based filtering. In: Doucet, A, de Freitas, J., Gordon, N.J. (eds.), Sequential Monte Carlo Methods in Practice. Springer-Verlag, New York.
Lin, M.T., Zhang, J.L., Cheng, Q. and Chen, R. (2005). Independent particle filters, Journal of American Statistical. Association, 100, 1412–21.
Lozano-Vivas, A., Pastor, J.T. and Pastor, J.M. (2002). An efficiency comparison of European banking systems operating under different environmental conditions, Journal of Productivity Analysis 18, 59–77.
Maudos, J. Pastor, J.M., Perez, F. and Quesada, J. (2002). Cost and profit efficiency in European banks. Journal of International Financial Markets, Institutions and Money 12, 33–58.
Mester, L. J. (1996). A study of bank efficiency taking into account financial stability-preferences, Journal of Banking and Finance 20, 1025-1045.
Nelson, W R, Perli, R (2005). Selected indicators of financial stability, 4th Joint Central Bank Research Conference on 'Financial stability Measurement and Systemic Financial stability', ECB Frankfurt am Main, November.
Nemeth, C., C. Sherlock, and Fearnhead, P. (2014). Particle metropolis adjusted Langevin algorithms for state-space models. Pre-print arXiv:1402.0694v1.

Pagano, M. and Jappelli, T. (1993) Information sharing in credit markets, Journal of Finance 48, 1693–1718.
Pitt, M. K., Silva, R. D. S., Giordani, P. and Kohn, R. (2012). On some properties of Markov chain Monte Carlo simulation methods based on the particle filter. Journal of Econometrics, 171, 134–151.
Pitt, Michael K. and N. Shephard (1999). Filtering via simulation: auxiliary particle filter, Journal of the American Statistical Association, 94, 590-599.
Qian J. and Strahan, P. E. (2007). How laws and institutions shape financial contracts: the case of bank loans, Journal of Finance, 62, 2803-2834.
Roberts, G.O. and J.S. Rosenthal (1998). Optimal scaling of discrete approximations to Langevin diffusions, Journal of Royal Statistical Society, B
60, 255–268.
Ristic, B., Arulampalam, S., and Gordon, N. (2004). Beyond the Kalman Filter: Particle Filters for Tracking Applications. Artech House.
Sealey, C. and Lindley, J. (1977). Inputs, outputs and a theory of production and cost of depository financial institutions, Journal of Finance 32, 1251-266.
Schinasi, Garry J. (2004). Defining Financial Stability, IMF Working Paper Series WP/04/187.
Sveriges Riksbank (2008), Financial Stability Report, no 2008:1, June.
Van den End, J.W.. (2006). Indicator and boundaries of financial stability, DNB Working Paper no 97, March.

Table 1. Descriptive statistics of the global sample.

		Advanced		
Variables	**Mean**	**SD**	**Min**	**Max**
Bank outputs and input prices				
Total assets	17951329	1.04E+08	242.6324	2.20E+09
Total costs	644465	3783047	11.79197	1.06E+08
Net loans	9036183	4.72E+07	157.0997	9.57E+08
Other earning assets	7354650	5.60E+07	25.15855	1.76E+09
Price of funds	2.4624	22.67846	0.0171721	2874.074
Price of physical capital	201.4653	698.7787	2.023717	52925
Price of labour	1.1191	0.6736921	0.0045845	15.29412
Nonperforming loans	336033	2211948	0.1085799	6.96E+07
Equity	1032482	460347	570612	1.47 E+08
Banks specific and control variables				
z-score	0.6965	0.6964944	0.222329	2.323605
Capital ratio	8.3162	4.8207	1.241	17.009
Liquidity ratio	15.1238	5.3712	0.3912	29.708
Securities	30.0283	4.98	5.63	141.301
GDP per capita	10.5394	0.2823201	8.517835	11.12438

		Emerging		
Variables	**Mean**	**SD**	**Min**	**Max**
Bank outputs and input prices				
Total assets	9659393	3377696	1804.803	4.03E+07
Total costs	441730	181108	315.2173	2814993
Net loans	5152601	1762677	1280.004	2.22E+07
Other earning assets	3796769	1526668	265.369	2.29E+07
Price of funds	8.9291	3.496504	0.1232221	29.88506
Price of physical capital	415.9367	182.7779	0.3626473	2966.667
Price of labour	2.5210	1.495676	0.0838574	14.39544
Nonperforming loans	179375	147383	0.5311663	1568410
Equity	754589	27063	352112	1.24E+07
Banks specific and control variables				
z-score	0.8081	0.89179	0.04664	6.093411
Capital ratio	14.7165	3.010	1.510	14.1007
Liquidity ratio	26.3849	1.4321	0.3912	39.7258
Securities	40.3673	3.753	2.5989	67.4336
GDP per capita	7.3914	1.090129	1.702363	11.31682

		Developing		
Variables	**Mean**	**SD**	**Min**	**Max**
Bank outputs and input prices				
Total assets	1255046	7.84E+07	116.3015	2.11E+09
Total costs	82203	2449796	27.03591	5.52E+07
Net loans	626854	4.68E+07	68.17879	1.40E+09
Other earning assets	449156	3.62E+07	20.52727	1.01E+09
Price of funds	5.7072	4.1883	0.0088802	30678.57
Price of physical capital	140.6929	1.726	1.502902	35732.28
Price of labour	2.1607	1.4733	0.0065974	19.8137
Nonperforming loans	48030	8858.8	5.53487	1.58E+07
Equity	133758	1094	4709	950519
Banks specific and control variables				
z-score	0.8443	0.2698	0.0177393	5. 0934
Capital ratio	13.0949	4.223	2.3611	22.4208
Liquidity ratio	23.4960	2.5312	0.7322	41.3248

Securities	32.3383	3.753	2.5989	52.4821
GDP per capita	7.6975	3.5125	0.8541	10.2432

Notes: The Table reports the average values of variables used for estimation in each group of economies. Total assets; total costs = total interest expenses + overheads; net loans = gross loans – nonperforming loans; other earning assets; nonperforming loans; equity are reported in thousand USD. Price of fund = total interest expenses/total customer deposits; price of physical capital = other operating expenses/fixed assets; price of labour = personnel expenses/total assets. z-score; Capital ratio = equity over total assets; Liquidity ratio= liquid assets over total assets; Securities/TA= total securities over total asset. As country variable we employ GDP per capita.

Table 2. Financial Stability for Advanced Economies.

Country	Fin stab	Country	Fin stab
Australia	0.27	Latvia	-0.45
Austria	0.21	Malta	-0.14
Belgium	0.15	Netherlands	0.16
Canada	0.32	New Zealand	0.16
Cyprus	-0.64	Norway	0.27
Czech Republic	-0.17	Portugal	-0.55
Denmark	0.07	Singapore	0.18
Finland	0.11	Slovakia	0.08
France	0.55	Slovenia	0.12
Germany	0.54	Spain	-0.28
Greece	-0.71	Sweden	0.10
Hong Kong	0.32	Switzerland	0.52
Ireland	-0.33	Taiwan	0.17
Israel	0.15	United Kingdom	0.52
Italy	-0.43	United States of America	0.59
Japan	0.12		

Note: Financial stability index as derived from equation (4); 20,000 particle filters, 120,000 MCMC iterations; sensitivity analysis of 50,000 and 100,000 particles per dynamic latent unobserved. The index is normalized to 0.00 in 2001.

Table 3. Financial Stability Index for Emerging economies.

Country	Fin stab	Country	Fin stab
Albania	-0.33	Namibia	-0.51
Angola	-0.45	Nigeria	-0.55
Argentina	-0.50	Oman	0.47
Azerbaijan	-0.31	Pakistan	-0.11
Bahrain	0.07	Peru	-0.33
Bolivia	-0.55	Philippines	0.23
Bosnia and Herzegovina	-0.20	Poland	0.13
Brazil	0.34	Qatar	0.40
Bulgaria	-0.28	Romania	-0.25
Chile	0.12	Russian Federation	-0.33
China	0.65	Saudi Arabia	0.55
Colombia	-0.17	South Africa	0.81
Hungary	0.09	Thailand	-0.21
India	0.35	Trinidad and Tobago	0.06

Indonesia	0.33	Turkey	0.25
Kazakhstan	0.06	United Arab Emirates	0.47
Kuwait	0.52	Venezuela	-0.33
Malaysia	0.15		

Note: Financial stability index as derived from equation (4); 20,000 particle filters, 120,000 MCMC iterations; sensitivity analysis of 50,000 and 100,000 particles per dynamic latent unobserved.

Table 4. Financial Stability Index for Developing Economies.

Country	Fin stab	Country	Fin stab
Andorra	0.55	Jordan	0.33
Armenia	-0.34	Kenya	0.15
Bahamas	-0.15	Lebanon	-0.25
Bangladesh	-0.07	Lithuania	-0.71
Belarus	-0.36	FYROM	0.15
Benin	-0.16	Mauritius	0.07
Bermuda	0.17	Moldova Rep.	-0.35
Botswana	-0.44	Mozambique	-0.55
Cambodia	-0.35	Nepal	-0.17
Costa Rica	-0.15	Panama	-0.06
Croatia	0.22	Senegal	-0.21
Dominican Republic	-0.15	Serbia	-0.36
Ecuador	-0.28	Sri Lanka	0.18
Egypt	-0.81	Swaziland	-0.01
El Salvador	-0.41	Tanzania United	0.06
Ethiopia	-0.77	Uganda	-0.63
Georgia	-0.21	Ukraine	-0.55
Ghana	-0.33	Uruguay	0.17
Honduras	-0.40	Vietnam	0.12
Jamaica	-0.10	Zambia	0.14

Note: Financial stability index as derived from equation (4); 20,000 particle filters, 120,000 MCMC iterations; sensitivity analysis of 50,000 and 100,000 particles per dynamic latent unobserved.

Table 5. Regression analysis for Volatility ($\log \sigma^2_{ict}$)

	Model 1	Model 2	Model 3	Model 4
Volatility ($\log \sigma^2_{ic,t-1}$)	0.235***	0.235***	0.221***	0.233***
	(0.021)	(0.015)	(0.033)	(0.025)
LLP ratio	0.122***	0.125***	0.120***	0.123***
	(0.013)	(0.013)	(0.015)	(0.013)
NIM	0.022***	0.013***	0.015***	0.013***
	(0.001)	(0.002)	(0.002)	(0.002)
Funding ratio	-0.015***		-0.011***	
	(0.003)		(0.001)	
Funding ratio		-0.015***		-0.012***
(broader)		(0.002)		(0.002)
OBS	-0.233***	-0.115***	-0.232***	-0.215***
	(0.013)	(0.012)	(0.012)	(0.012)
OBS^2	0.011	0.015***		
	(0.233)	(0.003)		
Liquid	-0.213***	-0.155***	-0.128**	-0.130***
	(0.013)	(0.011)	(0.032)	(0.015)
Cash ratio	-0.205***	-0.199***	-0.135***	-0.133***
	(0.002)	(0.001)	(0.001)	(0.001)
TA	0.013***	0.013***	0.020***	0.018***
	(0.003)	(0.002)	(0.005)	(0.003)
TA^2	-0.0013***	-0.011***		
	(0.0003)	(0.002)		
Eq./TA	-0.132***	-0.131***	-0.082***	-0.125***
	(0.002)	(0.003)	(0.005)	(0.005)

Notes: The Table reports posterior means and posterior standard deviations (in parentheses) obtained through MCMC over the period 2001 to 2013. The dependent variable is the Volatility ($\log \sigma^2_{ict}$). As bank-specific variables we employ: Loan Loss Provisions (LLP ratio); Net interest margin (NIM); Funding ratio (deposits to total assets) as well as a broader definition (deposits plus other funding to total assets); Off-balance sheet items in banks (OBS), as well as its square; Liquidity ratio as liquid assets over total assets (Liquid); Cash ratio as cash and due from banks to assets (Cash ratio); total assets as the size variable (TA) as well as its square; Capital ratio as equity over total assets (Eq./TA). For bank-specific variables we use FITCH Bankscope database while for country variables we use World Development indicators from World Bank. Posterior standard errors in parentheses.

Table 6. Regression results for financial stability (F^*_{ct}) at country level.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$F^*_{c,t-1}$	0.313**	0.302******	0.381***	0.335***	0.301***	0.313***
	(0.111)	(0.018)	(0.055)	(0.011)	(0.011)	(0.005)
$\log \sigma^2_{ic,t-1}$					-0.211***	-0.310***
					(0.008)	(0.003)
LLP ratio	-0.013***	-0.022	-0.011***	-0.022***	-0.033***	-0.025***
	(0.003)	(0.002)	(0.003)	(0.005)	(0.011)	(0.001)
NIM	-0.225***	-0.185***	-0.130***	-0.135***	-0.125***	-0.219***
	(0.015)	(0.011)	(0.015)	(0.002)	(0.001)	(0.003)
Funding ratio	0.129***		0.115***		0.133***	
	(0.003)		(0.003)		(0.005)	
Funding ratio (broader)		0.115***		0.155***		0.180***
		(0.022)		(0.005)		(0.003)
OBS	0.111***	0.088**	0.012	0.035***	0.011***	0.201***
	(0.011)	(0.021)	(0.011)	(0.008)	(0.003)	(0.005)
OBS^2	-0.003**	0.001			0.001***	0.003**
	(0.001)	(0.011)			(0.002)	(0.001)
Liquidity ratio	0.223***	0.201***	0.158***	0.221***	0.130***	0.101***
	(0.015)	(0.011)	(0.023)	(0.015)	(0.005)	(0.002)
Cash ratio	0.128**	0.111**	0.133***	0.115***	0.133***	0.155***
	(0.053)	(0.032)	(0.015)	(0.015)	(0.011)	(0.035)
TA	0.111***	0.053***	0.015***	0.082***	0.083***	0.095***
	(0.003)	(0.001)	(0.002)	(0.005)	(0.001)	(0.003)
TA^2	-0.001***	0.003**				
	(0.000)	(0.001)				
Eq./TA	0.220***	0.251***	0.180***	0.205***	0.251***	0.181***
	(0.005)	(0.002)	(0.003)	(0.005)	(0.003)	(0.001)
z-score$_{ict}$	0.353***	0.301***	0.215***	0.289***	0.301***	0.303***
	(0.015)	(0.008)	(0.009)	(0.003)	(0.003)	(0.003)

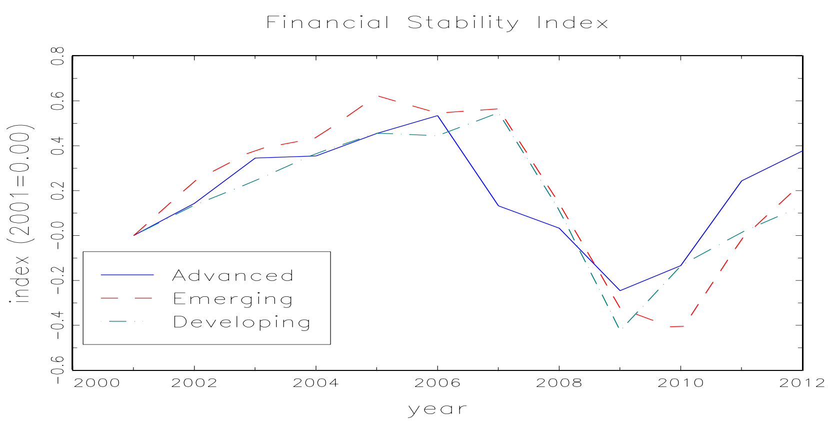
Notes: The Table reports posterior means and posterior standard deviations (in parentheses) obtained through MCMC. The dependent variable is our Financial Stability Indicator$\left(F^*_{ct} \right)$.As bank-specific variables we employ: Loan Loss Provisions (LLP ratio); Net interest margin (NIM); Funding ratio (deposits to total assets) as well as a broader definition (deposits plus other funding to total assets); Off-balance sheet items in banks (OBS, as well as its square; Liquidity ratio as liquid assets over total assets (Liquid); Cash ratio as cash and due from banks to assets (Cash ratio); total assets as the size variable (TA) as well as its square; Capital ratio as equity over total assets (Eq./TA). For bank-specific variables we use FITCH Bankscope database while for country variables we use World Development indicators from World Bank. Posterior standard errors in parentheses.

Table 7. Regression results for global financial stability (F_t^*).

	Model 1	Model 2	Model 3
F_{t-1}^*	0.313***	0.505***	0.235***
	(0.013)	(0.022)	(0.021)
GDP per capita	0.132***	0.130***	0.122***
	(0.001)	(0.005)	(0.003)
Global volatility ($\log\sigma_{t-1}^2$)		-0.331***	-0.221***
		(0.012)	(0.011)
LEGAL	0.120***	0.089***	
	(0.015)	(0.011)	
INSOLVENCY	0.235***	0.225***	
	(0.022)	(0.011)	
BUS. REGULATION	0.015	0.019	
	(0.033)	(0.022)	
CREDIT	0.110***	0.133***	
	(0.032)	(0.021)	
NIM	-0.251***	-0.180***	-0.221***
	(0.003)	(0.003)	(0.002)
Credit/Deposits	-0.223***	-0.235***	-0.331***
	(0.003)	(0.005)	(0.002)
NPL ratio	-0.301***	-0.211***	-0.151***
	(0.001)	(0.011)	(0.012)
z- score	0.210*	0.185	0.111
	(0.103)	(0.101)	(0.095)
CR3-ratio	0.011***	0.011***	0.015***
	(0.005)	(0.002)	(0.005)
TA	0.233***	0.135***	0.181***
	(0.029)	(0.012)	(0.022)
TA^2	-0.012	0.001	-0.011**
	(0.105)	(0.103)	(0.005)
Eq./TA	0.338***	0.212***	0.301***
	(0.003)	(0.002)	(0.011)

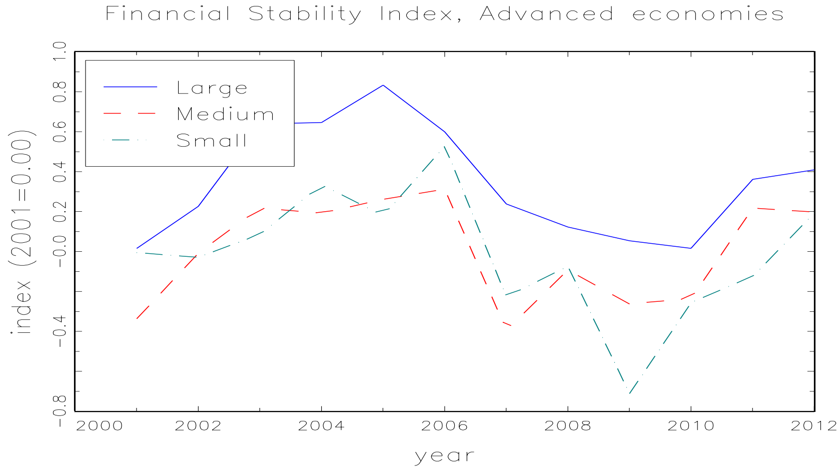
Notes: The Table reports posterior means and posterior standard deviations (in parentheses) obtained through MCMC. The dependent variable is the global financial stability (F_{ct}^*). We employ the following bank-specific variables: Net interest margin (NIM) at country level; Size as natural logarithm of total assets at country level (TA) as well as its square; Capital ratio as equity over total assets (Eq./TA) at country level;; the country total credit to deposits (Credit/deposits); the country non-performing loans (NPL); the C3 ratio at country level, the three five largest banks over all banking industry assets. As macro-economic variable we employ GDP per capita. We also include institutional and regulation variables; the enforcing contracts index (Legal); the index of resolving insolvency (Insolvency); the index of credit regulation (Credit); and the business index (Bus. Regulation). Lastly, we include a crisis dummy that takes the value of 1 for the 2007-2009 period and zero otherwise. For bank-specific variables we use FITCH Bankscope database while for country variables we use World Development indicators from World Bank. Posterior standard errors in parentheses

Figure 1: Global Financial Stability Index over time.



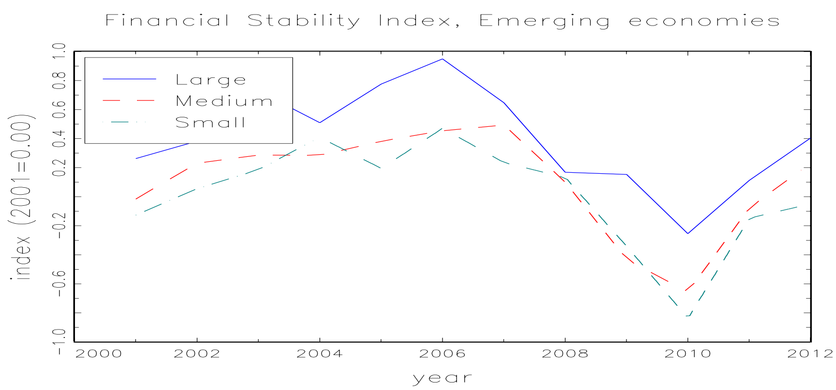
Note: Financial stability index as derived from equation (4); 20,000 particle filters, 120,000 MCMC iterations; sensitivity analysis of 50,000 and 100,000 particles per dynamic latent unobserved. The index is normalized to 0.00 in 2001.

Figure 2: Financial Stability for Advanced Economies over time; for large, medium, small banks.



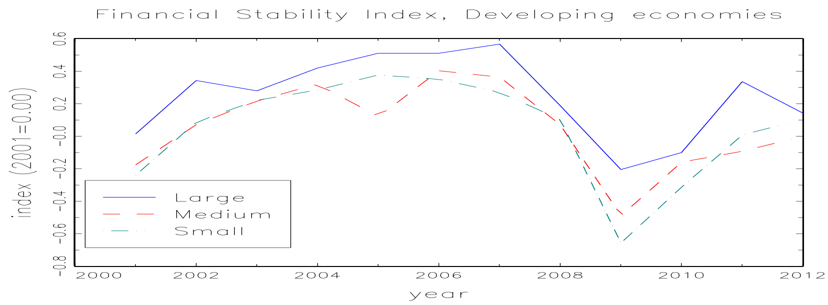
Note: Financial stability index as derived from equation (4); 20,000 particle filters, 120,000 MCMC iterations; sensitivity analysis of 50,000 and 100,000 particles per dynamic latent unobserved. The index is normalized to 0.00 in 2001.

Figure 3: Financial stability index for emerging economies over Time for large, medium, small banks.



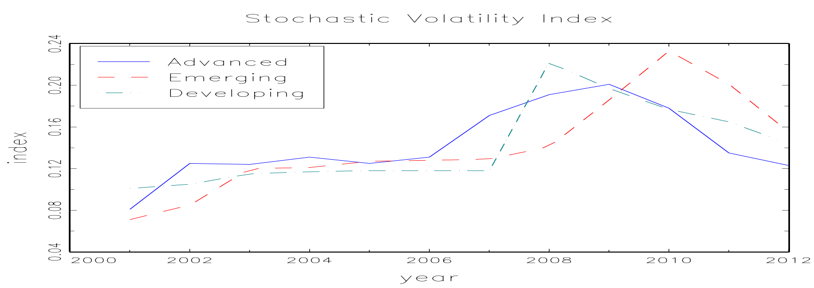
Note: Financial stability index as derived from equation (4); 20,000 particle filters, 120,000 MCMC iterations; sensitivity analysis of 50,000 and 100,000 particles per dynamic latent unobserved. The index is normalized to 0.00 in 2001.

Figure 4: Financial Stability for Developing Economies over Time; for large, medium, small banks.



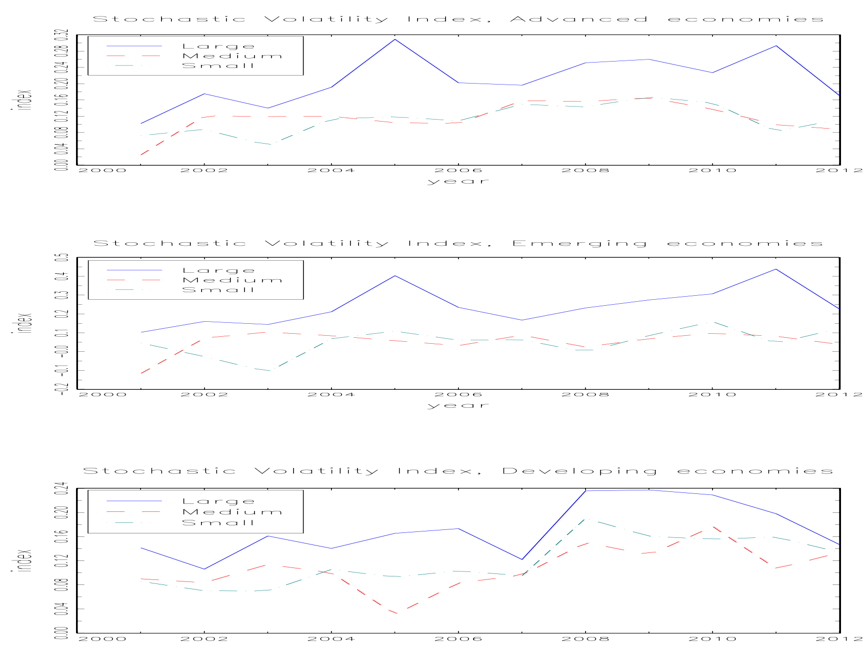
Note: Financial stability index as derived from equation (4); 20,000 particle filters, 120,000 MCMC iterations; sensitivity analysis of 50,000 and 100,000 particles per dynamic latent unobserved. The index is normalized to 0.00 in 2001.

Figure 5: Stochastic Volatility for Advance, Emerging and Developing Economies over time.



Note: Stochastic volatility estimation based on equation (3).

Figure 6: Stochastic Volatility According to Bank Size.



Note: Stochastic volatility estimation based on equation (3).