Does alternative finance moderate bank fragility? Evidence from the euro area.

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Abstract

Over recent years stricter EU capital requirements have resulted in constraining bank lending to SMEs. Alternative finance is expected to ease such constraints, but what would it be its impact on bank fragility? This paper examines whether alternative finance for Small and Medium Enterprises (SMEs) in the euro area would moderate bank fragility. We employ a bank profit model from which we derive a novel measure of bank fragility that is based on micro-foundations and is estimated in a single stage with Bayesian techniques. Controlling for many bank and firm specific variables, including bank capital adequacy ratios and volatility, we find that alternative finance overall strengthens bank stability, but that there is some variability in this impact over time and across countries. Interestingly, while higher bank capital adequacy ratios at times may even increase fragility, their interactions with alternative finance could help reduce it.

Keywords*:* Alternative finance, bank fragility, euro-area, Bayesian econometrics.
JEL Codes: C11, C13, G01, G17, E65.

1. Introduction

Finding ways to boost access to finance for firms has been a recurring theme for academics and policy makers alike in the aftermath of the financial crisis that has led to depletion of bank capital and curtailing of lending, imposing severe financial constraints in particular on small and medium-sized enterprises (SMEs hereafter). In addition, the 2013 Capital Requirements Directive IV of the EU imposes higher capital requirements on bank lending so as to reduce associated bank risks. These stricter EU capital requirements result in constraining bank lending to SMEs. From a policy point of view the EU responded to this challenge by supporting the creation of the Capital Market Union (CMU) in 2015 that in principle also aims to provide alternative finance resources to SMEs.

Alternative finance, which refers to funding outside the banking industry such as retained earnings, grants, trade credit, may offer a way of relaxing such financial constraints for firms (see Casey and O'Toole 2014) and of enhancing SMEs growth (see Campello et al., 2010; Jimenez et al., 2012; Ferrando et al., 2019). Indeed, higher capital requirements in the EU may have resulted in bank funding constraints for EU SMEs (Baker, et al. 2015; Behn, et al. 2016; Bams et al. 2019). A recent report by the EU (2016) argues that alternative finance could mitigate financial constraints imposed on SMEs by the higher bank capital requirements. We remain, however, in the dark if and how alternative financing could affect bank fragility in the euro area. Previous research seems to indicate that alternative finance could ease pressures on bank fragility (Vives 2001), as it eases information asymmetries that could cause adverse selection and moral hazard. Access to alternative finance, such as trade credit, could enhance the information content for all parties involved and could reduce bank fragility. However, though there is channel through which alternative finance could affect bank fragility there is no evidence.

We believe it is warranted to study this missing link and propose also a novel approach to model bank fragility. Our approach follows from previous research on bank risk (Brunnermeier, 2009; Allen and Carletti, 2010; Covitz et al., 2013) that identifies a critical failure to adequately measure bank fragility. As a first step, we propose an innovative way to measure bank fragility based on micro-foundations. The existing literature (Kaminsky et

al., 1998; Kaminsky and Reinhardt, 1999; Bordo and Schwartz, 2000; Gerdrup, 2003; Goodhart et al., 2006; Chan, 2017) focuses on handling banking volatility as the key to reducing uncertainty and risks so as keep the industry '*crisis free*'.[1] Alas, banking volatility and thereby fragility, are not directly observable given the high complexity of the banking industry.[2] Our model builds on the theoretical framework of Goodhart et al. (2006) who argue that an understanding of bank failure is key to understanding bank fragility. In some detail, we opt for an alternative bank profit function that provides a functional form for which bank fragility can be derived at the bank and country level. To be more precise, we employ a dynamic Bayesian modeling approach to describe bank fragility. This methodology explicitly models bank fragility, with an alternative bank profit function whose volatility is measured within a framework of panel stochastic volatility. Within this model bank volatility and fragility are latent variables that are not directly observable. To indirectly observe bank volatility and fragility we apply Bayesian inference procedures organized around Sequential Monte Carlo (SMC) techniques, also known as particle filtering. Thus, Bayesian inference is facilitated by using the SMC particle-filtering techniques to explore the posterior distribution of the model. The two dynamic unobserved latent variables, i.e., bank volatility and fragility, are integrated out using particle filtering. We then examine the nexus between bank fragility and alternative finance. Our interest focuses on SMEs access to alternative finance based on a semiannual Survey on the Access to Finance of Enterprises (SAFE) conducted by the ECB (see ECB, SAFE data base, 2018). When it comes to the underlying relationship between bank fragility and access to alternative finance, we explore this relationship in a single stage.

Our study contributes to the literature in the following ways: first, we employ the SAFE data set because it provides unique information of alternative access to funding at the firm level in the euro area. In some detail our alternative finance measure includes: internal funds, which are retained earnings, trade credit; grants that include subsidised loans; and equity that

[1]Chan (2017) proposes a new model of stochastic volatility that permits time-varying parameters in the conditional mean to show that inflation forecasting, a key variable on central banks` stability watch lists, is indeed subject to time variation in volatility.

[2]To date, bank volatility and thereby bank fragility are notoriously difficult to model and observe (Goodhart et al. 2006).

includes issuance of debt securities. We match this firm specific sample with bank specific data. Second, we provide a new measure of bank fragility based on Bayesian latent variable modeling, which relaxes previously maintained (rather strong) assumptions in the literature to examine the impact of alternative finance on bank fragility. Third, we provide single-stage estimations of the impact of alternative finance for SMEs on bank fragility while controlling for some key bank, firm and country specific variables and tackling issues of endogeneity. Last, but maybe not least, we perform sensitivity analysis by considering the impact of shocks in alternative finance on bank fragility using global impulse response functions and thereby addressing any remaining endogeneity issues.

We start from the premise that alternative finance by providing additional funding sources to SMEs will reduce borrower risk-taking incentives in financial markets and that thereby it may ease pressures on bank fragility. Higher capital adequacy ratios may increase bank fragility (if banks want to increase their return accordingly) but with the presence of alternative finance enhances bank stability. From a policy point of view, we show that alternative finance may act as a moderation mechanism for bank fragility.

The rest of the paper is structured as follows: Section 2 provide some stylized facts of alternative finance for SMEs in the EU. Section 3 presents our model. The data employed is provided in Section 4. Sections 5 and 6 provides the empirical estimations and discusses our results. Finally, section 7 offers some concluding remarks and policy implications.

2. Alternative finance funding for SMEs: some stylized facts for the EU

In the aftermath of the financial crisis the Capital Requirements Regulation (CRR) and the Capital Requirements Directive (CRD IV) were introduced in 2013 at the EU, aiming to increase minimum bank capital requirements. The objective has been to safeguard the soundness of the banking industry in the EU and thereby to enhance financial stability. Following these regulations, there is an on-going regulation financial reform in line with the implementation of both Basel III and the Basel IV. Under Basel III, the minimum capital requirement is increased from 8% to 10.5%. In addition, stricter collateral requirements, particularly for SMEs with below-average creditworthiness, are being applied that result in

an increase in the financing costs for SMEs. Evidence (Casey and O'Toole 2014) shows that the higher capital adequacy ratios and stricter collateral requirements could act as an impediment to bank lending to SMEs.

The EU Commission recognises the importance of SMEs for the EU economy, and has introduced a new Regulation No 575/2013 (EU) to support SMEs funding. This regulation is designed to partly offset the effect of the increase in capital adequacy ratios by proposing to use the so called '*supporting factor*' when it comes to SMEs funding.[3] This new regulation framework sets the prudential requirements for credit institutions and investment firms and amends Regulation (EU) No 648/2012. However, the supporting factor only applies to loans worth EUR 1.5 million or less, which covers around 30% of total bank new loans to SMEs in the Eurozone in 2016. As a further step towards supporting funding opportunities to SMEs, there was the introduction of CRR II towards the end of 2016 that increased bank loans coverage in excess of EUR 1.5 million, while the SME '*supporting factor*' also increased to 25%.[4]

Alas, an EU report (see EU, 2016) finds that the increase in the bank total capital ratios in the EU has a statistically significant negative impact on bank lending flows to SMEs, and a number of robustness analyses confirms this main finding. Along these lines, prior recent research has highlighted that the implementation of higher capital requirements in the EU squeezes SMEs out of bank funding (Baker, et al. 2015; Behn, et al. 2016; Bams et al. 2019).[5] Recognising the negative impact of increasing capital requirements on banks` SME lending,

[3]To alleviate the impact of higher capital requirements towards SMEs Article 501 of the EU Regulation (EU) No 648 proposes a supporting factor. This factor states that the capital requirements for credit risk on exposures to SMEs should be multiplied by 0.7619. However, the total amount owed to the bank institution shall not exceed EUR 1.5 million, though there is some leeway towards relaxing this threshold. Bank institutions shall report every three months on the total amount of exposures to SMEs. Examples of bank exposures include bank lending to SMEs, trade financing, including lending under official export credit insurance schemes.

[4]As enhancing funding resources to SMEs has been prominent within the EU, bank SME loans of EUR 1 million or less could be classified as retail exposures that are subjected to a lower risk weight of 75%. In addition, risk weight on bank exposures to SMEs could be lowered on SMEs with an annual turnover up to EUR 50 million.

[5]Bank competition also might play a role as previous research (Brunnermeier, 2009; Allen and Carletti, 2010; Covitz et al., 2013; Li and Zinna, 2014) highlighted that prior to the financial crisis in 2008 the banking industry was characterized by a higher number of banks competing to increase their market share at the expense of higher risk, though since the crisis h a prolonged period of consolidation led to a less crowded bank industry while risk appetite may have been diminishing.

the EU Commission proposed the creation of EU Capital Markets Union (CMU) in 2015, aiming to improve access to alternative finance for European SMEs, particularly with respect to equity and venture capital. The share of bank to total credit to non-financial corporations in the euro area was 70% between 2002 and 2008, whereas it dropped to around 50% in the period from 2002 to early 2016. Hence, alternative finance has gained in importance in the euro area. However, the euro-area is lagging quite significantly in comparison to the US where bank financing was 25% of total financing between 2002 and 2016, quarter 1.

Whereas the impact of alternative finance on relaxing financial constraints for SMEs is unequivocal (see EU, 2016), it remains unclear whether the former would affect financial stability. Vives (2001) for example argues that alternative finance could ease pressures on bank fragility. This follows from Stiglitz and Weiss (1981) argument that asymmetries in information exist in credit markets that are costly to overcome (Marquez, 2005; Hauswald and Marquez 2006). The information asymmetry could cause adverse selection and moral hazard when it comes to selection and thereafter monitoring of the creditworthiness of firms and this could increase bank fragility. Alternative finance, such as trade credit, could handle this asymmetry in information better as all parties involved have better access to all relevant information. In addition, alternative finance could enhance competition in banking industry and thereby increase the available funding at lower rates for firms that face credit constraints (Rice and Strahan 2010). In turn, low rates for credit should reduce borrower risk-taking as risk-shifting incentives would be subdued (Stiglitz and Weiss 1981). Lower risk taking would ease pressures on bank fragility. Despite the conceptualization of the possible impact of alternative finance on bank fragility, there is no direct evidence on whether alternative finance will modulate bank fragility.

3. Measuring bank fragility

We study the impact of alternative finance on bank stability at the bank level. Banks play a central role in many models of financial fragility (see Kaminsky and Reinhardt, 1999; Borio

and Lowe, 2002; Borio and Drehmann. 2009; Li and Zinna, 2014).[6] Alas, as often the case in finance, there is a plethora of models of financial fragility. Some studies predict bank failures and thereby financial fragility (Helmut et al., 2006; Gropp et al., 2006; Chan-Lau and Sy, 2007; Li and Zinna, 2014).[7] Other studies (see Nelson and Perli, 2005; Van den End, 2006) propose bank level indicators so as to measure bank fragility.[8]

3.1 Bank level fragility.

We depart from previous research and suggest a model based on the micro foundations of the banking industry. We opt for a simple alternative bank profit function that derives from the intermediate role of the banking industry (see Sealey and Lindley 1977; Berger and Mester 1997; Koutsomanoli-Filippaki and Mamatzakis 2009; Tsionas et al. 2020). Moreover, the intermediation approach considers that the bank employs inputs such as funds, physical capital, labour to produce loans while it also holds other earning assets and earns fees. The bank also uses as netput equity whereas nonperforming loans is treated as a negative quasi-fixed input. In simple form the bank profit before tax takes the form:

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

where $i = 1,...,B_c$ denotes bank, $c = 1,...,C$ country and $t = 1,...,T$ is time. The $k \times 1$ vector of regressors x_{ict} includes logs of output and input prices, log equity, a time trend and

[6]Kaminsky and Reinhardt (1999) focus on bank and balance of payment crises to provide a list of early warning indicators for banking 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. 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 banking stability indicator based on a plethora of relevant variables of financial systems. It follows from this literature that the quest for the "*holy grail*" of banking stability indicators has led policy-making institutions such as central banks (see Bank of England, 2008, Sveriges Riksbank, 2008) but also the IMF to define composite banking stability indicators (see IMF, 2006).

[7]Gropp et al. (2006) analyze the ability of the distance-to-default and bond spreads to predict bank fragility, whereas Chan-Lau and Sy (2007) introduce the concept of distance-to-capital, an extension of the distance-to-default concept. The IMF derives a market-based probability of default of each individual bank by estimating joint default probabilities, i.e., the expected number of bank defaults in the system given that at least one bank defaults (see IMF, 2008). Lepetit et al. (2008) opt for bank distance to default to examine the underlying association with product diversification in the European banking industry. In a recent paper Li and Zinna (2014) opt for a 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 leads to high risk premia.

[8]Most central banks employ weighted averages of banking indicators (i.e., capital adequacy, profitability, liquidity, asset quality) to construct a banking stability indicator. The ECB and BoE focus on liquidity ratios.

their squares and interactions. Here, $\pi_{i,c,t}$ represents bank profit and $v_{ict} \sim N\left(0,\sigma_{ict}^2\right)$, where $\sigma_{i,c,t}^2$ is bank volatility.[9] Note also the $v_{i,c,t}$ nests bank efficiency that measures how close the bank operates to the optimal bank frontier.

Bank volatility has been subject to measurement issues as it is unobservable. Herein, we model bank volatility as: $log\sigma_{i,c,t}^2 = \alpha_0 + \alpha_1 log\sigma_{i,c,t-1}^2 + \alpha_2 W'_{i,c,t} + \varepsilon_{i,c,t}$ where the vector $W'_{i,c,t}$ contains variables relevant to explain profit rate volatility. In the data section, we discuss in detail variables in $W'_{i,c,t}$. Such variables are bank and country specific, such as non-performing loans, equity, total assets, capital ratio, liquidity ratio, and GDP per capita, but also crucially alternative finance.

Note that we estimate the model in a single stage so all variables would have a simultaneous impact. In addition, one of the advantages of our modelling approach reveals bank level fragility

First, we propose the following efficiency-adjusted Z-type of bank risk:

$$Z_{i,c,t} = \frac{CAP_{i,c,t} + (x_{i,c,t}\beta_{i,c,t} - 1)}{\sigma_{i,c,t}} \qquad (2)$$

where $CAP_{i,c,t}$ stands for bank i capitalization and the remaining components come from equation (1).

The above bank risk is a modified Z-score that depends on standard parameters like $CAP_{i,c,t}$ and $\sigma_{i,c,t}$ but also importantly on the bank profit efficiency that derives from the bank profit function (1) as $x_{i,c,t}\beta_{i,c,t} - 1$. The efficiency adjusted Z score is bank-specific, country-specific and time varying.[10] It is crucial to take into account the bank efficiency into the Z-

[9] To keep the exposition of our modelling approach simple and efficient we opt for being laconic in parametrisation. It is worth noting that to capture the impact of all relevant factors of the bank profit fixed effects are employed that captures country heterogeneity and time fixed effects. Also note that fixed effects would capture institutional settings (see Bermpei, et al. 2020 for a discussion on the role of public corruption on bank lending). All variables are in logs unless otherwise is stated.

[10] There is a plethora of measures of bank risk, among others the distance to default. We opt for bank risk measure based on micro-foundations so as to include both listed and non-listed banks in our analysis. This is of particular importance as in the empirical application we focus on SMEs funding which rely on non-listed banks.

score as banks with superior performance in terms of efficiency would cope better with risk (see Tsionas et al. 2020 for further discussion, and Assaf et al. 2019; Tziogkidis, et al. 2020; Izzeldin et al. 2020).

In the following section we define in detail our bank fragility index. As the index is unobservable, we model it as a dynamic latent variable which, in turn, depends on certain observables at the bank and country-level, including the above efficiency-adjusted Z-score. The use of a dynamic latent variable (or state – space) model is justified on the grounds that we expect this variable to be persistent, although this can be examined empirically based on our parameter estimates.

3.2 The bank fragility index.

From the bank specific efficiency-adjusted $Z_{i,c,t}$ in equation (2), we derive the bank fragility index as:

$$F^*_{c,t} = \gamma_0 + \gamma_1 F^*_{c,t-1} + \alpha_2 \widetilde{w}'_{c,t} + \sum_{i=1}^{B_c} \lambda_{i,c,t} Z_{i,c,t} + \varepsilon_{i,c,t} \qquad (3)$$

where $\tilde{\mathbf{W}}'_{ct}$ is a vector of variables that include alternative finance (and macroeconomic, firm, country, bank specific) that contribute to the country-specific bank fragility, F^*_{ct}; λ_{ict} represents loadings of the Z-score. For these loadings, we assume $\lambda_{ict} = \zeta_{ico} + \zeta_{ic1}\lambda_{ic,t-1} + \varepsilon_{ict}$, subject to the restrictions: $\lambda_{ict} \geq 0$ and $\sum_{i=1}^{B_c} \lambda_{ict} = 1$.

The way we model fragility we do not constraint its sources. Bank fragility it is indeed bank specific, though the loadings allow to consider the impact of a plethora of factors that are captured through error terms in equations (2) and (3).

At the country level, the fragility index is given by a dynamic latent variable model that depends also on alternative finance measures as well as macroeconomic characteristics. Next, we aggregate the country level fragility indices using another dynamic latent variable model that depends on a vector of bank, firm, country and alternative finance specific variables as well as the country-level fragility indices using coefficients ω_{ct}.

Overall, bank fragility at an aggregate level, i.e., at the EU level, is:

$$F_t^* = \delta_o + \delta_1 F_{t-1}^* + \mathbf{G}'_t \delta_2 + \sum_{c=1}^{C} F_{ct}^* \omega_{ct} + \varepsilon_t, \qquad (4)$$

where $\mathbf{G}_t$ is a vector of bank, firm, country and alternative finance specific variables; ω_{ct} represents the loadings of country-specific bank fragility indicator on the aggregate indicator. The weights are determined endogenously at the country level from: $\omega_{ct} = \xi_{co} + \xi_{c1}\omega_{c,t-1} + \sum_{l=1}^{L} \frac{TA_{c,t-l}}{TA_{t-l}} \varphi_{cl} + \varepsilon_{ct}$, where $TA_{c,t-1}$ represent total assets at country level in the previous period. These weights are autoregressive and depend on the lagged value of the ratio of lagged each country's total assets in terms of grand total assets, informing about the size of the banking industry at country level. Both the autoregressive component ($\omega_{c,t-1}$) and the lagged ratio provide guidance how the weights ω_{ct} vary over time.

Note that equation (4) derives an aggregate indicator F_t^* based on its lagged value, other variables as well as a weighted average of each country's total assets in terms of grand total assets.

We believe it is highly unlikely that variables in $\tilde{\mathbf{W}}'_{ct}$ and/or $\mathbf{G}_t$ are completely exogenous or predetermined but also due to possible persistence in European banking (Tziogkidis, et al. 2020; Izzeldin et al. 2020). For this reason, we append to (3) and (4) the following vector autoregressive scheme (VAR):

$$\mathbf{Y}_{ct} \equiv \begin{bmatrix} \tilde{\mathbf{W}}_{ct} \\ \mathbf{G}_t \end{bmatrix} = \mathbf{a}_{ct} + \mathbf{A}\mathbf{Y}_{c,t-1} + \mathbf{b}F_t^* + \mathbf{e}_{ct}, \qquad (4b)$$

where $\mathbf{a}_{ct}$ denotes country and time effects, $\mathbf{b}$ is a vector of parameters, and errors $\mathbf{e}_{ct}$ are correlated with ε_t. The usefulness of (4b) is that: (i) we can deal with possible endogeneity problems, and (ii) we can also compute generalized impulse response functions within a panel VAR.

To estimate the above model and bank fragility, we apply Bayesian inference procedures organized around Sequential Monte Carlo (SMC) techniques also known as particle filtering (PF) so as to treat possible issues with endogeneity and enhance efficiency of parameter estimates. In some detail, SMC techniques are essentially algorithms (or Particle Filtering algorithms) that provide approximations to complicated, high-dimensional posterior distributions in Bayesian inference. Although a parameter vector $\mathbf{b}$ in Equation 4b is of our interest, it turns out that this vector, after conditioning on the data, also depends on a dynamic latent variable like bank fragility in our case. The SMC techniques allow us to observe the posterior distributions in Bayesian inference and to estimate the parameter vector $\mathbf{b}$.

Broadly speaking SMC or Particle Filtering algorithms build approximations to models of the form $y_t = f(x_t; \theta) + u_t$, where y_t is a certain dependent variable (possibly multivariate), u_t is an error term, and a (possibly multivariate) state or dynamic latent variable follows the process: $x_t = g(x_{t-1}; \theta)$ where f, g are known functions. The purpose of Bayesian inference is to provide access to the posterior $p(\theta|data)$ where the data consists of observations on $\{y_t\}_{t=1}^{n}$. The problem is difficult as multivariate integration with respect to $\{x_t\}_{t=1}^{n}$ is impossible. For this purpose, Particle Filtering is used to build reliable approximations, by importance sampling, to the conditional posteriors $p(x_t|\theta, x_{1:t-1}, y_{1:t})$, where $x_{1:t-1} = \{x_1, \dots, x_{t-1}\}$.

Thus, the dynamic unobserved latent variable, bank fragility as in (1) and (3), is integrated out using a SMC algorithm. The resulting posterior distribution, which includes only '*structural*' parameters, is then explored using the approach pioneered by Girolami and Calderhead (2011) that is the MCMC approach. All priors are as diffuse as possible, normal and chi-square. Appendix presents all details of our numerical techniques.

4. The EU data set.

4.1 Alternative access to finance in the EU: the ECB SAFE data.

We opt for a data set at the euro-area level over the period 2009 to 2016. The euro-area sample ensures variability across countries, firms and banks, while it ensures that it refers to

a single market with a common currency, and importantly with a common central bank and a common body of financial regulators. It also provides a rich set of information where our new measure of bank specific bank fragility can be applied. The euro area, in particular, provides since 2009 a firms' survey on their financing providing an opportunity to study firm access to alternative finance in relation to bank fragility.

Our main focus will be the euro-area firms' access to alternative finance as measured by the ECB`s Survey on the Access to Finance of Enterprises (ECB, SAFE data base 2017). This is so as bank capital constraints due to regulatory capital requirements have been mainly due to bank SME financing.[11] Our sample of euro-area member states contains Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal, and Spain. Remaining euro-area countries are not in the sample due to data availability issues.

We opt to include a comprehensive characterisation of firm-level access to alternative finance in line with Casey and O'Toole (2014) and Ferrando et al. (2019). The survey documents the financial conditions of EU firms and, importantly for the present study, records information regarding their financing. Our focus is on the financing of small medium enterprises (SMEs) and, in particular, on alternative finance that encompasses: retained earnings which are internal funds; grants and subsidised loans; trade credit; issuance/redemption of debt securities and equity; and other sources of financing.[12] To this end, alternative finance includes funding to SMEs other than bank related finance.

The data set is based on a binary survey that, for example, it takes the value of one if a firm has trade credit during the last six months or zero otherwise.[13] The SAFE data collects all

[11]Note that SMEs are of utmost importance of the euro-area, in 2016 99.8% of euro area firms are classified as SMEs with less than 250 employees and provide 70% of employment and 60% of value added. The remaining 0.2% of euro-area firms are classified as large and capture 30% share of employment and 40% of valued added. The vast majority of the SMEs, 92%, are very small firms, less than 10 employees, whilst the medium sized firms, more than 50 but less than 250 employees, captured just 1% of all SMEs.

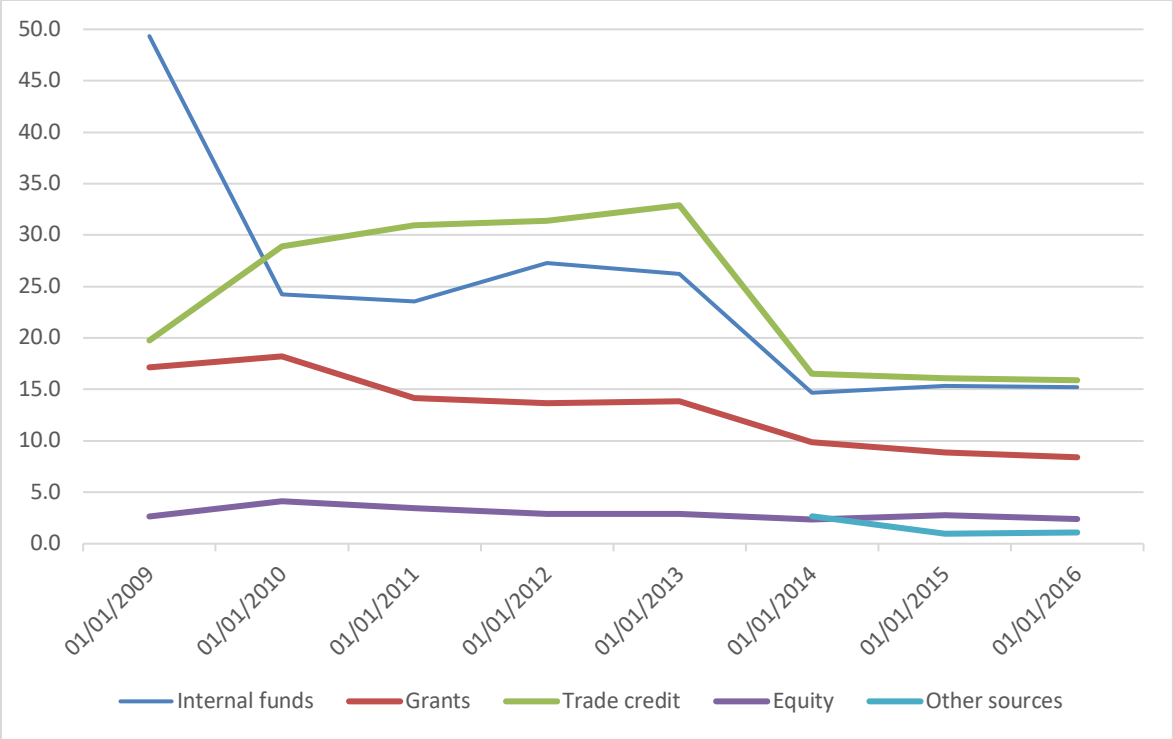
[12] Note that SAFE also includes information regarding factoring/hire and purchase/leasing. We do not include such facilitates into our measure of alternative finance as such facilities could be offered by the banking industry and thus can be classified as mainstream/formal bank finance.

[13] In some detail, the question of the ECB Safe regarding trade credit is: q4e2, have you obtained trade credit from your business partners in the past 6 months? And the data that are collected are: i) used in the past 6 months; ii) did not use in the past 6 months; iii) not relevant to enterprise; iv) relevant but do not know if used.

micro, firm level data, responses to its questionnaire. This is a unique data set as it reports information on alternative finance at the firm level. It also provides the percentage of all respondents that used, for example, trade credit during the last year.

To facilitate the empirical application of our modelling, Figure 1 shows the main components of alternative finance in our sample. Alternative finance includes internal funds, which are retained earnings, trade credit, grants that include subsidised loans and equity that includes issuance of debt securities. Following the financial crisis, internal funds as measured by retained earnings fell sharply, whereas this drop was partly counterbalanced by an increase in trade credit. In 2013 32.9% of respondents to the ECB SAFE survey reported that used trade credit in the last year. Trade credit remains the most important form, closely followed by internal funds, of alternative finance thereafter. Grants and subsidised loans follow a negative trend over time, from 18.2% of respondents to the ECB SAFE survey reporting their use compared to 8.4% in 2016. Equity and debt securitisations remain rather flat over the period at low levels of around 3% of respondents to the ECB SAFE survey reporting use for such form of alternative finance. Lastly, other sources of financing register a very low in magnitude, of around 1%.

Figure 1: Alternative finance in the euro-area.



Note: Euro-area include Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Netherland, Portugal and Spain. Internal funds refer to retained earnings; Grants include subsidised loans. Source: ECB's Safe Data Set.

Table 1 presents further statistical description (see Part A) of our survey-based data on alternative finance and firm specific variables (i.e., debt to asset, profits) and some economic sentiment data (general economic outlook and firm specific economic outlook) based on survey responses at firm level. The alternative finance is a geometric mean composite index that includes: internal funds, grants, trade credit, equity, and other sources of financing. We also report (see Part B) country level percentage response to the SAFE questionnaires regarding internal financing, grants, trade credit, equity and other source of financings. Clearly for some member states of the euro area, alternative finance is of great importance, i.e., for Ireland for which 28% of the SMEs report the use retained earnings, that is internal financing, and 57% the use of trade credit from business parties. Those two forms of financing, internal funds and trade credit, seem to be dominant forms of alternative funding, though grants that include subsidized loans also show some significant magnitude for member states such as Italy, France and Austria.

Table 1. ECB's SAFE Data on Alternative Finance.

PART A: firm specific characteristics.				
	Mean	S.D.	Min	Max
ALTFIN	10.192	7.557	0.70	49.30
DEBTASSET	-7.557883	11.99085	-26.4	24.2
PROFITFIRM	-11.39434	23.04996	-77.5	23
FIRMCAP	11.90513	16.81459	-27	31.7
ECONOUTLOOK	-10.856	23.419	-67.4	47.9
FIRMOUTLOOK	3.644	16.3583	-41.4	30.6

PART B: alternative finance country specific responses					
	Internal	Grants	Trade credit	Equity	Other
AT	19%	8%	15%	2%	2%
BE	12%	5%	13%	1%	2%
FI	18%	6%	24%	2%	0%
FR	17%	8%	8%	4%	1%
DE	16%	7%	9%	2%	2%
GR	7%	5%	34%	2%	0%
IE	28%	6%	57%	1%	1%
IT	16%	15%	24%	1%	0%
NL	9%	2%	17%	1%	2%
PT	6%	6%	20%	0%	0%
ES	12%	7%	23%	0%	2%

Note: Part A refers to a firm specific sample that includes 2,229 firms headquartered in the euro-area. The period is 2009-2016. The table provides descriptive statistics from the ECB SAFE data set. Alternative finance is ALTFIN, debt to asset is DEBTASSET; profit of the firm is PROFITFIRM; and firm capitalisation is FIRMCAP). Also, we display sentiment data such as economic outlook of the economy (ECONOUTLOOK), and firm-specific economic outlook (FIRMOUTLOOK).
Part B includes ECB SAFE country specific responses to alternative finance components, for example the first column reports the response to the question: have you authorise internal funding (retained earnings) during the last year. Equivalently for grants; trade credit; equity and securities capital and other sources of financing. AT is Austria, BE is Belgium, FI Finland, FR France, DE Germany, GR Greece, IE Ireland, IT Italy, NL Netherland, PT Portugal, ES Spain. Source: ECB's Safe Data Set.

4.2 The bank level data.

The above data set is matched with bank level data as we model bank fragility at the bank level. We obtain balance-sheet and income statement data from the Bankscope database, and SNL in recent years. Our bank level sample includes all euro-area banks in the Bankscope database.[14] Our final sample is an unbalanced dataset with banks from the euro-area

[14]We exclude banks for which: (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.

countries for the 2009-2016 period. The sample of this study includes 12,012 observations of 2,136 banks categorized as commercial.

For the alternative profit function, we opt for three outputs and three inputs as in Sealey and Lindley (1977), Koutsomanoli-Filippaki and Mamatzakis (2009), and Bermpei, et al. (2020). Moreover, this intermediation approach employs net loans (y_1) and other earning assets (y_2) as outputs, and fees as the 3rd output (y_3). The three inputs are 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), which is the 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. Profit is defined as profit before tax. In a recent paper Bermpei, et al. (2020) shed new light into the significance of strong institutions for bank lending, in particular they emphasise the role of public corruption at state level. We capture country specific effects such as institutional settings by having fixed effects in the estimation.

In addition, to examine the association of bank fragility, at the country and euro-area level, with some control variables we employ a number of bank-specific variables. With regards to the bank-specific variables, we use the natural logarithm of total assets to proxy for the size of banks. We further employ a non-interest income ratio, estimated by the sum of the net fees and commissions over total assets; and the securities over total assets ratio to proxy for the non-lending activities of banks. In addition, we include the ratio of non-performing loans to total loans to control for differences in banks' loan quality, the capitalization ratio to control for the part of bank fragility that is attributed to the overall system, the interest rate spread, which is used as a proxy for competition for banking services, the ratio of bank liquid assets to total assets at the country level to capture liquidity bank fragility. To consider concentration in the banking industry we also employ the C3 ratio, which is assets of the three five largest banks over all banking industry assets.

Following a number of cross-country studies (Barth et al., 2004; Fries and Taci, 2005), we also include variables to account for the macroeconomic environment in particular the real sector of the economy. Such macroeconomic variables also account for cross-country differences in the underlying economy in structural terms. To control for the general level of economic development we use real GDP growth. The summary statistics of bank specific variables are provided in Table 2.

Table 2. Bank Level Data Descriptive Statistics.

Variable	Mean	S.D.	Min	Max
BOONE	-0.2067	0.0296	-0.284	0.16108
LERNER	0.3202	0.0735	0.2066	0.44092
Ln(Z-score)	1.8379	0.9164	0.0000	5.6529
SIZE	13.9240	1.8887	6.0798	21.907
ROAA	0.36052	2.4006	1.1432	18.609
ASSETDIV	0.2314	0.1572	0.0000	0.9990
LIQRAT	0.1785	0.1726	0.0000	1.0000
REVDIV	0.2014	0.2834	0.0239	0.9999
COST2INC	0.8078	0.8688	0.0128	105.875
INFLATION	0.0167	0.0109	0.0447	0.15430
GDP	0.6180	2.8244	-14.8142	11.0870

Notes: This table reports the descriptive statistics for the key variables employed in the alternative profit function. The Z-score is defined in the main text in equation (2). SIZE = *ln*(total assets) by bank; ASSETDIV: asset diversification = securities/assets; LIQRAT: liquidity ratio = liquid assets/total assets, REVDIV: revenue diversification = non-interest incomes/total operating income; COST2INC: cost to total income ratio; ROAA: return on average weekly assets over a calendar year; INFLATION: inflation rate in the country where bank is headquartered (%); GDP: GDP growth (%); N: the number of observations; standard errors are in parentheses. The sample includes 2136 banks headquartered in the euro-area. The period is 2009-2016.

Lastly, we would like to note that bank risk could be measured using market-based data, i.e. to derive the distance to default. However, as the focus herein is on SMEs' funding that relates to banks that are not listed, we model bank fragility with our model of equations (1) to (4) which is based on balance sheet data and thereby on the micro foundations.

5 Empirical results.

The estimation stage itself is somewhat convoluted as we mobilize 20,000 particle filters for all computations of our model and 120,000 MCMC iterations, 20,000 of which are discarded to mitigate start up effects. However, this approach provides robust computations. In addition, convergence is tested using Geweke's (1992) diagnostics. The retained 100,000 particles draws satisfy convergence. Sensitivity analysis is performed using 50,000 and 100,000 particles per dynamic latent unobserved variable and the results were found to be the same, i.e., differences were within the bounds predicted by numerical standard errors (NSE).

5.1 The euro-area bank fragility index.

Our proposed measure of bank fragility as depicted in equation (2) is offering a new measure that considers also issues related with the underlying volatility and bank efficiency. In some detail, Table 3 provides the bank fragility per country. Some euro-area countries in the periphery such as Greece, Portugal, Italy Spain and Ireland show considerable weaknesses in bank fragility. On the other hand, the core of the euro-area appears to show strong resilience by reporting low levels of bank fragility (see Germany, France, Austria).

Table 3. Overall posterior mean bank fragility in the euro-area.

Country	Bank Fragility	Country	Bank Fragility
Austria	0.021	Ireland	0.210
Belgium	0.035	Italy	0.521
Finland	0.091	Netherlands	0.129
France	0.017	Portugal	0.442
Germany	0.013	Spain	0.344
Greece	0.903		

Note: Bank fragility 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.

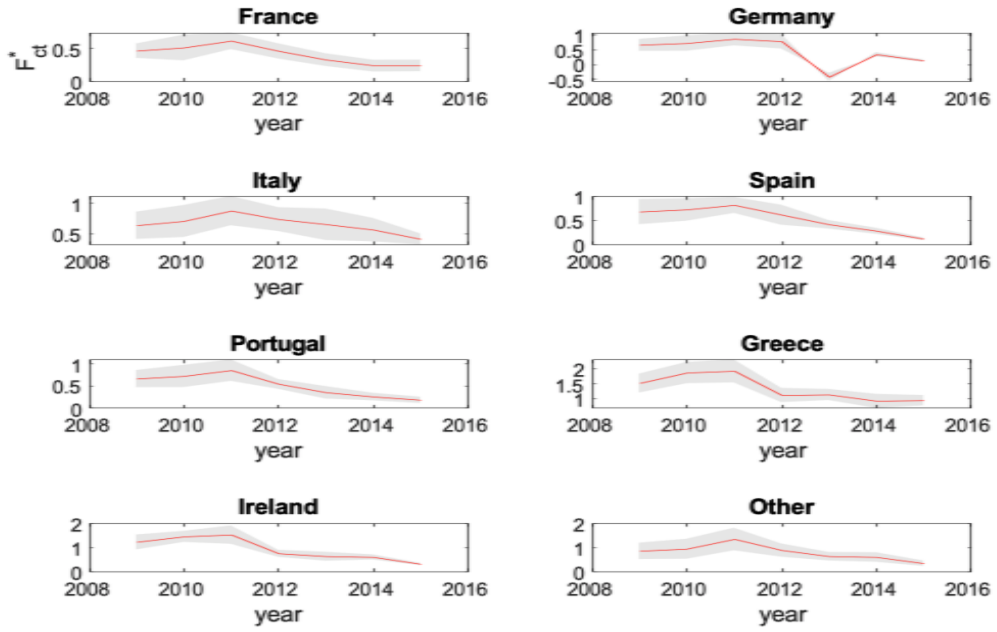
To observe bank fragility over time, as well as for the selected euro-area countries, Figure 2 reports posterior means (with 95% probability intervals) of the fragility indicator, F_{ct}^{*}. It shows that bank fragility remains an issue for some euro-area countries, in particular for Greece. The euro-area appears recovering from the financial crisis, yet it seems that it does

so in an uncharacteristic manner compared to other economies that have been through financial crises in a shorter period of time. In the euro-area the crisis remerged in 2012-13 albeit with less severity than in 2010. It is of importance as a result to have a high level of alertness about banking stability.

As expected, there is some variability, in particular in recent years, though as the credit crunch eases, bank stability improves in recent years, across all countries and in particular for Greece and Ireland. For the rest of the countries although there is a steady recovery after the financial crisis, banking stability remains constant, around zero.

From Figure 2 one could identify two distinct periods; from 2009 to 2011, from 2012 to 2016 s. During the first period, banking fragility shows evidence of some deterioration in the euro-area as the waves follow a positive trajectory. There is somewhat of a recovery in banking stability in the second period from 2012 to 2016 with some variability as, for example, in Germany there is a small upwards movement in bank fragility in 2014 whilst there is a correction thereafter.

Figure 2: The euro-area bank fragility index over time.



Note: Financial fragility 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. Other is Netherlands. The index is normalized in 2009.

Interestingly, our new index of banking stability effectively captures the credit crunch of the last decade. This is of importance as our index could be employed to show the exact period that the financial crisis hit the euro-area. One of the main concerns that have been raised since the credit crunch is the low degree of alertness of banking systems prior to the crisis (Brunnermeier, 2009; Allen and Carletti, 2010; Covitz et al., 2013). Following our modeling, our results show that the crisis has not been spreading uniformly across the banking markets. Some recovery since the all-time low in 2014 occurs in recent years.[15]

To prove the validity of our model we proceed to various specification tests. Appendix B provides details of our specification tests. The reported statistics are in favour of our modelling approach.

5.2 The nexus between firms' access to alternative finance and bank fragility.

Having derived banking fragility at bank and country level we examine next their interplay with firms' level access to alternative finance. In some detail, we include the following bank specific variables: LNNPL is the log of non-performing loans to capture portfolio quality and as such credit risk; to capture bank capital adequacy TIER1 which is Tier 1 capital adequacy; as the accounting ratio of performance the return on average weekly assets over a calendar year (ROAA); the net interest margin (NIM) to incorporate competition and profit margin; funding ratio (deposits to total assets) as well as a broader definition (deposits plus other funding to total assets) so as account for the underlying funding base of bank *i* at *t*; off-balance sheet items (OBS), as well as its square, measuring the plurality of bank activities beyond the mainstream one; SIZE as natural logarithm of total assets to consider the *'too big to fail hypothesis'*; the liquidity ratio as liquid assets over total assets (Liquidity) to capture

[15] Results are available that present a prior sensitivity analysis of the banking stability index. We test for 20 different alternative paths for the banking stability index, similar to the analysis for volatility, resulting from 20 different representative priors taken at random from the set of 10,000 priors. Results confirm the findings of Figure 1.

liquidity risk; the asset diversification which equals securities/assets (ASSETDIV) to assert whether banks are well diversified; the revenue diversification that is non-interest incomes/total operating income (REVDIV); and lastly the cost to total income ratio (COST2INC). We also include an adjusted Z-score (see equation 2) at the bank level to consider the bank risk. Hannes and Forletta (2020) discuss recent developments on bank profitability in EU, showing evidence of some persistence. In addition to capture impact related to competition we include the Boone indicator and Lerner (see Muzzupappa, et al. 2020 for a recent paper on the impact of competition on EU banks). We include SMEs specific variables that could impact upon bank fragility and are: debt to asset (DEBTASSET); profit of the firm (PROFITFIRM); and firm capitalisation (FIRMCAP). Lastly the general macroeconomy could have an impact and to this end we include GDP growth and inflation.

Table 4 presents regression results for bank fragility in relation to the impact of alternative finance access. To facilitate the identification of the impact of alternative finance we follow a specific to general approach. To this end, in model 1 we report results that include alternative finance, bank characteristics, and market structure with country and time fixed effects. Model 2 augments previous model and adds firm specific and country-specific control variables, as well as additional bank controls.

Table 4. The impact of alternative finance on bank fragility (F_{ct}^{*})

	model (1)	model (2)	model (3)	model (4)	model (5)	model (6)
$F_{c,t-1}^{*}$			-0.244***	-0.270***	-0.269***	-0.269***
			(0.0116)	(0.0131)	(0.0131)	(0.0131)
ALTFIN	-0.00033***	-0.00148**	-0.00119	-0.000698*	-0.00584***	-0.00343***
	(0.000085)	(0.0091)	(0.0087)	(0.00036)	(0.00135)	(0.00158)
DEBTASSET		0.000198	5.56e-05	-1.92e-06		-0.000178
		(0.000365)	(0.000319)	(0.000398)		(0.000360)
PROFITFIRM		0.000173	2.95e-05	1.16e-05		-4.14e-05
		(0.000361)	(0.000377)	(0.000422)		(0.000437)
FIRMCAP		0.000266	-0.000185	3.65e-05		-0.000377
		(0.000528)	(0.000641)	(0.000822)		(0.000704)
BOONE	0.0584*	0.0880	0.0558	0.0664		
	(0.0341)	(0.0586)	(0.0592)	(0.0730)		
OBS	0.0044***	0.002***	0.003***	0.011*	0.00980**	0.0011**
	(0.0009)	(0.0007)	(0.0001)	(0.009)	(0.0008)	(0.0009)
LNNPL		-0.00438		-0.00701*	-0.00799*	-0.00819*
		(0.00343)		(0.00412)	(0.00428)	(0.00427)
TIER1		0.000100	0.000669*	0.000492	0.000124	0.000180
		(0.000355)	(0.000393)	(0.000423)	(0.000694)	(0.000704)

ROAA		0.00137	0.000854	-4.42e-05	-0.000172	-0.000243
		(0.00175)	(0.00131)	(0.00186)	(0.00187)	(0.00188)
SIZE	-0.00660	0.0125	0.00795	0.0180	0.0228	0.0201
	(0.00595)	(0.0113)	(0.0136)	(0.0156)	(0.0150)	(0.0154)
LIQUIDITY	-0.0101	0.0385	0.00830	0.0392	0.0276	0.0252
	(0.0193)	(0.0373)	(0.0362)	(0.0453)	(0.0441)	(0.0450)
ASSSETDIV	0.0238	0.0508	0.0528	0.0476	0.0351	0.0365
	(0.0202)	(0.0349)	(0.0371)	(0.0434)	(0.0401)	(0.0406)
REVDIV	-0.00521***	-0.0152	-0.0114***	-0.0236	-0.0202	-0.0209
	(0.00150)	(0.00988)	(0.00303)	(0.0200)	(0.0221)	(0.0223)
COSTTOINC	-0.00248***	-0.0134	-0.00624***	-0.0238	-0.000381	0.0162
	(0.000318)	(0.00984)	(0.00100)	(0.0234)	(0.102)	(0.105)
GDP	-0.0865**	-0.0168	0.173	0.184	0.226	0.297
	(0.0398)	(0.101)	(0.192)	(0.225)	(0.145)	(0.200)
INFLATION		-0.0751	0.252	0.0308	0.0522	0.0136
		(0.246)	(0.292)	(0.337)	(0.314)	(0.336)
LERNER					0.0238	0.0459
					(0.121)	(0.126)
CONSTANT	0.106	-0.134	-0.107	-0.177	-0.262	-0.237
	(0.0835)	(0.154)	(0.193)	(0.215)	(0.250)	(0.257)
Obs	12,012	12,012	8,804	8,804	8,804	8,804
R-squared	0.001	0.003	0.061	0.076	0.075	0.075

Notes: The Table reports posterior means and posterior standard deviations (in parentheses) obtained through MCMC over the period 2009 to 2016. The dependent variable is the fragility (F_{ct}^{*}). As bank-specific variables we employ: LNNPL captures the log of non-performing loans; 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); Liquidity ratio as liquid assets over total assets (Liquid); Cash ratio as cash and due from banks to assets (Cash ratio); size is measured by total assets (SIZE); return on average weekly assets over a calendar year (ROAA) and lastly TIER1capturing bank specific Tier 1 capital adequacy. In addition, ASSETDIV: asset diversification = securities/assets; LIQRAT: liquidity ratio = liquid assets/total assets, REVDIV: revenue diversification = non-interest incomes/total operating income; COST2INC: cost to total income ratio. As firm specific variables we employ: debt to asset (DEBTASSET); profit of the firm (PROFITFIRM); and firm capitalisation (FIRMCAP). For bank-specific variables we use Bankscope database while for country variables we use World Development indicators from World Bank. Lastly, GDP is growth and also inflation. And for firm specific variables we employ the SAFE data set of the ECB. Posterior standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Clearly, the access to alternative finance has a negative and significant impact on bank level fragility (see Models 1 and 2). This finding shows the importance of securing alternative finance to firms as a way of reducing bank level risk and uncertainty. This is the first time that evidence is provided of the direct impact of alternative access to finance on banking stability. Previously in the literature it has been argued that financial innovation and new financial products available to firms would ease pressures on bank fragility (see Vives, 2001; Stiglitz and Weiss 1981). Alternative finance would enhance financial innovation, thereby easing credit constraints at the firm level (Rice and Strahan 2010). Herein our findings show that alternative finance has a significant impact on bank fragility. The main channel that

alternative finance affects bank fragility is through providing additional funding sources to the firms and thereby reducing borrower risk-taking as risk-shifting incentives in banking markets would be subdued in line Stiglitz and Weiss (1981). In turn, the subduing of risk taking in banking markets would ease pressures on bank fragility.

Models 3 to 6 include in addition the lagged bank fragility, $F^*_{c,t-1}$, so to capture any underlying dynamics while we also also tests for persistency. Note that our identification implies that bank-level and aggregate fragility are autoregressive, that implies persistency. We test for by estimating the coefficients γ_1 and δ_1 in Equations (3) and (4). If they are different that zero, our idendification is correct. It is also worth emphasising that most studies construct a measure of fragility and then regress it on the explanatory variables in (3) and (4) in what it is essentially a two stages procedure. Such two-stage approach would deliver biased and inconsistent estimators/estimates as bank fragility itself cannot be estimated separately from the variable in the model. In a two-stage approach, the consequences would not be unlike those of ignoring endogeneity.

Turning to market structure, we report results on the impact of bank competition. At the outset it is worth noting that the evidence is rather mixed when it comes to the interaction between bank competition and bank fragility. Some studies argue that bank fragility and the probability of a systemic crisis is lower in countries with competitive banking systems (Schaeck et al., 2009; Boyd et al., 2009), where other research shows that lower bank competition is associated with higher bank stability (Beck et al., 2013). Our results show limited significance for the Boone variable. However, Table 4 reports a positive sign on the Boone variable across all models while it shows some significance for model 1. This positive sign implies that lower bank competition, as measured by higher levels of the Boone indicator, would increase bank fragility. Note that the Lerner index, capturing bank competition, carries also a positive coefficient (see models 5 and 6) though it is not significant.

Revenue diversification and cost to income ratio are negative across all models, indicating that a higher ratio of customer deposits, which are considered a more stable source of funding

for banks, would reduce funding uncertainty and thereby reduce bank return-to-dollar fragility. The sign of the OBS ratio is positive and significant, suggesting that higher degree of investment diversification infuses fragility. It is of interest that bank fragility is significantly and negatively associated with lagged fragility. Moreover, there exists a negative relationship between bank fragility and non-performing loans in line with the '*bad management hypothesis'* (Koutsomanoli and Mamatzakis, 2009). Regarding performance, in terms of the ROAA variable, results are insignificant.[16]

Regarding the coefficient of Tier 1 capital, counting for core capital (equity capital and reserves), we observe a positive sign, suggesting that it would contribute to bank fragility, though it is low in significance. This result is in line with Miles et al. (2013) who argue that increasing bank capital requirements would raise the cost of capital for banks and in turn it would increase the risk taking of the type that has been theorised by Dell'Ariccia et al. (2014). They provide a theory that shows the trade-off between bank risk and capital requirement. In light of these findings, it is worth noting that since 2013 the EU has introduced higher regulatory capital ratios as part of the Capital Requirements Regulation (CRR) and the Capital Requirements Directive (CRD IV). The reported findings show that some caution is warranted as higher capital adequacy ratios would increase bank fragility. To some extent this has been taken into account as the EU Commission introduces regulation that enhances bank credit to SMEs in particular by employing a 'supporting factor' to such funding. We shall look into this in some detail in the next section.

The size variable, SIZE, is highly significant and positive suggesting that large banks positively contribute to bank fragility (Koutsomanoli and Mamatzakis, 2009; Laeven et al., 2014). This is of interest as it implies for policy makers who ought to pay particular attention to large institutions in line with the underlying consequences of '*too large to fail'*. Lastly, country level variables, GDP growth and inflation, seem to subdue bank fragility, though caution is warranted as the level of significance varies.

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

In Appendix A we report as part of sensitivity analysis the impact of alternative finance on bank volatility rather than on bank fragility as derived from Equation (1), showing similar findings as in Table 4.

5.3 Controlling for capital adequacy ratios and bank volatility.

The EU has introduced more stringent regulation and higher bank capital adequacy ratios. These regulation changes could impair credit expansion to firm funding, in particular for the SMEs which are the backbone of the EU economy. The EU has responded by employing a 'supporting factor' when it comes to provide loans to SMEs and also by proposing the acceleration of the EU Capital Markets Union (CMU) that would enhance alternative finance. The reported above results justify such policy initiatives as alternative finance subdues bank fragility.

In this section, as part of sensitivity analysis we look into more detail on the impact of capital adequacy ratios and we also control for bank volatility. Table 5 represents regression results for euro-area bank fragility **(** F_t^* **)** and reports similar findings as above, that is access to alternative finance enhances bank stability by reducing bank fragility. The capital adequacy ratio, TIER1, similarly with previous results has a positive and significant impact on bank fragility, suggestiong that there is a trade off between bank adequacy ratios and bank stability. Note, however, that the interaction (see Model 2) between TIER1 and alternative finance is significant and negative, justifying the policy interventions to boost alternative finance in the EU as this, besides providing funding to SMEs, would also subdue bank risks.

Table 5. The impact of bank fragility (F_t^* **): controlling for capital adequacy ratios.**

VARIABLES	model (1)	model (2)
$F^*_{c,t-1}$		-0.270***
		(0.0131)
$\log \sigma^2_{ic,t-1}$	-0.00229	-0.00434
	(0.00280)	(0.00412)
ALTFIN	-0.000636	0.000671
	(0.000534)	(0.00157)

TIER1	0.0603*	0.0178***
	(0.00801)	(0.0055)
DEBTASET		6.50e-06
		(0.000399)
PROFITFIRM		1.47e-05
		(0.000422)
FIRMCAPITAL		2.85e-05
		(0.000822)
BOONE	0.0574	0.0677
	(0.0360)	(0.0730)
OBS	0.001**	0.092**
	(0.0003)	(0.01)
LNNPL		-0.00698*
		(0.00413)
ALTFIN*TIER1		-0.000488**
		(0.000226)
ROAA		-5.65e-05
		(0.00186)
LIQUIDITY	-0.0186	0.0399
	(0.0250)	(0.0452)
ASSSETDIV	0.0134	0.0481
	(0.0237)	(0.0434)
REVDIV	-0.00957***	-0.0238
	(0.00315)	(0.0200)
COSTTOINC	-0.00425***	-0.0237
	(0.00102)	(0.0234)
GDP	-0.0226	0.185
	(0.0789)	(0.225)
INFLATION		0.0295
		(0.337)
CONSTANT	0.109	-0.169
	(0.112)	(0.215)
Observations	8,804	8,804
R-squared	0.001	0.076

Notes: The Table reports posterior means and posterior standard deviations (in parentheses) obtained through MCMC. The dependent variable is the banking stability (F_{ct}^{*}) and volatility ($\log \sigma_{ict}^{2}$). As bank-specific variables we employ: LNNPL captures the log of non-performing loans; 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); Liquidity ratio as liquid assets over total assets (Liquid); Cash ratio as cash and due from banks to assets (Cash ratio); size is measured by total assets (SIZE); return on average weekly assets over a calendar year (ROAA) and lastly TIER1capturing bank specific Tier 1 capital adequacy. In addition, ASSETDIV: asset diversification = securities/assets; LIQRAT: liquidity ratio = liquid assets/total assets, REVDIV: revenue diversification = non-interest incomes/total operating income; COST2INC: cost to total income ratio. As firm specific variables we employ: debt to asset (DEBTASSET); profit of the firm (PROFITFIRM); and firm capitalisation (FIRMCAP). For bank-specific variables we use Bankscope database while for country variables we use World Development indicators from World Bank. Lastly, GDP is growth and also inflation. And for firm specific variables we employ the SAFE data set of the ECB. Posterior standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Note that bank volatility carries a negative sign though is not significant in neither of the models. The remaining of the variables show similar magnitudes as the ones reported in Table 4. Again, revenue diversification and cost to income ratio are negative. The sign of the OBS ratio is positive and significant, while bank fragility is significantly and negatively associated with lagged fragility. Moreover, there exists a negative relationship between bank fragility and non-performing loans. Regarding ROAA, liquidity and asset diversification variable, results are insignificant.

6 Generalized impulse response functions (GIRF): controlling for endogeneity.

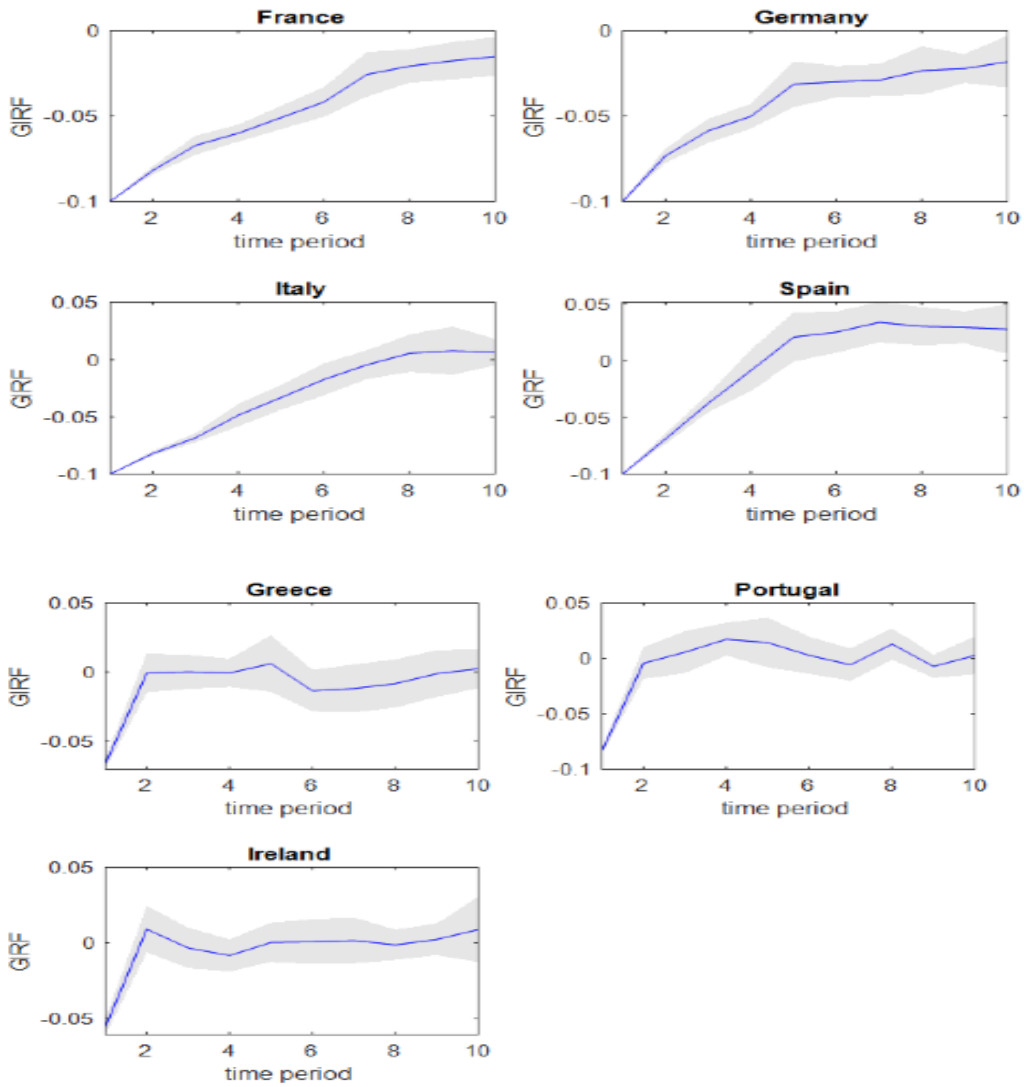
Further to the above, we examine next the response of bank fragility to shocks in access to alternative finance. We take up Bayesian Generalized Impulse Response Function (GIRF) analysis based on panel VAR specification that controls for endogeneity. Note that all variables enter the VAR as endogenous while the underlying dynamics are also modelled controlling for persistence, i.e., in bank profit. Such GIRFs can be derived using the vector autoregressive formulations in Equations (3), (4) and (4b). In this connection see Koop, et al. (1996). Posterior means of IRFs and 95% Bayes probability intervals are reported.

6.1 GIRFs for a shock in access to alternative finance.

In Figure 3 we report the GIRF of bank fragility to a standard-deviation-shock of firm specific access to alternative finance. We report GIRFs per country to capture country heterogeneity. To this end, these GIRFs are impulses from shocks in alternative finance in a given country to the euro-area as a whole. The response of bank fragility across euro-area countries to alternative finance is following an upward trend towards the zero line over the ten periods and remains negative. To this end, a shock in alternative finance would cause a one standard deviation reduction in bank fragility, though this effect would ease over time. It is of interest that the response from a shock in alternative finance in Greece, Portugal and Ireland (smaller Member States of the periphery in the euro-area) converges to zero within two to three periods, showing less persistence compared to France, Germany and Italy. These GIRFs imply that for the euro-area bank fragility it is of particular importance to develop

alternative finance in the large Member States, such as France, Italy, Spain and Germany, for which the positive impact of a shock in the former on bank stability lasts for longer.

Figure 3: Generalized Impulse Response Functions (GIRFs) to a Shock in Access to Alternative Finance at country level.



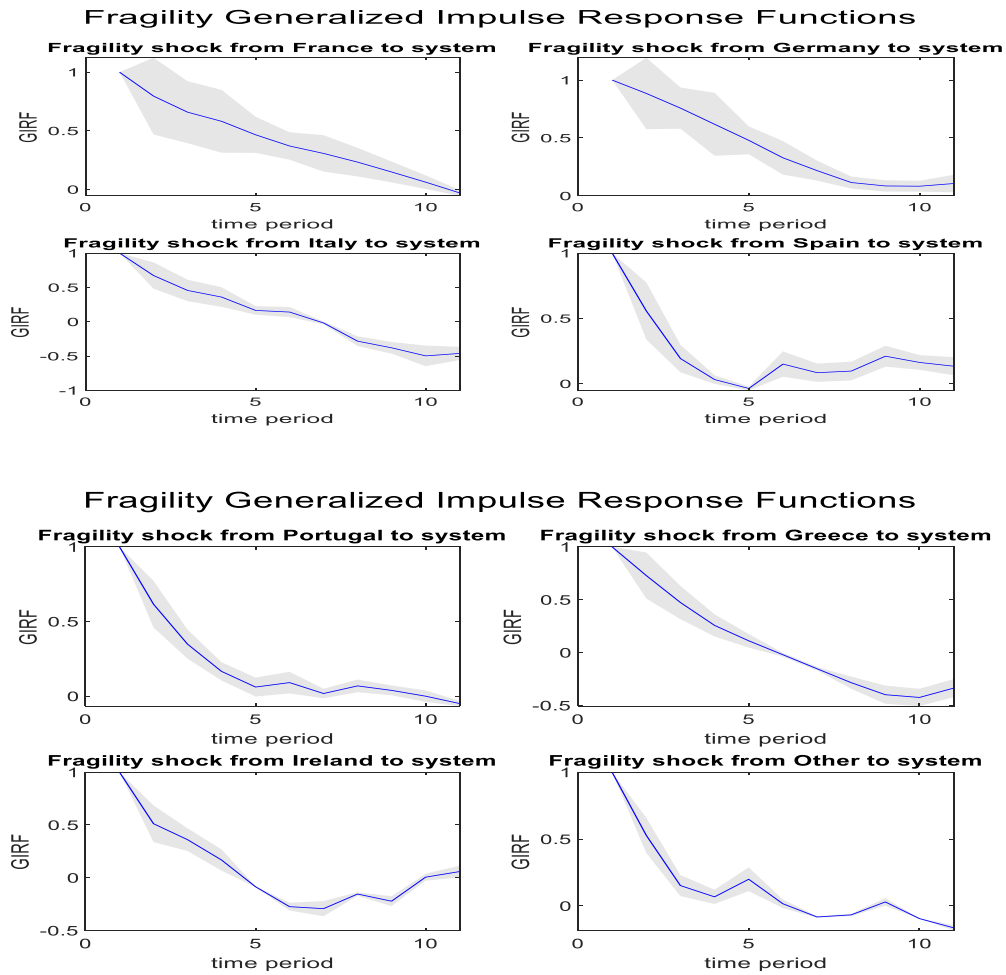
Note: The generalized impulse response function shows the response of one variable to one standard deviation shock in another variable. We omit error bands, as they are quite tight around the reported posterior mean GIRFs.

Similarly, the GIRFs do not alter the above when we reverse the ordering to test for the underlying endogeneity.

6.2 GIRFs for a shock in bank fragility.

As part of sensitivity analysis, Figure 4 reports the GIRF that show the responses of bank fragility to a shock in itself as in previous section we find evidence of auto regressive elements in the modeling of alternative finance. The bank fragility is observed at the bank level and for facilitating the reporting of GIRF we model for a shock in fragility at the country level. Reported also, are two posterior standard deviation bands for the GIRF.

Figure 4: Generalized Impulse Response Functions (GIRFs) to a Shock in Bank fragility at country level.



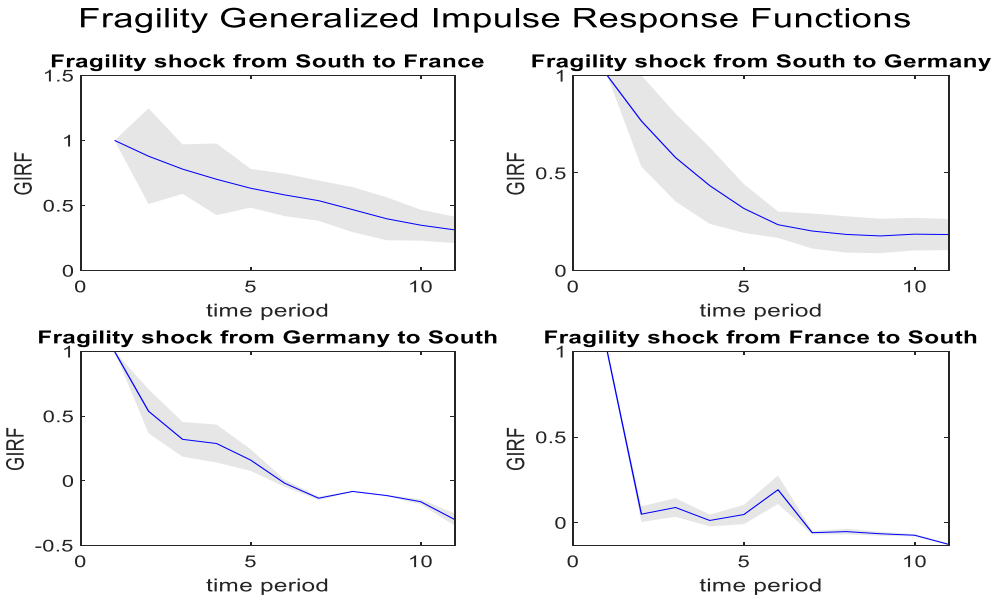
Note: The shaded area notes two posterior standard deviations banks. The generalized impulse response function shows the response of one variable to one standard deviation shock in another variable. Other covers Netherlands.

Note that across all sub-figures it becomes apparent that there is negative trend though it is positive in the shock of bank fragility at the country level to the bank fragility of the euro-

area. Moreover, a shock in bank fragility at country level would increase bank fragility at the whole euro-area though this impact would eventually die out within ten periods ahead. It is worth noting that a shock in bank fragility in some Member States, like Ireland, Spain and Portugal, dies out much quicker (within five periods) compared to the rest Member States. One would expect similar GIRF for bank fragility shocks also for the case of Greece, given that is in the periphery and is also small Member States. However, it seems that shocks in bank fragility in Greece would have a lasted impact on the euro-area.

It would be of interest to show what is the response when the shock is derived from the periphery of the euro-area that has been rather financially vulnerable for some time after the financial crisis when most countries in the periphery had to request financial assistance. Figure 5 reports the GIRF of the bank fragility index when the shock comes from the fragility in the periphery, which includes banks in Greece, Italy, Spain, Portugal (that is the south of the euro area) plus Ireland.

Figure 5: Generalized Impulse Response Functions (GIRFs) to a Shock in Bank fragility at the periphery of the euro-area.



Note: The shaded area notes two posterior standard deviations banks. The generalized impulse response function shows the response of one variable to one standard deviation shock in another variable.

Figure 5 shows the impact of the shock in the alternative finance of the south on the two larger economies, France and Germany, that have been heavily involved in financially assisting the south. A shock in bank fragility in the south would increase bank fragility of both France and Germany, though the reported responses would return to equilibrium within ten periods. However, the reported positive response to a shock in the bank fragility of the south would last much longer, twice as much, in the case of France compared to the case of Germany. On the other hand, reverse causality cannot be excluded as a shock in bank fragility in France and Germany would also positively affect bank fragility in south. It seems that the shock in bank fragility in France, though drops to close to zero within two periods it remains positive before picking up in periods 4, 5 and 6, converging to equilibrium thereafter. In the case of Germany, the response to shock drops to zero within five periods. Thus, alternative finance shocks in France would last longer and thereby are of more significance for the south of the euro-area.

7. Conclusions

This paper proposes a new way of modeling alternative finance in the euro area in relation to bank fragility. We model bank fragility within the profit function whose volatility is measured within a framework of panel stochastic volatility. To observe bank fragility, we employ a Bayesian inference procedure organized around Sequential Monte Carlo (SMC) technique and particle filtering.

In a single-stage estimation, we allow for alternative finance at the firm level to interact with bank fragility. In an empirical application, we provide evidence for the euro area. Results are of interest, in particular in the aftermath of the financial crisis as they provide evidence that alternative finance can help reduce bank fragility. Alternative finance would ease credit constraints faced by SMEs in the EU, in light of the higher imposed bank adequacy ratios. Alternative finance would increase the available funding at lower rates for firms. This, in turn, should reduce borrower risk-taking as risk-shifting incentives should be subdued (Stiglitz and Weiss 1981; Rice and Strahan 2010). As a consequence, lower risk taking would ease pressures on bank fragility. We find evidence for the first time that this is true;

alternative finance reduces bank fragility. Results show some variability over time and across countries, though over the main finding holds.

These findings have significant implications for regulators and supervisors, whose task it is to establish a secure as well as financially stable banking system. Our model of bank fragility shows the importance of providing alternative finances for safeguarding bank stability and to avoid crisis strongly associated with credit and liquidity constraints. Providing alternative finance appears to ease risk pressures in banks. Along these lines, and in terms of policy implications, our findings seem to support the EU Commission's recommendation to accelerate the creation of the Capital Markets Union (CMU). The CMU would provide alternative finance sources for SMEs that it would also improve bank stability.

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APPENDIX

A. Sensitivity analysis: the impact of alternative finance on bank volatility

In parallel with bank fragility, we also estimate volatility at bank level from equation (1). Table A1 presents regression results for bank volatility. The alternative finance has a negative and significant impact on bank level volatility.

Table A1. The impact of alternative finance on bank volatility ($\log \sigma_{ict}^2$) at country level.

	model (1)	model (2)	model (3)	model (4)	model (5)	model (6)
$\log \sigma_{ic,t-1}^2$			-0.241***	-0.266***	-0.266***	-0.266***
			(0.0117)	(0.0134)	(0.0134)	(0.0134)
ALTFIN	-0.0192***	-0.053***	-0.00153***	-0.00474*	-0.00191	-0.0039***
	(0.003)	(0.022)	(0.0003)	(0.0095)	(0.00423)	(0.0010)
DEBTASET		3.24e-06	0.000457	0.000384		0.000563
		(0.00126)	(0.00108)	(0.00134)		(0.00119)
PROFITFIRM		0.000804	0.00207	0.00141		0.00198
		(0.00113)	(0.00129)	(0.00145)		(0.00149)
FIRMCAPITAL		-0.000284	-0.000256	-0.00111		-0.00196
		(0.00178)	(0.00207)	(0.00259)		(0.00239)
BOONE	0.108	0.0778	0.0871	0.114		
	(0.116)	(0.208)	(0.199)	(0.237)		
LERNER					-0.582	-0.689
					(0.423)	(0.433)
LNNPL		-0.0148		-0.00302	-0.0101	-0.0102
		(0.0177)		(0.0184)	(0.0182)	(0.0184)
TIER1RATIO		-0.000593	0.00108	0.000283	-0.00143	-0.00169
		(0.00158)	(0.00118)	(0.00186)	(0.00278)	(0.00283)
ROAA		-0.0161	-0.0129	-0.0196	-0.0184	-0.0180
		(0.0134)	(0.0112)	(0.0153)	(0.0156)	(0.0157)
SIZE	-0.0260	0.0160	0.0145	-0.00182	0.00657	0.000288
	(0.0215)	(0.0492)	(0.0490)	(0.0653)	(0.0623)	(0.0642)
LIQUIDRATIO	-0.00615	0.0486	0.0311	-0.0386	-0.0630	-0.0555
	(0.0673)	(0.127)	(0.128)	(0.159)	(0.155)	(0.155)
ASSSETDIV	-0.0506	-0.0477	-0.201	-0.157	-0.179	-0.176
	(0.0675)	(0.124)	(0.132)	(0.163)	(0.151)	(0.153)
REVDIV	0.0265**	0.0574	0.0441***	0.0595	0.0547	0.0573
	(0.0132)	(0.0416)	(0.0135)	(0.0785)	(0.0872)	(0.0881)
COSTTOINC	0.00200	0.0198	0.00858**	0.0244	-0.443	-0.524
	(0.00179)	(0.0384)	(0.00406)	(0.0923)	(0.359)	(0.366)
GDP	-0.126	-0.259	-0.725	-0.154	0.137	-0.181
	(0.136)	(0.341)	(0.611)	(0.699)	(0.491)	(0.637)
INFLATION		-0.612	0.390	-0.857	-1.606	-1.219
		(0.829)	(1.058)	(1.239)	(1.125)	(1.219)
CONSTANT	1.478***	0.964	1.165*	1.433	1.958*	2.184**
	(0.305)	(0.676)	(0.686)	(0.938)	(1.050)	(1.078)
Obs	12,012	12,012	8,804	8,804	8,804	8,804
R-squared	0.001	0.003	0.060	0.074	0.075	0.075

Notes: The Table reports posterior means and posterior standard deviations (in parentheses) obtained through MCMC. The dependent variable is bank volatility ($\log \sigma_{ict}^2$). As bank-specific variables we employ: LNNPL captures the log of non-performing loans; 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); Liquidity ratio as liquid assets over total assets (Liquid); Cash ratio as cash and due from banks to assets (Cash ratio); size is measured by total assets (SIZE); return on average weekly assets over a calendar year (ROAA) and lastly TIER1capturing bank specific Tier 1 capital adequacy. As firm specific variables we employ: debt to asset (DEBTASSET); profit of the firm (PROFITFIRM); and firm capitalisation (FIRMCAP). For bank-specific variables we use FITCH Bankscope database. And for firm specific variables we employ the SAFE data set of the ECB. Posterior standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

As expected there exists a positive relationship between return-to-dollar volatility and loan loss provision that is in line with the '*bad management hypothesis'* (Berger and Mester, 1997, Koutsomanoli and Mamatzakis, 2009). The estimated positive sign of NIM is compatible with Berger and Mester, (1997). The funding ratio takes a negative coefficient across all models, whether we use the simple or the 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 the OBS ratio is negative suggesting that higher degree of investment diversification infuses volatility. The size variable, ln of TA, is highly significant and positive suggesting that large banks positively contribute to volatility (Laeven et al., 2014), though what is the optimal bank size remains questionable as the squared term of size is negative suggesting non-linearities.

Table A2 represents regression results for bank volatility $\log \sigma_{ict}^2$ while controlling for capital adequacy ratios. The capital adequacy ratio at the bank level also has a negative impact on bank fragility and bank volatility.

Table A2. The impact of alternative finance on bank volatility ($\log \sigma^2_{ict}$): controlling for capital adequacy ratios.

VARIABLES	model (1)	model (2)
$F^*_{c,t-1}$	0.0166	0.0591
	(0.0320)	(0.0492)
$\log \sigma^2_{ic,t-1}$	-0.199***	-0.266***
	(0.00867)	(0.0134)
ALTFIN	-0.00183	0.00483
	(0.00188)	(0.00495)
CAP	-0.0426*	-0.0464
	(0.0219)	(0.0653)
DEBTASET		0.000427
		(0.00134)
PROFITFIRM		0.00143
		(0.00145)
FIRMCAPITAL		-0.00108
		(0.00260)
BOONE	0.111	0.119
	(0.117)	(0.237)
OBS	0.081**	0.007**
	(0.04)	(0.003)
LNNPL		-0.00301
		(0.0184)
TIER1RATIO		0.000236
		(0.00186)
ROAA		-0.0192
		(0.0153)
LIQUIDITYRATIO	0.0545	-0.0355
	(0.0912)	(0.159)
ASSSETDIV	-0.0232	-0.156
	(0.0857)	(0.163)
REVDIV	0.0473***	0.0585
	(0.0143)	(0.0787)
COSTTOINC	0.0134***	0.0235
	(0.00420)	(0.0926)
GDP	-0.217	-0.201
	(0.270)	(0.701)
INFLATION		-0.883
		(1.239)
CONSTANT	1.891***	1.475
	(0.421)	(0.939)
Observations	8,804	8,804
R-squared	0.041	0.074

Notes: The Table reports posterior means and posterior standard deviations (in parentheses) obtained through MCMC. The dependent variable is the financial stability (F^*_{ct}) and volatility ($\log \sigma^2_{ict}$).As bank-specific variables we employ: LNNPL captures the log of non-performing loans; 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); Liquidity ratio as liquid assets over total assets (Liquid); Cash ratio as cash and due from banks to assets (Cash ratio); size is measured by total assets (SIZE);; return on average weekly assets over a calendar year

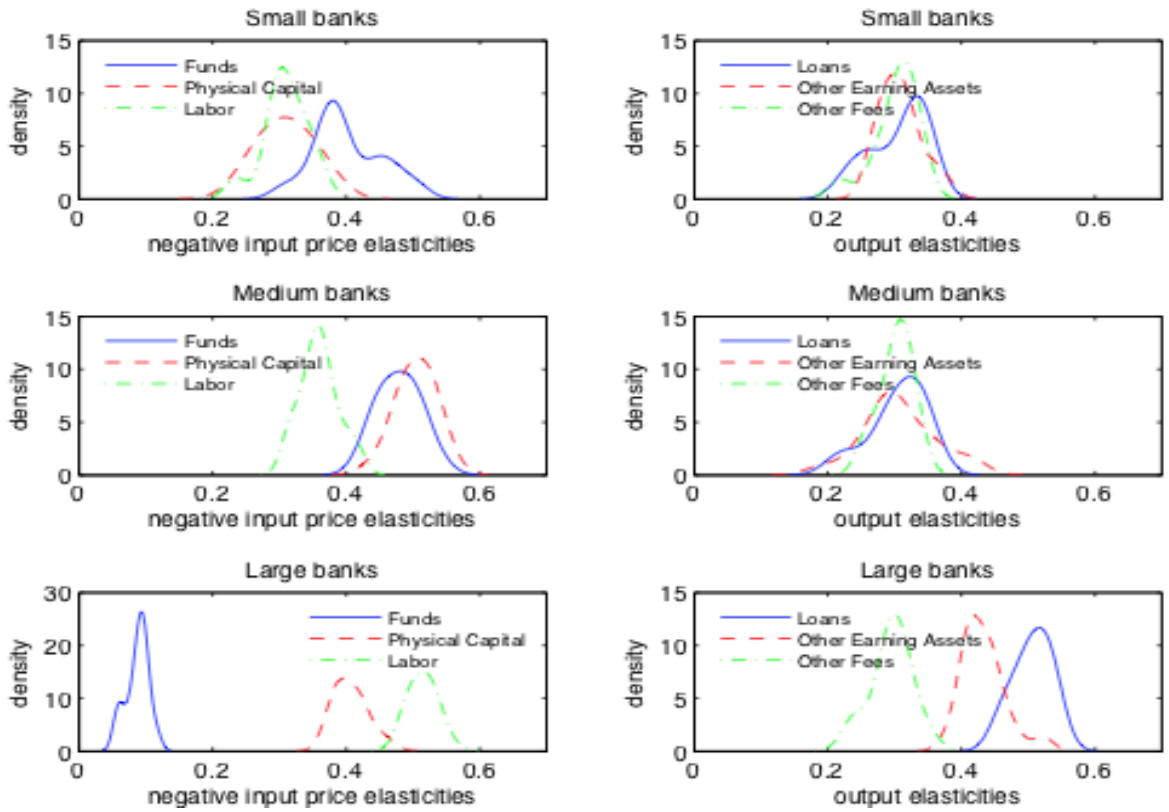
(ROAA) and lastly TIER1capturing bank specific Tier 1 capital adequacy. As firm specific variables we employ: debt to asset (DEBTASSET); profit of the firm (PROFITFIRM); and firm capitalisation (FIRMCAP). For bank-specific variables we use Bankscope database while for country variables we use World Development indicators from World Bank. And for firm specific variables we employ the SAFE data set of the ECB. Posterior standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

B. Specification tests for bank fragility.

To prove the validity of our new measure of banking stability we perform some specification tests. In Figure B1 we report sample distributions of minus the input price elasticities (left panel) and output price elasticities (right panel) from the alternative profit function. The input price elasticities are restricted to be negative and output price elasticities are restricted to be positive.[17] We report results for small, medium and large banks across the euro-area to facilitate comparison across banks of different size. It appears that the size of bank matters for the input price elasticities, for large and medium banks there is strong variability in the underlying densities of those elasticities. Similar variability is not observed for output price elasticities though we report that those elasticities for large banks vary considerably.

Figure B1: Distributions of minus the input price elasticities (left panel) and output price elasticities (right panel).

[17] The restrictions are first imposed at the means of the data. Then, they are imposed at a number of points (say N) in the hyper-rectangle $\bar{x}+2s$ where $\bar{x}$ is the vector of means and S is the vector of standard deviations of the variables in the alternative profit function. We experiment with N and finally set N=10 so that, approximately, 90% of the data satisfy the restrictions. In Figure 1 the sample distributions correspond to the posterior means of parameters and they are taken across the data.



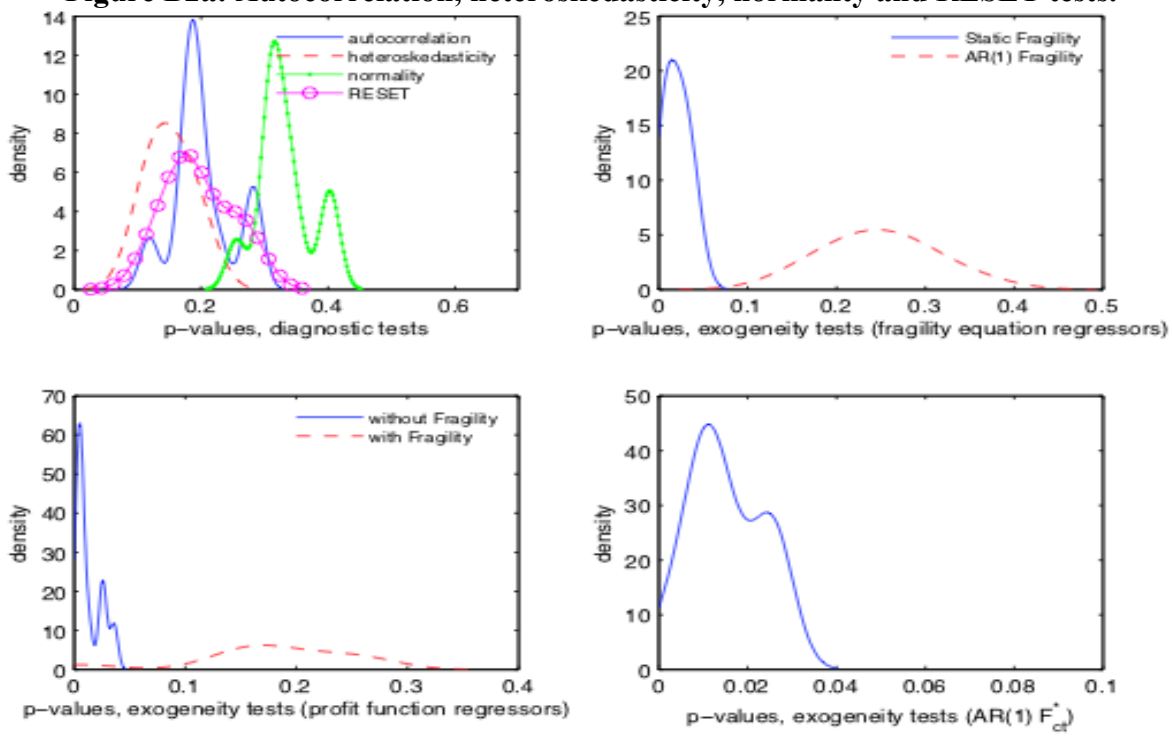
Note: These elasticities are derived from equation (4); 20,000 particle filters, 120,000 MCMC iterations; sensitivity analysis of 50,000 and 100,000 particles per dynamic latent unobserved.

Next, we subject our estimations of bank fragility to further specification tests. In Figure B2a (upper left panel) we report posterior distributions of p-values from four diagnostic tests: Autocorrelation, heteroskedasticity, normality and RESET test.[18] In the upper right panel, we report posterior distributions of p-values of an exogeneity test between the fragility equation regressors and the alternative profit function errors under two assumptions:[19] First, that fragility is static and, second, that fragility follows the current AR(1) specification. In the former case, the regressors do not seem to be exogenous as the p-values are heavily concentrated around zero. In the lower left panel, we report posterior distributions of p-

[18]Examination of these tests in a Bayesian context appears to be novel. For the autocorrelation test we assume the alternative profit function errors follow a panel AR(4) specification. The p-values correspond to the F-test that the AR(4) coefficients are zero. In turn we report the marginal posterior distribution of p-values corresponding to different MCMC draws, in standard Bayesian fashion. To implement the heteroskedasticity test, the alternative profit function squared errors are regressed on squares and cross-products of the regressors. For the normality test, we use the standard Jarque – Bera specification. For the RESET test, the alternative profit function errors are regressed on squares and third powers of the alternative profit function fitted values.
[19]The exogeneity test is based on regressing alternative profit function errors on a group of covariates and considering, for each MCMC draw, the p-value of the F-test that the coefficients are zero.

values from an orthogonality test between alternative profit function errors and alternative profit function regressors under the same two assumptions.

Figure B2a: Autocorrelation, heteroskedasticity, normality and RESET tests.



Note: These tests are specification test for estimations of equation (4); 20,000 particle filters, 120,000 MCMC iterations; sensitivity analysis of 50,000 and 100,000 particles per dynamic latent unobserved.

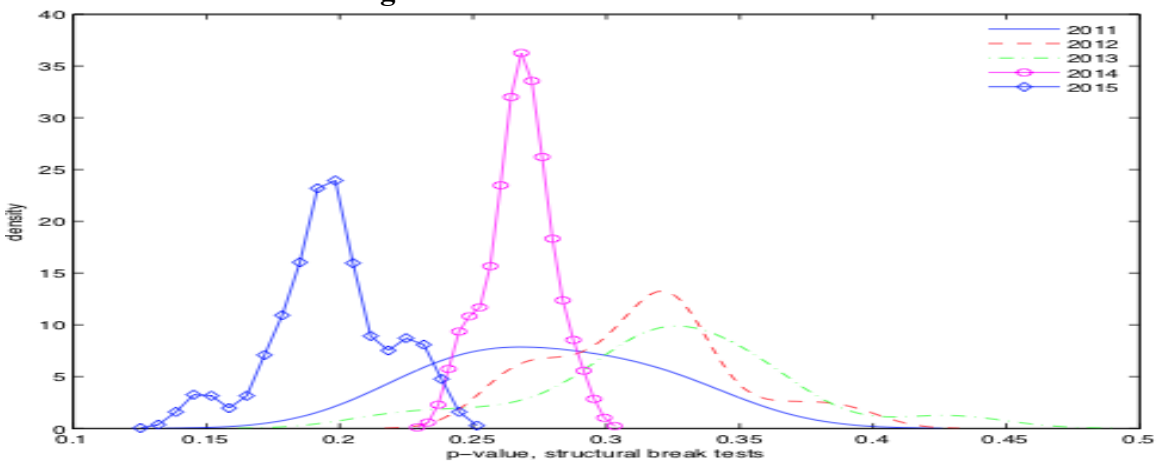
Evidently, in the absence of fragility, exogeneity fails. Finally, in the lower right panel, we report posterior distributions of p-values from a specification where the Fragility indicator, F_{ct}^{*} follows a standard, agnostic, AR(1) model, without covariates. Again, orthogonality fails under this specification as most p-values are concentrated in the neighborhood of zero and certainly at values much lower than 0.05 or 0.10.

In Figure B2b, we report posterior distributions of p-values corresponding to a structural break test for the years 2011-2016.[20] It appears that we do not have structural breaks: This may be surprising. However, if the model does not merely reflect statistical correlations but

[20] The way we implement the "structural break" test is by considering the chi-square statistic: $\chi^2 = \left(\hat{\theta} - \hat{\theta}_o\right)' \hat{V}^{-1} \left(\hat{\theta} - \hat{\theta}_o\right)$, where $\hat{\theta}$ is a given MCMC draw for the alternative profit function parameter vector, $\hat{\theta}_o$ is a given MCMC draw for the alternative profit function parameter vector only for a certain year, and $\hat{V}$ is the covariance matrix of the difference between the two parameter vectors, estimated from the MCMC draws.

deeper relations this is something highly desirable. We may take this as direct evidence that the model is "correctly specified", at least for working purposes.

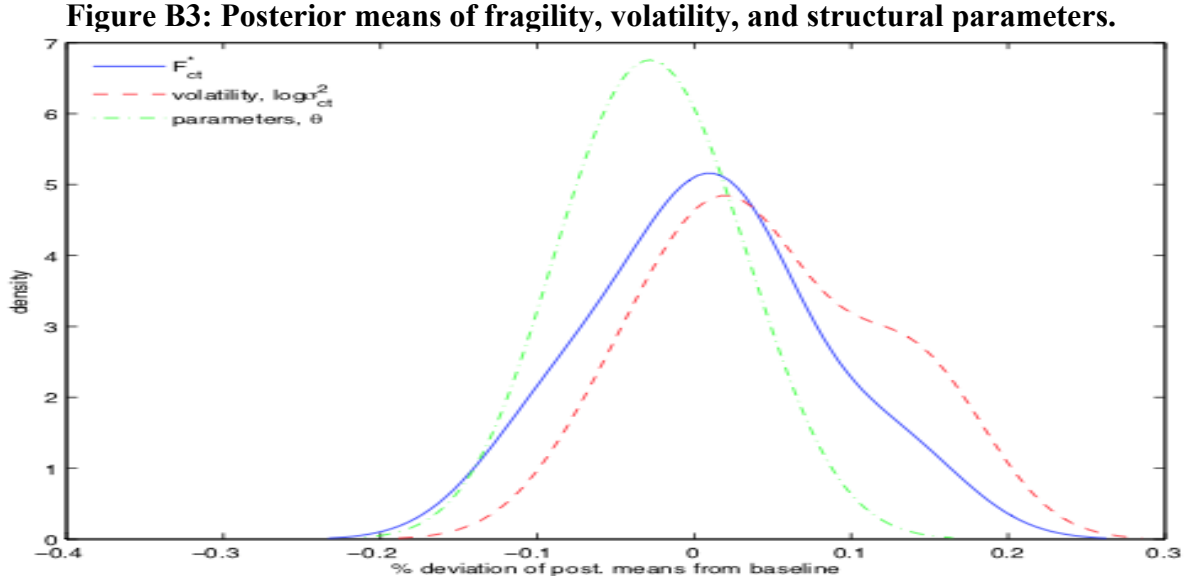
Figure B2b: Structural break tests.



Note: These structural break tests are for the model of equation (4); 20,000 particle filters, 120,000 MCMC iterations; sensitivity analysis of 50,000 and 100,000 particles per dynamic latent unobserved.

In Figure B3 we take up prior sensitivity analysis and we report distributions of percentage deviations of posterior means of the fragility indicator F_{ct}^{*}, volatility $\log \sigma_{ct}^{2}$, and structural parameters θ, for 100 different priors relative to our baseline prior.[21]

Figure B3: Posterior means of fragility, volatility, and structural parameters.

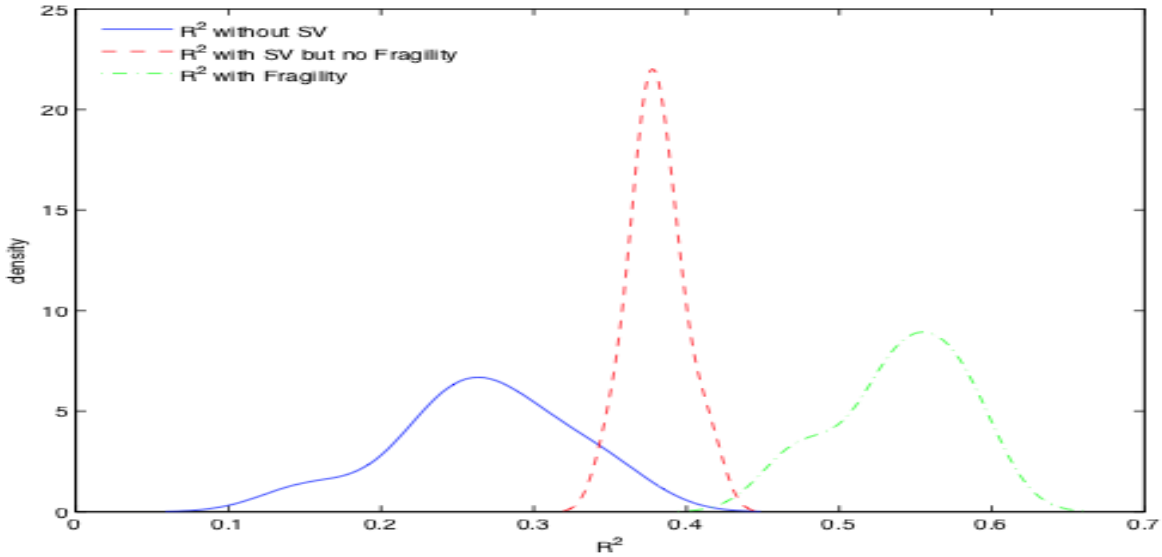


Note: 100 different priors relative to our baseline prior.

[21]The 100 different priors are constructed from the baseline multiplying all its hyperparameters by random numbers uniformly distributed in the interval (0.1, 10).

Lastly, to test for the model fit of (4) we proceed with an assessment using posterior distributions of R^2. We report, in Figure A4, posterior distributions of R^2 for three specifications: First without stochastic volatility, second with stochastic volatility but without the fragility indicator, and third, for our full specification.

Figure A4: Posterior distributions of R^2.

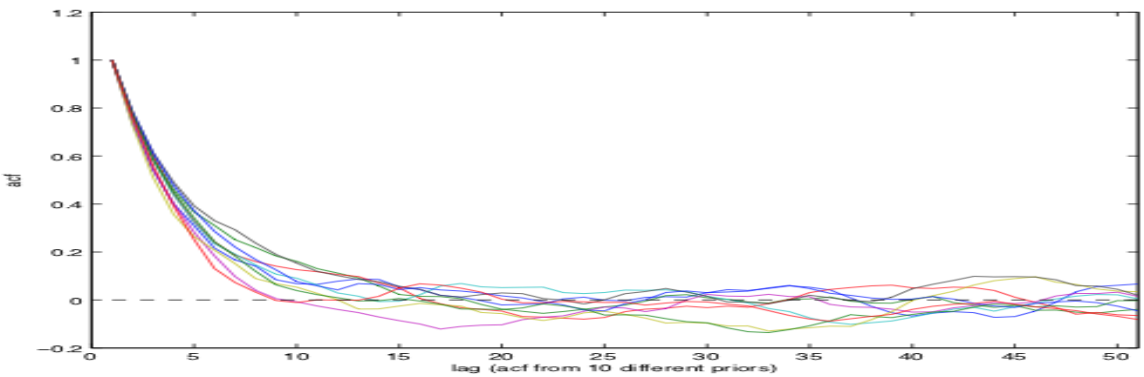


Note: R^2 posterior distributions for three models.

B2. Autocorrelations functions.

Autocorrelation functions (ACF) corresponding to 10 different priors are reported in Figure B2.1. After about lag 10, the values of acf are quite small so our MCMC procedure mixes well and explores the posterior efficiently. The ACF, for each lag, is the median autocorrelation of all MCMC draws for the structural parameters, volatility and the fragility indicator. Therefore, the fact that autocorrelations are relatively small, is very encouraging for the behavior of the MCMC sampler.

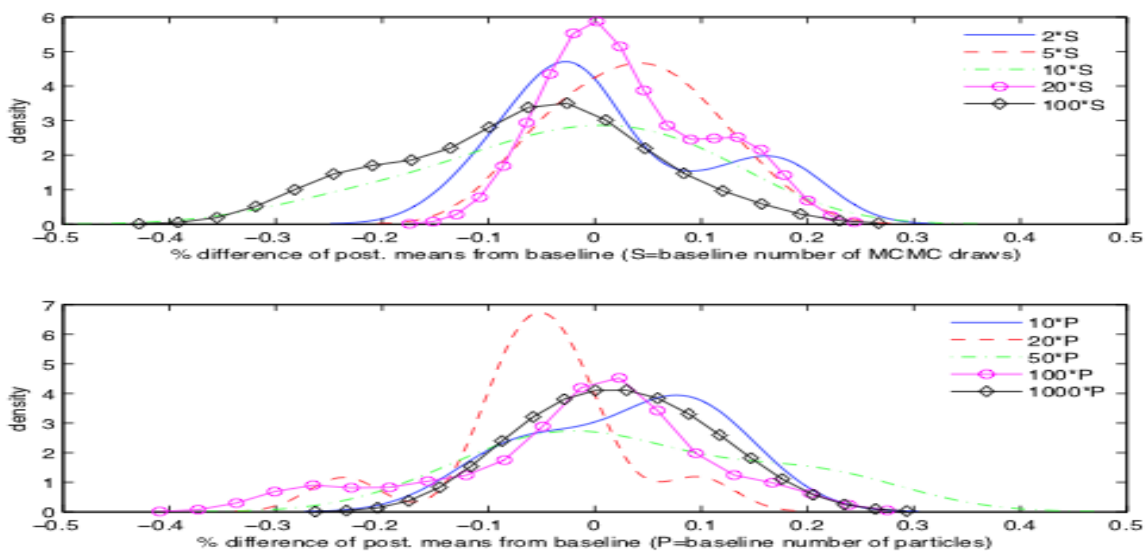
Figure B2.1: Autocorrelation functions (acf) corresponding to 10 different priors.



Note: Authors' estimations.

The following figures Figure B2.2 report sensitivity with respect to number of particles (S) and median autocorrelation functions (acf) of all structural parameters. Moreover, we proceed with sensitivity analysis with respect to the number of draws (S) in the upper panel, and the number of particles (P) in the lower panel

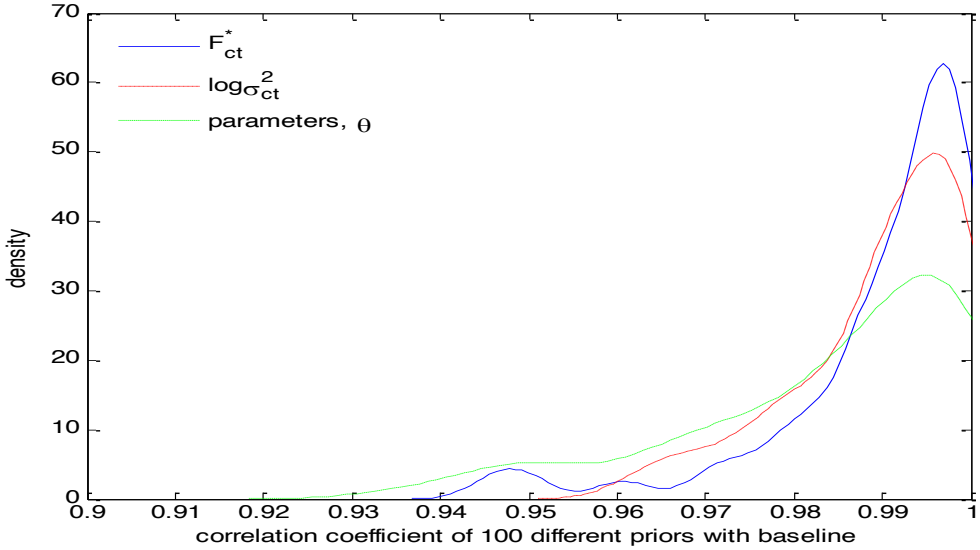
Figure B2.2: sensitivity analysis with respect to the number of draws (S).



Note: Authors' estimations.

In Figure B2.3, we report posterior distributions of correlation coefficients between 100 different priors and the baseline prior for the posterior draws of the bank fragility indicator, F_{ct}^{*}, volatility, $\log \sigma_{ct}^{2}$, and structural parameters θ. As the correlation coefficients are very high, MCMC draws corresponding to different S and different P are quite similar.

Figure B2.3: sensitivity analysis with respect to bank fragility indicator, F_{ct}^{*}, volatility, $\log\sigma_{ct}^{2}$, and structural parameters θ.



Note: Authors' estimations.