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Abstract

In response to the 2007-2008 global financial crisis, the G20 mandated the Basel Committee to put in place prudential regulations capable of ensuring financial stability: the Basel III agreements. This paper tackles this issue by investigating the impact of capital and liquidity ratios on financial stability for a sample of 1600 banks aggregated at the level of 23 countries over the 2005-2016 period. We pay particular attention to the nonlinear character of this potential effect through the estimation of a polynomial model with interaction terms and a panel smooth transition regression. Distinguishing between different types of banks depending on their level of systemicity, we find evidence of a nonlinear effect of prudential ratios on financial stability: a low level of capital and liquidity improves financial stability, but those effects tend to diminish for higher values. Finally, we show that bank profitability is a significant determinant of financial stability.

Key Words: Basel III ratios ; financial stability ; interaction effects ; Panel Smooth Transition Regression
JEL classification : C33, G21, G38

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1 Introduction

Over the past 30 years there have been 30 banking crises in Basel Committee-member countries, corresponding to a 5% probability of a Basel-Committee member facing a crisis in any given year (S. Walter, *Basel III, Stronger banks and more resilient financial system*, BIS speech conference, April 6th 2011). In the aftermath of the recent financial crisis, G20 felt the urgent need to ask the Basel Committee to reassess prudential banking regulation. Finding a solution to insure financial stability became a priority for international leaders and regulators. It is in this context that Basel III agreements were born. The overall idea of this reform is to ensure financial stability by improving the banking system resiliency, decreasing systemic risk and contagion effects, and preventing spillovers from the financial sphere to the real one (BCBS, 2010). This paper falls within this context by proposing an in-depth analysis of financial stability based on prudential ratios.

Several important changes have been made since the first two sets of agreements in order to reach this goal. To capture those developments, let us briefly look back at what happened before 2007 in terms of regulation. After a period of troubles in the 1970s and the deregulation trend of the 1980s, a wish for a more stable and resilient financial system emerged. That is when, in June 1988, the Basel Capital Accord (Basel I) took place, mandated by the G10 in the perspective of limiting credit risks. The flagship ratio of this series of agreements is the Cooke ratio designed for solvency purposes.[1] But an important issue with this ratio is its accounting methodology for credit amount, as it neglects borrowers' quality. That is why, after the internet bubble of the early 2000s, the Basel Committee came with new regulatory recommendations in 2004, namely Basel II. The capital adequacy framework is reassessed under three pillars.[2]
The 2007-2008 financial crisis once again questioned the ability of regulatory requirements to ensure financial stability and a new set of regulation recommendations has been proposed in December 2010. Basel III agreements are based on four main points: (i) the need for financial institutions' reinforcement by setting new standards (equity, liquidity, risk management and compensation policies); (ii) struggling against the "too big to fail" paradigm identifying systemic institutions, imposing them more important absorption capacity requirements and establishing recovery and resolution plans; (iii) making over the counter derivatives market safer; (iv) and making the shadow banking finance sector healthier and safer. This reform keeps Basel II's functioning system articulated around three pillars, adding a macroprudential component. Specifically, equity requirements are organized on three pillars. [3] Besides those equity require-

[1] It stipulates that banks with an international presence are required to hold capital equal to 8% of their risk-weighted assets.

[2] The first one reviews equity requirements resulting in the McDonough ratio. The second one establishes a prudential surveillance. The third one sets the market discipline by enforcing disclosure and transparency rules. Considerations on trading book were added in 2006.

[3] Pillar 1 contains equity requirements setting new solvency ratios. The Common Equity Tier 1 (CET1) ratio (4.5%), the Tier 1 ratio (6%) and the Total Capital ratio (8%), weighted by assets' risks. A conservation

ments, Basel III agreements define two liquidity ratios: (i) the Liquidity Coverage Ratio (LCR) that should prevent a financial institution from a 30 days' period of liquidity crisis, (ii) and the Net Stable Funding Ratio (NSFR) making financial institutions able to face maturity mismatch risk.

In that way, we can notice at least three main developments specific to Basel III. The first one consists in giving a much more prominent place to liquidity matters which were absent from previous Basel agreements. A second important adjustment is the introduction of the concept of systemicity. Basel III aims at ending the "Too Big To Fail" paradigm by defining three groups of banks: global systemically important banks (GSIBs), domestic systemically important banks (DSIBs) and others. This means that not only does the new regulatory framework propose a measure of systemicity, but it also applied differently to banks depending on this measure. Indeed, in the Basel III logic, the more systemic a bank is, the more its default will induce important and spread negative consequences on the overall economy. Therefore, the more systemic a bank is, the stricter its regulation will be. The third important change implemented in the last regulatory framework is the introduction of a macroprudential strand. While microprudential regulation seeks both to ensure individual institutions stability and depositors and creditors' protection, the macroprudential part is aimed to provide financial stability limiting systemic risk (large perturbations having consequences on the real sphere) in a preventive perspective (Bennani et al., 2017). It works by adding capital or liquidity requirements, credit constraints, or taking measures against the shadow banking. This evolution, specific to the latest agreements, is crucial in the way that it gives more importance to the financial stability part of prudential regulation goals. The main purpose of improving financial stability is nevertheless a common denominator to all Basel reforms.

Moreover, there is a commonly accepted assumption among those agreements specifying that increasing prudential ratios is necessarily improving financial stability. However to the best of our knowledge, this hypothesis has onl received very few attention from an empirical point of view. The economic literature has obviously already questioned the impact of prudential regulation but it has never assessed its empirical effect on financial stability. One of the major reasons explaining this lack of investigation is that defining and measuring financial stability is far from being trivial. A second important difficulty in analysing Basel agreements' impact, is the increasing complexity of regulatory framework. From this perspective, the presence of both interaction effects and nonlinearities emerges from the regulation-financial stability nexus, making it more challenging to investigate.

buffer is fixed to 2.5% of CET1. A countercyclical buffer is added for systemic banks (between 0 and 2.5% of CET1 depending on the level of systemicity of the bank). A leverage ratio is also added (not risk weighted) in order to prevent from excessive leveraged banks. The two macroprudential buffers are the conservation and the Global Systemically Important Banks (GSIBs) buffers. Pillar 2 includes individual requirements for prudential surveillance and risk management purposes. It takes into account securitization and off-balance sheet activities; stress-tests implementation; valuation practices revision; and revision of accounting treatment of financial instrument. Pillar 3 sets market discipline and disclosure requirements.

Therefore, our aim in this paper is to assess empirically the hypothesis according to which an increase in prudential ratios leads to a more stable financial system. To this end, we propose our own financial stability composite index using a Principal Component Analysis. We account for the existence of potential nonlinearities in the impact of requirement ratios, and separate banks depending on their level of systemicity. More specifically, the main question we adress in this paper is: from an empirical point of view, do regulatory capital and liquidity requirements nonlinearly impact financial stability when accounting for systemicity levels?

Our contribution is plural: (i) we tackle a commonly accepted assumption among regulators stating that increasing requirement ratios improves financial stability, which has never been verified empirically; (ii) we propose a financial stability composite indicator; (iii) we investigate the nonlinearity of Basel III's impact; (iv) and we integrate systemicity in our approach which has not been widely studied.

Relying on a sample of 23 countries, our results confirm the presence of nonlinearity in the financial stability - capital and liquidity ratios nexus. We also show that this relationship is not as automatic as the regulators' assumption suggests it. While we find that for low level of capital and liquidity, those ratios have a positive effect on financial stability, this impact partially disappears for higher levels. In addition, we show interconnexion between banks' subgroups confirming the relevance of separating banks according to their level of systemicity.

The remainder of the paper is organized as follows: Section **??** reviews the related literature. Section 3 discusses financial stability matters and the construction of our financial stability indicator. We describe our data and methodology in Section 4. Section 5 displays descriptive statistics and tests. Results and robustness checks are presented in Section 6. Section 7 concludes.

2 A brief review of the literature

2.1 Prudential regulation impact [4]

Empirical literature

There are some attempts in the literature to assess empirically Basel III's impact. Kim and Sohn (2017), calculate the effect of liquidity and capital requirements on lending, using a fixed effect regression including interaction variables. They find a positive relationship between credit growth and increases in capital and bank liquidity. However this result only holds for large banks and was even more pronounced during the slump. Those authors show the existence of nonlinearity in the impact of capital on lending depending on the level of liquidity. Indeed, a cumulative effect was expected since both capital and liquidity have a positive impact on lending

[4] See Tables 6 and 8 in appendix A for a synthetic presentation

(Cornett et al., 2011, Carlson et al., 2013). Catalan et al. (2017) investigate a nonlinear effect of prudential regulation on lending, but they are focusing only on capital requirements. Their study is based on a theoretical framework in order to determine a loan growth rate expression that they use in an ARDL (auto-regressive distributed lag) model. The authors highlight that the impact of a bank recapitalization on loan growth depends not only on the initial level of capital but also on banks' strength. On their side, Giordana and Schumacher (2017) investigate the impact of Basel III liquidity and leverage requirements on Luxembourgian banks' risk default, measured by the z-score. They find, in a system-GMM analysis (system generalized method of moments), that if Basel III had been implemented before the crisis it would have cost 75 basis points of ROA (Return on Assets), but it would also have implied a decrease in default's probability.

Theoretical literature

In a theoretical modelling perspective, Krug et al. (2015) consider an agent-based credit network approach in order to assess the impact of Basel III in terms of financial system resiliency. In this article, financial stability is measured by the banking system's ability to survive over 500 crisis experiments. The study includes several requirements and gives results for a large set of initial conditions. The findings show that (i) the positive joint impact is larger than the sum of individual contributions, and (ii) macroprudential's impact is insignificant or negative, especially when looking at the systemic buffer. In addition, a significant number of studies use DSGE (dynamic stochastic general equilibrium) models in order to predict Basel III's impact following its implementation. Angelini et al. (2015), in the context of a BIS's (Bank of International Settlements) study, use that kind of model in order to assess the impact of the reform on the long term economic performance and fluctuations. They show a positive and marginally decreasing impact of Basel III requirements, meaning that an asymptotic limit exists in the reform's benefits. Those results are consistent with MAG (Macroeconomic Assessment Group; BCBS-MAG (2010)) and LEI (Long-term Economic Impact; BCBS-LEI (2010)) analyses. More recently, Quignon (2016) conducted a study reusing BIS's methodology taking into consideration real observations on Basel III's implementation to recalibrate Basel Committee's models. He finds that not only the marginal effect of regulatory requirements is decreasing but also that, beyond a certain limit, it becomes negative. Either way, this literature tends to underline the existence of a nonlinear impact of requirements depending on their level.

Studying systemicity

Because some banks are large enough to perturbe a whole system in case of default, they are associated with the benefit of governmental guarantee. For this reason, the economic literature tends to support the idea according to which systemic banks increase their risk in order to augment their returns. Brandao et al. (2013) show that moral hazard emerges from public

support to banks, especially during the recent crisis: risk accumulation in the United-States was permitted by implied governmental warranty, while market participants get less suspicious considering that those banks will be bailed out in case of difficulties. The underlying idea is that the existence of a lender of last resort contributes to make large banks increase their risks (Gropp et al., 2013). These reasons prompted G20 to reconsider the "too-big-to-fail" status of certain banks and urged the Basel Committee to think a specific reglementation for systemic banks.[5] Shortly after, in November 2011, BCBS published a methodology to identify GSIBs, based on five criteria: size, interconnectedness, availability of substitutes, global activity and complexity (FSB, 2011, BCBS, 2011, 2013).
Recent studies on systemicity under Basel III framework focus their analysis on GSIBs (not DSIBs). Moenninghoff et al. (2015) study the impact of GSIB requirements on the market value of large banks. In an event analysis, this paper gives a first look at the inexplicit aim of those rules, namely market discipline. Indeed, following designation events, negative abnormal returns appear for systemic banks meaning additional market cost for those banks. Schich and Toader (2017), in a difference-in-difference regression over 204 banks (of which 27 GSIBs) for the 2007 to 2015 period, show that GSIB treatment was not able to significantly reduce special government guarantees; although national tightening resolution practices were. Another difference-in-difference regression to analyse GSIB treatment effect is applied by Violon et al. (2017). Their assessment concludes that GSIB designation led to a very significant slowdown in the expansion of their balance sheets, improving leverage ratio and weighing on profitability, whereas risk weighted assets seemed to increase and no impact on yield have been shown. Overall, the literature tends to show that GSIB special treatment and designation are not neutral and have some effects on those banks. Therefore different banks have not the same impact on financial stability and must be differentiated.

Several conclusions can be drawn from this literature. Attempts in assessing the impact of regulatory reforms on financial stability are mainly analytical. Empirical studies are essentially looking at the effects on variables such as profitability or lending but rarely on financial system resiliency. No privileged methodology emerges from the empirical literature whereas theoretical analyses generally use DSGE models. Another aspect of those studies we noticed is the fact that few consider more than one component of Basel III reform and they generally show partition between micro- and macroprudential. Finally, whereas systemicity is at the center of Basel III, few investigations on this topic have been conducted. Our aim in this paper is to overcome those limits of the literature in our empirical investigation. In addition to those general findings, the literature on regulatory impact financial stability seems to bring out two forms of nonlinearities, as detailed below.

[5] Starting from 2010, international regulators initiated works in order to answer the "too-big-to-fail" issue and the quantification of systemicity (FSB, 2010).

2.2 Focusing on nonlinearities

Let us provide some economic intuitions regarding the presence of nonlinearities in regulatory requirements' impact on financial stability. First, as shown by both empirical (Kim and Sohn, 2017, Catalan et al., 2017), and theoretical (Krug et al., 2015, BCBS-MAG, 2010, Quignon, 2016) studies, standalone impacts are not additive. Second, benefits of ratios' increase diminish depending on the level of the concerned ratio: ratios' rises display an asymptotic limit.[6]

In a first place, reglementary public intervention is justified by the need to correct market imperfections: negative externalities, asymmetry of information, self-nuisance and monopolistic/oligopolistic market (Tirole, 2016). In this context, prudential regulation is aimed to both ameliorate stability and prevent from a systemic crisis. To do so, Basel III ratios are expected to answer several issues: (i) solvency ratios ensure perenniality of banks in the case of borrowers' default; (ii) liquidity ratios are aimed to support markets in terms of liquidity in a stress scenario and prevent banks from maturity mismatch risks; (iii) leverage ratios mitigate self-nuisance risks, GSIB surcharges are supposed to prevent from systemic and contagion risks, and disclosure requirements are thought in order to reduce information asymmetries and exacerbate market discipline.

It shoud not be believed that each rule or ratio answers a single stability problem. Actually, every requirement can have an effect on several criteria supporting financial stability. For instance, almost every ratio will help preventing from systemic shocks after a bank's default; or detaining more cash (therefore improving High Quality Liquid Asset and Liquidity Coverage Ratio) is certainly brightening solvency, etc. This explains why one cannot consider the impact of ratios taken independently of each other (Krug et al., 2015): studying Basel III's impact, a variety of ratios should be taken into account. As stressed above, if both R1 and R2, two ratios, are preventing from a same risk then we will have to consider the impact of R1 conditionally to the level of R2 and upside down.

In a second place, another nonlinearity we identify from the literature lies in the impact of a ratio depending on its own level. As a matter, a large strand of the literature investigates the impact of prudential ratios on variables such as profitability and lending. For instance, Mundt (2017) shows that a negative relationship links liquidity to profitability. Moreover, Lee and Hsieh (2013) find an ambiguous link between bank capital and profitability. In a context of exacerbated competitiveness with shadow banking, over-regulation could therefore lead to a weakening financial system. On the contrary, as the last crisis has shown, Basel II requirements were not enough to prevent and absorb an important economic shock. Economically, the marginally decreasing impact of prudential ratios can be justified by the fact that it could prevent banks from financing conveniently the economy. For instance, Bredl (2018) shows that in compensation to provisions for loss, banks offer higher origination rates. Therefore our intuition is the following one: increasing capital and liquidity requirement is essential to improve financial

[6] Moreover, Quignon (2016) highlighted a trend reversal above a certain threshold.

stability; but it is possible that reaching high levels, those ratios create negative externalities. Consequently, enhancing prudential regulation could not only mean increasing prudential ratios but also diversifying the risks taken into account.[7]

Our aim is to assess the implicit hypothesis made by regulators: increasing quality and quantity of capital and liquidity ensures financial stability. Reviewing the literature, we show that there might be two kinds of nonlinearities in Basel III's impact on financial stability: a nonlinearity in parameter for a given ratio, and another one in the influence of a ratio considering the level of the other.

3 Financial stability

3.1 Financial stability: survey and methodology for a composite indicator

Gadanecz and Jayaram (2009) highlight the fact that financial stability is as hard to define as to measure, even though researchers have been taking a serious interest in it for two decades.

The first difficulty in studying financial stability is to capture its definition. A common mistake made in the literature is to define financial stability through the lens of instability. From this point of view, financial stability would describe an economic environment which is not in a financial crisis situation, where volatility is high, or in which trust in the banking system is low. This methodology is often adopted in the analysis of early warning indicators (Bussiere and Fratzscher, 2006, Drehmann and Juselius, 2014).

The definition gave by Bennani et al. (2017) is as follows: "a financial system is stable when it is resilient to episodes of financial stress or real shocks", in other words, resilient to systemic risk. But those authors also introduce the idea that this definition should consider the fact that a stable financial system is a prosperous environment. Indeed, as being in a slump context creates negative externalities and can generate vicious circles, evolving in a strong economic scope might generate positive dynamic on the overall system. But as true as this argument is, it raises an important issue that is the problem of quantifying qualitative measures.

An easier way to make the link between financial stability's definition and its measure is to think in terms of systemic risk. In a comprehensive survey, Benoit et al. (2017) identify three main sources of systemic risk highlighted in the literature: systemic risk-taking (correlation risk, liquidity risk and leverage cycles); contagion (balance-sheet contagion, payment and clearing infrastructures, informational contagion); and amplification (liquidity crises, market freezes and runs). For each category and subcategory, they identify the theoretical framework and the regulation in place to counter each risk. What we can notice is the small number of listed policy evaluation studies. Indeed, since Basel III is a relatively recent agreement, not all policies have

[7] From this point of view, the regulation of shadow banking is a typical example.

been studied. Apprehending systemic risk seems to take more place in the economic literature every year, responding to a need from regulators. The main issue remains the lack of an overall measure in the sense that the proposed ones are generally defined in function of risk type. As Benoit et al. (2017) underline, "more structural models would be useful to regulators".

Regulators also try to better capture financial stability, as notably shown by the intensification of regulators' financial stability reviews and their growing importance. We summarize some of them that have been published recently, to give an overview of regulators' approach of financial stability (see Table 1).

Table 1 – Regulators' recent "Financial Stability Reviews" overview

Jurisdiction	**Frequency**	**Variables/themes adressed recently**
BDF (2018)	Annually since 2006	April 2018: shadow banking and interconnectedness
BDI (2018)	Bi-annually since 2010	April 2018: approach by sector (macroeconomic, national and household / financial, monetary, banks and insurance)
ECB (2017)	Bi-annually since 2002	November 2017: NPL market, cross-border banking area, repo market, financial market volatility
Federal Reserve (2016)	Annually since 2014	February 2017: monitoring risk, systemic institutions, coordination
FSB (2018)	Monthly since 2009	January 2018: cross-border resolution, FinTech, reporting data, compensation tools
IMF (2018)	Bi-annually since 2002	April 2018: monetary policy and inflation, riskiness of credit allocation and house price synchronization
NBB (2017)	Annually since 2002	June 2017: same approach
RBA (2018)	Bi-annually since 2004	April 2018: interest rates and asset prices, credit trends, crypto currency, Basel III capital ratios

Sources: last Financial Stability Reviews of each regulator mentionned.

The large majority of those financial stability reviews gives an insight in particular sectors. Revealing financial instability in some areas, regulators can thereafter orientate their policy on those specific sectors. For instance, during their last financial stability review presentation (April 25th 2018), Banque de France expressed its desire to focus on shadow banking. But regulators are rarely proposing composite indicators that could take into account several sectors. Gadanecz and Jayaram (2009) also make this observation in a survey in which they list developments on quantitative measures of financial stability. Furthermore, they classify key variables from regulators' financial stability reviews into six categories:

1. Real sector: GDP growth, government fiscal position and inflation
2. Corporate sector: total debt to equity, earning to interest and principal expenses, net foreign exposure to equity, corporate default
3. Household sector: household assets and debt, household income, debt service and consumption
4. External sector: real exchange rate, foreign exchange reserves, current account, maturity/currency mismatches
5. Financial sector: monetary aggregate, real interest rates, growth in bank credit, CDS spread, NPLs, concentration of systemic risk/ sectorial concentration
6. Market financial conditions: volatility, change in equity, market liquidity, house prices

Hence, we consider that financial stability cannot be studied using one sector measure apart from others. Following Gadanecz and Jayaram (2009), and the comprehensive co-written handbook on constructing composite indicators by OECD and European Commission-JRC (Joint Research Centre-European Commission, 2008), we rely on Principal Component Analysis (PCA) to build our financial stability indicator. It is worth mentioning that although Dumičić (2016) implemented a PCA to construct a systemic risk accumulation index, this methodology has not been widely used for our purpose.

3.2 Financial Stability Indicator (FSI)

Since no composite index can only consider one sector of the economy in order to measure financial stability, we rely on a Principal Component Analysis.[8] We first provide an overview on our expectations regarding the performance of the financial stability indicator in light of the economic conditions in the recent years. Then, we describe our database and procedure to calculate our FSI.

3.2.1 Expectations

The positive momentum in the developed economies from 2004 to 2007 should reflect a relatively stable system.[9] However, it is highly likely that an indicator of the financial system resilience

[8]See appendix B for a presentation of this methodology and results.

[9]Note that financial instability could raise at the same time in the extent that a stable financial system can still be at risk. That what happened just before the recent financial crisis: while the system was characterised

will decline during this period. At the beginning of the crisis, financial instability is intended to reach high peaks while FSI is supposed to rapidly decrease. During the slump and first political reactions, we expect a slowdown in the decline of the FSI followed by a progressive recovery. According to our literature review, this recovery should be nonlinear and marginally decreasing. We also expect that the FSI will reflect, at least for European countries, the debt crisis. Figures 1 and 2 summarize those intuitions.

Figure 1: expected growth rate of FSI

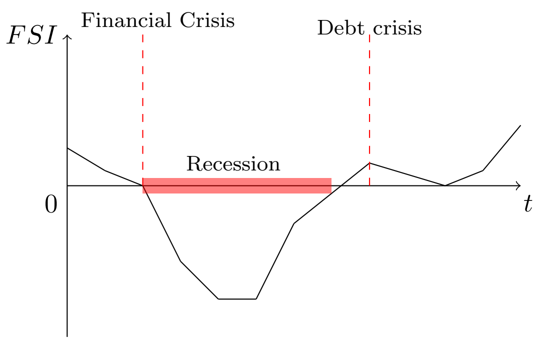
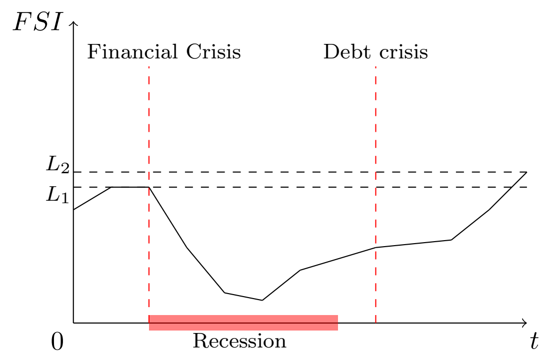


Figure 2: expected level of FSI



As can be seen, these figures show that financial stability is supposed to rise in the aftermath of the financial crisis. Especially, the behaviour of this increase is expected to be nonlinear (describing an asymptote in the long run), and it is intended that financial stability reaches a level superior to the one before the crisis. These two assumptions reflect (i) the results of the theoretical analyses conducted during the implementation of Basel III, and (ii) the regulators' own view that financial stability must be higher than its pre-crisis level (or at least move to a higher level) through regulation.

3.2.2 Financial stability indicator: a "two-step" PCA

Because PCA does not support easily a large number of variables, we start by reducing the number of categories we consider.[10] Whereas Gadanecz and Jayaram (2009) distinguish six categories of variables representative of financial stability, we focus our analysis on the three following main sectors: real, financial and external. Our study goes from 2005 to 2016, for 23 countries.[11] Depending on the availability of data in space and time, we select a first set constituted by 20

by a stable and prosperous environment, the risk of a crisis gradually increased until it triggered the financial collapse.

[10] Above all, let us note that we move the entire panel into growth rates, allowing us to guide our final interpretation of PCA results in terms of financial stability growth rates. This approach also serves as standardization of the sample, and establishes a common measure to all our variables.

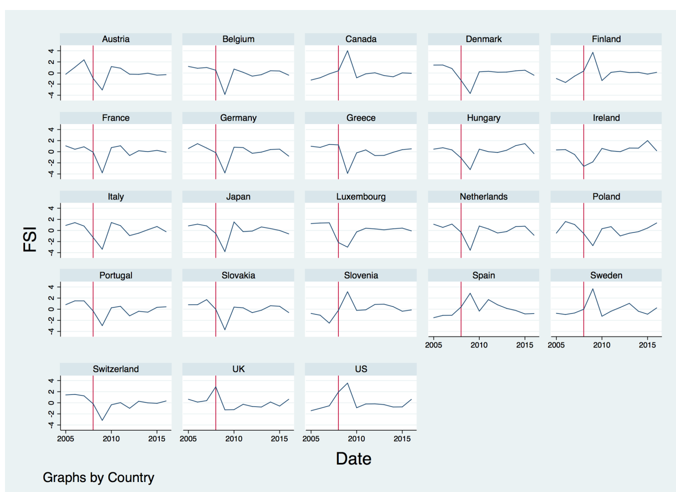
[11] Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Japan, Luxembourg, Netherlands, Poland, Portugal, Slovakia, Slovenia, Spain, Sweden, Switzerland, United Kingdom and United States.

variables (see appendix B.1 for definition and sources). As 20 variables is a large number for a PCA, we select a dataset maximizing correlation in every pair of variables and keeping enough variables to account for the three sectors we retained.[12] This procedure leads us to select 12 variables: local and worldwide GDP, government debt and deficit, Treasury-Eurodollar spread, credit to non-financial institutions, non-performing loans and openness, monetary supply M3, financial stress, foreign reserves and VIX. For these variables we first build sub-indicators for each of the three sectors, and then run a PCA between those three sub-indicators. The common component is therefore supposed to be the better part of financial stability we can extract from our dataset.

The approach we use in order to construct those intermediate indicators follows Nicoletti et al. (1999). It consists in running PCA among variables that compose the sub-group, retrieving the weights given by factor loadings after rotation and applying them to the group. Once this procedure is complete, we run a PCA using the three sub-indicators as the new variables. We implement a new correlation analysis to check that the correlation intra-groups remains enough elevated.[13] We keep the all 12 variables selected in the first correlation analysis and run a PCA in two steps to obtain our final FSI.

Our results are presented in Figure 3. As shown, great geographical homogeneity is present in this analysis. Indeed, the countries of Central, Southern and Eastern Europe present an indicator relatively close to our expectations.[14]

Figure 3 – Financial Stability Indicator (growth rate) - PCA 2 steps



Source: author's calculations. Note: in red, 2008.

[12]See the appendix B.2 for details regarding our approach.

[13]Tables 10 and 11 in appendix B.3 show how many times each variable is significantly correlated to an other one for every countries.

[14]In a robustness analysis, we also performed the one step PCA. The differences between countries in the indicator obtained with this one-step PCA are much more erratic and do not seem to reflect regional specificities.

4 Data and methodology

4.1 Fitch Connect

We use the filters - accounting standards, consolidated data and country - provided by the database to select the data we need. For each bank of the 23 countries, we download data for more than 50 variables from 2004 to 2017. This procedure led us to retain 1646 banks, among which we have 31 GSIBs. The list of GSIBs is published every year by the Financial Stability Board, we retain all banks that have been at least once in this list. Our sample also contains DSIBs, the list of those banks being not as easy to find as the GSIBs one. For Europe we use the European Banking Authority's 2017 list, and retain 111 banks. For Canada we use the Office of Superintendent of Financial Institutions's list called "formally designated as DSIBs", leading us to select 6 DSIBs. Regarding U.S., we use the BIS 2016 RCAP - Regulatory Consistency Assessment Programme - and the Federal Reserve's statistical release of large commercial banks. According to the Dodd-Frank act (2010), the Federal Reserve assesses the systemic importance of subsidiaries of foreign banking organisations with more than USD 50 billion in assets in US subsidiaries. We therefore apply this rule to the list released by the Federal Reserve, leading us to select 25 US DSIBs. The BIS's 2016 RCAP also gives us the 4 Japanese DSIBs.
In order to homogenize and balance our database as much as possible, we use banks' date of creation, study cases of merger and aquisition, and delete banks for which missing data was not justified by one of those two criteria. Applying those restrictions we retain 962 banks among which 31 GSIBs and 80 DSIBs. Because there is too many missing data in 2004 and because our FSI starts in 2005, we do not take this year into account.
In order to aggregate data at the national level, we use the following weighting method:

$$Weight_{i,t,l} = \frac{TotalAssets_{i,t,l}}{\sum_{j=1}^{n_{l,t}} TotalAssets_{j,t,l}}$$

Where $i \in [\![1; n_l]\!]$ designates the bank, $t \in [\![2005; 2016]\!]$ the date, $l \in [\![1; 23]\!]$ the country and $n_{l,t} \in \mathbb{N}$ the number of banks in the country l during the year t. Therefore the sum of all $Weight_i$ for a given t and l is always equal to 1 and the weight of all banks evolves between years in function of the banking system changes. The same method is used in order to aggregate data at subgroups levels (n_l becomes the number of banks in a subgroup for a given country).
Three proxys can be considered for capital and liquidity, respectively.[15] In order to select the two variables to be incorporated in the regression, we compare their evolution with those published by the regulators to focus our analysis on variables showing statistical coherence with what is observed by the BCBS and EBA. Specifically, all capital variables seem to follow the general trend of Basel III capital requirements. We choose Equity to Total Assets, which is the more close to capital ratios. In order to perform robustness checks, we also estimate a number of

[15]Capital: Total Equity, Common Equity and, Equity to Total Assets. Liquidity: Liquid Assets to Wholesale Funding, Liquid Assets to Total Assets, and Wholesale Funding to Total Funding.

regressions with Common Equity. Regarding liquidity, only Liquid Asset to Wholesale Funding follows the same trend as the Liquidity Coverage Ratio as it is relased by the BCBS and EBA.[16]

4.2 Control variables

To avoid an omitted variables bias, we also introduce control variables into the model. These are divided into two groups. On the one hand, we take into account the specific banking characteristics that may have an impact on financial stability. These variables are selected from those we have extracted from the FitchConnect database and we apply the same weighting method as for the variables of interest. The three candidate variables we use are the total loans granted by each bank, their income and their profit rate (measured by the Return On Assets). On the other hand, we control for macroeconomic effects introducing some variables related to financial stability that we have not included in the construction of our FSI indicator. We retain the interbanking interest rate (IIR), inflation rate and national banking Zscores.

4.3 Methodology

The baseline and interaction effect models

We aim at analysing the behaviour of the impact in variations of capital and liquidity on financial stability, using the FSI we constructed. Therefore, the baseline model we estimate is the following one:[17]

$$FSI_{i,t} = \alpha_i + \beta_1 Cap_{i,t} + \beta_2 Liq_{i,t} + \beta_3 X_{i,t} + \epsilon_{i,t} \tag{1.1}$$

where FSI is our Financial Stablity Indicator, Cap and Liq are the main interest variables (capital and liquidity) and X is the vector of control variables.[18] α refers to the constant and ϵ is the error term. According to the literature we discussed earlier, we are expecting β_1 and β_2 to be positive.

The relation linking regulatory requirements and financial stability being potentially nonlinear, we introduce quadratic and interaction terms in this initial model following the standard literature on this kind of realtionship (Kim and Sohn, 2017). Remaining cautious about multicollinearity and interpretation issues associated with those terms, we refer to Balli and Sørensen (2013), as well as Chatelain and Ralf (2012) recommendations.[19] So, in a first step, we center the quadratic and interaction variables in order to facilitate the statistical interpretation of the estimated coefficients. In a second step we test for colinearity as well as for cross dependence. We then reproduce those two steps on the model with orthogonalized variables in the interaction

[16] See the Descriptive Statistics in section 5.1.
[17] This baseline model will be called (1.2) for GSIBs, (1.3) for DSIBs and (1.4) for the other banks.
[18] Profitability, loans, inflation, national zscore and interbank interest rate.
[19] Those authors give recommandations regarding interaction effects and the risks of spurious regression when introducing variables that are highly correlated to each other into a model.

term. In the case of all banks, those models are written as follows:[20]

$$\begin{aligned} FSI_{i,t} = \alpha_i + \beta_1 Cap_{i,t} + \beta_4 (Cap_{i,t} - \bar{Cap}_{i,.})^2 + \beta_2 Liq_{i,t} \\ + \beta_5 (Liq_{i,t} - \bar{Liq}_{i,.})^2 + \beta_6 Interac_{i,t} + \beta_3 X_{i,t} + \epsilon_{i,t} \end{aligned} \tag{2.1}$$

where $Interac$ is the interaction term between capital and liquidity centered variables, and $v\bar{a}r_{i,.}$ refers to the intertemporal mean of each individual, with var detoning the considered variable. From now, centered variables will be called $CenterVar$. Note that models with interaction effect will be refered as $(2..')$. According to the literature, we should expect that β_1 and β_2 to be positive, while the coefficients associated to the quadratic terms should be negative. No sign is expected for the interaction term, but it should be logically positive, the idea being that the higher the ratios increase, the more their combined effect improves financial stability. Regarding sub-groups specifications, because the endogenous variable does not change from a model to another, we can give insight on the contribution of each category of banks to financial stability. From this point of view we expect that GSIBs coefficient will be higher than those associated to the two other types of banks.

Going further in the analysis of nonlinearity, we estimate a PSTR specification. This allows us to focus more precisely on the existence of the regimes mentioned in the literature, the value of the parameters in these regimes and the value of the threshold above which the reversal takes place. This method also makes it possible to study the influence of capital and liquidity between banking subgroups.

The panel smooth transition regression (PSTR) model

PSTR model is used to report on the individual or temporal heterogeneity of a relationship. Specifically, in this specification, the observations in the panel are divided into two regimes depending on whether a transition variable is lower or larger than a threshold value. PSTR is a generalization of the threshold model of Hansen (1999) to account for smooth and gradual transition between the two regimes. We seek to evaluate two types of nonlinearity that the PSTR can capture. On the one hand, we test the interaction of effects (the impact of a variation of one variable on the effect of another), and on the other hand, we evaluate the evolution of the behaviour of the effect of a variable according to its own the level. The PSTR meets these requirements and the heterogeneity we characterize takes the form of a continuous bounded function of a transition variable. For each category of banks, we estimate two PSTR models, depending on our variables of interest (liquidity or capital).

As shown in Table 15 displaying the Hausman (1978) test, the fixed effect specification is retained only for the GSIBs and DSIBs subgroups. As fixed effects must be included in PSTR, we estimate such models only for these two subgroups.

[20] See appendix C.1 for the orthogonalized and the three other subgroups models.

To estimate the PSTR, we rely on Gonzalez et al. (2017) and we use the procedure implemented by Colletaz (2018) in RATS. As previously shown, capital and liquidity are expected to have a positive impact on financial stability, but in a decreasing way, so that this influence could become negative. In addition, we expect the effect of one ratio on the FSI to change with the level of the other. As stressed above, by allowing for heterogeneity, the PSTR makes it possible to invest these two points.
The model is specified as follows:[21]
- GSIBs model:

$$\begin{aligned} FSI_{i,t} = \mu_i &+ \beta_1 GCap_{i,t} + \beta_2 GLiq_{i,t} + \beta_3 DCap_{i,t} + \beta_4 DLiq_{i,t} + \beta_5 OCap_{i,t} \\ &+ \beta_6 OLiq_{i,t} + \beta_7 GX_{i,t} + (\beta_1^* GCap_{i,t} + \beta_2^* GLiq_{i,t} + \beta_3^* DCap_{i,t} \\ &+ \beta_4^* DLiq_{i,t} + \beta_5^* OCap_{i,t} + \beta_6^* OLiq_{i,t}) g(Cap_{i,t}; \gamma, c) + u_{i,t} \end{aligned} \tag{3.1}$$

- DSIBs model:

$$\begin{aligned} FSI_{i,t} = \mu_i &+ \beta_1 GCap_{i,t} + \beta_2 GLiq_{i,t} + \beta_3 DCap_{i,t} + \beta_4 DLiq_{i,t} + \beta_5 OCap_{i,t} \\ &+ \beta_6 OLiq_{i,t} + \beta_7 DX_{i,t} + (\beta_3^* DCap_{i,t} + \beta_4^* DLiq_{i,t} + \beta_5^* OCap_{i,t} \\ &+ \beta_6^* OLiq_{i,t}) g(Cap_{i,t}; \gamma, c) + u_{i,t} \end{aligned} \tag{3.2}$$

where μ_i denotes individual fixed effects and $u_{i,t}$ is the error term. Cap refers to capital variable, Liq refers to liquidity variable, and X refers to control variables. Prefix G (respectively D and O) refers to GSIBs' variables (respectively DSIBs and Others). g is the transition function. It is continuous in the observable variable $Cap_{i,t}$ and normalized to be bound between 0 and 1. γ denotes the transition speed and c is the transition threshold. We follow the same procedure as in Gonzalez et al. (2017) by using the logistic specification for the function:

$$g(Cap_{i,t}; \gamma, c) = \left(1 + exp\left(-\gamma \prod_{j=1}^{m} (Cap_{i,t} - c_j)\right)\right)^{-1} \tag{4.1}$$

Note that the specification is strictly the same for the model in which liquidity is the transtition variable, Cap being replaced by Liq in g. Those models will be refered as (3..').
It is worth mentioning that capital and liquidity variables of smaller groups are also interacted with the transition function, allowing us to account for the interaction between subgroups. We intend at controling for spillover effects from large banks to smaller ones, and therefore, for systemicity and in a way for contagion effects.
Before estimating the PSTR, several specification tests must be implemented. More specifically, tests are conducted (i) to assess homogeneity of the model, (ii) to select the most appropriate

[21] The general model, allowing for more than two regimes is written with an additive form (for capital as the transition variable): $FSI_{i,t} = \mu_i + \beta_0^{'} Z_{i,t} + \sum_{j=1}^{r} \beta_j^{'} Z_{i,t} g(Cap_{i,t}; \gamma, c) + u_{i,t}$, where Z is the vector of interest variables and β are vectors of parameters. This form is used when implementing the specification tests.

transition variable and (iii) to determine the most appropriate number m of regimes. In our case, two transition variables are considered, namely capital and liquidity. After the variables have been centered to eliminate the individual effects, the estimation of the parameters is performed by iteration using the nonlinear least squares method.
The last step of the PSTR procedure consists in two tests: constancy and no-remaining heterogeneity. In order to assess parameters' constancy we test the PSTR specification against a TV-PSTR (time-varying PSTR). To this aim, a second transition function is introduced in the model where the transition variable depends on time. It consists basically in testing if time has a significant effect in the nonlinear dynamic of the relation. The second test is for no remaining heterogeneity which is implemented in the same way as in the specification part. It aims at verifying that all the heterogeneity of the relation has been taken into account.

5 Descriptive statistics and specification tests

5.1 Descriptive statistics

We now present the variables of interest in our model, namely capital and liquidity. We begin by comparing the variables we selected from FitchConnect to the evolution of regulatory ratios published in BCBS and EBA reports. First, we present in Figures 4a and 4b the latest publications on the evolution of these ratios which are only calculated for the years 2010s.

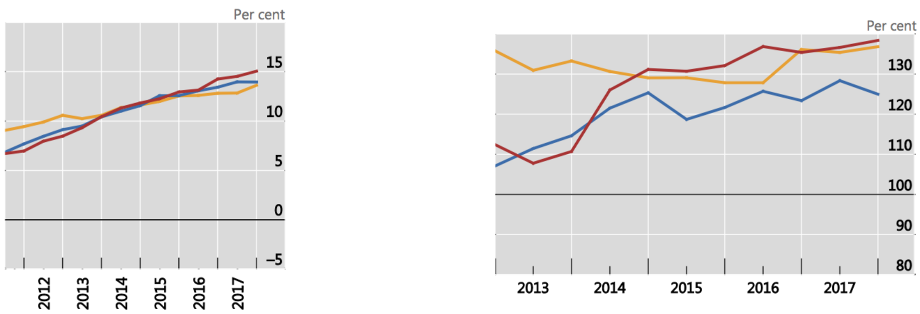
The overall observation is that capital and liquidity ratios have increased since the implementation of Basel III, the rise in capital being more frank than the increase in liquidity. In addition, while the short-term liquidity ratio of "small banks" in Europe has increased since 2011, this trend seems to have stopped since June 2014.
Figure 5 shows the evolution for all banks since 2010 of the variables we have selected to account for these regulatory ratios (see appendix C.2 for the evolution of the three subgroups).

As can be seen, our variables follow a trend close to regulators. However, several remarks can be made. First, the increase in capital is less pronounced. We rely on the ratio of equity to total assets, whereas Basel's solvency ratios use Risk Weighted Assets (RWA) as the denominator. As RWAs are lower than total assets, it is normal for our ratios to be lower than those in Basel. In addition, in order to meet regulatory objectives, regulated banks have sought to increase their ratios by augmenting the numerator (equity) while reducing the denominator (RWAs). We therefore capture the capital increase but not the decrease in weighted assets. On the contrary, for many banks total assets have tended to rise since the crisis.
Second, the liquidity variables are expressed in logarithmic terms[22] in order to cushion the large disparities that could arise between countries. An increase can be perceived while remaining largely smaller than the one observed in EBA and BCBS publications. In order to better high-

[22] Explaining why those values are so low.

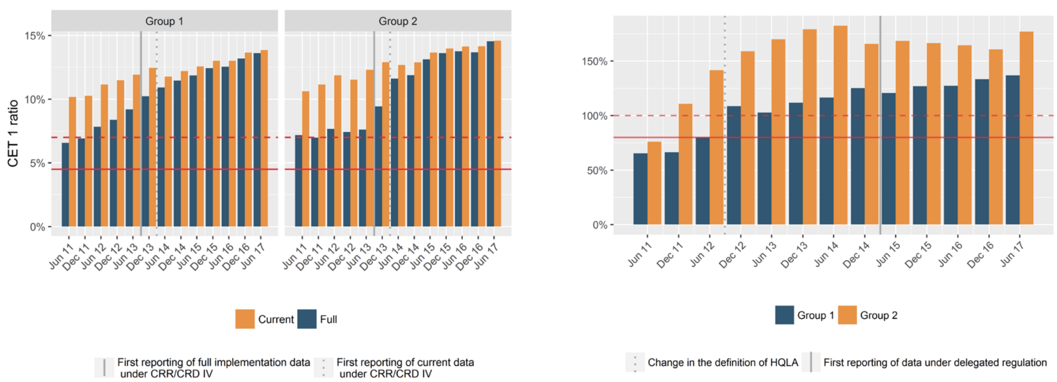
Figure 4 – Capital (Tier 1) and liquidity (LCR) evolution over time and regions

(a) BCBS - Basel III monitoring report, October 2018



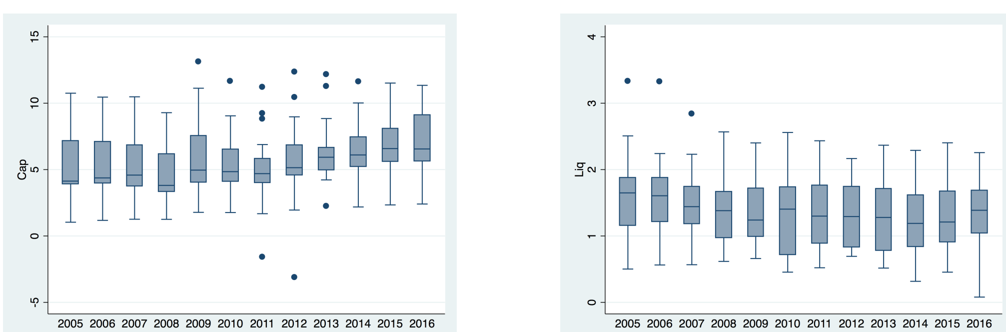
Source: BCBS. In red, blue and yellow, respectively, Europe, Americas and rest of the world

(b) EBA - CRD IV–CRR/Basel III Monitoring Exercise - March 2018



Source: EBA. Group 1 banks are banks with Tier 1 capital in excess of EUR 3 billion and which are internationally active. All other banks are categorised as Group 2 banks.

Figure 5 – Capital and liquidity - All banks - FitchConnect



Source: Author's calculations from FitchConnect data.

light the general trends we display in Figures 6a to 6c medians of capital and liquidity variables for each banks subgroups.

Figure 6 – Capital and liquidity medians

(a) GSIBs - FitchConnect

(b) DSIBs - FitchConnect

(c) Others - FitchConnect

We notice that capital variables seem to follow the same trend as those disclosed by regulators. However, even if for GSIBs our liquidity proxy shows a positive trend as expected, the same conclusion cannot be drawn for the other two groups of banks. For DSIBs and small banks, liquidity decreases describing less continuous movements. To better understand those observations we break down liquidity ratios in Figure 7 (see Figure 15 in appendix C.2 for the capital case).

As can be seen, all three ratios show decreasing numerator and denominator. The fact that liquid assets (numerator) is declining slower than wholesale funding in the GSIBs case explains

Figure 7 – Breaking down liquidity proxies - FitchConnect

Source: Author's calculations from FitchConnect data.

why the GSIBs ratio follows a trend closer to the one expected. For both DSIBs and small banks, liquid assets are declining more rapidly than wholesale funding. It explains the decrease in their liquidity ratios. As shown, liquid assets have negative trends for a large part of our sample, going against what is observed from the LCR. This results from the fact that the numerator of LCR is only composed of high quality liquid assets. Our liquid asset variable accounts for more asset classes and may therefore show a different trend, we thus have to be cautious in the interpretation of our results regarding liquidity.

5.2 Specification tests [23]

There is a debate on the need to test for non stationarity in panel data, as discussed in Baltagi (2008). This debate was born with the growing possibility of being able to extend the temporal dimension of the panels calling into question the supposed homogeneity of pooled regressions. As we are dealing with part of a micro-panel (12 observations for 23 individuals), we are not concerned by these issues. However, for the sake of completeness and rigour, we check the stationarity of our variables. As shown in appendix D.2, although the results are somewhat mixed, we do not transform our original series as (i) we work on a micro panel and (ii) some variables are ratios, which are by definition bounded.

As discussed above, the introduction of quadratic and interaction terms can create multicollinearity within the model. Although we control for this effect by orthogonalizing the terms

[23] The results from specification tests are reported in appendix D

in the interaction variable (as recommended by Balli and Sørensen (2013)), we check for the absence of collinearity using VIF (Variance Inflation Factor).

For all models we find evidence that profitability and income, when simultaneously included in the regression, are at the origin of multicollinearity. Therefore, we remove income from all models.

6 Results

6.1 The baseline model: results of the linear specification

As shown in Table 2, the model (1.1) involving all banks is not conclusive, probably due to the aggregation of bank groups. The capital variable, on the other hand, is significant for models involving GSIBs and DSIBs: it has a small but positive impact on financial stability for both groups. An increase in capital therefore improves financial stability. The same remarks hold about liquidity. Regarding the model (1.4) with small banks, results for capital and liquidty appear no significant which could be due to the fact that this group contains too small and too few banks to capture the impact of their prudential ratios on financial stability.

Table 2 – Results - Linear Model

Variables	Models			
	(1.1)	(1.2)	(1.3)	(1.4)
	All	GSIBs	DSIBs	Others
	re	fe	fe	re
Capital	-0.013	0.445**	0.704***	0.038
	(0.865)	(0.016)	(0.001)	(0.316)
Liquidity	-0.062	1.536***	0.800*	-0.033
	(0.845)	(0.005)	(0.053)	(0.003)
Profitability	0.265**	-0.729**	-0.807***	0.176***
	(0.017)	(0.041)	(0.010)	(0.003)
Loan	-0.057***	-0.054***	-0.063***	-0.018**
	(0.001)	(0.002)	(0.004)	(0.033)
IIR	0.086	0.303	0.214**	0.119*
	(0.212)	(0.015)	(0.030)	(0.079)
Inflation	0.105*	-0.080	0.057	0.081
	(0.072)	(0.516)	(0.645)	(0.163)
Zscore	-0.044	-0.037	-0.088	-0.081**
	(0.258)	(0.535)	(0.177)	(0.016)
Constant	101.855***	97.734***	98.887***	100.3285***
	(0.000)	(0.000)	(0.000)	(0.000)

Source: Author's calculations. Note: p-values in parentheses. Significance at 1%, 5%, 10% identified by ***, **, and *, respectively. fe and re refer to fixed effects and random effects respectively.

6.2 Accounting for interaction effects and quadratic terms

Results of the polynomial models with interaction effects ((2..)) are reported in Table 3. Confirming the findings obtained with the linear specification, when aggregating all banks (model (2.1)), no significant effect appears between capital and liquidity ratios and financial stability. Moreover, the absence of significant effect in the model with small banks is also confirmed in the polynomial model with interaction variable (2.4). It corroborates our intuition that this groups contains too small and too few banks for the model to capture its effect.

Regarding models (2.2) and (2.3), the effect of capital at low levels is positive and significant, in line with the literature: variations of systemic banks' capital improves their solvency and therefore financial stability. In the GSIBs model we also remark that the effect of capital remains significant for high levels: the coefficient associated with the capital quadratic term is negative and smaller than the simple coefficient in absolute terms. This finding is in line with the economic literature in both ways: (i) it corroborates the presence of nonlinearity, and (ii) it is consistent with BCBS-MAG (2010) and Quignon (2016) results regarding the existence of a decreasing effect of the benefit from capital ratios' increase. The impact of liquidity ratios is not as perceived as capital's one. As already mentioned, this is explained by the low variations of our liquidity variable. However, these ratios have a positive influence for low levels in the GSIB model, suggesting that this group contains banks that are large enough for their liquidity ratios (as we measure it) to influence significantly financial stability. The significance of the interaction term in the model with DSIBs might suggest that this group is constituted of banks that have more difficulties in achieving regulatory objectives simultaneously. Consequently, the increase in one ratio may affect their ability to maintain the other through profitability, monitoring or internal managerial policy constraints. With more flexibility, GSIBs can more easily adjust different ratios at the same time, which explains the lack of significance of the interaction term for this group of banks. This confirms that the more systemic a bank is, the higher its influence on financial stability. We will test this intuition in the PSTR regression. Finally, profitability has a negative and significant impact on financial stability in line with the literature dealing with the pursuit of risk.

Overall, our results show that the more systemic a bank is, the more the impact of its capital on financial stability is important. This is consistent with Basel III regulatory framework. But we also show that, at least for GSIBs, there is a turning point in the trend from which the marginal effect of an increase in capital becomes negative. Our interpretation is that GSIBs play a substantial role in financing a large set of diversified activities. Therefore constraining them could create viscosities in the financing market. Let us now investigate this finding in more detail through the estimation of the PSTR model.

Table 3 – Results - Polynomial Model with Interaction Effects

Variables	Models - Before Orthogonalization											
	(2.1) All			(2.2) GSIBs			(2.3) DSIBs			(2.4) Others		
	re			fe			fe			re		
Capital	-0.002	0.021	0.020	0.413**	0.486***	0.459**	0.837***	0.734***	0.846***	0.028	0.033	0.028
	(0.976)	(0.790)	(0.813)	(0.024)	(0.009)	(0.014)	(0.000)	(0.001)	(0.000)	(0.465)	(0.418)	(0.487)
Liquidity	-0.070	0.020	0.026	1.236**	1.281**	1.100*	0.222	0.758*	0.187	-0.017	-0.005	-0.004
	(0.828)	(0.950)	(0.935)	(0.031)	(0.023)	(0.058)	(0.617)	(0.067)	(0.678)	(0.924)	(0.976)	(0.981)
Interaction	0.068	-	-0.017	-0.843*	-	-0.678	-1.606***	-	-1.528***	0.048	-	0.034
	(0.703)		(0.925)	(0.088)		(0.239)	(0.004)		(0.007)	(0.129)		(0.392)
Capital^2	-	0.036**	0.036**	-	-0.212**	-0.168**	-	-0.209*	-0.138	-	0.002	0.001
		(0.070)	(0.016)		(0.050)	(0.140)		(0.250)	(0.415)		(0.695)	(0.851)
Liquidity^2	-	-0.846	-0.841	-	0.143	0.591	-	-0.573	-0.833	-	-0.253	-0.135
		(0.473)	(0.218)		(0.877)	(0.553)		(0.282)	(0.961)		(0.171)	(0.557)
Profitability	0.280**	0.332***	0.328***	-0.668*	-0.890**	-0.791**	-0.569***	-0.956***	-0.679**	0.185***	0.169***	0.179***
	(0.018)	(0.004)	(0.006)	(0.060)	(0.015)	(0.034)	(0.068)	(0.003)	(0.039)	(0.002)	(0.005)	(0.004)
Loan	-0.058***	-0.064***	-0.064	-0.064***	-0.056***	-0.062***	-0.103***	-0.079***	-0.115***	-0.018**	-0.0197**	-0.019**
	(0.001)	(0.000)	(0.000)	(0.001)	(0.002)	(0.001)	(0.000)	(0.001)	(0.000)	(0.035)	(0.030)	(0.033)
IIR	0.088	0.103	0.103*	0.301**	0.371***	0.350***	0.272***	0.326***	0.301***	0.126*	0.121*	0.125*
	(0.202)	(0.135)	(0.138)	(0.015)	(0.004)	(0.007)	(0.006)	(0.010)	(0.003)	(0.063)	(0.074)	(0.066)
Inflation	0.102*	0.090	0.090	-0.109	-0.116	-0.131	0.043	0.033	-0.065	0.100	0.078	0.068
	(0.083)	(0.127)	(0.127)	(0.378	(0.348)	(0.293)	(0.720)	(0.793)	(0.785)	(0.268)	(0.179)	(0.251)
Zscore	-0.047	-0.057	-0.057	-0.042	-0.039	-0.0461	-0.102	-0.065**	-0.086	-0.084**	-0.084**	-0.085**
	(0.238)	(0.146)	(0.154)	(0.478)	(0.509)	(0.448)	(0.108)	(0.320)	(0.184)	(0.013)	(0.013)	(0.012)
Constant	101.88***	102.0***	101.98***	99.09***	98.4***	99.18***	101.29***	99.61***	101.95***	100.44***	100.47***	100.51***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Source: Author's calculations. Note: p-values in parentheses. fe and re refer to fixed effects and random effects respectively.
Significance at 1%, 5%, 10% identified by ***, **, and *, respectively.

6.3 Nonlinearities and cumulative impact: results of the PSTR regression

The first step consists in testing homogeneity and nonlinearity. As shown in Tables 18 and 19 in appendix E.1, homogeneity is rejected and two regimes are retained for the two transition variables. Table 4 reports the results of PSTR estimation[24] and Figures 8 to 11 display the transition functions.

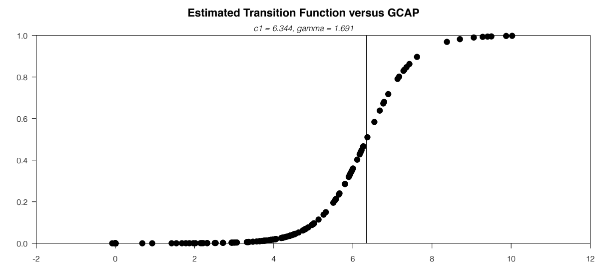
Table 4 – PSTR - estimation resuts

Model - Q	(3.1) - Capital		(3.1') - Liquidity		(3.2) - Capital		(3.2') - Liquidity	
Variable	Coeff	Robust SE	Coeff	Robust SE	Coeff	Robust SE	Coeff	Robust SE
Coefficients in the first regime (effect for low values of the transition variable)								
Profitability	-0.694***	0.265	-0.814***	0.287	-0.569*	0.343	-0.537	0.333
Loan	-0.037***	0.013	-0.035**	0.014	-0.124***	0.029	-0.102***	0.029
Inflation	0.054	0.052	0.053	0.053	0.088	0.055	0.038	0.057
Zscore	-0.068	0.046	-0.065	0.049	-0.102**	0.079	-0.105**	0.049
IIR	0.286***	0.074	0.274***	0.077	0.256***	0.073	0.318	0.080
GCAP	0.027	0.180	0.674***	0.166	0.318*	0.166	0.154	0.154
GLIQ	1.568***	0.499	2.192***	0.715	0.794	0.537	1.237**	0.553
DCAP	0.116	0.145	0.161	0.168	1.623**	0.840	0.600***	0.159
DLIQ	-0.006	0.376	-0.012	0.455	1.731	1.598	1.592***	0.534
OCAP	0.079**	0.041	0.060	0.044	0.096**	0.043	0.069	0.049
OLIQ	0.119	0.175	-0.028	0.182	-0.116	0.184	-0.167	0.186
Coefficients in the second regime (effect when the transition variable increases)								
GCAP$\times g(Q,\gamma,c1)$	0.226	0.704	-0.835***	0.287	-	-	-	-
GLIQ$\times g(Q,\gamma,c1)$	-0.875	2.280	0.223	0.846	-	-	-	-
DCAP$\times g(Q,\gamma,c1)$	0.677	0.438	0.214	0.232	-0.734	0.847	-0.481***	0.198
DLIQ$\times g(Q,\gamma,c1)$	1.532	1.518	-0.172	0.657	-1.739	1.588	-1.557	0.626
OCAP$\times g(Q,\gamma,c1)$	0.497	0.384	-0.116	0.156	-0.326***	0.116	0.053	0.039
OLIQ$\times g(Q,\gamma,c1)$	-4.643***	1.930	1.000	0.517	0.785*	0.447	1.891***	0.497
Sum of coefficients when transition=1 (overall effect, both regimes taken into account)								
GCAP	0.253	0.725	-0.161	0.262	-	-	-	-
GLIQ	0.692	2.302	2.416***	0.843	-	-	-	-
DCAP	0.794*	0.470	0.376	0.231	0.889***	0.180	0.118	0.212
DLIQ	1.526	1.398	-0.184	0.483	-0.008	0.374	0.035	0.641
OCAP	0.577	0.380	-0.056	0.151	-0.230**	0.107	0.122***	0.043
OLIQ	-4.524***	1.909	0.971**	0.505	0.669	0.409	1.723***	0.474
γ	1.691	0.317	105.707	79.805	5.053	1.275	15.695	0.000
c_1	6.343	0.287	1.848	0.011	2.999	0.082	1.675	0.0352

Source: Author's calculations. g refers to the transition variable. Significance at 1%, 5%, 10% identified by ***, **, and *, respectively.

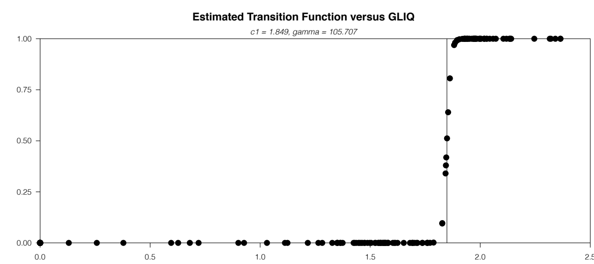
[24] We do not report the estimation of model (3.3') due to convergence issues.

Figure 8 – Transition function - Capital - model (3.1)



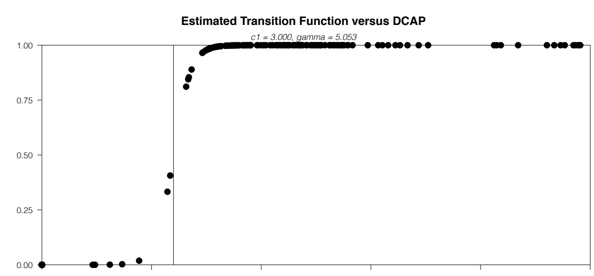
Source: Author's calculations.

Figure 9 – Transition function - Liquidity - model (3.1')



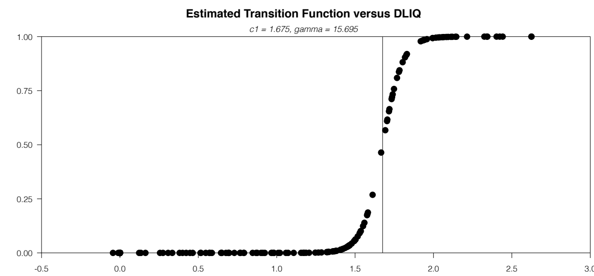
Source: Author's calculations.

Figure 10 – Transition function - Capital - model (3.2)



Source: Author's calculations.

Figure 11 – Transition function - Capital - model (3.2')



Source: Author's calculations.

Looking at GSIBs (models (3.1) and (3.1')), capital and liquidity appear positive and significant for low levels of both transition variables. It confirms the regulators' intuition: increasing regulatory ratios improves financial stability. Nonlinearity in the dynamics of capital and liquidity impact is not captured by the model. Indeed, if the impact of those ratios has an asymptotic limit, it should be more difficult to capt their effect for high values. Moreover, no negative significant impact is captured either, which leads us to reject the hypothesis that there is a reversal of the impact of regulation on stability. Regarding interaction effects, model (3.1') shows that there is a significant and negative effect of liquidity on capital's impact, equal to -0.835, while the opposite is not true. The overall impact of GSIBs' liquidity is found significant and positive in the model (3.1'), equal to 2.416. This corroborates the results of the polynomial model (2.2): GSIBs' liquidity has a significant impact on financial stability.

Those results are consistent with our intuitions and with the economic literature: (i) the impact of a ratio marginally decreases as this ratio increases, and (ii) the accumulation of rules can create negative externalities. The transition appears smooth in the model (3.1) with capital as a transition variable (see Figure 8), and the threshold ($c_1 = 6.343$) is in line with the literature.[25] However, the transition function in the model (3.1') shows abrupt transition with few observations in the second regime (see Figure 9). We attribute this finding to our liquidity measure as the logarithmic transformation may have overwritten the transition speed.

Regarding models (3.2) and (3.2') which assess nonlinearities in DSIBs' ratios, results also confirm that for low levels, capital and liquidity improve financial stability. Regarding the impact in the second regime (with high values for both transition variables), findings are similar to those obtained with the GSIB model: (i) each ratio has a marginally decreasing, but not negative, impact (which can be seen by the absence of strong significant effect for high values of capital and liquidity), and (ii) an interaction negative effect appears from liquidity to capital (with a

[25]In fact it is slightly too low, which is related to the fact that our numerator is composed of total assets and not risk-weighted assets only.

coefficient of -0.481). Note that, as shown by Figure 10, the low regime contains very few observations, a fact that may explain the low threshold value in the case of capital as a transition variable.

Regarding the interactions between groups of banks, capital of both GSIBs (-4.643) and DSIBs (-0.326) impacts negatively the group of small banks, while liquidity has positive effects (0.971 for GSIBs and 0.122 and 1.723 for DSIB effect on small banks). This could be explained by the fact that if important banks are highly resilient on a liquidity point of view, small banks have better access to the interbank market and therefore meet their regulatory requirement easier. On the other hand, capital ratios concern the way a bank finance itself. Therefore, it might be possible that the more important banks have to provision their capital, the fewer are opportunities for smaller banks to finance themselves.

It is worth mentioning that for all models, bank profitability has a significant and negative impact on stability. This can be explained by the fact that the pursuit of profit sometimes encourages risk-taking behaviours that lead to an increase in exposure. These findings corroborate those obtained with the interaction effect model.

Finally, as shown in Table 20 in appendix E.2, our models are well specified since in each case, the alternative TV-PSTR model is rejected, and it seems that all heterogeneity has been taken into account.

6.4 Robustness checks

We check for the robustness of our findings to the choice of the endogenous variable.[26] Specifically, we consider two variables, which are representative of part of financial stability: the Interbank Interest Rate (IIR) and the national bank Zscore.[27]

As shown in Table 5,[28] the variables of interest in the model (2.1*), when considering IIR as the dependent variable, are not significant, corroborating the fact that an aggregated model cannot take into account each group special characteristics. In the GSIB model (2.2*), results obtained are in line with the interaction model (2.2): the effect of capital ratio on IIR, -0.809, is negative and significant for low levels and becomes positive but absolutly lower for high levels taking a value of 0.258. In the model with DSIBs, we also find that low levels of capital ratio impact positively the IIR, the coefficient being equal to -0.615, and that high levels of capital impact negatively the IIR (0.260). In model (2.4*) with small banks, the impact of capital on financial stability as proxied by IIR is negative for low levels but not significant for high levels. Liquidity's impact is either too small or unperceived in all models due to lack of variations, consistent with our previous observations. Those findings using IIR as the dependent variable are all corroborating our previous results, as well as those obtained in the literature.

[26]Note that using orthogonalization to control for cross-dependence and multicolinearity lead to similar results.

[27]IIR is representative of interbank trust in each other and Zscore of the distance to default. Therefore, an improvement of financial stability corresponds to a decrease in IIR and an increase in Zscore.

[28]We only report the results with interaction effects, due to convergence issues with the PSTR specification.

Table 5 – Robustness - Polynomial Model with Interaction Effect

Variables	(2.1*) All		(2.2*) GSIBs		(2.3*) DSIBs		(2.4*) Others	
	fe	fe	fe	re	fe	re	re	fe
	IIR	Zscore	IIR	Zscore	IIR	Zscore	IIR	Zscore
Capital	-0.408***	1.094***	-0.809***	0.572**	-0.615***	1.283***	-0.053*	0.315***
	(0.000)	(0.000)	(0.000)	(0.027)	(0.001)	(0.000)	(0.063)	(0.000)
Liquidity	0.011	-1.365***	0.284	-4.257***	0.134	-3.327***	0.426***	0.265
	(0.969)	(0.002)	(0.484)	(0.000)	(0.746)	(0.000)	(0.007)	(0.425)
Interaction	-0.269	0.766***	-0.633	-0.779	0.850*	-0.522	-0.045	0.039
	(0.107)	(0.002)	(0.117)	(0.342)	(0.094)	(0.446)	(0.219)	(0.569)
Capital^2	-0.008	0.054***	0.258***	0.005	0.260**	0.412**	-0.004	-0.009
	(0.558)	(0.007)	(0.001)	(0.972)	(0.017)	(0.011)	(0.462)	(0.365)
Liquidity^2	1.201*	1.554*	0.593	1.734	-0.064	0.039	-0.105	0.089
	(0.054)	(0.092)	(0.398)	(0.227)	(0.927)	(0.970)	(0.617)	(0.825)
Profitability	0.430***	0.549***	1.694***	1.872***	0.789***	1.214***	-0.000	0.286***
	(0.000)	(0.044)	(0.000)	(0.000)	(0.007)	(0.005)	(0.001)	(0.007)
Loan	0.004	0.048*	-0.004	-0.032	0.033	-0.067**	2.26e-06	0.035*
	(0.136)	(0.056)	(0.748)	(0.208)	(0.164)	(0.027)	(0.917)	(0.091)
Inflation	0.481***	-0.189**	0.365***	-0.146	0.480***	-0.013	0.517***	-0.308***
	(0.000)	(0.018)	(0.000)	(0.417)	(0.000)	(0.935)	(0.000)	(0.002)
Zscore	-0.006	-	-0.135 ***	-	-0.158***	-	-0.057***	-
	(0.692)		(0.001)		(-0.158)		(0.007)	
IIR	-	0.037	-	-0.577***		-0.379***	-	-0.174
		(0.692)		(0.001)		(0.003)	-	(0.136)
Constant	2.511**	5.561***	5.055***	11.298***	3.683**	14.087***	1.310***	8.211***
	(0.019)	(0.000)	(0.000)	(0.000)	(0.011)	(0.000)	(0.009)	(0.000)

Source: Author's calculations. Note: p-values in parentheses. fe and re refer to fixed effects and random effects respectively. Significance at 1%, 5%, 10% identified by ***, **, and *, respectively.

Turning to the case where financial stability is proxied by Zscore,[29] the results for capital and liquidity ratios in subgroups models are in line with our previous findings and the literature. Capital has a positive and marginally decreasing impact on financial stability: in the case of GSIBs the impact is positive for low levels of capital and becomes non-significant when getting higher, and in the case of DSIBs, the impact of capital is positive in both regimes but becomes lower for high values of capital (going from 1.283 to 0.412). However, liquidity shows strong negative and significant effect which is in contradiction with our previous results and the literature. Z-score integrating profitability in its calculation, a variable we also introduced in our set of control variables, endogeneity issues can therefore be at play.

In both models, the interaction effect shows unperceived impact on financial stability. Finally, for all models, our findings confirm that banks' profitability is an important determinant of financial stability.

[29] For the sake of transparency, note that as Zscore integrates profitability which is also introduced as a control variable, in its calculation, endogeneity issues may be at play. The interpretation of the models is thus subject to some caution.

7 Conclusion

In this paper, we aim at investigating regulators' assumption, stating that increasing banks' capital and liquidity improves financial stability. To this end, we propose a measure of financial stability based on a principal component analysis, and explain this composite indicator using capital and liquidity variables. Paying particular attention to nonlinear effects of these variables on financial stability, we estimate a polynomial model with interaction effects and a panel smooth transition regression model.

Our findings show that the impact of capital on financial stability is nonlinear: capital has a positive impact on financial stability for low levels, and this effect becomes weaker in most cases when capital increases. Turning to the liquidity variable, the same conclusion can be drawn. We find that interactions exist between groups of banks, going from important banks to smaller ones. We also show that the impact of prudential ratios on financial stability is different from a group to another. This justifies regulators' approach of treating important banks (GSIBs and DSIBs) differently. Finally, we show that profitability plays a significant role in financial stability.

Our findings have important policy implications. First, it is mandatory for regulators to have the necessary tools to carry out an assessment of the rules they put in place. Measuring financial stability by variables referring to regulatory requirements that are intended to improve financial stability - as proposed by the IMF - does not seem fully satisfactory. From a resiliency point of view, regulators should propose an aggregated and comprehensive measure of financial stability, which could evolve in time according to economic developments and new springs of instability. In this way, reglementation could prevent the economy from new shocks and prepare it to absorb them. Second and following the work carried out by the FSB since 2017, there is a need to assess the impact of regulations in order to adjust them if necessary to ensure the stability of the system. This analysis must account for nonlinear effects, in particular interactions between rules.

A promising extension of this paper would be to work on non-aggregated banks, by analysing the impact of capital and liquidity ratios on individual z-scores. By the way, this will increase the number of observations and, in turn, improve the reliability of our findings. Finally, integrating contagion effects in the analysis will be of interest for future research to account for resiliency, in particular when measuring financial stability.

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A Literature review

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Table 6 – Literature: Basel III impact, nonlinearities

Authors	Variables	Impact/result	Type	Model and Data
Angelini et al. (2015)	Cap, liq, buffer	NL ⊕	Analytical	DSGE
Carlson et al. (2013)	Cap, LR, loan growth	⊕	Empirical	FE, MSA-FE, US, 2001-2009, FDIC and Call reports
Catalan et al. (2017)	Cap, lending	NL ⊕	Empirical	FE, 2SFE, Indonesia, 2001Q1-20015Q4, Bank of Indonesia
Cornett et al. (2011)	Cap, liq, loan groth, credit	⊕	Empirical	FE, US, 2006Q1-2009Q2, Call Reports and FFIEC
Giordana and Schumacher (2017)	Z-score, ROA, cap, liq	⊕/⊝	Empirical	Sys-GMM, 2003Q2-2011Q3, BCL
Kim and Sohn (2017)	Cap, liq, loan growth	NL ⊕/⊝	Empirical	FE, US, 1993Q1-2010Q4, FDIC SDI
Krug et al. (2015)	Cap, liq, LR, GSIB	NL ⊕/⊝	Analytical	Agent-Based Model
Lee and Hsieh (2013)	CAP, Profitability	⊕/⊝	Empirircal	GMM
Mundt (2017)	Liqu, profitability	⊝	Empirical	GMM
Quignon (2016)	Cap, Liq, GDP, GSIB	NL ⊕/⊝	Analytical	DSGE
Tirole (2016)	-	-	Book	Market imperfections

Note: DSGE, Dynamic Stochastic General Equilibrium; PP, position paper; LR, Leverage Ratio; FE, fixed-effect; MSA-FE, Measurement system analysis FE; 2SFE, Two Step FE; NL, Nonlinearities: GMM, Generalized Method of Moments. ⊕/⊝: positive/negative effect

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Table 7 – Literature: Systemicity

Authors	**Type**	**Method**	**Content**
BCBS (2011, 2013), FSB (2011)	RP	Arithmetical average on market share	GSIB designation: calculation of GSIB score
Brandao et al. (2013)	Empirical	FE - IV	Government guarantees positive impact on Moral hazard
FSB (2010)	RP	-	Quantification of systemicity
Gropp et al. (2013)	Empirical	SUR	Removal of a government guarantee negative impact on risk-taking
Moenninghoff et al. (2015)	Empirical	Event study	GSIB special treatment negative impact on market value
Schich and Toader (2017)	Empirical	Diff-in-diff	No significant impact of GSIB treatment on government guarantee. Positive impact of national resolution.
Violon et al. (2017)	Empirical	Diff-in-diff	Negative impact of GSIB treatment on balance sheet expansion and on profitability. No impact on yield.

Note: RP, Regulation Paper; FSB, Financial stability board; FE, Fixed-Effect; IV, Intrumental Variables; TLAC, Total-loss-absorbing-capacity; SUR, Seemingly Unrelated Regressions

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Table 8 – Literature: financial stability

Authors	**Type**	**Topics**	**Methodology and conclusions**
Bennani et al. (2017)	Book	Macroprudential policy	-
Benoit et al. (2017)	Survey	Systemic Risks	Three origins to systemic risks: systemic risk taking, contagion and amplification
Bussiere and Fratzscher (2006)	Empirical	Early warning indicators	Multinomial logit. Variables: overvaluations, lending boom, growth, current account, short-term debt/reserves, domestic credit, financial interdependence
Drehmann and Juselius (2014)	Empirical	Early warning indicators	Non-parametric. Variables: credit to GDP, debt to service ratio, non-core liability

Dumičić (2016)	Empirical	Financial stability indicator	PCA. 6 groups of variables (15[30]): banks, corporate, households, government, macroeconomic developments, system resilience
Gadanecz and Jayaram (2009)	Survey	Financial stability measures	PCA, CFA, weighted index, cumulative simulation function, variance equal method
IMF, ECB, Fed, BdF, BD'I, RBA	FSR	Stability indicators/secors of interest	See Table 1
Joint Research Centre-European Commission (2008)	Survey	Methodology for composite indicators	Multivariate analysis (among which: PCA), normalisation, weighting methods, aggregation methods, uncertainty and sensitivity analysis

Note: PCA, Principal Component Analysis; CFA, Common factor Analysis; PP, Position Paper; NPL, Non-Performing Loans; CNB, Central National Bank, FSR, Financial Stability Review

[30]The variables are: NPL/total loans for corporate and households, ROA banks, inventories/operating income, short-term asset turn over ratio, profitability, share of interest expense in income, registered unemployment rate, real wage bill, tax revenues, annual rate of change in consumer price, country risk premium, capital assets, bank reserves with the CNB/banks assets, international reserves/GDP

B Financial Stability Indicator: results, technical appendices and robustness discussion

B.1 Data description

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Table 9 – Data description

Topic	Variable name	Measure	Comment	Source
• External sector	Openness	Percentage of GDP	Sum of exports and imports of goods and services measured as a share of gross domestic product.	World Bank
• External sector	Current Account (CA)	Percentage of GDP	Sum of net exports of goods and services, net primary income, and net secondary income.	World Bank
• External sector	Real Effective Exchange Rate (REER)	Index based on 2010=100	Weighted average of a country's currency in relation to an index or basket of other major currencies, adjusted for the effect of inflation.	CEPII[31]
• External sector	Foreign reserves (FXR)	Level/US dollar		IMF[32]
• Financial sector	Credit to non-financial sector (CredNF)	Percentage of GDP	Collected at the end of period. Adjusted fo breaks.	BIS
• Financial sector	Real Interest Rate (RIR)	Percentage	Interest rate adjusted to remove the effect of inflation.	OECD
• Financial sector	Financial Integration (FI)	Percentage of GDP	Calculated as the sum between total liabilities and total assets in percentage of GDP in local currency (Lane and Milesi-Ferretti (2018) methodology).	IMF
• Financial sector	Non-performing loans to total gross loans (NPL)	Percentage	Value of nonperforming loans divided by the total value of the loan portfolio (including nonperforming loans before the deduction of specific loan-loss provisions).	IMF (GFSR)

[31] EQCHANGE database, Couharde et al. (2018)
[32] Lane and Milesi-Ferretti (2018)'s database

• Financial sector	Interbank interest rate (IIR)	Percentage	Gives the level of trust in the interbanking sector	Fed
• Financial sector	Financial Stress (Stress)	Growth rate	Capture local-regional financial stress. CISS for European countries / Fed Saint Louis for US and Canada.	ECB and Fed
• Financial sector	Banks' z-score (Zscore)		It captures the distance to default of a country's commercial banking system.[33]	World Bank
• Financial sector	Volatility Index (VIX)	Percentage	Captures the volatility risk and is supposed to report for financial integration on the European/Japan side.	Fed
• Financial sector	Treasury-Eurodollar Spread (TEDS)	Percent	Calculated as the spread between 3-Month LIBOR based on US dollars and 3-Month Treasury Bill. The series is lagged by one week because the LIBOR series is lagged by one week due to an agreement with the source. In our study we used annual average.	Fed
• Financial sector	House Prices (HP)	Nominal/US dollar	Those data were not satisfying and therefore not retained for the study.	BIS
• Real sector	Growth rate of gross domestic product per capita (GDP)	Growth rate	Annual percentage growth rate of GDP at market prices based on constant local currency. Aggregates are based on constant 2010 U.S. dollars.	World Bank
• Real sector	Inflation (Inf)	Growth rate	Sustainable, general, self-sustaining increase in the prices of goods and services.	World Bank
• Real sector	Public Deficit (GovDef)	Percentage of GDP	Fiscal position of government after accounting for capital expenditures.	World Bank

[33] Z-score compares the buffer of a country's commercial banking system (capitalization and returns) with the volatility of those returns. It is estimated as $\frac{ROA+\frac{equity}{assets}}{sd(ROA)}$; sd(ROA) is the standard deviation of ROA. ROA, equity, and assets are country-level aggregate figures Calculated from underlying bank-by-bank unconsolidated data from Bankscope.

• Real Sector	Broad money M3 (M3)	Index based on 2010=100	Includes currency, deposits with an agreed maturity of up to two years, deposits redeemable at notice of up to three months and repurchase agreements, money market fund shares/units and debt securities up to two years.	OECD
• Real sector	World GDP growth rate per capita (WGDP)	Growth rate	Same variable for every countries	World Bank
• Real sector	General government debt (GovDebt)	Percent (GDP)	Amount of a country's total gross government debt as a percentage of its GDP. It is an indicator of an economy's health and a key factor for the sustainability of government finance.	OECD

Note: all variables were found available for the period 2004-2016 except for rare observations. If necessary, we applied a projection on the previous (or next) years of the missing value in order to obtain a completely balanced panel.

B.2 Principal component analysis (PCA)

The principle of this multivariate technique is to capture the common variation from a set of variables correlated[34] with each other, and to resituate it in the form of orthogonal variables. Those are called principal components. Therefore, implementing principal component analysis on variables representing commonly financial stability, we intend to extract an indicator of financial stability.[35] Besides, PCA allows us to considerably reduce the number of variables considered. Therefore, it fits our study since we need to account for different sectors and variables through one single indicator.

Overall PCA extracts most information of a dataset, reduces its size and allows for a better interpretation of the panel. To do so, principal components, or factors, are obtained from a singular value decomposition of the original dataset. The procedure computes factors in such a way that the first component is associated to the highest explained variance and higher eigenvalue, the second one corresponds to the second highest variance and eigenvalue, and so on for the other factors.

Several criteria exist to select the number of components to retain. The most common one is Kaiser (1958) criterion which advise to drop all factors with eigenvalue below 1. This approach regularly leads to results close to those of the scree plot method (Cattell, 1966) or the elbow method. Typically, researchers retain enough components to explain at least 80 to 90% of the variance.

It is common to perform a rotation after factors' selection. The most popular method is the *varimax* methodology (Kaiser, 1958), which considers that components are associated to few large loadings[36] and many small loadings. *Varimax* procedure looks for a linear combination of the original factors maximizing the variance of the loadings.

B.3 Correlation analysis

In this subsection, we give insight on our correlation analysis and data selection. We have to deal with an important number of variables since financial stability measurement requires to take into account many sectors. From variables we need to select those which are strongly correlated with each other for all countries.

To this end, we follow a procedure of variable selection based on correlation analysis. First, and for all 20 initial variables, we calculate the correlation matrices. For each of them and for all countries, we associate a new matrix scoring 1 if the correlation for a given variable pair is statistically significant, and 0 if not.[37] Therefore, summing all the new matrices, we have a general symmetric table, a hit map after removing the first variables (see Table 10) giving for

[34] See Abdi and Williams (2010).

[35] As we shown it in the literature review, this approach is also recommended in Gadanecz and Jayaram (2009).

[36] The loadings are the correlation coefficients between the principal components and the variables, giving contribution of an observation to a component.

[37] The new matrices are also scoring 0 on the diagonal ($corr(X_i; X_i) = 1$).

each line i and each raw j ($i \neq j$) the number of times a couple of variables is being statistically significantly correlated among the 23 countries. This approach reveals wich variables are the most correlated with each other for all our panel. Then, we sum for each variable the score it obtained with all the other ones and use this score to conduct our first selection. Using this procedure, we select 12 variables (GDP, world GDP, M3, government deficit, government debt, TEDS, stress, credit to non-financial institutions, non-performing loans, openness, foreign exchange rate and VIX) and reject the following 8 variables: inflation, Z-score, real interest rate, financial integration, current account, real effective exchange rate, house prices and interbank interest rate.

Table 10 – Hit map after removing lowest correlated variables

	GDP	WGDP	M3	GovDef	GovDebt	TEDS	Stress	CredNF	NPL	Openess	FXR	VIX
GDP	0											
WGDP	21	0										
M3	0	1	0									
GovDef	11	13	1	0								
GovDebt	15	11	3	7	0							
TEDS	21	23	0	5	9	0						
Stress	0	0	17	3	1	0	0					
CredNF	9	9	2	9	10	6	4	0				
NPL	10	9	1	8	12	6	4	7	0			
Openess	14	20	0	11	3	7	0	2	4	0		
FXR	9	11	1	6	2	4	0	2	4	7	0	
VIX	0	0	16	3	0	0	22	3	4	0	0	0
Total	110	119	43	75	72	83	53	64	71	68	46	48

Source: author's calculations. Interpretation: cell i, j gives the number of times the variable pair (X_i, X_j) is significantly correlated for all 23 countries. For instance: out of 23 countries, there are 21 for which GDP per capita is significantly correlated with world GDP.

Note: in red scores up to 8, in yellow scores going from 5 to 7, in light blue scores going from 1 to 4, and in blue scores equal to 0.

As implementing PCA on this set of 12 variables does not lead to conclusive results, we separate the dataset into three sectors. Before conducting the two steps PCA, we had to verify that variables were still higly correlated inside each sector. We adopt the same approach as described above for each group, and show that the 2 steps PCA is relevant (see Table 11).

Table 11 – Subsectors' correlation analysis

Financial sector

	Stress	CredNF	NPL	VIX	M3
Stress	0				
CredNF	4	0			
NPL	6	7	0		
VIX	22	3	4	0	
M3	17	2	2	16	0
Total	49	16	19	45	37

Real sector

	GDP	WGDP	GovDebt	TEDS
GDP	0			
WGDP	20	0		
GovDebt	15	10	0	
TEDS	21	23	8	0
Total	56	53	33	52

External sector

	Openness	FXR	GovDef
Openness	0		
FXR	7	0	
GovDef	11	6	0
Total	18	13	17

Source: author's calculation.

C Models and descriptive statistics

C.1 Models: sub-groups interaction

Here we present the models with interaction effects and quadratic terms for the three subgroups of banks. Models with the orthogonalized interaction variables are referred as (2.2') for GSIBs, (2.3') for DSIBs and (2.4') for others.

- GSIBs:

$$\begin{aligned} FSI_{i,t} = \alpha_i + \beta_1 GCap_{i,t} + \beta_4 GCenterCap^2_{i,t} + \beta_2 GLiq_{i,t} \\ + \beta_5 GCenterLiq^2_{i,t} + \beta_6 GInterac_{i,t} + \beta_3 GX_{i,t} + \epsilon_{i,t} \end{aligned} \tag{2.2}$$

- DSIBs:

$$\begin{aligned} FSI_{i,t} = \alpha_i + \beta_1 DCap_{i,t} + \beta_4 DCenterCap^2_{i,t} + \beta_2 DLiq_{i,t} \\ +\beta_5 DCenterLiq^2_{i,t} + \beta_6 DInterac_{i,t} + \beta_3 DX_{i,t} + \epsilon_{i,t} \end{aligned} \tag{2.3}$$

- Others:

$$\begin{aligned} FSI_{i,t} = \alpha_i + \beta_1 OCap_{i,t} + \beta_4 OCenterCap^2_{i,t} + \beta_2 OLiq_{i,t} \\ +\beta_5 OCenterLiq^2_{i,t} + \beta_6 OInterac_{i,t} + \beta_3 OX_{i,t} + \epsilon_{i,t} \end{aligned} \tag{2.4}$$

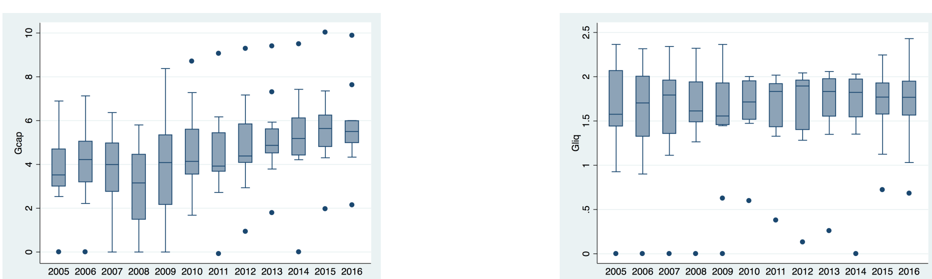
where the letters G, D and O are standing respectively for GSIBs, DSIBs and Others. For each sub-group, the model is estimated before and after the orthogonalization process.
The orthogonalized interaction model with quadratic terms in the case of all banks is written as follows:

$$\begin{aligned} FSI_{i,t} = \alpha_i + \beta_1 Cap_{i,t} + \beta_4 (Cap_{i,t} - \bar{Cap}_{i,.})^2 + \beta_2 Liq_{i,t} \\ +\beta_5 (Liq_{i,t} - \bar{Liq}_{i,.})^2 + \beta_6 Interac^{\psi}_{i,t} + \beta_3 X_{i,t} + \epsilon_{i,t} \end{aligned} \tag{2.1'}$$

where $Interac^{\psi}$ is the interaction term between capital and liquidity orthogonalized variables. Following Balli and Sorensen's (2013) recommendation: $Interac = Cap^{\psi} Liq^{\psi}$, where $Cap^{\psi} = M_{cap} Cap$ and M_{cap} is the residual from regressing Cap on a constant (and upside down for Liq^{ψ}). $v\bar{a}r_{i,.}$ refers to the intertemporal mean of each individual, with var denoting the considered variable.

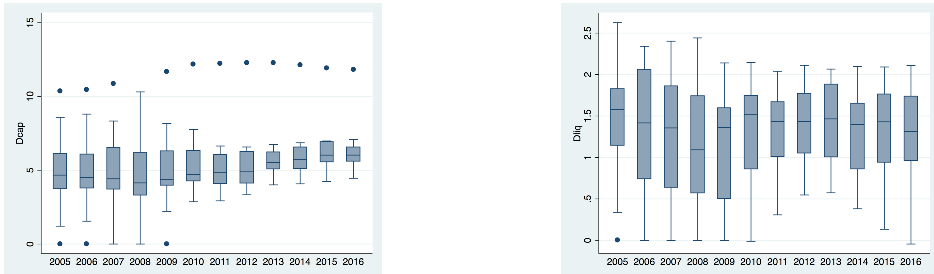
C.2 Descriptive statistic

Figure 12 – Capital and liquidity - GSIBs - FitchConnect



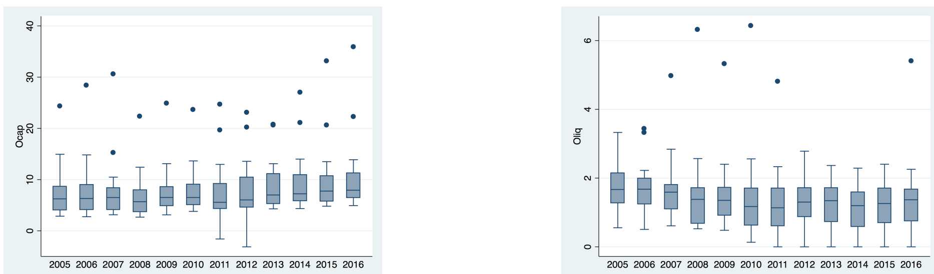
Source: Author's calculations from FitchConnect data.

Figure 13 – Capital and liquidity - DSIBs - FitchConnect



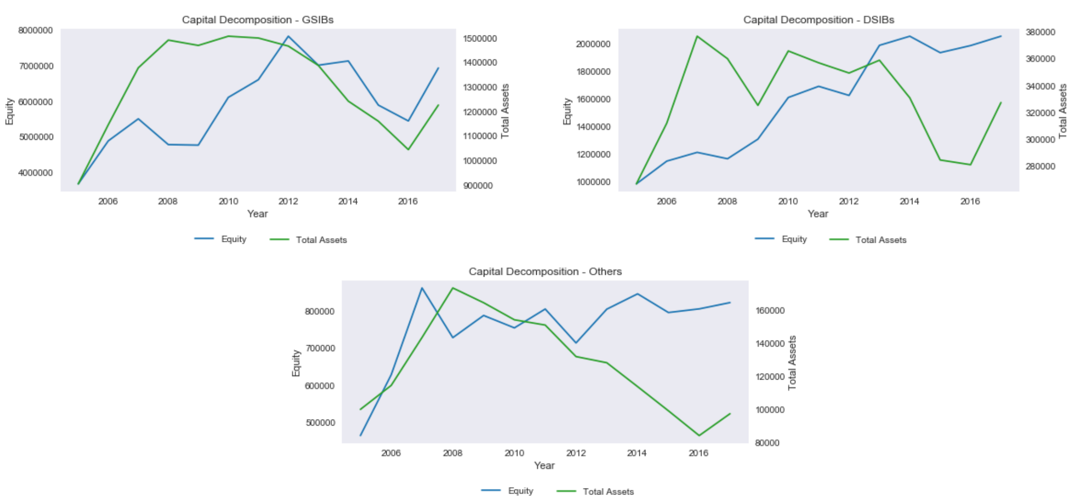
Source: Author's calculations from FitchConnect data.

Figure 14 – Capital and liquidity - Others - FitchConnect



Source: Author's calculations from FitchConnect data.

Figure 15 – Breaking down capital proxies - FitchConnect



Source: Author's calculations from FitchConnect data.

D Specification tests

D.1 Cross-dependence tests

Table 12 – Cross-dependence tests

Models	Before orthogonalization				After orthogonalization			
	Pesaran		Fisher		Pesaran		Fisher	
	Statistic	P-Value	Statistic	P-Value	Statistic	P-Value	Statistic	P-Value
(2.1)	4.875	0.0000	28.946	0.1464	4.877	0.0000	30.231	0.1130
(2.2)	-0.815	0.153	7.115	0.7897	-0.613	0.5398	8.269	0.6890
(2.3)	-0.910	0.3627	5.974	0.8751	-0.835	0.4035	7.987	0.7145
(2.4)	5.089	0.0000	30.926	0.0976	4.828	0.0000	29.468	0.1320

Source: Author's calculations.

D.2 Unit root tests

Table 13 – Harris and Tzavalis test

Variable	Models			
	(1.2)		(1.3)	
	Statistic	P-Value	Statistic	P-Value
FSI2007	0.600	0.008	0.600	0.008
Capital	0.770	0.506	0.826	0.799
Liquidity	0.757	0.431	0.658	0.051
Profitablity	0.374	0.000	0.410	0.000
Loan	0.509	0.001	0.797	0.659
IIR	0.781	0.567	0.781	0.567
Zscore	0.693	0.141	0.693	0.141
Inflation	0.269	0.000	0.269	0.000

Source: Author's calculations.

The CIPS (Pesaran, 2007) test statistic is calculated as a Cross-sectional Augmented Dickey-Fuller (CADF) average. In the same way as for a conventional ADF test, under the null hypothesis, the series has at least one single root and is not stationary. The test is divided into three models: (a), the model with constant and trend; (b), the model with constant without trend; and (c), the model without constant and trend. The critical values of the CIPS test are as follows: model (a) -2.66 at the 10% threshold, -2.76 at the 5% threshold and -2.93 at the 1% threshold; model (b) -2.14 at the 10% threshold, -2.25 at the 5% threshold and -2.44 at the 1% threshold; model (c) -1.52 at the 10% threshold, -1.64 at the 5% threshold and -1.86 at the 1% threshold.

Table 14 – CIPS test

Variables	Test models	Regression models	
		(1.1)	(1.4)
Capital	a	-2.312	-2.474
	b	-1.424	-1.507
	c	-1.374	-1.458
Liquidity	a	-2.270	-2.391
	b	-1.980	-2.439
	c	-1.861	-1.897
Profitability	a	-2.410	-2.775
	b	-2.368	-2.590
	c	-1.338	-1.411
Loan	a	-2.860	-2.714
	b	-1.491	-1.808
	c	-1.110	-1.368
IIR	a	-1.700	-1.700
	b	-1.343	-1.343
	c	-1.231	-1.231
Zscore	a	-2.319	-2.319
	b	-1.597	-1.597
	c	-1.343	-1.343
Inflation	a	-2.178	-2.178
	b	-2.310	-2.310
	c	-2.125	-2.125

Source: Author's calculations.

D.3 Hausman test

Table 15 – Hausman test

Models	(2.1)	(2.2)	(2.3)	(2.4)
Statistic	7.01	34.14	80.62	6.12
P-Value	0.7246	0.0002	0.0000	0.8052

Source: Author's calculations.

E PSTR

E.1 Results - Homogeneity and nonlinearity tests

Table 16 – Results - Homogeneity tests

Transition Variable: Capital								
Model	Hypothesis	Test	Value	SL	Robust	Value	SL
(3.2)	H_0: $\beta_1 = \beta_2 = \beta_3 = 0$	F(18,213)	2.349	0.002	Chi2(18)	80.927	0.000
GSIBs	$H_{03} : \beta_3 = 0$	F(6,213)	2.440	0.026	Chi2(6)	39.899	0.000
	$H_{02} : \beta_2 = 0 \| \beta_3 = 0$	F(6,219)	1.433	0.202	Chi2(6)	10.591	0.101
	$H_{01} : \beta_1 = 0 \| \beta_2 = \beta_3 = 0$	F(6,225)	2.966	0.008	Chi2(6)	28.091	0.000
(3.3)	H_0: $\beta_1 = \beta_2 = \beta_3 = 0$	F(12,219)	2.533	0.003	Chi2(12)	52.236	0.000
DSIBs	$H_{03} : \beta_3 = 0$	F(4,219)	1.427	0.225	Chi2(4)	9.771	0.044
	$H_{02} : \beta_2 = 0 \| \beta_3 = 0$	F(4,223)	2.370	0.053	Chi2(4)	13.735	0.008
	$H_{01} : \beta_1 = 0 \| \beta_2 = \beta_3 = 0$	F(4,227)	3.667	0.006	Chi2(4)	20.004	0.000

Source: Author's calculations.

Table 17 – Test of Linearity vs PSTR

Transition Variable: Capital								
Model	m	Hypothesis	Test	Value	SL	Robust	Value	SL
(3.2)	1	$H_0 : \beta_1 = 0$	F(6,225)	2.966	0.008	Chi2(6)	28.091	0.000
(3.3)	1	$H_0 : \beta_1 = 0$	F(4,227)	3.667	0.006	Chi2(4)	20.004	0.000

Source: Author's calculations. Note: m is the number of threshold selected by the model.
β_1 is the vector of parameters for variables associated with the transition function

Table 18 – Results - Homogeneity tests

Transition Variable: Liquidity							
Model	Hypothesis	Test	Value	SL	Robust	Value	SL
(3.2')	H_0: $\beta_1 = \beta_2 = \beta_3 = 0$	F(18,213)	1.622	0.056	Chi2(18)	59.849	0.000
GSIBs	$H_{03} : \beta_3 = 0$	F(6,213)	0.851	0.531	Chi2(6)	8.879	0.180
	$H_{02} : \beta_2 = 0 \vert \beta_3 = 0$	F(6,219)	2.043	0.061	Chi2(6)	22.762	0.000
.	$H_{01} : \beta_1 = 0 \vert \beta_2 = \beta_3 = 0$	F(6,225)	1.934	0.076	Chi2(6)	23.160	0.000
(3.3')	H_0: $beta_1 = beta_2 = beta_3 = 0$	F(12,219)	4.072	0.000	Chi2(12)	120.471	0.000
DSIBs	$H_{03} : \beta_3 = 0$	F(4,219)	4.741	0.001	Chi2(4)	50.423	0.000
	$H_{02} : \beta_2 = 0 \vert \beta_3 = 0$	F(4,223)	3.355	0.010	Chi2(4)	26.967	0.000
	$H_{01} : \beta_1 = 0 \vert \beta_2 = \beta_3 = 0$	F(4,227)	3.504	0.008	Chi2(4)	22.389	0.000

Source: Author's calculations.

Table 19 – Test of Linearity vs PSTR

Transition Variable: Liquidity								
Model	m	Hypothesis	Test	Value	SL	Robust	Value	SL
(3.2')	1	$H_0 : \beta_1 = 0$	F(6,225)	1.934	0.076	Chi2(6)	23.160	0.000
(3.3')	1	$H_0 : \beta_1 = 0$	F(4,227)	3.504	0.008	Chi2(4)	22.389	0.000

Source: Author's calculations. Note: m is the number of threshold selected by the model. β_1 is the vector of parameters for variables associated with the transition function

E.2 Results - Constancy and no remaining heterogeneity tests

Table 20 – No-remaining heterogeneity tests and constancy

Test of no remaining heterogeneity							
$H_0' : G_2 = 0$							
Model	Hypothesis	Test	Value	SL	Robust	Value	SL
(3.2)	$\gamma_2 = 0 \| m = 2$, adding GCAP	F(12,213)	1.388	0.172	Chi2(12)	32.335	0.001
	$\gamma_2 = 0 \| m = 1$, adding GCAP	F(6,219)	1.880	0.085	Chi2(6)	18.558	0.004
(3.2')	$\gamma_2 = 0 \| m = 2$, adding GLIQ	F(12,213)	1.398	0.168	Chi2(12)	31.714	0.001
	$\gamma_2 = 0 \| m = 1$, adding GLIQ	F(6,219)	1.638	0.137	Chi2(6)	20.067	0.002
(3.3)	$\gamma_2 = 0 \| m = 2$, adding DCAP	F(8,219)	1.090	0.370	Chi2(8)	14.407	0.071
	$\gamma_2 = 0 \| m = 1$, adding DACP	F(4,223)	1.363	0.247	Chi2(4)	8.965	0.061
(3.3')	$\gamma_2 = 0 \| m = 2$, adding DLIQ	F(8,219)	2.444	0.014	Chi2(8)	49.796	0.000
	$\gamma_2 = 0 \| m = 1$, adding DLIQ	F(4,223)	3.618	0.007	Chi2(4)	30.930	0.000
Test of parameter constancy							
$H_0' : G_2 = 0$							
Model	Hypothesis	Test	Value	SL	Robust	Value	SL
(3.2)	$\gamma_2 = 0 \| m = 2$, adding (t/T)	F(24,201)	2.687	0.000	Chi2(24)	117.502	0.000
	$\gamma_2 = 0 \| m = 1$, adding (t/T)	F(12,213)	1.869	0.039	Chi2(12)	56.931	0.000
(3.2')	$\gamma_2 = 0 \| m = 2$, adding (t/T)	F(24,201)	1.925	0.008	Chi2(24)	93.182	0.000
	$\gamma_2 = 0 \| m = 1$, adding (t/T)	F(12,213)	1.355	0.189	Chi2(12)	27.437	0.006
(3.3)	$\gamma_2 = 0 \| m = 2$, adding (t/T)	F(16,211)	2.471	0.001	Chi2(16)	101.851	0.000
	$\gamma_2 = 0 \| m = 1$, adding (t/T)	F(8,219)	2.107	0.036	Chi2(8)	38.498	0.000
(3.3')	$\gamma_2 = 0 \| m = 2$, adding (t/T)	F(16,211)	3.027	0.000	Chi2(16)	101.443	0.000
	$\gamma_2 = 0 \| m = 1$, adding (t/T)	F(8,219)	2.359	0.018	Chi2(8)	32.719	0.000

Source: Author's calculations.