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Do we need a stable funding ratio? Banks' funding in the global financial crisis

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Abstract

We use data from the recent global financial crisis to study the importance of several structural funding metrics in characterising banks' resilience. We find that structural funding ratios, including the Basel Committee's Net Stable Funding Ratio (NSFR) which will soon become a new requirement, would have helped detect, back in 2006, which banks were to subsequently fail, even controlling for the banks' solvency ratios. Their predictive power seems to come from the liability side and in particular from the fact that they count retail deposits as a highly stable funding source. Indeed, a deposits-to-assets ratio would outperform the other structural metrics we investigated as failure predictors for this crisis. Our findings suggest that this crisis was a crisis of banks' funding structures.

Key words: Banking, bank regulation, deposits, funding.

JEL classification: G21, G18, G01.

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I. Introduction

In 2010, the Basel Committee for Banking Supervision started introducing a new package of regulations for internationally active banks ("Basel III"). These regulations aim to reduce both the probability of bank failures and the impact of these failures on the economy. For the first time, the Basel Committee introduced liquidity and funding requirements alongside solvency requirements.

Structural funding and capital requirements can be thought of as partial substitutes (Schanz, 2009, Kato et al., 2010). A highly capitalised bank might have more headroom to increase the interest rate it promises on short-term liabilities, without jeopardising its solvency in the long term. Or a highly capitalised bank might be able to meet a large liquidity demand from its creditors in a perfect market storm, by selling its illiquid assets at heavily discounted prices and absorbing realised losses by its ample capital buffer. This could enable it to retain short-term funding through a stress.

But it would probably take a solvency requirement higher than those we currently observe to suppress the additional stabilising effect of a more stable (i.e. more long-term or more retail-oriented) funding structure. Thus, the structure of banks' funding – beyond the level of capital they maintain – can be expected to be an important determinant of resilience.

While maturity mismatch is a socially valuable feature of banks (Diamond and Dybvig, 1983), the equilibrium level of mismatch chosen by banks may be excessive from a social viewpoint, due to externalities associated with interconnectedness (Morris and Shin, 2008), fire sales of collateral (Dávila, 2014; Shleifer and Vishny, 2011) and expectations of public support[1]

[1] The public interventions considered by Farhi and Tirole (2012) include exceptional monetary policy, debt guarantees to financial institutions, changes in central bank collateral acceptance, recapitalisations, and purchases of legacy assets. But several countries including the UK and the US now have resolution regimes which are likely to curb such expectations (Gracie et al., 2014).

in case of widespread liquidity and funding difficulties in the banking system (Farhi and Tirole, 2012).

Since the recent global crisis was a strong impetus to investigate funding regulation, it is interesting to test which structural funding metrics would have (counterfactually) been helpful in identifying less resilient banks back in 2006, ahead of the turmoil. Our dataset carefully constructs a set of structural funding, risk-weighted capital and leverage ratios for a sample of 121 banks at end 2006. Located in various countries, most of these banks were large and internationally active.

This paper considers a set of structural funding ratios measuring funding stability and investigates whether some of them would have been good predictors of subsequent difficulties in the crisis even once controlling for the banks' solvency ratios, measured by their Risk-weighted Tier 1 Capital and accounting Leverage Ratios. In particular, we look at the Net Stable Funding Ratio (NSFR) agreed by the Basel Committee (BCBS, 2014) and we compare its performance with that of alternative structural funding metrics, such as a core funding ratio (CFR), a loans-to-deposits ratio (LtDR), or a deposit-to-assets ratio (DtAR).

We first assess whether these banks subsequently failed during the crisis. We use several definitions of failure in our analysis – all of them very broad, to account for the variety of ways in which bank failures have manifested themselves in the crisis. Our baseline definition captures bankruptcy, nationalisation, distressed sale of the bank, and (individual) capital injections. Our broader definition adds collective capital injections (as in the US Troubled Asset Relief Program) and bank bond guarantees guarantees by governments.

We find that the Net Stable Funding Ratio agreed in 2014 by the Basel Committee contributes to predicting failure in this crisis, even once controlling for the banks' solvency ratios, a Liquid Asset Ratio(LAR), and a couple of macroeconomic indicators. In addition, we find the DtAR would outperform the NSFR as failure predictors for this crisis, suggesting that its predictive power mainly comes from the liability side and, within liabilities, from the high weight on non-bank deposits and low weight on wholesale funding.

In addition to measuring their statistical power as predictors of future *failure*, we also investigate whether lower levels of these structural funding ratios contribute to predicting *deleveraging* for surviving banks, measured as the percent change in total assets and their sub-components during this crisis.

We find that the CFR and especially the DtAR is a significant predictor of *deleveraging* for surviving banks during this crisis, along with the leverage ratio. We also find that banks with weaker structural funding ratios shrunk their intra-financial assets, i.e., short-term loans to banks, derivatives, and trading securities more rapidly than their retail and wholesale loans.

These results suggest the following: first, the crisis for banks was not just a solvency crisis, but also a crisis of banks' funding structures. Second, at a given level of solvency ratio and liquid asset ratio, the structures most prone to failure were those relying on wholesale funding. But somewhat puzzlingly, we do not find evidence that wholesale funding with long maturities (defined as 1 year or longer) led to higher resilience than short-term wholesale funding.

The rest of the paper is organised as follows. Section II discusses the related literature. Section III describes our dataset. Section IV presents our methodology and our results. Finally, section V concludes.

II. Related Literature

Our paper relates to two strands of literature. First, it tests theories which predict that banks' balance sheet structures (and in particular the illiquidity of their assets relative to the maturity of their liabilities) determine their resilience. In a seminal paper, Diamond and Dybvig (1983) explain that uninsured deposits can run in a rational equilibrium. Using different techniques, Goldstein and Pauzner (2005) and Rochet and Vives (2004) obtain the same result, but in their setup a run occurs only in certain parameter regions, and as a *unique* equilibrium. These models can be used to discuss the determinants or the probability of runs. In these unique equilibrium models, as Morris and Shin (2001, 2008) highlighted, the key determinant of whether a run equilibrium prevails is a comparison of the amount of liabilities that are able to run relative to the amount of cash that can be made available (by selling or pledging assets). In other words, the probability of a run depends on the comparison between "runnable" liabilities and "pledgeable" assets.

Recognising this, Brunnermeier et al. (2014) suggest constructing a liquidity mismatch index (LMI) for individual banks – the difference between their asset illiquidity and their funding stability – so as to then aggregate it and measure liquidity risk in the financial system. This suggestion was implemented by Bai et al. (2015), but while they investigated some macroprudential properties of their indicator, they did not test its power in predicting bank failures directly, although they did test its power in predicting banks' (i) reliance on government liquidity backstop and (ii) stock market crash risk. Our exercise in this paper can be seen as a series of tests (at the single bank level) on various potential LMI definitions (e.g. the NSFR, the DtAR) in terms of predictive power and usefulness when it comes to supervising banks' funding resilience.

Following Brunnermeier et al. (2014), all the structural funding ratios that we test reflect the discrepancy between banks' asset illiquidity and their funding stability. These ratios only differ according to the weights they give to each asset and liability type (to reflect assets' illiquidity and liabilities' stability). For instance, the NSFR sets relatively granular weights on assets (for its denominator) and liabilities (for its numerator). In contrast, the DtAR's denominator is the unweighted sum of a bank's assets and the numerator puts a zero weight on all liabilities except retail deposits.

Contrary to Diamond and Dybvig (1983), another theoretical branch (Calomiris and Kahn, 1991; Flannery, 1994; Diamond and Rajan, 2001) has emphasised the socially beneficial role of uninsured demand deposits, arguing that reliance on such volatile funding sources can impose discipline on the banks' management, with a positive impact on its governance and its profitability. These studies are worth noting because they imply that wholesale funding would make banks safer through the market discipline. But Calomiris (1999) argues that market discipline is best achieved with imposing a minimum amount of long-term subordinated debt funding and thus need not necessarily rely on the threat of deposit runs. Our investigation does not directly test such theories, as we do not look directly at the interaction between a bank's balance sheet structure and management's incentives, but rather at the interaction between structure on the eve of the crisis and resilience during the crisis.

The second strand of literature relevant for our paper focuses on empirically predicting bank failures and takes into account measures of banks' funding structure. Vazquez and Federico (2012) find that both the NSFR and leverage are important determinants of bank failures, although the latter is a stronger determinant. Kapan and Minoiu (2013) find that the NSFR is a good predictor of the amount by which banks reduce their lending, and they also find that better capitalised banks reduced lending less. Vazquez and Federico (2012) and Kapan and Minoiu (2013) proxy the NSFR for much larger samples of banks than in our paper. However, this comes at the cost of lesser precision in the proxy. They use a calibration which is less granular, and is quite close to the CFR[2].

In various contexts, Andersen (2008), Bologna (2011), Giordana and Schumacher (2012), Goldsmith-Pinkham and Yorulmazer (2010), Ratnovski and Huang (2009), and Hahm et al. (2013) all point to the importance of banks' funding stability. They find that measures of non-core liabilities are good failure predictors.These studies explicitly or implicitly use either the CFR or the DtAR as their definition of stable funding[3].

Relative to these papers, our contribution is in carefully constructing close proxies of the key ratios (the NSFR, the CFR the LtDR, and the DtAR) which enables us to meaningfully compare their respective qualities as failure predictors for a set of international banks. We construct our dataset using data from Liquidatum Ltd. Their data are standardised among banks in different jurisdictions and more granular compared to the conventionally available data, which will be detailed in the next section.

In addition, abovementioned studies, except for Ratnovski and Huang (2009), do not consider any interacting effects between structural funding and solvency ratios in their failure predictions[4]. Since these ratios can be thought of as partial substitutes for various reasons suggested by, for example, Schanz (2009) and Kato et al. (2010), we examine their interacting relationships in bank failure predictions.Our more precise calibrations, albeit on a smaller sample than the studies cited, confirm their findings regarding the importance of banks' funding structure as a predictor of subsequent failure and subsequent

[2] For lack of detailed information on the asset side, they give excessively high weights to mortgage loans (100%, instead of 65- 85% in the Basel text) and to most short-term financial transactions (35% instead of 10-15%). They give 70% to 85% weights to all customer deposits, which are likely to contain some wholesale deposits (e.g. from non-financial corporates) in their dataset. Their sources do not have as precise a maturity breakdown.

[3] One notable exception is Giordana and Schumacher (2012) who calculate NSFR for banks in Luxembourg using banks' granular statistical reporting to the central bank.

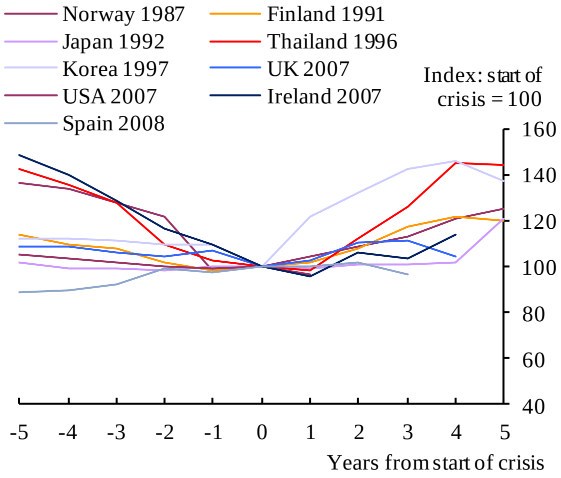
[4] Ratnovski and Huang (2009) find substitutability between capital and deposits: a bank with higher capital needs fewer deposits, and a bank with more deposits can sustain lower capital, for the same degree of resilience.

reduction in lending. We are able to go further and differentiate between the NSFR, the CFR and a simple DtAR. We find that the DtAR performs best in tests of predictive power. These new results suggest that in the global financial crisis, all types of wholesale funding were associated with lower resilience, not just short-term wholesale funding.

Deposit funding in other crises

The deposit-to-assets ratio seems a particularly powerful predictor of bank difficulties in this crisis. As shown in figure 1, over-reliance on wholesale funding is not a special feature of the recent crisis, but a relatively common feature of past crises as well[5].

Figure 1: Deposit-to-asset ratio before and after major crises



Sources: IMF and authors' calculations.

III. Data

We construct our bank-level dataset primarily using the data from Liquidatum Ltd., consisting of 121 financial companies, at the consolidated level, in 30 countries (but mostly located in Europe and North America).

[5] See Kato et al. (2010) and Hahm et al. (2013) for cross-country econometric work which finds that countries with higher reliance on deposit funding were less likely to be exposed to a financial crisis.

Our dataset has some similarities with other datasets which are regularly used in empirical work, such as Bankscope. However, those types of datasets only provide granularity down to each line item on a bank's balance sheet. Our dataset is different to most others due to the fact that it breaks down assets and liabilities into maturity buckets by using a variety of sources for each bank.

There are many variables in the dataset including retail and wholesale loans and deposits, loans to and deposits from banks, senior paper and subordinated and securitised debt all split into maturity buckets of 'unspecified', '0 to 3 months', '3 to 12 months', '1 to 5 years' and 'greater than 5 years'. The dataset also includes derivative assets and liabilities, collateralised financing (repo and reverse-repo), trading securities and loans, cash and balances with banks, capital and shareholders' funds, tier 1 capital and risk weighted assets. Other assets and liabilities are split into insurance and non-insurance assets/liabilities. The final two variables included are total assets and liabilities. This granular breakdown allows for the calculation of more precise liquidity metrics, such as the NSFR.

More importantly, the degree of validation of our database is much higher than that of many similar databases. It is worth emphasising that the simple comparison of liquidity positions across banks using published accounts can be misleading because the reporting formats are very heterogeneous. For example, quite a few banks report (i) interbank deposits, including repos, as customer deposits and/or (ii) highly-liquid securities held by their insurance subsidiaries as available-for-sales securities in consolidated accounts without segregation. This implies that, without making appropriate adjustments on the headline data, even the comparisons of some "simple" metrics, such as the LtDR, the DtAR, and the LAR, would not be reliable.

To our knowledge, few publicly-available datasets make appropriate adjustments or supply sufficient information for making reconciliations necessary for cross-sectional empirical analysis of banks, especially in different jurisdictions. One major advantage of our analysis is that we use internationally standardised bank liquidity data supplied by Liquidatum Ltd. They conduct careful analysis of all the published material (notes, management analysis in annual reports, Pillar 3 documents, investor relations presentations, fact books, etc.) and convert accounting-driven information into liquidity-focused balance sheets of sufficient granularity to enable detailed peer comparison and analysis. The data reflect the product types (loans, securities, derivatives, reverse repos, etc.) rather than their accounting treatment (held for trading, fair value, available for sale, securities and repos in loan books, etc.)[6].

Using the dataset, we estimate various funding metrics, defined in the table below. More details on the calculations are given in the appendix.

Indicator	Definition
Capital Adequacy Ratio	$\frac{\text{Tier 1 capital}}{\text{Risk weighted assets}} * 100$
Leverage Ratio	$\frac{\text{Tier 1 capital}}{\text{Total assets}} * 100$
Core Funding Ratio	$\frac{\text{Retail deposits} + \text{longterm} (> 1 \text{ year}) \text{ wholesale funding}}{\text{Total assets}}$
Loan to Deposit Ratio	$\frac{\text{Retail loans}}{\text{Retail deposits}}$
Asset to Deposit Ratio	$\frac{\text{Retail deposits}}{\text{Total assets}}$
Net Stable Funding Ratio	$\frac{\text{Available stable funding (ASF)}}{\text{Required stable funding (RSF)}}$
Liquid Asset Ratio	$\frac{\text{Cash \& balances with central banks} + \text{government bonds}}{\text{Total assets}}$

Structural funding ratios often define funding stability and asset liquidity in reference to a time horizon. The horizon in the NSFR is one year (although recognition is given to some liabilities and assets with 6 to 12 months of remaining maturity). By contrast, the Basel Committee’s Liquidity Coverage

[6] Liquidatum Ltd. claim that “our data is unique as it is hand collected and processed by ex-treasurers and staff from a balance sheet management background. It is then formatted to fit a standardised template. This ensures consistency in information processing and makes reliable benchmarking possible, ensuring like for like comparisons.”

Ratio[7] has a horizon of 30 days and is therefore not considered a structural funding ratio – but it does relate some liabilities (those which can run within a 30 day stress) to assets (those that can be liquidated within that horizon). Although it can certainly mitigate certain types of miscoordination and buy time for central bank or regulatory intervention, the LCR is not designed to improve coordination and potential stabilising actions beyond a few weeks.

Due to the lack of sufficiently granular balance sheet information, we do not attempt to proxy the LCR closely but instead we rely on a simple Liquid Asset Ratio (LAR), defined as cash, claims on central banks, plus government bonds divided by total assets[8].

We use two definitions of the NSFR: the NSFR 2010, which is the initial design of the ratio (when the Basel Committee first defined it in 2010) and the NSFR 2014, the ratio finally endorsed by the Committee after a public consultation in 2014.

Failure definition

We identify for each firm whether it failed during the crisis, using a broad definition that captures various forms of public intervention or rescue by other banks, in addition to outright failure. For this classification, we follow the classification by Laeven and Valencia (2010), which combines information from several sources[9] except for four banks[10].

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[7] BCBS (2013).

[8] As a robustness check, we tried using slightly more complex approximations of the LCR with the data we have and found that this did not significantly affect our results.

[9] The first is status change in Bankscope, (banks that changed status from "active" to either: "under receivership", "bankruptcy", "dissolved", "dissolved by merger", or "in liquidation". Another source is the evolution of the Basel capital (CAR) for each bank, to single out the banks for which CAR dropped below the 8 percent threshold in the post crisis period. Third, Moody's bank financial strength ratings are used to single out banks that were downgraded to rating E+ or E (in distress). Fourth, to capture large cross-border banks which were assisted by their government and thus generally not captured by these criteria, the information on failing banks in Laeven and Valencia (2010) is used, updated to capture failures since that dataset was collected.

[10] The reasoning behind these deviations are as follows: Swedbank and UniCredit were classified as failed by Laeven and Valencia despite the fact that the first benefited from market-wide support schemes in the same way that other Swedish banks that are not defined as failing did. UniCredit did not take the government assistance it once considered taking. This proposed government assistance was the

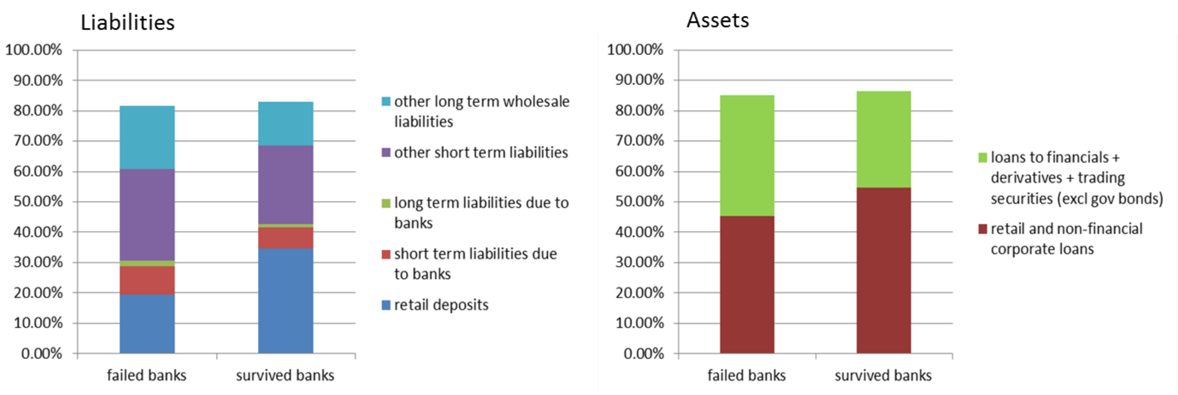
A difference between our failure definitions and others which have been published recently, such as the classifications published in Arjani and Paulin (2013), is that we do not classify all banks which took TARP as failed. Our broader definition adds collective capital injections (as in the US Troubled Asset Relief Program) and bank bond guarantees other types of guarantees by governments.

IV. Initial Findings, Methodology and Results

Figure 2 compares the balance sheet structure of surviving and failed banks (using simple averages of the proportion of some balance sheet items). Only key balance sheet items are included, corresponding to more than 80% of balance sheet size in each of the bar charts.

On average, banks that failed during the crisis relied more strongly on wholesale funding (and less on retail deposits) than the banks which survived. Thus, retail deposit funding was associated with greater resilience.

Figure 2: average balance sheet structure for failed banks versus survived banks



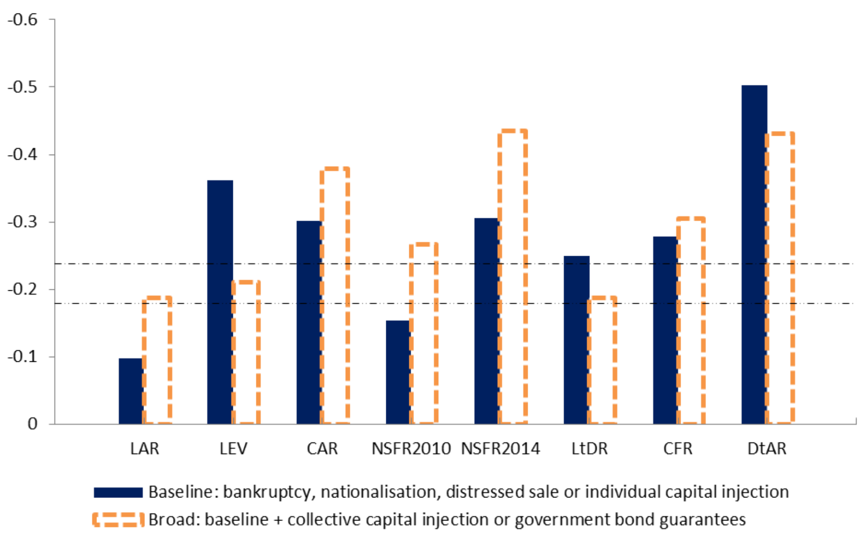
On the asset side, the average failed bank's balance sheet had a larger proportion of loans to financials, derivative, and trading securities, and a

basis behind Laeven and Valencia's classification of failed. This database also departs from Laeven and Valencia's classification of Banca Intesa as failing as it too considered government support but did not take it and Nordea as surviving as their 2009 rights issue was partly funded the Swedish government and under EU law was classified as 'State Aid'.

smaller proportion of retail and non-financial corporate loans. Loans to financials, derivative, and trading securities would *a priori* seem easier to liquidate than retail and non-financial corporate loans. This suggests that the banks which failed did not necessarily have more illiquid assets on average.

In a self-fulfilling run (Goldstein and Pauzner, 2005), investors coordinate on withdrawing their deposits if they believe that the proportion of liabilities that could 'run' is large relative to the amount of assets that could be liquidated or pledged. Figure 2 suggests that higher proportions of short-term loans to banks, trading securities, and derivatives, were not able to 'cover' failed banks' higher reliance on short-term wholesale funding (more runnable liabilities). It may not have been much easier to terminate or liquidate (via outright sales or pledges securing new funding) these contracts and securities than to terminate or liquidate retail and corporate loans.

Figure 3: simple correlations between regulatory ratios and failure indicator



The correlation between regulatory ratios and failure offers another, perhaps more telling characterisation of failed banks' balance sheets just before the crisis (figure3). We find that some calibrations of a structural funding ratio – a simple Deposit-to-Asset ratio in particular – have good statistical power to predict subsequent failure. In this univariate assessment of predictive power, the leverage ratio performs quite well for predicting failure in our baseline definition, but less well when we use a broader definition of failure which includes collective capital injections (as in the US Trouble Asset Relief Program) and bank bond guarantees by governments.

The NSFR 2010 (the NSFR's initial design) is not well correlated with failure in this crisis. But the revised NSFR that the Basel Committee finally adopted (NSFR 2014) has better univariate power. The NSFR 2014 specification of the ratio puts a higher weight on retail deposits (as a stable funding source) and also differentiates less sharply between different types of assets than the original NSFR 2010 measure. This, in view of figure 2, explains why the correlation with failure is higher: the average surviving bank in our sample had a larger share of retail deposits and more illiquid assets than the average failed bank.

Multivariate analysis

We estimate a multivariate Logit model to examine the predictive power of several structural funding ratios once controlling for the solvency ratios:

$$P(F_i = 1|X) = G(\beta_1 + \beta_2 SFR_i + \beta_3 LAR_i + \beta_4 LEV_i + \beta_5 CAR_i + \beta_6{}' controls_i) = G(\beta X)$$

$$G(\beta X) = \exp(\beta X)\,/\{1 + \exp(\beta X)\}$$

where F_i represents the failure indicator for bank *i*. SFR_i is a stable funding requirement measured as of 2006 (each specification uses one of the following ratios: the NSFR 2010, the NSFR 2014, the LtDR, the CFR, and the DtAR). LAR_i, LEV_i, CAR_i respectively denote the accounting Leverage Ratio, the Risk-weighted Tier 1 Capital Ratio and the Liquid Asset Ratio of bank *i* in 2006. Additional macro controls are the five-year average (from 2002 to 2006) of pre-crisis (i) current account deficit of bank *i*'s home country, and (ii) the ratio of gross government debt to GDP in that country, in order to control for country-level accumulation of potential financial vulnerabilities that might have resulted heterogeneous impact of the shock on different countries' banking system in this crisis. By measuring all explanatory variables before the crisis (as of 2006), we hope to capture variations across banks in the resilience of their balance sheet as they entered the crisis several months later.

We find that, for the baseline definition of failure, the NSFR 2014, the CFR and the DtAR are are shown to be statistically significant predictors, once controlling for the LAR, LEV, and CAR (table 2). The maximum pseudo R-squared and the minimum Akaike Information Criterion (AIC)[11] among different specification are achieved when the DtAR is included in the regression (last column of table 2). When using the broader definition of failure (table 3), we find that the NSFR 2010 is also statistically significant at the 10% level. The worst model in terms of AIC, however, is the one where the NSFR 2010 is added, suggesting that the increase in the predictive power of adding the NSFR 2010 as a structural funding ratio is marginal.

The inclusion of the current account deficit and gross government debt as additional controls (for the probability of currency and/or sovereign crises) did not change these results (tables 4 and 5). In sum, these results indicate that, in a linear setup, some structural funding ratios, including the Basel Committee's NSFR, would have helped detect, back in 2006, which banks were to subsequently fail even once we control for the banks' solvency ratios, the Liquid Asset Ratio and macro-financial vulnerabilities. It is also worth noting that the DtAR has uniformly strong predictive power among alternative specifications of the structural funding ratios.

Including interaction terms

The above tests of predictive power only consider models where a structural funding ratio is added to LAR, LEV, and CAR, without considering the possibility that interaction terms could significantly improve model quality.

[11] This criterion of model quality expresses the trade-off between fit and complexity, or in other words, parsimony against predictive power.

It could be that when supervising banks, the information from observed ratios also comes from their interactions, if these ratios are partial substitutes in predicting bank failures – for instance if a high capital ratio and leverage ratio imply that the funding ratios are less relevant as failure predictors.

To take into account the potential value in interaction terms, we ran three tests of whether the inclusion of a structural funding ratio could add predictive power to the LAR, LEV, and CAR.

Each of our tests uses a model-quality criterion to compare an "incumbent" model to a "challenger" model. There are 63 possible specifications of a model with a selection of variables from the LAR, LEV, and CAR and their interaction terms. The "incumbent" model is the best among these specifications, ranked by a model-quality criterion. The "challenger" model is the best among all possible specifications with variables selected from the solvency and liquidity ratios, plus at least one of our structural funding ratios and their interaction terms. There are 960 possible specifications for the "challenger" model.

We use three standard model-quality criteria to rank models, select the incumbent and the challenger, and finally test whether the challenger significantly outperforms the incumbent given the possibility that the incumbent model may not always be nested by the challenger model.

The first criterion we use is the area under the Receiver Operating Characteristic (AUROC) curve. This curve plots true positive rates and false positive rates when using the logit scores of a regression specification as metric for the test, varying the threshold of the test. This approach enables all specifications to be compared on the basis of how well they tell apart failed banks from non-failed ones – penalising both types of prediction errors (wrongly predicting a failure when a bank actually survived, failing to predict a failure). Without macro controls, the selected incumbent specification under this criterion is:

$G_{incumbent}(\beta X) = G(\beta_1 LEV_i + \beta_2 CAR_i + \beta_3 LEV_i \times CAR_i)$.The AUROC curve for this incumbent specification is 0.772, as shown in the top-left of the table 1.

The second and third tests are based on criteria developed by Vuong (1989). These criteria generalise the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) to cases where models are not necessarily nested.

Without macro controls, the preferred incumbent specification under both the AIC and the BIC criteria is:

$$G_{incumbent}(\beta X) = G(\beta_1 LEV_i \times CAR_i).$$

This case is striking because the preferred specification under these information criteria is an univariate logit model with the interaction term of LEV and CAR. The estimated coefficient for β_1 is indeed negative, suggesting that the two solvency ratios are partial substitutes in predicting bank failure.

The results are presented in table 1. Under the baseline definition of bank failure, we find that relative to an approach where only LAR, LEV, and CAR (and their interactions) are considered to be included as regressors, adding the DtAR results in a significant improvement in modelling quality under multiple criteria we considered. We do not, however, observe evidence of a significant improvement when adding one of the other structural funding ratios (LtDR, CFR, or the NSFRs) under multiple criteria[12]. In conclusion, these tests confirm our previous finding that the DtAR adds predictive power, taking LAR, LEV, and CAR and macro controls as given.

[12] The challenger model with the NSFR 2014 shows a significantly better predictive power at the 10% level under the AUROC curve criterion when broad definition of failure is used without macro controls. It is almost universally true, however, that the DtAR has an overwhelmingly strong predictive power.

Table 1: tests including interaction terms

Dependent variable: bank stress indicator (1, if stressed)

Stress definition: **baseline** (bankruptcy, nationalisation, distressed sale, individual capital injection)

Areas under the ROC curve	Incumbent	Challenger				
	No SFR	NSFR2010	NSFR2014	LtDR	CFR	DtAR
No macro controls	0.772	0.783	0.791	0.797	0.798	0.839 **
With macro controls	0.777	0.805	0.799	0.797	0.811 *	0.850 **

***, **, and * indicate that the area under the ROC curve of the challenger model is significantly larger than that of the incumbent model at the 1%, 5% and 10% levels, respectively.

Vuong/ Akaike Info. Crit. (AIC)	Incumbent	Challenger				
	No SFR	NSFR2010	NSFR2014	LtDR	CFR	DtAR
No macro controls	133.210	134.239	131.771	131.986	131.542	116.197 **
With macro controls	133.890	135.156	133.173	128.872	132.419	119.660 **

***, **, and * indicate that the AIC of the challenger model is significantly smaller than that of the incumbent model at the 1%, 5% and 10% levels, respectively.

Vuong/ Bayesian Info. Crit. (BIC)	Incumbent	Challenger				
	No SFR	NSFR2010	NSFR2014	LtDR	CFR	DtAR
No macro controls	138.802	142.627	140.158	140.373	139.929	121.789 **
With macro controls	145.074	148.427	146.265	142.851	146.433	131.121 **

***, **, and * indicate that the BIC of the challenger model is significantly smaller than that of the incumbent model at the 1%, 5% and 10% levels, respectively.

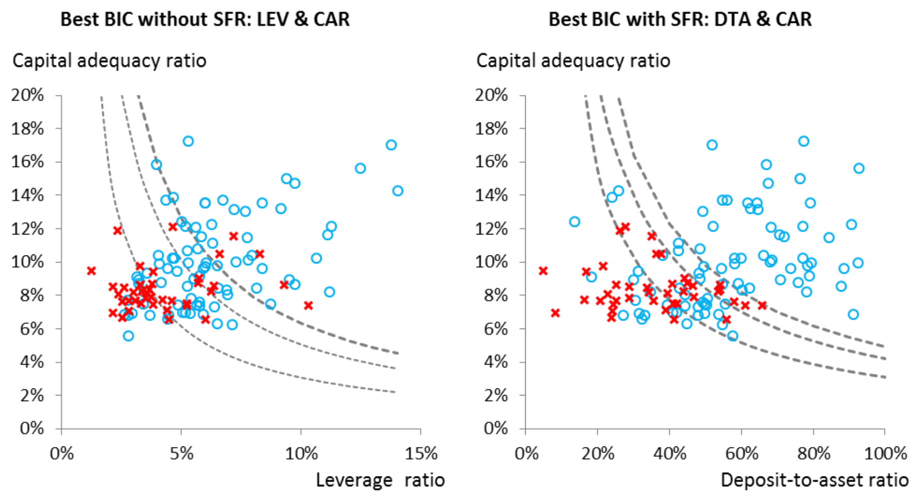
Of the three criteria used in table 1, the BIC's specificity is to be particularly tough against additional variables and thus tend to select parsimonious models. In the test where we use this criterion, the selected incumbent model (without including any structural funding ratio) is a univariate regression of the failure indicator against the interaction term of the LEV and CAR.

Once the DtAR is included in the list of potential variables (and interaction terms), the "challenger" model selected by the BIC (and the AIC) is again, a univariate regression of the failure indicator against the interaction term of the DtAR and CAR:

$$G_{challenger}(\beta X) = G(\beta_1 DtAR_i \times CAR_i).$$

To illustrate, figure 4 shows a plot of observations in the (LEV, CAR) and the (DtAR, CAR) planes, where hyperboles have been fitted to separate failed banks (the red crosses) from surviving banks (the blue dots). These hyperboles are the estimated "iso-failure probability" contours for the incumbent and the challenger models. They represent 20%, 30% and 50% iso-failure probabilities, respectively.

Figure 4: simple correlations between regulatory ratios and failure indicator



Two things are worth noting. First, the solvency and structural funding ratios are likely to be partial substitutes in predicting bank failure in this crisis. It implies that banks could have achieved the same level of resilience by raising the solvency ratio and by lowering the structural funding ratio (or vice versa). Indeed, the curvature of the contour is a marginal rate of substitution.

Second, it may be hard to tell, by simple eyeball-testing, that the right specification (DtAR, CAR) is statistically far better than the left specification (LEV, CAR) under standard model-quality criteria to rank models.

Deleveraging

The tests considered so far measure the power of structural funding ratios for predicting bank *failures*. In this subsection we turn to assessing their power for predicting *asset growth* (and deleveraging) between the end of 2007 and the end of 2009. There are several reasons why this analysis usefully complements our previous tests.

First, it is a robustness check to the complexity and possible subjectivity of our failure indicators. Indeed, although these indicators are built thoroughly and rigorously, they are complex and involve judgement.

Second, testing the power of regulatory metrics to predict subsequent asset growth takes into account another way in which banks' health is of interest to regulators – because of its impact on credit available to the economy.

We regress asset growth using the following specification:

$$AG_i = \beta_1 + \beta_2 SFR_i + \beta_3 LEV_i + \beta_4 CAR_i + \beta_5 LAR_i + \beta_6{}' controls_i + \varepsilon_i$$

where AG_i represents bank i's asset growth between the end of 2007 and the end of 2009, and other notations are the same as in our Logit model.

We find that the DtAR is a significant predictor of asset growth, along with the leverage ratio (table 6). When the DtAR increases by one standard deviation, asset growth increases by about 8.0 percentage points. A one-standard deviation increase of the leverage ratio (i.e. a less leveraged bank) increases asset growth by 3.9 percentage points. The capital adequacy ratio is also significant but a high CAR implies lower asset growth (or more severe deleveraging) which is puzzling.

As tables 7 and 8 show, the DtAR significantly explains both the changes in retail and wholesale loans and intra-financial assets (loans to banks, reverse repos and trading assets). Once again, we find that retail deposit funding was associated with resilience in the global financial crisis.

V. Conclusion

In this paper, we used the recent global crisis to study the incremental impact that a structural funding regulation could have on banks' resilience. We investigated the statistical power of various structural funding metrics as predictors of future failure or reduction in lending (i.e., as counterfactually effective financial stability policies).

We find that structural funding ratios, including the Basel Committee's Net Stable Funding Ratio (NSFR) which will soon become a new requirement, would have helped detect, back in 2006, which banks were to subsequently fail even controlling for the banks' solvency ratios. Their predictive power comes from the liability side, and within liabilities, from the fact that they count retail deposits as a highly stable funding source. Indeed, a deposits-to-assets ratio would outperform the other structural funding metrics we investigated as failure predictor for this crisis. Also, some results suggest that the solvency and structural funding ratios are likely to be partial substitutes in predicting bank failure in this crisis.

These results suggest the following: first, the crisis was not just a solvency crisis, but also a crisis of banks' funding structures. Second, at a given level of solvency, the most problematic structures were those relying on wholesale funding. Interestingly, we do not find evidence that wholesale funding with long remaining maturities (defined as one year or longer) led to higher resilience than short-term wholesale funding.

We would not conclude on this basis that regulators should impose a deposit-to-asset ratio instead of the Basel NSFR. The lack of association in our data between longer-term wholesale funding and resilience may have to do with the fact that the global financial crisis was of such severity and such length that a large amount of liabilities with a year or longer in remaining maturity as of 2006 ended up needing to be rolled over during the crisis (and therefore would not have provided resilience).

Besides, the past performance of structural funding metrics as predictors need not be a good indication of their future performance as regulatory requirements enhancing financial stability. Indeed, even if past observations of high structural funding ratios reflect a type of prudent funding management, this does not imply that banks meeting these ratios in the future would necessarily display the same type of prudent funding management. As Goodhart (1981) put it: “Any observed statistical regularity will tend to collapse once pressure is placed upon it for control purposes”. Nevertheless, we believe banking supervision needs to exert some control on banks’ funding structures and measuring banks’ NSFR is a good starting point.

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APPENDIX

The tables below explain the calibration of the Net Stable Funding Ratio, as agreed by the Basel Committe in October 2014. The NSFR defines for each asset and off-balance sheet commitment a Required Stable Funding factor (RSF) and for each liability an Available Stable Funding (ASF) factor. Items receive a high RSF if they are difficult to liquidate or terminate. High ASF liabilities are those which are least likely to run.

Summary of asset categories and associated RSF factors — Table 2

RSF factor	Components of RSF category
0%	• Coins and banknotes • All central bank reserves • All claims on central banks with residual maturities of less than six months • "Trade date" receivables arising from sales of financial instruments, foreign currencies and commodities.
5%	• Unencumbered Level 1 assets, excluding coins, banknotes and central bank reserves
10%	• Unencumbered loans to financial institutions with residual maturities of less than six months, where the loan is secured against Level 1 assets as defined in LCR paragraph 50, and where the bank has the ability to freely rehypothecate the received collateral for the life of the loan
15%	• All other unencumbered loans to financial institutions with residual maturities of less than six months not included in the above categories • Unencumbered Level 2A assets
50%	• Unencumbered Level 2B assets • HQLA encumbered for a period of six months or more and less than one year • Loans to financial institutions and central banks with residual maturities between six months and less than one year • Deposits held at other financial institutions for operational purposes • All other assets not included in the above categories with residual maturity of less than one year, including loans to non-financial corporate clients, loans to retail and small business customers, and loans to sovereigns and PSEs
65%	• Unencumbered residential mortgages with a residual maturity of one year or more and with a risk weight of less than or equal to 35% under the Standardised Approach • Other unencumbered loans not included in the above categories, excluding loans to financial institutions, with a residual maturity of one year or more and with a risk weight of less than or equal to 35% under the standardised approach
85%	• Cash, securities or other assets posted as initial margin for derivative contracts and cash or other assets provided to contribute to the default fund of a CCP • Other unencumbered performing loans with risk weights greater than 35% under the standardised approach and residual maturities of one year or more, excluding loans to financial institutions • Unencumbered securities that are not in default and do not qualify as HQLA with a remaining maturity of one year or more and exchange-traded equities • Physical traded commodities, including gold
100%	• All assets that are encumbered for a period of one year or more • NSFR derivative assets net of NSFR derivative liabilities if NSFR derivative assets are greater than NSFR derivative liabilities • 20% of derivative liabilities as calculated according to paragraph 19 • All other assets not included in the above categories, including non-performing loans, loans to financial institutions with a residual maturity of one year or more, non-exchange-traded equities, fixed assets, items deducted from regulatory capital, retained interest, insurance assets, subsidiary interests and defaulted securities

Summary of liability categories and associated ASF factors

Table 1

ASF factor	Components of ASF category
100%	• Total regulatory capital (excluding Tier 2 instruments with residual maturity of less than one year) • Other capital instruments and liabilities with effective residual maturity of one year or more
95%	• Stable non-maturity (demand) deposits and term deposits with residual maturity of less than one year provided by retail and small business customers
90%	• Less stable non-maturity deposits and term deposits with residual maturity of less than one year provided by retail and small business customers
50%	• Funding with residual maturity of less than one year provided by non-financial corporate customers • Operational deposits • Funding with residual maturity of less than one year from sovereigns, PSEs, and multilateral and national development banks • Other funding with residual maturity between six months and less than one year not included in the above categories, including funding provided by central banks and financial institutions
0%	• All other liabilities and equity not included in the above categories, including liabilities without a stated maturity (with a specific treatment for deferred tax liabilities and minority interests) • NSFR derivative liabilities net of NSFR derivative assets if NSFR derivative liabilities are greater than NSFR derivative assets • "Trade date" payables arising from purchases of financial instruments, foreign currencies and commodities

Failure prediction (logit regressions)

TABLE 2

Dependent variable: bank stress indicator (1, if stressed)

Stress definition: **baseline** (bankruptcy, nationalisation, distressed sale, individual capital injection)

	No SFR	NSFR2010	NSFR2014	LtDR	CFR	DtAR
SFR		-0.881	-1.859 **	0.494	-2.885 ***	-6.628 ***
		(0.979)	(0.821)	(0.485)	(1.023)	(1.350)
LAR	-2.347	-2.114	-1.509	-1.485	-4.527	0.229
	(2.968)	(3.140)	(3.415)	(3.540)	(3.584)	(4.578)
LEV	-36.508 **	-37.318 *	-30.654 *	-32.287 *	-30.169 *	-10.428
	(18.409)	(19.794)	(16.774)	(18.091)	(17.645)	(19.886)
CAR	-21.226 **	-20.614 **	-21.414 **	-19.019 *	-24.114 **	-22.976 **
	(10.155)	(9.905)	(9.640)	(10.391)	(10.000)	(10.142)
_cons	3.239 ***	4.035 **	4.760 ***	2.174	4.778 ***	4.903 ***
	(1.148)	(1.628)	(1.563)	(1.339)	(1.524)	(1.268)
# of samples	121	121	121	121	121	121
AIC	137.4	138.4	135.9	136.6	134.2	121.6
Pseudo R2	0.158	0.164	0.180	0.176	0.191	0.273

The cluster-robust standard errors (by country) are in the parentheses.

***, **, and * indicate that the coefficients are significant at the 1%, 5% and 10% level, respectively.

TABLE 3

Dependent variable: bank stress indicator (1, if stressed)

Stress definition: **broad** (baseline + collective capital injection + government's bond guarantee)

	No SFR	NSFR2010	NSFR2014	LtDR	CFR	DtAR
SFR		-1.592 *	-3.666 ***	0.316	-3.902 **	-4.693 ***
		(0.826)	(1.022)	(0.388)	(1.568)	(1.578)
LAR	-5.874	-5.445	-4.759	-5.896	-9.444 **	-4.230
	(3.844)	(4.178)	(4.601)	(3.774)	(4.196)	(4.407)
LEV	-3.423	-1.859	10.249	-0.189	7.617	12.298
	(12.261)	(12.831)	(14.744)	(11.026)	(16.740)	(18.097)
CAR	-33.086 **	-31.208 **	-31.544 **	-32.911 **	-34.527 **	-32.888 **
	(13.591)	(13.906)	(14.313)	(13.810)	(14.013)	(14.085)
_cons	3.883 ***	5.122 ***	6.710 ***	3.304 **	5.730 ***	5.189 ***
	(1.279)	(1.376)	(1.425)	(1.315)	(1.317)	(1.576)
# of samples	121	121	121	121	121	121
AIC	152.0	150.5	139.4	151.5	143.0	140.2
Pseudo R2	0.136	0.157	0.224	0.151	0.203	0.219

The Cluster-robust standard errors (by country) are in the parentheses.

***, **, and * indicate that the coefficients are significant at the 1%, 5% and 10% level, respectively.

TABLE 4

Dependent variable: bank stress indicator (1, if stressed)

Stress definition: **baseline** (bankruptcy, nationalisation, distressed sale, individual capital injection)

	No SFR	NSFR2010	NSFR2014	LtDR	CFR	DtAR
SFR		-0.740	-1.574 *	0.714	-2.613 **	-6.166 ***
		(1.204)	(0.913)	(0.482)	(1.197)	(1.349)
LAR	-2.816	-2.716	-2.454	-1.151	-5.017	-0.737
	(2.952)	(3.112)	(3.498)	(3.728)	(3.553)	(4.554)
LEV	-46.275 **	-46.082 **	-39.818 **	-43.191 **	-39.684 **	-20.008
	(18.737)	(19.520)	(16.866)	(18.445)	(18.378)	(20.902)
CAR	-11.956	-12.424	-14.386	-6.752	-16.996	-16.261
	(10.597)	(10.518)	(10.677)	(11.495)	(10.793)	(11.372)
Current account/	-8.343 **	-7.646 **	-6.807 *	-9.121 **	-7.126 **	-5.735
GDP	(3.460)	(3.782)	(3.763)	(4.055)	(3.766)	(4.002)
Gross govt debt/ GDP	1.251	1.354	1.268	1.692	1.198	0.837
	(1.328)	(1.363)	(1.380)	(1.497)	(1.395)	(1.484)
_cons	2.304 *	2.955	3.705 **	0.495	3.888 **	4.215 ***
	(1.380)	(1.906)	(1.881)	(1.708)	(1.820)	(1.517)
# of samples	121	121	121	121	121	121
AIC	137.0	138.5	136.8	135.1	135.1	124.0
Pseudo R2	0.186	0.189	0.200	0.211	0.211	0.284

The cluster-robust standard errors (by country) are in the parentheses.

***, **, and * indicate that the coefficients are significant at the 1%, 5% and 10% level, respectively.

Current account/GDP are 5-year average between 2002-06.

TABLE 5

Dependent variable: bank stress indicator (1, if stressed)

Stress definition: **broad** (baseline + collective capital injection + government's bond guarantee)

	No SFR	NSFR2010	NSFR2014	LtDR	CFR	DtAR
SFR		-0.486	-3.014 ***	0.536	-3.565 **	-5.081 ***
		(0.957)	(0.908)	(0.639)	(1.485)	(1.364)
LAR	-6.578 *	-6.433 *	-5.680	-5.244	-9.392 **	-4.015
	(3.432)	(3.568)	(4.369)	(4.099)	(4.313)	(4.310)
LEV	-25.759 **	-24.415 *	-11.189	-23.835 *	-14.661	-8.086
	(13.050)	(12.796)	(14.564)	(13.174)	(15.218)	(14.692)
CAR	-15.339	-15.265	-17.529	-11.601	-20.340 *	-14.541
	(11.568)	(11.763)	(12.472)	(11.682)	(11.490)	(10.567)
Current account/	-22.304 ***	-21.623 ***	-19.087 ***	-23.072 ***	-20.832 ***	-22.367 ***
GDP	(5.977)	(6.132)	(4.566)	(6.378)	(5.234)	(6.772)
Gross govt debt/ GDP	-1.284	-1.248	-1.660	-1.083	-1.576	-2.010
	(1.615)	(1.649)	(1.661)	(1.678)	(1.696)	(1.671)
_cons	4.409 ***	4.763 ***	7.032 ***	3.164 *	6.460 ***	6.101 ***
	(1.440)	(1.584)	(1.653)	(1.661)	(1.557)	(1.540)
# of samples	121	121	121	121	121	121
AIC	129.1	130.9	123.8	129.0	125.0	119.6
Pseudo R2	0.298	0.299	0.341	0.310	0.335	0.367

The Cluster-robust standard errors (by country) are in the parentheses.

***, **, and * indicate that the coefficients are significant at the 1%, 5% and 10% level, respectively.

Current account/GDP are 5-year average between 2002-06.

Asset growth analysis

TABLE 6

Dependent variable: total assets growth 07-09

	No SFR	NSFR2010	NSFR2014	LtDR	CFR	DtAR
SFR		-0.096	0.031	0.000	0.227 **	0.408 ***
		(0.065)	(0.086)	(0.015)	(0.098)	(0.121)
LAR	-0.327	-0.217	-0.354	-0.328	-0.179	-0.513 **
	(0.267)	(0.250)	(0.310)	(0.256)	(0.266)	(0.247)
LEV	2.792 ***	3.042 ***	2.632 ***	2.789 ***	2.068 ***	1.590 *
	(0.662)	(0.578)	(0.540)	(0.712)	(0.586)	(0.835)
CAR	-2.362 ***	-2.251 ***	-2.389 ***	-2.363 ***	-2.334 **	-2.611 ***
	(0.803)	(0.795)	(0.815)	(0.805)	(0.876)	(0.723)
Current	0.214	0.359	0.173	0.214	0.017	0.083
account/	(0.300)	(0.275)	(0.292)	(0.300)	(0.294)	(0.278)
Gross	-0.041	-0.059	-0.035	-0.041	-0.026	-0.003
govt	(0.092)	(0.074)	(0.091)	(0.092)	(0.088)	(0.081)
Nominal	1.503 ***	1.368 ***	1.514 ***	1.502 ***	1.524 ***	1.303 ***
GDP	(0.308)	(0.250)	(0.319)	(0.312)	(0.303)	(0.242)
_cons	0.183 **	0.253 ***	0.160	0.183 **	0.082	0.063
	(0.077)	(0.072)	(0.113)	(0.086)	(0.097)	(0.087)
# of obs.	103	103	103	103	103	103
R2	0.364	0.376	0.366	0.364	0.402	0.462

The cluster-robust standard errors (by country) are in the parentheses.
***, **, and * indicate that the coefficients are significant at the 1%, 5% and 10% level, respectively.
Current account/GDP and Gross govt debt/GDP are 5-year average between 2002-06.

TABLE 7

Dep. var. : contribution to total assets growth from loans to banks, rev. repos, and trading assets 07-09

	No SFR	NSFR2010	NSFR2014	LtDR	CFR	DtAR
SFR		-0.045	0.031	0.008	0.171 **	0.263 ***
		(0.045)	(0.059)	(0.006)	(0.072)	(0.069)
LAR	-0.029	0.023	-0.056	-0.017	0.082	-0.149
	(0.183)	(0.170)	(0.212)	(0.183)	(0.153)	(0.166)
LEV	1.757 ***	1.875 ***	1.598 **	1.815 ***	1.212 **	0.983 **
	(0.600)	(0.630)	(0.624)	(0.631)	(0.605)	(0.374)
CAR	-0.532	-0.480	-0.559	-0.512	-0.511	-0.693 *
	(0.419)	(0.419)	(0.422)	(0.433)	(0.460)	(0.382)
Current	-0.171	-0.103	-0.212	-0.174	-0.319 *	-0.256
account/	(0.154)	(0.168)	(0.164)	(0.155)	(0.174)	(0.154)
Gross	0.028	0.020	0.035	0.028	0.039	0.053 *
govt	(0.042)	(0.031)	(0.043)	(0.043)	(0.042)	(0.030)
Nominal	0.374 **	0.311 **	0.385 **	0.379 **	0.390 **	0.245 **
GDP	(0.169)	(0.143)	(0.172)	(0.172)	(0.146)	(0.118)
_cons	-0.074 *	-0.041	-0.096	-0.090 *	-0.150 **	-0.151 ***
	(0.042)	(0.044)	(0.065)	(0.046)	(0.055)	(0.053)
# of obs.	103	103	103	103	103	103
R2	0.218	0.227	0.222	0.223	0.293	0.362

The cluster-robust standard errors (by country) are in the parentheses.
***, **, and * indicate that the coefficients are significant at the 1%, 5% and 10% level, respectively.
Current account/GDP and Gross govt debt/GDP are 5-year average between 2002-06.

Asset growth analysis (continued)

TABLE 8

Dependent variable: Contribution to total assets growth from retail and wholesale loans 07-09

	No SFR	NSFR2010	NSFR2014	LtDR	CFR	DtAR
SFR		-0.036	-0.003	-0.012	0.021	0.122 *
		(0.028)	(0.038)	(0.014)	(0.060)	(0.067)
LAR	-0.104	-0.062	-0.101	-0.122	-0.090	-0.159
	(0.136)	(0.148)	(0.153)	(0.129)	(0.130)	(0.138)
LEV	1.353 **	1.448 **	1.368 *	1.268 **	1.285 *	0.996
	(0.575)	(0.575)	(0.706)	(0.519)	(0.711)	(0.608)
CAR	-1.159 **	-1.117 **	-1.157 **	-1.189 **	-1.157 **	-1.233 **
	(0.467)	(0.454)	(0.455)	(0.456)	(0.480)	(0.475)
Current	0.289 *	0.343 **	0.293 *	0.293 *	0.270	0.250
account/	(0.146)	(0.156)	(0.163)	(0.158)	(0.173)	(0.153)
Gross	-0.063	-0.070	-0.064	-0.063	-0.062	-0.052
govt	(0.056)	(0.054)	(0.055)	(0.059)	(0.055)	(0.056)
Nominal	0.792 ***	0.741 ***	0.791 ***	0.784 ***	0.794 ***	0.733 ***
GDP	(0.181)	(0.187)	(0.185)	(0.187)	(0.183)	(0.180)
_cons	0.130 **	0.157 ***	0.132 **	0.154 ***	0.120 **	0.094 *
	(0.049)	(0.045)	(0.051)	(0.052)	(0.051)	(0.054)
of sample	103	103	103	103	103	103
R2	0.332	0.337	0.332	0.340	0.333	0.356

The cluster-robust standard errors (by country) are in the parentheses.

***, **, and * indicate that the coefficients are significant at the 1%, 5% and 10% level, respectively.

Current account/GDP and Gross govt debt/GDP are 5-year average between 2002-06.

Definitions and calibration of ratios used

	Indicator	Definition	
1	**Capital Adequacy Ratio**	$\frac{\text{Tier 1 capital}}{\text{Risk weighted assets}} * 100$	
2	**Leverage Ratio**	$\frac{\text{Capital and shareholder funds}}{\text{Total assets}} * 100$	
3	**Core Funding Ratio**	$\frac{\text{Retail deposits } + \text{ long} - \text{term wholesale funding } > 1\,yr}{\text{Total assets}}$	*See below for weights*
4	**Loan to Deposit Ratio**[13]	$\frac{\text{Non} - \text{bank loans}}{\text{Non} - \text{bank deposits} + \text{Capital and shareholder funds}}$	
5	**Deposits to Asset Ratio**	$\frac{\text{Non} - \text{bank deposits}}{\text{Total assets}}$	
6	**Net Stable Funding Ratio**	$\frac{\text{Available stable funding (ASF)}}{\text{Required stable funding (RSF)}}$	*See below for weights*
7	**Liquid Asset Ratio**	$\frac{\text{Cash \& balances with central banks} + \text{government bonds}}{\text{Total assets}}$	

Balance sheet variable with maturity breakdown	**NSFR 2014**	**NSFR 2010**	**CFR**	**LtDR**
	ASF	**ASF**		**Liabilities**
Bank Deposits Unspecified	**0.191**	**0.140**	**0.140**	**0**
Bank Deposits 0 to 3 months	**0.000**	**0.000**	**0.000**	**0**
Bank Deposits 3 to 12 months	**0.333**	**0.000**	**0.000**	**0**
Bank Deposits 1 to 5 years	**1.000**	**1.000**	**1.000**	**0**
Bank Deposits Greater than 5 years	**1.000**	**1.000**	**1.000**	**0**
Retail Deposits Unspecified	**0.864**	**0.816**	**1.000**	**1**
Retail Deposits 0 to 3 months	**0.850**	**0.800**	**1.000**	**1**
Retail Deposits 3 to 12 months	**0.950**	**0.900**	**1.000**	**1**
Retail Deposits 1 to 5 years	**1.000**	**1.000**	**1.000**	**1**
Retail Deposits Greater than 5 years	**1.000**	**1.000**	**1.000**	**1**
Wholesale Deposits Unspecified	**0.150**	**0.025**	**0.000**	**1**
Wholesale Deposits 0 to 3 months	**0.150**	**0.025**	**0.000**	**1**
Wholesale Deposits 3 to 12 months	**0.383**	**0.025**	**0.000**	**1**
Wholesale Deposits 1 to 5 years	**1.000**	**1.000**	**1.000**	**1**
Wholesale Deposits Greater than 5 years	**1.000**	**1.000**	**1.000**	**1**
Senior Paper Unspecified	**0.637**	**0.567**	**0.567**	**0**
Senior Paper 0 to 3 months	**0.000**	**0.000**	**0.000**	**0**

[13] This is our preferred measure. For some banks, it is not possible to distinguish between retail deposits and deposits placed by non-bank financial corporations – in these instances, we proxy the loan-to-deposit ratio by (Customer loans / Customer deposits).

Senior Paper 3 to 12 months	**0.333**	**0.000**	**0.000**	**0**
Senior Paper 1 to 5 years	**1.000**	**1.000**	**1.000**	**0**
Senior Paper Greater than 5 years	**1.000**	**1.000**	**1.000**	**0**
Subordinated Debt Unspecified	**0.945**	**0.928**	**0.928**	**0**
Subordinated debt 0 to 3 months	**0.000**	**0.000**	**0.000**	**0**
Subordinated Debt 3 to 12 months	**0.333**	**0.000**	**0.000**	**0**
Subordinated Debt 1 to 5 years	**1.000**	**1.000**	**1.000**	**0**
Subordinated Debt Greater than 5 years	**1.000**	**1.000**	**1.000**	**0**
Capital and Shareholder Funds	**1.000**	**1.000**	**1.000**	**1**
Derivatives (Liabilities)	**0.200**			**0**
Collateralised Financing	**0.000**	**0.000**	**0.000**	**0**
Short Positions	**0.000**	**0.000**	**0.000**	**0**
Other Liabilities	**0.000**	**0.000**	**0.000**	**0**
Insurance Liabilities				
Non-Insurance Liabilities				
Securitised Debt Unspecified	**0.890**	**0.858**	**0.858**	**0**
Securitised Debt 0 to 3 months	**0.000**	**0.000**	**0.000**	**0**
Securitised Debt 3 to 12 months	**0.333**	**0.000**	**0.000**	**0**
Securitised Debt 1 to 5 years	**1.000**	**1.000**	**1.000**	**0**
Securitised Debt Greater than 5 years	**1.000**	**1.000**	**1.000**	**0**

Balance sheet variable with maturity breakdown	**NSFR 2014**	**NSFR 2010**		**LtDR**
	RSF	**RSF**		**Assets**
Retail Loans to Customers Unspecified	**0.664**	**0.796**		**1**
Retail Loans to Customers 0 to 3 months	**0.500**	**0.850**		**1**
Retail Loans to Customers 3 to 12 months	**0.500**	**0.850**		**1**
Retail Loans to Customers 1 to 5 years	**0.719**	**0.761**		**1**
Retail Loans to Customers Greater than 5 years	**0.736**	**0.781**		**1**
Wholesale Loans Unspecified	**0.754**	**0.552**		**1**
Wholesale Loans 0 to 3 months	**0.500**	**0.250**		**1**
Wholesale Loans 3 to 12 months	**0.500**	**0.250**		**1**
Wholesale Loans 1 to 5 years	**0.925**	**1.000**		**1**
Wholesale Loans Greater than 5 years	**0.925**	**1.000**		**1**
Loans to Banks Unspecified	**0.404**	**0.144**		**0**
Loans to Banks 0 to 3 months	**0.150**	**0.000**		**0**
Loans to Banks 3 to 12 months	**0.383**	**0.000**		**0**
Loans to Banks 1 to 5 years	**1.000**	**1.000**		**0**
Loans to Banks Greater than 5 years	**1.000**	**1.000**		**0**

Derivatives (Net for NSFR, Assets for L-D Ratio)[5]	*****	*****		**0**
Collateralised Financing	**0.125**	**0.000**		**0**
Trading Securities and Loans				**0**
Other Assets				**0**
Insurance Assets	**0.000**	**0.000**		**0**
Non-Insurance Assets	**0.925**	**1.000**		**0**
Cash and balances with Central Banks	**0.000**	**0.000**		**0**
Government Gilts	**0.050**	**0.025**		**0**
Equities (Trading Assets)	**0.500**	**0.500**		**0**
Commodities (Trading Assets)	**0.850**	**0.500**		**0**
Trading Assets Other (MBS, ABS, FI/Corp,Other)	**0.350**	**0.100**		**0**
Other Trading Assets	**0.850**	**1.000**		**0**
Risk Transfer Assets Unspecified	**1.000**	**1.000**		**1**
Risk Transfer Assets 0 to 3 months	**0.000**	**0.000**		**1**
Risk Transfer Assets 3 to 12 months	**0.333**	**0.000**		**1**
Risk Transfer Assets 1 to 5 years	**1.000**	**1.000**		**1**
Risk Transfer Assets Greater than 5 years	**1.000**	**1.000**		**1**

This appendix shows the calibrated weights for the NSFR 2010, the NSFR 2014 and the LCR. The weights for the NSFR 2014 were not calibrated from the scratch, but calibrated through amending the weights for the 2010 NSFR. The following assumptions are made for the calibration of the 2010 NSFR and 2014 NSFR.

i. Numbers in “unspecified” cells are the weighted average of the other four cells with one exception: for the case of wholesale deposits, “unspecified” is likely to be dominated by the very short-term (or operational) deposits. When we aggregate four weights, they are weighted by the amount of total USD share of each tenor bucket relative to the total USD amount of the item for all 121 banks in our sample. This vector is computed using data from banks for which the maturity data exists.

ii. Retail loans with a maturity of less than 1 year are dominated by non-mortgage (eg credit card loans) and remaining part is roughly divided into half by unencumbered (65%) and encumbered (100%) high quality (HQ) mortgages. This roughly justifies 85% required stable funding (RSF) for the first two cells, 0-3M and 3-12M for the 2010 NSFR. For the 2014 NSFR, RSF for residential mortgages is reduced to 50%.

iii. Retail loans in 1-5Y and greater than 5Y are mostly dominated by unencumbered HQ mortgages (70%, in our assumption). This is confirmed by the Liquidatum’s data that roughly 10-20% of the sum of these two

[5] Derivatives for NSFR (both 2010 and 2014) are calculated using the maximum of 0 and ‘derivative assets – derivative liabilities’.

cells equals to the sum of “Risk Transferred Assets (RTAs)” which represents encumbered mortgages for banks that reported RTAs. It is also realistic, from the data, to assume that the encumbrance ratio for retail loans greater than 5Y (7.5%, in our assumption) is higher than that of retail loans 1-5Y (2.5%, in our assumption).

iv. 50% of Wholesale loans with a maturity greater than 1yr are assumed to have 50%RSF.

v. Retail deposits in financial reports (Liquidatum) are highly likely to include “wholesale funding provided by non-financial corporate customers” which gets 50% available stable funding (ASF). It is also likely that the contamination stated above is occurring mainly in the first cell “0-3M,” given the nature of non-financial cooperate deposits.

vi. Equities (Trading Assets) are all listed and unencumbered.

(Necessary assumptions for the calibration of NSFR 2014)

i. 20% of “Reverse repo” is for banks <1yr.

ii. 25% of wholesale deposits <6m are operational deposits.

iii. 25% of trading assets (MBS/ABS/FI/Corp,Other) are non LCR-level2<1yr.

iv. Half of the wholesale loans>1y and other assets are items that attract 85%RSF and the remaining half of those attract 100%RSF.