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Applications for Macro Stress Testing in Times of Crisis

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This thesis discusses a number of potential applications for macro stress tests while focusing on the differences in the behaviors of banks between normal times and times of crisis. It comprises elements related to macro stress tests and profitability, the responses of banks to a monetary policy shock, the transmission channel of solvency risk on the funding of banks as well as the interaction between capital injections and liquidity measures that took place in the US in the aftermath of the subprime crisis. The work investigates these issues using innovative econometric techniques, in particular dynamic factor analysis, panel data econometric and quasi-natural experiments.

Franco Stragiotti is born in Italy in 1973. He has been working as economist for the Central Bank of Luxembourg since 2007. For 2 years he worked at the European Central Bank as Financial Expert. Before, he has worked as treasurer in a holding company and in an investment fund in Luxembourg and briefly as consultant. Franco holds also a Master degree in Monetary Economics from the Katholieke Universiteit Leuven and a Bachelor Degree in Economics and Commerce from the Catholic University of Milan, Italy.

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Disclaimer

The view expressed in this PhD dissertation are mine and do not represent the view of any other individual or organization. The opinions, conclusions and recommendations presented herein are those of the author and do not necessarily reflect those of European Central Bank, The Banque centrale du Luxembourg or the Eurosystem or The Université Catholique de Louvain. All remaining errors are my own.

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Chapter 1

Macro Stress Tests and Crises

1. Introduction

Economic history has provided us with various episodes of economic crises: the Tulip mania of the beginning of the 17th century, the Great Depression that took place during the 1930s, the Asian and Russian Financial Crises of 1997-1998 and the subprime mortgage crisis that led to the default of Lehman Brothers in 2008, to name a few. All these crises entailed dire consequences and triggered policy responses aimed to reduce the adverse effects and to prevent further crises in the future (see e.g. Laeven and Valencia, 2012, Mishkin and White, 2002 and Romer, 1988).

While economic crises "play havoc" with societies and welfare, and institutions implement measures to deal with these events, their occurrence gives academics and analysts the opportunity to study how economies and economic agents behave under stress. Crises can also offer insights to policy makers, which can draw lessons on how to implement measures for reducing the frequency of episodes of stress, or to mitigate their effects. Indeed, studying different crises over time provides invaluable knowledge about their evolution and causes.

For these reasons, it is important to study macroeconomic crises as it is possibly more important than understanding economies in normal times. Indeed, crises may create new dynamics in an economic system as agents may behave differently than in "normal" times. Investigating the mechanisms at work during these events can, thus, play a crucial role in implementing effective policies or increasing our understanding of the behaviours of economic agents and policy makers when stressful episodes occur.

Amongst the economic agents that shape the responses and implement the policies needed to counterbalance the effects of crises, commercial and central banks play an essential role in the functioning of financial markets. To enable these institutions to detect, avoid or mitigate the effects of economic crises it is pivotal to raise the awareness of the risks and scenarios that may entail potential failures in their processes or businesses. Amid the tools available to assess vulnerabilities and to manage risks, there are micro and macro stress tests, the latter being the focus of this study.

2. Stress Tests: Macro and Micro Perspectives

Understanding the differences between stressful and normal periods is the baseline to perform meaningful stress tests. Their quintessence consists in modelling economies and agents under severe but plausible episodes of crisis. More in detail, stress tests are one of the risk management tools available to the financial industry for micro-based analysis and to supervisors for macro-prudential purposes. They gauge the impact of a shock often encompassing credit, liquidity, market and/or operational risks on a set of variables of interest. At times, stress tests may consist in a sensitivity analysis; when complexity is added, stress tests can be scenario analysis that combine several risks at once and entail interactions between different risk categories. Policy makers, supervisors, banks but also financial institutions in a broader sense, make use of the outcome of stress test exercises for internal or external purposes.

For a bank or a financial institution, stress test results can materialize in capital needs, in the setting of risk tolerance levels or in communication tools that can be disclosed to rating agencies. Usually the results of a stress test is accompanied by a set of mitigating actions aimed to improve a bank's financial robustness, e.g. a liquidity stress tests can be used to fine-tune a contingency funding plan, i.e. a set of actions defined by an institution to address a liquidity crisis[1].

While stress tests are regularly performed by banks and other financial institutions at a micro level, for central banks and regulators, stress tests are mostly intended as macro-prudential tools used to assess the risk of the banking sector or a group of banks with respect to the occurrence of a specific scenario[2]. In this context, the Bank for International Settlements defines macro stress tests as "(...) techniques (which) have been employed to test the stability of groups of financial institutions that, taken together, can have an impact on the economy as a whole" (see Borio *et al.,* 2012).

[1] See e.g. https://www.ecb.europa.eu/pub/pdf/other/eubanksliquiditystresstesting200811en.pdf

[2] Although nothing prevents their use for micro-prudential purposes, also by supervisors.

Macro stress test exercises have been performed regularly, before and in the aftermath of the subprime crisis, while aiming to restore financial stability in the ailing banking sectors of several OECD countries (e.g. the United States, the European Union, the United Kingdom, etc.). Among these we can include the Supervisory Capital Assessment Program and the Comprehensive Capital Analysis and Review, performed by the Federal Reserve in the United States , the European Banking Authority Stress Tests, the Financial Services Authority's stress and scenario testing and the Bank of England stress tests for the United Kingdom. Other macro stress tests were performed worldwide after the default of Lehman Brothers, e.g. for Brazil, Singapore, Japan, Australia and China, among others.

3. Macro Stress Tests in Times of Crisis

This study investigates several aspects of the behaviour of banks during crises and in normal times. The US banking sector is selected as playing field for two important reasons: first, the US remains the largest world economy and its banking and financial sectors are among the most important worldwide, hence the findings are of interest also to a broader audience, outside the US. Second, the US have been collecting data on balance sheet of banks and on macroeconomic variables since long time. For banks, the availability of data on commercial banks dates back to 1976 while for bank holding companies this starts later in 1986. This study could hence benefit from an access to a vast dataset in terms of depth (30 years of data) and breadth (thousands of banks reported over time during these years). The characteristics of the datasets allowed to investigate US banks over different recessions, also including several banking crises, i.e. the savings and loans crisis, with the regional crises of the end of 1980s, the less developed countries' crisis as well as the default of Lehman Brothers. In addition, several regulatory framework were implemented during the observation periods, from the pre-Basel to Basel III banking regulations and may have played a role in the findings.

This work contributes to the existing literature in stress testing along several dimensions:

1. The analysis investigates the impact of macroeconomic scenarios and policy shocks on the profitability of banks measured by return on assets and net interest margins in an innovative approach comprising macro and microeconomic information leveraging on a dynamic factor model. In addition, the study discusses the capability of this framework of identifying weaker banks under different scenario assumptions, over several years and different macroeconomic and risk environments. The findings stress that microeconomic measures of profitability, namely return on assets and net interest margin, contain important information about macroeconomic conditions and business models of banks. Eventually, it indicates that conditional forecasts are able to capture differences, across the sample in terms of risk profiles and sensitivities to macroeconomic variables.

2. The study provides corroborating evidence of the existence of the solvency-liquidity channel as well as useful estimations for these effects for practical applications to stress tests. Moreover, it elaborates on how banks respond to solvency issues, identified by capital and profitability shortfall. The findings illustrate to what extent previous assumptions concerning "bad press" coverage, which triggered bank runs, are supported by evidence. These assumptions are particularly relevant for liquidity stress tests, also for practical applications. In addition, the study investigates how funding costs react to solvency issues. Several tests are performed over a time horizon spanning from 1986 until 2013 covering several episodes of macroeconomic and banking crises in the US, as mentioned above.

3. Finally, the analysis focuses on the policy area of stress tests, i.e. recapitalization of ailing banks. Using an innovative approach, the analysis find the effects of the Troubled Asset Relief Program to be questionable in boosting lending activities in the US. This latter result indicates that while stress tests may be effective in identifying ailing banks, the design of policy measures is critical to achieve the desired goals. The study exploits the latest crisis in the banking sector, which led to the interventions of the US Government and of the Federal Reserve System to mitigate the effects of the shock. In a quasi-natural experiment

setup, the analysis examines how excess reserves and capital injections interact with lending. The investigation makes use of a series of least squares regressions, first performed on a large sample of banks (including the largest ones) and, after eliminating the self-selection bias, second, on a subset of comparable banks accepting (the "treatment" group) or declining (the "control" group) the funds provided by the Troubled Assets Relief Program, in particular the Capital Purchase Program. The results do not provide strong support to the belief that the Troubled Assets Relief Program effectively boosted lending in the US in the aftermath of the default of Lehman. At last, it highlights as paying interests on excess reserves of commercial banks may have acted as incentive to discourage them from lending to the real economy. This chapter provides evidence of the effects unfolded by potentially diverging policies.

The above ideas are eventually the basis of this study. Using well-known and theoretically sound models, this study aims to fill several gaps in the literature of stress testing that so far has largely been neglected, from profitability to the solvency-liquidity channel to the effectiveness of policy measures that may unfold from stress test exercises, e.g. recapitalizations.

4. Shortcomings of Macro Stress Tests

Recent developments in macro stress testing have pointed to a number of weaknesses in the exercises performed across the banking and financial sectors of several countries. In particular, researchers highlighted the lack of a proper understanding of banks' behaviour when faced with a severe shock. A number of authors have pointed out that the lack of specification of the interactions of banks and other financial players within a stress-testing framework is a critical shortcoming, which deserves further investigation. Among others, Bookstaber *et al.* (2013) highlight that a better understanding of the dynamics underlying banks' responses to stressful events in financial markets (e.g. fire-sales and funding runs) is a critical point for further research. Schmieder *et al.* (2012) also point to the need of additional analysis regarding banks' behaviours in their balance sheet approach for liquidity stress tests. Kapinos, Martin and Mitnik (2015) also propose to incorporate capital and liquidity aspects of banking risk in stress testing.

Integrating profitability is also pivotal for stress testing of banks. First, banks' profits are a precondition for their healthy and soundness, as a failure to generate earnings often anticipates a solvency issue. In addition, profits enable banks to strengthen their capital position via retained earnings. Duane, Schuermann and Reynolds (2013) emphasize the role of creating profits as an alternative to focusing on mere losses for stress testing banks. At last, as Tarullo (2012) highlighted that the projections of revenues were crucial to the success of the Supervisory Capital Assessment Program. These arguments call for an integrated stress testing framework where profits of banks are included in the stress testing exercise. In this respect, the stress tests planned in the Euro-Area for the year 2017[3] focus on the impact of the low interest rate environment on net interest income, underlying the importance of integrating interactions between macroeconomic conditions and banks' profits.

In addition, macro stress tests entail policy initiatives. Supervisory stress tests have been used as intermediary steps to implement measures aiming to strengthen the capital and/or the liquidity positions of banks. These initiatives intended to achieve an ultimate goal, i.e. to effectively support the bank lending channel by maintaining the financial soundness of the banking sector and of its efficacy in its role of financial intermediation. The supervisory stress tests performed by the Federal Reserve, the European Banking Authority and the Bank of England are in fact mostly characterized by these features. At last, also the Troubled Assets Relief Program, the policy initiative of the US Government in the aftermath of the subprime crisis, aimed to restore the capital strength of banks. The identification of the efficacy of the policy interventions following a stress test exercise is therefore equally important for stress testers.

[3] For more information see: https://www.bankingsupervision.europa.eu/about/ssmexplained/html/2017_stress_test_FAQ.en.html

5. The Role of Stress Tests as Supervisory Tool

It has been widely debated if stress tests have been useful as risk management tools for individual banks as well as a valid supervisory tool for macro-prudential purposes. In particular, in the relevant literature a large number of articles debate the utility, the reliability of the results and the methodology adopted for stress tests, both in the US and in the EU[4]. Overall, while it was widely acknowledged that the scenarios have been often unrealistically optimistic, the discussion on the use and methodology were less critical of these tools. In the end, stress tests appear to be valid instruments for assessing the risks faced by banks to pre-defined scenarios and they have been observed to carry information that reflect changes in the solvency and liquidity risk levels of banks and they may be helpful to reduce the opacity and asymmetry of information in financial markets (Petrella and Resti, 2012).

The future of stress tests rely on their credibility to investors, financial markets and the general public. In particular, while complexity is embedded in stress tests, it is important to clearly define credible modelling assumptions and policy objectives in order to communicate effectively to the general public or to stakeholders (e.g. rating agencies and investors). Credibility has been often pinpointed as a major weakness of stress tests as discussed by Ong and Pazarbasioglu (2013) but also in a comprehensive article, by Engelen (2014). A major challenge ahead for stress tests is going to be adhering to clear methodological rules based on economic and risk assessment. It is therefore important to develop a sound methodology for stress test exercises to provide supervisors with reliable and credible outcomes.

Supervisors and investors should also be aware of the limits of stress tests as they cannot provide for the full spectrum of occurrences of adverse scenarios. The limits and shortcomings of stress tests (as for any risk management tool) should not be underestimated when the results of stress tests are used for

[4] Among the many articles debating stress tests: https://www.bloomberg.com/view/articles/2016-08-01/europe-s-bank-stress-tests-fail-again, https://www.bloomberg.com/news/articles/2016-08-11/european-bank-stress-tests-get-more-stressful-when-you-make-them-american, http://www.spiegel.de/international/europe/a-702183.html, http://www.economist.com/blogs/freeexchange/2014/04/european-stress-tests, http://www.cnbc.com/2014/10/24/whats-missing-from-the-eu-bank-stress-tests.html, http://www.politico.eu/article/regulators-say-eu-banks-are-healthy-stress-test-renzi-eu/, http://www.reuters.com/article/italy-banks-monte-dei-paschi-idUSL8N1DO4YU, http://voxeu.org/article/defence-european-banking-authority, http://www.telegraph.co.uk/finance/financialcrisis/8642492/European-Banking-Authority-was-hobbled-over-stress-tests.html, among others.

policy interventions, as these risk management tools are complementary to human judgement and not substitute for it. Alas, one cannot demand from stress tests what they cannot provide to us, i.e. certainty and infallibility.

Indeed, stress tests remain a highly effective risk analysis tool: first, when performed on the basis of economic rationales, they allow for a reliable scenario analysis and are effective in identifying potential issues at the level of individual banks as well as at the aggregate (systemic) level, for an entire banking sector.

Finally, when aiming to "stress-testing macro stress testing", as suggested in Borio, Drehmann and Tsatsaronis (2012), nothing is more suitable than financial and economic crises. These stressful events de facto checked stress tests "in action". They allow risk managers to validate, improve and eventually dismiss issues and shortcomings in the methodology of these tools. More, observing different crises gives the opportunity of testing consistency of assumptions in different economic environments. In the end, crises are the fittest reality check for stress tests.

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Chapter 2

Stress testing profitability in US commercial banks: a dynamic factor model approach

(Joint work with Michele Lenza)

1. Introduction: Profitability and Default Risk

The profitability of the banking sector is an important component of financial stability. Profits can improve the financial soundness of banks through several channels. A profitable bank can use the proceeds as retained earnings and strengthen its capital base or redistribute part of these earnings as dividends to shareholders; moreover, profits can finance takeovers or acquisitions to allow a bank to grow with internal funds. While financial markets favour profitable banks, regulators are also interested in banks to be profitable as a strong nexus exists between financial soundness and probability of failure[5].

Lack of profitability and likelihood to fail are two sides of the same coin. Gopalan (2010) stresses the importance of earnings for banks looking at how bank crises in the US in the 80s' unfolded. Deterioration of asset quality forced banks to provision for future losses. Hence a deterioration of the capability of a bank to generate profits was the "canary in the mine" of a future situation of financial distress. The author illustrates, using supervisory ratings in the US, that a decline in earnings is mainly a reflection of asset quality deterioration.

The argument for falling profitability and increase in likelihood to fail is illustrated in figure 1. The chart shows the evolution of failed banks according to the Federal Deposit Insurance Corporation[6] which is compared with a dummy that matches a loss with a capital shortfall in a US commercial bank. The dummy is equal to 1 if the bank reports a loss and a capital shortfall in the same quarter, 0 otherwise:

$$\text{DLR} = \begin{cases} 1 \rightarrow \text{[Loss reported]} \\ 0 \rightarrow \text{[No loss]} \end{cases} \tag{1}$$

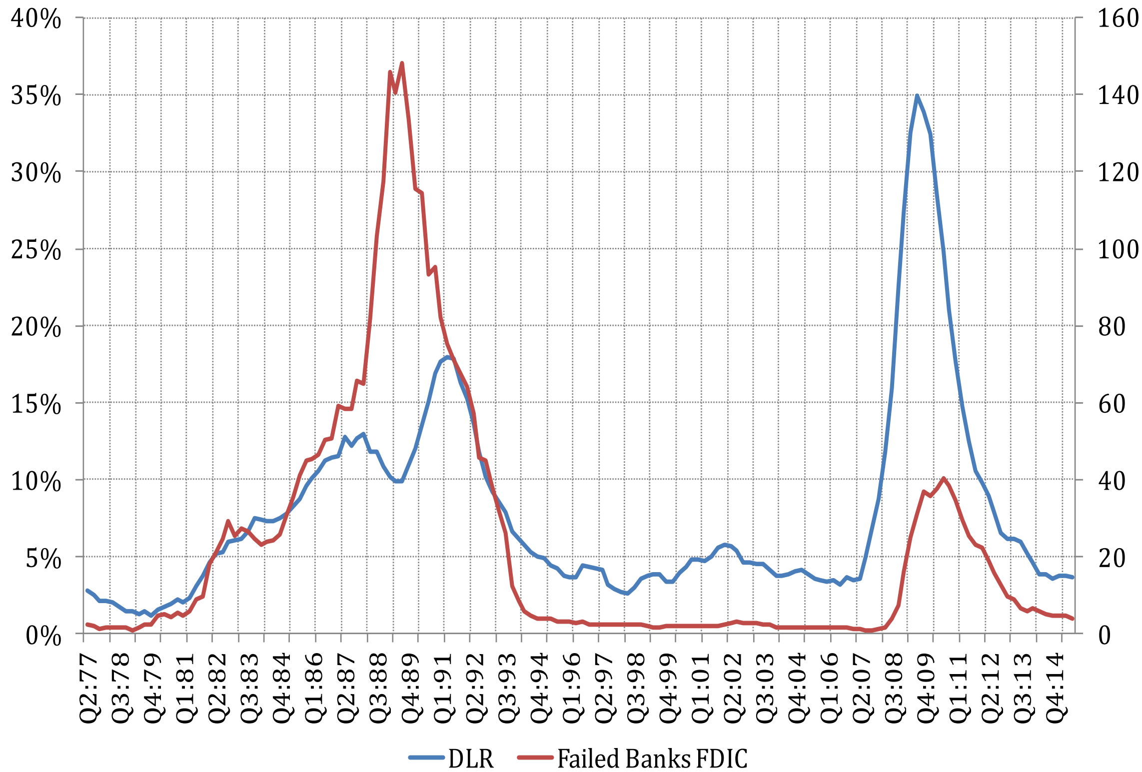
The figure supports the view that losses and bank failures are strongly linked and constitute a valid proxy for risk of default. The significant role of profitability in the estimation of default risk can also be found in Altman (1968) and the z-score, a proxy for a firm's distance to default. Later applications of

[5] Policy makers have stressed the accrued importance of profitability in supervisory and regulatory discussions (see Tarullo, 2012 and Duane et al., 2013).

[6] For more information on failed banks, see: http://www.fdic.gov/bank/individual/failed/banklist.html.

the z-score to banking that can be found e.g. in Demirguc-Kunt and Huizinga (2012) and Kölher (2012).

Figure 1: number of failed banks by quarter, quarterly moving average based on FDIC dataset (rhs) vs. DLR(lhs)[7]



The figures for DLR represent the moving average of the percentage of banks reporting DLR equal to one (lhs) over the sample used in this study. The banks declared failed by the FDIC (rhs) are reported in absolute number, as a yearly moving average.

The above evidence indicates that the ability to forecast profits of banks and the capability to link these forecasts to macroeconomic scenarios could be useful to regulators as it would enable them to identify banks that would experience financial distress when faced with specific macroeconomic scenarios. In particular, it would justify to use stress testing tools to assess the impact of macroeconomic shocks to bank profitability.

[7] The differences in the data refers to the threshold selected for our dataset, which is set at 1bn USD of total assets. This removes most small banks which constituted the largest amount of failing institutions during the Savings & Loans Crisis of the 80s and 90s.

This study focuses on forecasting profits under conditional scenarios using a Dynamic Factor Model (DFM hereinafter). The innovation of the study consists in establishing a reliable methodology to conduct stress-tests in a framework which is able to encompass both microeconomic information, required to assess the soundness of the banking sector, and the macroeconomic information needed to design the stress-test scenarios. The study is therefore able to integrate in one single framework both types of information usually required to perform a stress test, i.e. the bank level data and the macroeconomic scenario going in the direction of comprehensive stress tests design (see Schuermann, 2012). This new approach bypasses the canonical stress testing framework where satellite models interact with a macro-financial scenario generator, such as the ones described e.g. in Jakubik and Sutton (2011).

The measure of choice for the exercises is Return on Assets (RoA hereinafter); this is linked to a number of desirable features: first, RoA is an overall indicator of operational performance for banks. It measures the aggregate level of profitability, while being independent from leverage (to the contrary of the Return on Equity). In addition, the RoA is a component of the z-score[8], which shows its importance also for risk-related analysis. At last, it is widely used, also by practitioners, and its merits and flaws are easy to understand and to interpret.

The results indicate that the forecasts of individual bank RoAs, based on macroeconomic conditions, are generally more reliable than the unconditional forecasts. This finding reflects the existence of non-trivial relationship between the macroeconomic US environment and individual banks' profitability and the ability of the model to capture such relationship. These findings can be interpreted as an important empirical validation of the methodology used in this study to conduct stress-test exercises. The findings also demonstrate that the model outperforms popular naïve benchmarks (essentially autoregressive models) of statistical accuracy over the different forecast horizons. This is true for RoAs but especially for some of its sub-components, namely Net Interest Margin, Non Interest Income and Non Interest Expense. The latter result shows that this methodology can be successfully applied also to consider more

[8] See e.g. Altman E. I. (1968).

granular applications devoted to investigate the impact of scenarios on different indicators.

The structure of the paper is the following. Section 2 describes the aim and setup of the study, section 3 discusses the literature of reference, section 4 the dataset and the model used in the study. Eventually, section 5 presents the empirical results and Section 6 concludes.

2. Profitability and Stress Tests Modelling

Banking stress-test exercises assess the resilience of the financial sector in unfavourable economic regimes, while making use of macroeconomic and microeconomic information[9]. Stress tests usually require modelling frameworks which aim to identify prudential corrective measures for a group of financial institutions considered critical. To achieve this goal this study defines a comprehensive stress testing framework, where macroeconomic variables and RoAs interact to generate forecasts of RoAs for each bank.

More precisely, the study models the dynamic interlinkages between bank profitability, and the set of financial and macroeconomic variables for the US by means of a DFM (see Stock and Watson, 2002; Forni et al., 2000 and Doz et al., 2011). DFMs describe a large set of N variables using an extremely parsimonious representation in which the bulk of the co-movement is described by a very small set of common factors. In particular, each variable is represented as the sum of two components: the common ones, driven only by a small number r ($r \ll N$) of common factors, and the variable specific idiosyncratic ones, which are only mildly cross-correlated. The heterogeneity in variables is captured by the idiosyncratic components and by the variable specific loadings on the common factors.

Appendix B provides the complete list of all variables included in the model. The microeconomic block of the model consists in a relatively large set of RoAs of US commercial banks (176 banks are considered in the exercises). The

[9] Among those, the European Banking Authority (EBA) Stress Testing, the Federal Reserve's Comprehensive Capital Analysis & Review (CCAR) and Supervisory Capital Assessment Program (SCAP) exercises featured these characteristics.

macro block includes the most relevant macroeconomic (e.g. GDP, unemployment, federal funds rate, inflation, capacity utilization) and financial variables (e.g. loans, lending rates, house prices, total assets of banks) describing the US economy, for a total of 31 variables. These variables are likely to capture the main dynamics of the US economy and of financial markets.

The model is validated as a tool for conducting stress-tests by assessing the accuracy of forecasts of banks' RoAs, conditional on the aggregate macroeconomic and financial environment. In particular, forecasts of RoAs are observed up to a horizon of four quarters ahead, conditional on the past development of all the variables in the model. The estimated coefficients are observed up to the time where the forecasting evaluation starts and the actual future path (up to the end of the forecast horizon) of different sets of macroeconomic and financial aggregate variables in the model.

The model is tested mainly on the basis of conditional forecast accuracy because the stress-test exercises are essentially scenarios, evaluating the reactions of bank level variables, conditional on specific paths of various sets of selected financial and macroeconomic variables. Consequently, an adequate tool for conducting stress-test scenarios should be able to provide accurate conditional forecasts. Clark and McCracken (2014) show that the popular statistical measures of forecast accuracy retain their statistical properties for conditional forecasts, only when the conditions are given by the actual paths of a set of variables. Hence, the choice of the actual path of macroeconomic and financial variables as conditions is also a reasonable choice, given that a "good" model should provide accurate conditional forecasts when the conditioning paths are "reasonable".

3. Literature

The paper is related to the literature assessing the relationship of bank profitability with the macroeconomic environment. Already before stress testing exercises became widespread tools across supervisors and central banks, a number of studies focused on commercial banks' profitability by looking at financial indicators for performance as, for example, RoE and RoA (see Berger, 1995, Demirgüç-kunt and Huizinga, 1999; Jiang et al., 2003; Goddard et al., 2004; Stiroh, 2004; Albertazzi and Gambacorta, 2009; Rumler and Waschiczek, 2010). Although results vary to a certain extent, generally the evidence is that some macroeconomic variables are related to bank earning power (for example real GDP growth, inflation and real interest rates are significant in most cases). The study builds on these insights, by including a rich macroeconomic block in the model.

The large majority of macro stress testing models focus on risks and spillovers from the financial sector to the real economy and on key vulnerabilities of the macroeconomic and financial system. A few recent studies also connect stress tests with the analysis of bank profitability as the one proposed by Andersen and Berge (2008) from The Norges Bank. The structure of their stress testing framework involves four models: a macro financial model for Norway, a model for individual households' default probabilities, another for firms' default probabilities and a micro model for banks. Guerrieri and Welch (2012) investigate the relationship between macroeconomic variables and two indicators of bank performance (i.e. net interest margin and pre-provision net revenues). This study compares a number of relatively simple models on the basis of criteria of forecasting accuracy, showing a relatively low improvement in predicting performance when compared with a random walk (the baseline model). Duane et al. (2013) investigate bank profitability in the US, by focusing on bank holding co. reporting data.

Bolotny et al. (2014) focus on stress testing of US banks' profitability for interest rate risk, assessing the ability of a number of models to provide an accurate forecast of Net Interest Margin. Covas et al. (2010) develop a macro stress testing framework for 15 US bank holding companies, finding that profitability ratios are more sensitive to financial indicators, in particular to the slope of the yield curve (i.e. 10Y vs. 3M Treasury rates) and corporate credit spreads for net interest income. Coffinet et al. (2012) develop a model to evaluate the impact of an adverse macroeconomic scenario on banks' profitability (i.e. RoA, RoE and Net Interest Margin). GDP growth, inflation and yield spreads are found to be positively correlated with RoA although only a severe recessive scenario could generate negative profits.

Buch et al. (2010) propose an approach based on a Factor Augmented Vector Auto-Regression (FAVAR) model investigating risks in the banking sector. The authors include large bank-level data to model the linkages between each individual bank and macroeconomic shocks. They include RoA as profitability measure and growth of total bank loans for measuring bank activities and business expansion. Their findings show that micro level banking data carry important information to estimate the response of macroeconomic variables to a macroeconomic shock. Banbura et al. (2015) develop a large scale VAR estimated by means of Bayesian techniques in order to assess the effects of the adverse macroeconomic scenarios devised in the banking stress-tests on a large number of Euro area macroeconomic variables, among which the aggregate credit variables. The validation strategy proposed in this paper is based on out-of-sample criteria, is close to the logic used by Banbura et al. (2015) but focus on individual US banks over an extended sample.

4. Data and Model

4.1 The Dataset

The dataset can be split in a microeconomic and an aggregate (macroeconomic/financial) block.[10] The majority of aggregate macroeconomic and financial variables is collected from the FRED database of the Federal Reserve Bank of St. Louis, with a small number of exceptions. Overall, the database includes all the most relevant categories of macroeconomic and financial variables for the US banking sector.

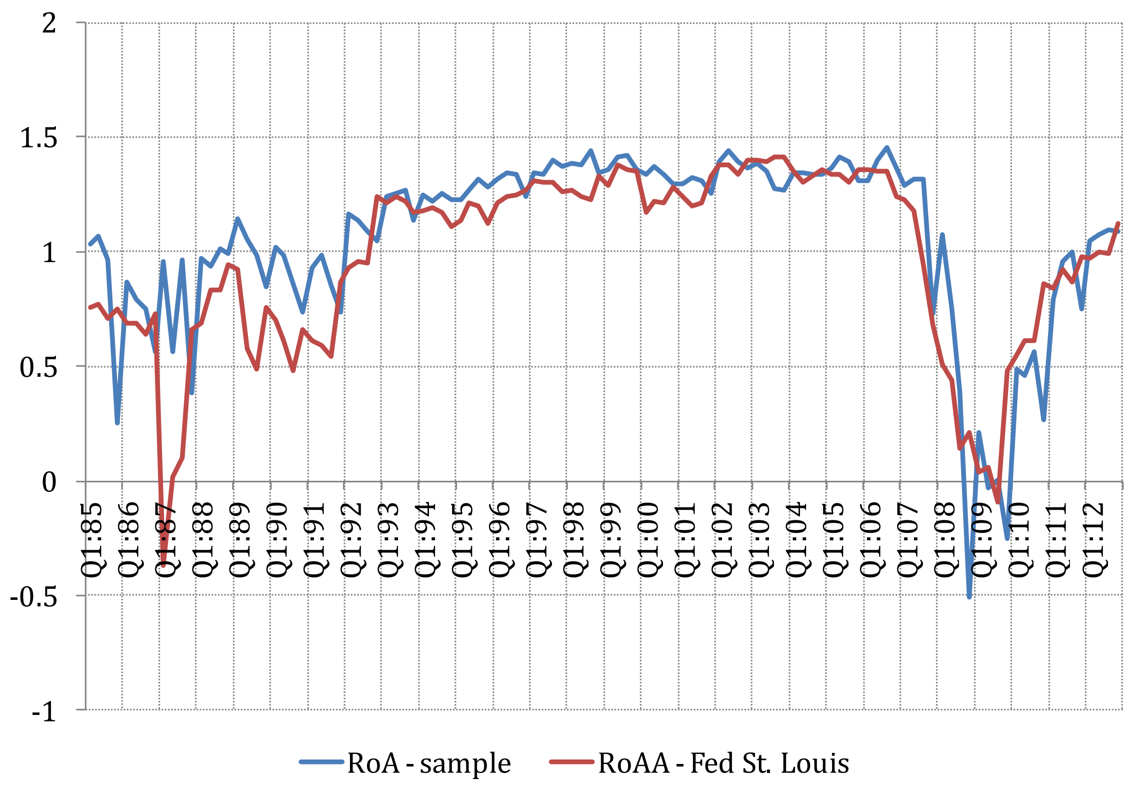
The source for the microeconomic data (banks' RoAs) is the Federal Financial Institution Examination Council's (FFEIC) report 041, also known as "call report". This database collects information for all commercial banks in the US, at quarterly frequency. The main items needed to estimate each individual RoA are: the quarterly income/loss before extraordinary items and other adjustments (RIAD4300) and total assets (RCFD2170)[11]. After having adjusted RIAD4300 to obtain quarterly values for net income, $RoA_{b,t}$ is defined as:

[10] See data appendix A, for details.
[11] These items are reported in the FFEIC041.

$$RoA_{bt} = \frac{RIAD4300_{bt}}{RCFD2170_{bt}} \tag{2}$$

$RoA_{b,t}$ is calculated for each bank b and each quarter t. The study focuses on the 300 largest banks in terms of total assets as of the second quarter of 2015 and excludes those which did not report for the full sample considered (i.e. 1985Q1 – 2015Q2). This reduces the number of banks to 176 (see appendix A).

Figure 2: RoAAs of all US FDIC-insured commercial banks vs. aggregate RoAs in the cross-section.



The source of the main difference in Q1:1987 is due to the composition of the sample, which is limited to the largest 176 banks for the study sample. The chart reports annualized figures for RoA and RoAA.

Figure 2 reports a comparison of the Return on Quarterly Average Assets for all U.S. banks based on the data from the Federal Reserve Bank of St. Louis and the simple average of the individual bank RoAs in the sample[12]. The chart shows that an aggregate of RoAs captures the salient features driving profitability in the full universe of US banks and, hence, the available cross-section seems appropriate for the goal of this study to describe the common driving factors of US RoAs. Table 1 reports the descriptive statistics for the RoAs in the sample.

Table 1: RoA's sample statistics (figures in %)

Average	25th Percentile	Median	75th Percentile	Standard Deviation
1.057	0.914	1.123	1.328	0.340

The panel of banks is not adjusted for mergers and acquisitions (M&A). Several banks in the sample underwent a number of M&A operations. This implies that a number of banks stopped reporting to the FFIEC, hence discontinuing the time series, due to acquisition or merger operations with another bank. In order to address this issue, two approaches are generally considered: the first reconstructs the time series of the merged/absorbed institutions into a unique entity, creating a fictitious bank for the period prior to the M&A operation[13]. The second approach disregards the institution that has been the target of the M&A, which drops out of the panel, and keeps only the "absorbing" institution.

The second approach is selected for two reasons. First, reconstructing time series and adjusting for M&A may be very difficult and prone to errors as banks often merge with institutions which do not report to the FFEIC (such as securities brokerage firms, investment banks, thrifts) rendering the exercise incomplete or unfeasible. Second, in reflecting the guidance of a unique management, before and after a M&A, the RoAs in the panel are characterized by time-consistency. Hence it is preferable to discard the option of summing the RoAs of the different banks, combining diverse management styles in one fictitious entity. In addition, the way the RoAs of merged banks are considered may not be so relevant. For instance Kashyap and Stein (1999) investigate a

[12] The source for this aggregate measure is the database of the Federal Reserve Bank of St. Louis. See https://research.stlouisfed.org/fred2/series/USROA.

[13] Covas, Rump and Zakrajsek (2012) adopt a similar approach in their study but their focus is on bank holding companies, while our study only include commercial banks.

dataset of US commercial banks similar to the one used in this analysis and found no difference in their results by using one or the other approach. Finally, they choose the same approach that adopted here.

In order to complement the results based on RoAs, the same analysis is conducted for its main sub-components. In particular, "Net Interest Margin" (NIM hereinafter), "Non Interest Income" (NII hereinafter), "Non Interest Expenses" (NIE hereinafter) and "Provisions for losses on loans" (PROV hereinafter) are investigated. The NIM represents the share of income generated by the difference between interest income (e.g. amount of interest received on loans) and the related cost of funding (e.g. amount of interest paid to depositors). This ratio describes mostly the revenues of the traditional banking business (lending and deposit-taking). The NII represents the share of income mainly generated by banking fees and fiduciary income. It includes most service-related, non-interest driven, incomes. The NIE comprises fixed costs, salaries and benefits paid by the bank. PROV represents the amount set aside by a bank as a precautionary measure to compensate for future losses on loans.

4.2 The Modelling Framework

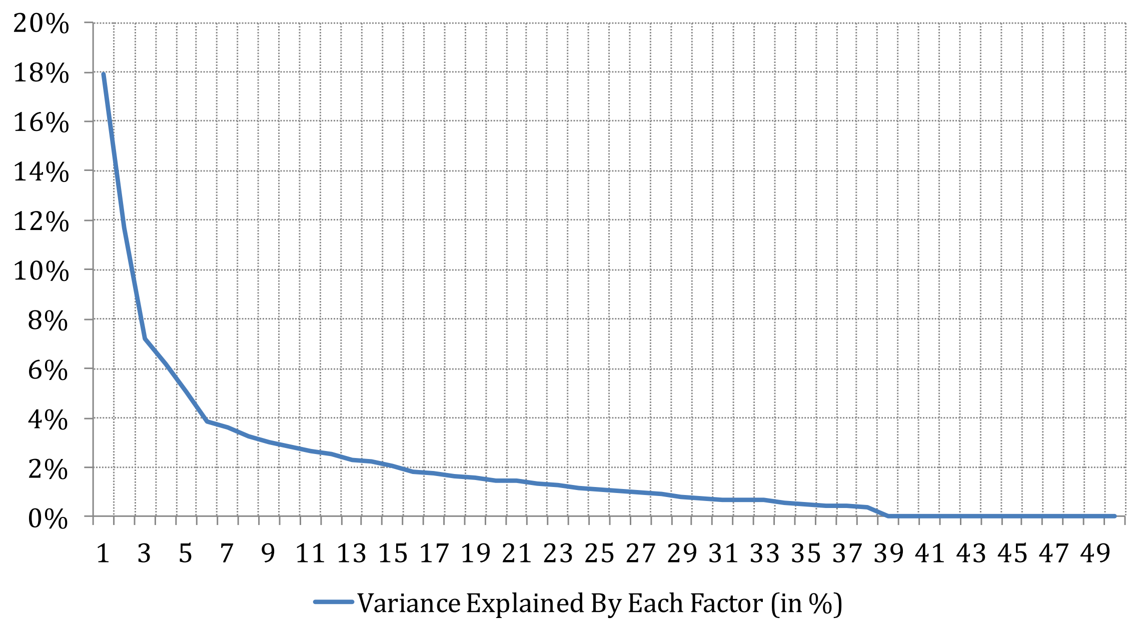
The modelling framework captures the idea that micro banking data reflects both aggregate (common to all banks) and individual bank specific sources of fluctuations. In particular, a DFM as defined in Stock and Watson (2002) and Forni et al. (2000) is adopted. The model is described by two sets of equations for the set of micro and macro variables ($Y_{i,t}$, $i=1\ldots N$):

$$Y_{i,t} = \lambda_i f_t + \xi_{i,t} \tag{3.a}$$

$$f_t = A(L) f_{t-1} + e_t \tag{3.b}$$

where the common component ($\lambda_i f_t$) collects the bulk of the correlation among variables and depends on the product of the r-dimensional vector of common factors f_t and the $N \times r$ matrix of factor loadings $\Lambda = [\lambda_1' \ldots \lambda_N]$. The dynamics of the common factors is described by a vector autoregression. The idiosyncratic component of each generic variable *i* is allowed to be mildly cross-correlated. The model is estimated by means of the two-steps approach described in Doz et al. (2011). All data are transformed into stationary time series, when necessary (see Appendix B for further information). Three common factors are used in all exercises since one additional factor[14] explains less than 5% while accounting for about 40% of the total panel variance, as illustrated in the figure below:

Figure 3: variance explained by each additional factor, in % - top 50 factors



The y-axis reports the percentage of variance explained by each individual factor, while the x-axis reports the number of factors.

5. DFM and Stress Testing: Accuracy of Conditional Forecasts

In this section, the results of the empirical analysis are reported. An out-of-sample forecasting evaluation, both for the RoAs and its subcomponents, is performed.

[14] Notice, however, that the main results in the paper are robust to adding and dropping the next factor in terms of explained variance.

5.1 Out-of-Sample Forecasting Evaluation

In order to validate the DFM model as a tool to conduct macro stress test exercises, it is pivotal to assess its accuracy to produce "conditional forecasts", i.e. forecasts of the individual bank RoAs (and subcomponents) based on specific future paths taken by some specific macroeconomic variables included in the dataset. Indeed, stress-test exercises entail computing the path of individual bank variables under a set of assumptions on the future path of aggregate variables. Formally, the conditional forecasts for the RoA of bank *b*, $RoA^{CX}_{b,t+h}$, can be defined as

$$RoA^{CX}_{b,t+H} = E_t\left(RoA_{b,t+H} | I_t, X_{t+1} \dots X_{t+H}\right) \tag{4}$$

where I_t is the whole set of macro and micro variables until time *t* and $X_{t+1} \dots X_{t+h}$ represents the "conditions", i.e. the *actual* path of a subset of variables over the period ranging from *t+1* to *t+h*, where *h* is the horizon upon which the forecasts are conditional. These latter forecasts are computed by means of the Kalman filter based algorithm described in Banbura et al. (2015). The derived conditional forecasts provide the "most likely" path for the RoA of bank *b,* given the knowledge of the actual path of a set of variables. In other words, these forecasts will be based on the most likely combination of economic shocks that may explain the future path of the variables in the conditioning set, according to the historical regularities captured by the estimated DFM model.

The baseline conditional forecast (defined *CM*), is based on the knowledge of the future path of GDP, unemployment rate, PMI manufacturing index and Federal Funds' Rate, which is defined as the "macro assumptions". In order to assess the informational content for bank RoAs beyond what is already included in the "macro assumptions", the analysis also looks at a set of alternative conditional forecasts (defined *CMB*), which adds a number of aggregate banking variables (i.e. the Freddie Mac House Price Index, the aggregate volume of credit in the US, the volume of outstanding mortgage backed-securities in the US, the spread between the 3M and 10YR US

Treasuries constant maturity rates and the delinquency rates on loans reported by the US Federal Reserve) to the macro assumptions. This extended set of assumptions is defined as "macro-level banking assumptions".

The conditional forecasts are compared with two benchmarks, i.e. a naïve benchmark model, the autoregressive model of order one for the bank RoAs, and the unconditional forecasts of the DFM model, i.e.

$$RoA^{U}_{b,t+H} = E_t(\mathrm{RoA_{b,t+H}}|\mathrm{I_t}) \tag{5}$$

which is a special case of the conditional forecast where nothing on the future path of the macro and the aggregate banking variables is assumed to be known at time *t*. The measure of the accuracy of the above-described predictions is the Mean Squared Forecasting Error (MSFE), defined for each bank *b* and a generic forecast F as:

$$MSFE_b = \frac{\sum_{t=1}^{T}[RoA^{F}_{b,t+H} - RoA_{b,t+H}]^2}{T} \tag{6}$$

A recursive scheme is adopted here, according to which the model is estimated for the first time in the sample 1985:Q1 to 1994:Q4 and the forecasts are computed for the horizons of one quarter ahead (H=1) and one year ahead (H=4). The estimation sample is therefore updated by adding one more quarter and the full exercise is carried out again. The updating continues until the exhaustion of the available sample.

Table 2 reports the outcomes of the forecasting evaluation. Panel *a* refers to the comparison with the unconditional forecasts, panel *b* to the comparison with the autoregressive forecasts. The results are reported for the full sample of banks (see row *All banks* in table 2) and for subsets of 60 banks[15], aggregated in terms of size of total assets at the end of the sample (e.g. row *1-60* includes the 60 largest US banks as at 2015Q2). The figures reported are "success rates", i.e. the percentages of banks whose conditional forecast MSE is smaller than the one of the benchmark model. Finally, in the four columns the results for

[15] Each subset includes 60 banks with the exception of the last subset including the remaining 67 banks.

two forecasting horizons (H=1 and H=4, one and four quarters ahead) and the two types of conditional forecasts based on macroeconomic conditions (CM) and macroeconomic and aggregate banking conditions (CMB) are reported.

Table 2: out-of-sample forecasting evaluation, RoA

a) *Comparison with unconditional forecast*

RoA	*CM/U (H=1)*	*CM/U (H=4)*	*CMB/U (H=1)*	*CMB/U (H=4)*
1-60	0.683	0.716	0.650	0.683
61-120	0.667	0.767	0.683	0.783
121-end	0.571	0.536	0.571	0.536
All banks	0.642	0.676	0.636	0.670

b) *Comparison with AR forecast*

RoA	*CM/AR (H=1)*	*CM/AR (H=4)*	*CMB/AR (H=1)*	*CMB/AR (H=4)*
1-60	0.550	0.567	0.533	0.516
61-120	0.583	0.533	0.567	0.567
121-end	0.518	0.464	0.500	0.482
All banks	0.551	0.523	0.534	0.523

The table reports percentage values of success rates of forecasts of RoAs, across the sample and by subset for the selected forecast horizons of H=1 and H=4. CM indicates conditional macro forecasting, i.e. the forecasts obtained when conditioning on macroeconomic variables and CMB reports the forecasts obtained by conditioning on macroeconomic and aggregate banking variables.

The comparison between conditional and unconditional forecasts suggests that the aggregate information on the economy is important to capture the fluctuations in RoAs of individual bank. In fact, as it can be seen by observing Table 2.a, for about 70% of the largest 120 banks in the sample, the knowledge of the evolution of macroeconomic variables allows a more accurate forecast compared to the unconditional forecast, both at short and long horizons. Interestingly, however, only for half of the smallest banks in the sample, the conditional forecasts based on the macroeconomic assumptions are more accurate than the unconditional forecasts. A possible interpretation of this result might be that the largest banks are more "systemic" and, hence, more related to the aggregate business cycle. Another aspect of the results is that adding banking assumptions (i.e. using CMB) to the macroeconomic variables does not really change the results. In other words, imposing a small number of assumptions is enough to capture the common features of individual bank RoAs.

Notice, however, that this does not imply that aggregate banking variables are irrelevant to explain individual bank RoAs. Actually, conditional forecasts based exclusively on the aggregate banking variables are about as accurate as the conditional forecasts reported in Table 2[16]. The interpretation for this result is that the aggregate banking ratios themselves are related to the macroeconomic variables through macro-financial linkages and, hence, imposing the macroeconomic conditions is enough to capture the common dynamics of individual bank RoAs.

Table 3: out-of-sample forecasting evaluation, RoA sub-components (% of success)

NIM	*CM/AR (H=1)*	*CM/AR (H=4)*	*CMB/AR (H=1)*	*CMB/AR (H=4)*
1-60	0.700	0.750	0.700	0.750
61-120	0.650	0.767	0.667	0.750
121-end	0.561	0.702	0.561	0.649
All banks	0.638	0.740	0.644	0.717

[16] These results are not reported but are available on demand.

NII	CM/AR (H=1)	CM/AR (H=4)	CMB/AR (H=1)	CMB/AR (H=4)
1-60	0.733	0.783	0.733	0.767
61-120	0.750	0.667	0.750	0.733
121-end	0.702	0.684	0.702	0.719
All banks	0.730	0.712	0.730	0.740

NIE	CM/AR (H=1)	CM/AR (H=4)	CMB/AR (H=1)	CMB/AR (H=4)
1-60	0.667	0.717	0.667	0.717
61-120	0.600	0.567	0.600	0.567
121-end	0.597	0.684	0.632	0.702
All banks	0.621	0.655	0.633	0.661

PROV	CM/AR (H=1)	CM/AR (H=4)	CMB/AR (H=1)	CMB/AR (H=4)
1-60	0.617	0.483	0.617	0.450
61-120	0.517	0.600	0.483	0.583
121-end	0.536	0.321	0.464	0.375
All banks	0.557	0.472	0.523	0.472

The table reports percentage values of success rates of forecasts of the subcomponents of RoAs, across the sample and by subset for the selected forecast horizons of H=1 and H=4. CM indicates conditional macro forecasting, i.e. the forecasts obtained when conditioning on macroeconomic variables and CMB reports the forecasts obtained by conditioning on macroeconomic and aggregate banking variables.

In general, the outcomes of the exercises suggest that the model is able to accurately capture non-trivial relationships between the aggregate economy and individual bank profitability and, hence, it is well suited to conduct stress-test analysis aiming to assess the effects of adverse macroeconomic scenarios on individual banks.

A final comment on Table 2 is that, although for the majority of US banks' RoAs the conditional forecasts are more accurate than those of an autoregressive model, the result is weaker than for the comparison with unconditional forecasts. In order to assess whether this result is related to some specific aspect of banking activity or it is broadly based over the sub-components of bank RoAs, the latter is split in sub-components and the forecasting evaluation is conducted also in terms of the sub-components. The four sub-components of RoAs considered are: NIM, NII, NIE and PROV[17]. The subcomponents are normalized by total assets, as in the case of RoAs. Table 3 reports the outcomes of the forecasting evaluation on the RoA sub-components, with results organized along the same lines as those in Table 2.

The forecasting evaluation for the sub-components of RoA reveals that the conditional forecasts are more accurate when compared to the AR naive model. A percentage of banks that ranges between 65 and 70% for all sub-components confirms these results with the exception of provisions, for which the autoregressive model is more competitive. An interpretation of the results is that provisions for losses on loans do not properly originate from the business of the bank, but rather reflect accounting standards, regulatory requests and managerial decisions. They are known for instance, to be used for window dressing of financial statements aimed to smooth a bank's earnings (see Bikker and Hu, 2002 and Norden and Stoian, 2013) and hence are more difficult to forecast by model based procedures like the one described in this study. In general, the analysis of sub-components suggests that the methodology described in this paper is fit for stress-testing, also at a more granular level than RoAs and also at the disaggregated levels for NIM, NII and NIE.

5.2 Success Rates in Times of Crisis

To further validate the behaviour of the model during period of stress, a number of tests are performed. First, two episodes of crisis that could be

[17] These items are indicated as NIM: RIAD4074, NII: RIAD4079, NIE: RIAD4093 and PROV: RIAD4230 in the FFEIC041 reporting.

suitable to verify the performance of the model are identified, i.e. the short recession of 2001, related to the burst of the internet bubble, and the subprime crisis. To estimate the MSE the study makes use as reference periods of the dates indicated by the NBER for these recessionary episodes[18], i.e. 2001:Q1 to 2001:Q3 and 2007:Q4 to 2009:Q2 respectively. The MSE is calculated for these periods following the same methodology used for the overall exercise (an extended period of reference with fixed starting quarter) and described by equation (6). These tests are performed on RoAs and on the subcomponents defined in section 4.1. Table 4.a below illustrates the results for H=1.

Table 4.a: out-of-sample forecasting evaluation, RoA and its sub-components observed during recessionary episodes in the US (% of success)

Internet Bubble	*H=1*				
CM/AR	*ROA*	*NIM*	*NII*	*NIE*	*PROV*
1-60	0.550	0.450	0.600	0.650	0.433
60-120	0.517	0.533	0.700	0.583	0.367
120-end	0.446	0.509	0.596	0.719	0.339
All banks	0.506	0.497	0.633	0.650	0.381
CMB/AR	*ROA*	*NIM*	*NII*	*NIE*	*PROV*
1-60	0.600	0.467	0.600	0.667	0.367
60-120	0.467	0.533	0.700	0.633	0.400
120-end	0.446	0.544	0.596	0.737	0.286
All banks	0.506	0.514	0.633	0.678	0.352

[18] For more information on dates of recessions, see http://www.nber.org/cycles.html.

Subprime Crisis	*H=1*				
CM/AR	*ROA*	*NIM*	*NII*	*NIE*	*PROV*
1-60	0.417	0.650	0.467	0.450	0.500
60-120	0.433	0.633	0.483	0.550	0.283
120-end	0.357	0.633	0.474	0.474	0.286
All banks	0.403	0.638	0.475	0.492	0.358
CMB/AR	*ROA*	*NIM*	*NII*	*NIE*	*PROV*
1-60	0.433	0.650	0.467	0.450	0.483
60-120	0.483	0.600	0.450	0.550	0.283
120-end	0.393	0.632	0.509	0.474	0.321
All banks	0.438	0.627	0.475	0.492	0.364

The table reports percentage values of success rates of forecasts of the RoAs and its subcomponents, across the sample and by subset for the selected forecast horizons of H=1 for the two periods of crisis "Subprime" and "Internet Bubble". The crisis periods are identified using as reference the recession dates of the National Bureau of Economic Research (NBER). CM indicates conditional macro forecasting, i.e. the forecasts obtained when conditioning on macroeconomic variables and CMB reports the forecasts obtained by conditioning on macroeconomic and aggregate banking variables.

To further validate the exercise and to assess to what extent the model captures changes in the macroeconomic environment, a series of exercises using a rolling window reference period is also performed. In this setup the period of reference remains fixed to a length of 10 years, i.e. each year the starting point of the reference period increases by one quarter. In this case the model uses information that is more recent to generate forecasts. The results are illustrated in table 4.b below for H=1.

The results confirm by and large the general results. A significant difference emerges from the comparison of the extended framework. While the success rates during the internet bubble are in general higher using the rolling window, for NIM, NII and NIE using the extended window would have generated better success rates. The same is true for NIM in the Lehman crisis. This difference in the performance may be partly explained by differences in the macroeconomic environment as well as in the regulatory environment. At last, the evolution in the business model of banks, with the increase in relevance of the "originate-to-distribute" banking model linked to securitization may have played a role in the different performances of the model.

Table 4.b: out-of-sample forecasting evaluation, RoA and its sub-components observed during recessionary episodes in the US (% of success)

Internet Bubble	*Rolling Window*		*H=1*		
CM/AR	*ROA*	*NIM*	*NII*	*NIE*	*PROV*
1-60	0.546	0.454	0.563	0.519	0.432
60-120	0.541	0.525	0.590	0.568	0.339
120-end	0.552	0.536	0.554	0.607	0.339
All banks	0.541	0.511	0.567	0.559	0.414
CMB/AR	*ROA*	*NIM*	*NII*	*NIE*	*PROV*
1-60	0.514	0.454	0.557	0.530	0.383
60-120	0.426	0.525	0.596	0.590	0.361
120-end	0.412	0.530	0.548	0.637	0.352
All banks	0.480	0.524	0.575	0.588	0.414

Subprime Crisis	*Rolling Window*		*H=1*		
CM/AR	*ROA*	*NIM*	*NII*	*NIE*	*PROV*
1-60	0.525	0.562	0.457	0.525	0.513
60-120	0.564	0.571	0.501	0.527	0.424
120-end	0.538	0.589	0.497	0.551	0.473
All banks	0.518	0.579	0.499	0.538	0.485
CMB/AR	*ROA*	*NIM*	*NII*	*NIE*	*PROV*
1-60	0.553	0.557	0.473	0.525	0.504
60-120	0.508	0.569	0.518	0.534	0.386
120-end	0.486	0.579	0.508	0.531	0.436
All banks	0.533	0.586	0.527	0.548	0.477

The table reports percentage values of success rates of forecasts of the RoAs and its subcomponents, across the sample and by subset for the selected forecast horizons of H=1 for the two periods of crisis "Subprime" and "Internet Bubble". The crisis periods are identified using as reference the recession dates of the National Bureau of Economic Research (NBER). CM indicates conditional macro forecasting, i.e. the forecasts obtained when conditioning on macroeconomic variables and CMB reports the forecasts obtained by conditioning on macroeconomic and aggregate banking variables.

5.3 The Role of Uncertainty and Simulation in the Exercises

In this last section the methodology adopted in this study is applied to a practical stress testing exercise. In general, the aim is to integrate the impact of uncertainty in the model and to capture the behaviors of the selected target variables during stressful periods, often characterized by nonlinear variables' patterns. In addition, this exercise should allow testing the efficiency of the model on a practical exercise that could be run for policy reasons and/or scenario analysis. Moreover, it may serve the purpose of to gaining a better understanding of the roles played by uncertainty in forecasting RoAs by including a Monte-Carlo simulation approach in the model. This section takes the point of view of a practitioner, which intends to run a stress test on the banking sector's RoAs. As discussed in chapter 5, conditioning on the future path of variables is not possible in real-life exercises as the real values of the variables observed are not known at the time when the exercise is run.

Table 5: recessionary episodes, out-of-sample forecasting evaluation using Gaussian copula, RoA

Internet Bubble Recession: 2001:4 to 2001:10 - Gaussian Copula				
RoA	*CM/UC (H=4)*	*SIM1%/UC (H=4)*	*SIM5%/UC (H=4)*	*SIM95%/UC (H=4)*
1-60	0.333	0.405	0.451	0.501
61-120	0.387	0.373	0.439	0.428
121-end	0.343	0.381	0.415	0.543
All banks	0.348	0.384	0.434	0.487
Subprime Crisis: 2008:1 to 2009:7 - Gaussian Copula				
RoA	*CM/UC (H=4)*	*SIM1%/UC (H=4)*	*SIM5%/UC (H=4)*	*SIM95%/UC (H=4)*
1-60	0.580	0.750	0.450	0.175
61-120	0.503	0.673	0.451	0.352
121-end	0.464	0.681	0.575	0.291
All banks	0.521	0.705	0.489	0.270

The table reports percentage values of success rates of forecasts of the RoAs across the sample and by subset for the selected forecast horizons of H=1 for the two periods of crisis "Subprime" and "Internet Bubble". The crisis periods are identified using as reference the recession dates of the National Bureau of Economic Research (NBER). CM indicates conditional macro forecasting, i.e. the forecasts obtained when conditioning on macroeconomic variables and CMB reports the forecasts obtained by conditioning on macroeconomic and aggregate banking variables.

To circumvent this problem, a scenario must be generated to perform a conditional forecasting. One way to perform this is by means of a simulation approach. Indeed, Monte-Carlo simulations are embedded in stress testing exercises as they are used (see e.g. Pritsker 2012 and Van den End 2010) to generate scenarios.

The exercise is structured in several steps. At first, it simulates the joint distribution of four macro-economic variables (i.e. GDP, unemployment rate, PMI manufacturing index and Federal Funds Rate) which previously was used in the first of the conditional exercises described in chapter 5.1. To perform the exercise, the model runs 1000 trials, using a Gaussian copula distribution to generate dependencies across the variables while exploiting copula's fat tails. The idea of using copula functions to simulate macroeconomic scenarios is discussed in Chollette and Ning (2012), where the authors highlight the advantages of using copula functions when non-linearities are present in the data. Since during severe crises non-linear relationships could materialize, as described by Drehmann (2006), copula functions shall help us capture this particular feature. Moreover, since the variance captured by the factors in the model depends also on the degree of linearity observed in the data, using copula functions to simulate scenarios may lessen the impact of this specific aspect in the results.

In a second step, the values set by the 5% confidence levels obtained from simulated data are selected, which can be thought as a severe scenario for the four conditional macro variables. Moreover, as an even more severe stress scenario, the 1% joint distribution of the variables is considered, which represent a shock of even larger magnitude. At last a positive scenario (95% confidence level) is simulated, that shall provide with a better understanding of the efficacy of the forecasts in normal times. One quarter is recursively added in each simulation, as data become available to the practitioner[19], hence obtaining a full set of historical simulated scenarios for each quarter.

In a third step, the forecasts are conditional on the path of the simulated variables at the 1%, 5% and 95% confidence levels for each quarter. Hence a set of forecasted RoAs is obtained and successively compared with the results

[19] In this exercise real-time issues with data availability are not considered as the aim is simply to evaluate the impact of uncertainty in the model's results.

of the unconditional forecasts. The results are highlighted in table 5, and over time in figure 2.a only for H=4, which in the previous exercises produces better results. The conditional scenarios at the 1% and 5% should result in lower quarterly success rates than unconditional and autoregressive forecasts but significantly higher during the crisis episodes which are captured by the dataset, namely the *internet bubble* recessionary episode and the *subprime crisis*. The reason for this expectation is that these events were characterized by a nonlinear behavior of a number of macroeconomic variables. Overall, success rates behave as expected. In both cases conditional forecasts (CM) and autoregressive (AR) models are better at forecasting RoAs than simulated exercises.

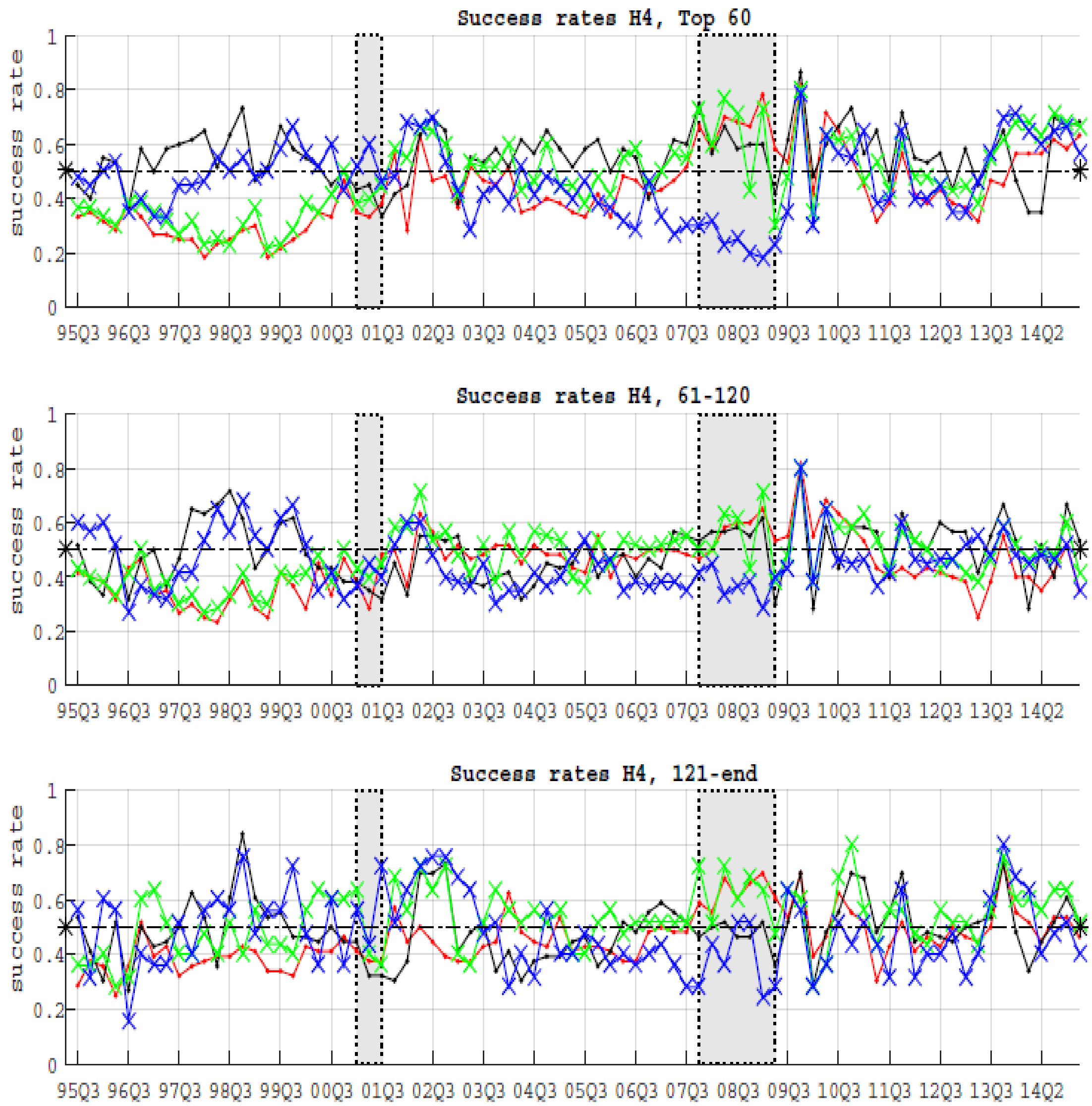
This pattern should be different during crises episodes. Table 5 supports this view. As regards the early 2000s recession, the simulations produce less accurate forecasts than the unconditional forecasts. As described by Aoki and Nikolov (2012), this outcome may be due to the fact that bubbles originating in assets held by investors other than banks are not likely to trigger a banking crisis, as those non-bank investors are less critical in the credit allocation mechanism. As the dot-com bubble is identified by the authors as an investors' triggered bubble, banks' profitability was not significantly affected during the 2001 recession, to the contrary of previous recessionary episodes.

The forecasts obtained through simulations at the 1% confidence level are considerably more reliable during the subprime crisis, where CM, and SIM1% success rates are significantly higher than the unconditional forecast. This can be explained by the presence of nonlinearities in this period of stress in financial markets (Mishkin 2012). It appears as copula functions support the model in capturing tail events and nonlinearities in the macroeconomic variables, as also argued by Cholette and Ning (2012).

At last, the historical quarterly average success rates of each subset of banks, ordered by size of total assets, is investigated. The results are reported in figure 3. In the chart the black and red dotted lines represent respectively the conditional macro (CM) and the simulated tail (1%) forecasts (SIM). The crossed lines, green and blue, represent respectively the upper and lower simulated bounds for forecasts at the 5% (UB) and 95% (LB) confidence levels.

The areas in shaded grey colour illustrate the recessions as identified by the National Bureau of Economic Research[20].

Figure 3: success rates for RoA over time.



The table illustrates success rates for Horizon=4 quarters, SIM1% (red), LB5% (green), UB95% (blue), CM (black) vs. UC using a Gaussian copula. Grey areas represent recessions as defined by the National Bureau of Economic Research (NBER).

[20] For more information on business cycles dates, see: www.nber.org/

The observation of the figure indicates that success rates are higher for SIM1% during the subprime crisis, in particular when compared to the CM forecasts. The relatively high success rates of SIM95% during the pre-2001 recessionary episode are explained by the underlying macroeconomic conditions, which were characterized by a long-lasting period of growth in the US. This factual evidence supports the intuition that in times of stress resorting to simulation technique which capture nonlinear behaviours may enhance the forecasting ability of the model.

6. Conclusions

This study presents a modelling framework for stress testing, based on a dynamic factor model, which combines individual banks' profitability, measured by RoAs and a set of macroeconomic and financial aggregate US variables. The model produces conditional forecasts at predefined horizons and it is therefore potentially suitable for scenario based *("what if")* analysis. IN particular, the framework defined by the DFM allows for a number of potential applications in the domain of stress testing. First, the model can be considered for benchmark analysis, as it is flexible enough to allow for sensitivity and scenario based investigations on banks' profitability.

Secondly, more complex models produce results that are affected by the accuracy of the various components of stress tests, e.g. the macroeconomic scenario or the types of setup chosen for the exercise, i.e. top-down vs. bottom-up. The framework adopted in this study is more direct and its interpretation more straightforward. Hence, the model can easily be adapted and implemented to identify potential sources of risk at an early stage, given that it is relatively simple to run and the interactions with the macroeconomic variables are defined by the DFM.

Overall the results highlight that banks' RoAs reflect a considerable degree of macroeconomic information, given that forecasts of individual bank profitability based on the actual paths of aggregate variables are consistently more accurate than forecasts obtained via a naive autoregressive model. This is true for RoAs but even more for some sub-components of RoAs, namely Net Interest Margin, Non Interest Income and Non Interest Expense. The latter result shows that the methodology can be meaningfully applied also to consider lower levels of granularity.

Furthermore, the use of different methodologies to generate the forecasts, i.e. using a fixed starting period or a rolling window setup highlights that the performance of the model is significantly affected by these changes. In general, using a rolling window allows to obtain better performances during periods of crisis, potentially because this framework is capable of capturing the evolution of the business model, of the regulatory and of the macroeconomic environment of banks. It also emerges that during the subprime crisis, the use of simulation techniques based on Copula´s functions increases the forecasting ability of the model for RoAs. This indicates that some degree of non-linearity may be present in the data during the subprime crisis.

One major shortcoming of RoAs as an indicator is embedded in its accounting nature, lacking the perspective of value creation. Indeed, some studies, for instance Fiordelisi and Molyneux (2010) highlight several shortcomings related to the identification of profit creation from an accounting perspective with performance and value creation. In the end, the modelling framework is relatively flexible and might easily accommodate alternative measures of bank performance among other variables.

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Appendix A: list of commercial banks used in the exercise - part I

1	JPMORGAN CHASE BANK, NATIONAL ASSOCIATION	89	1ST SOURCE BANK
2	BANK OF AMERICA, NATIONAL ASSOCIATION	90	FIRST FINANCIAL BANK, NATIONAL ASSOCIATION
3	CITIBANK, N.A.	91	WASHINGTON TRUST BANK
4	WELLS FARGO BANK, NATIONAL ASSOCIATION	92	S & T BANK
5	U.S. BANK NATIONAL ASSOCIATION	93	CENTRAL PACIFIC BANK
6	PNC BANK, NATIONAL ASSOCIATION	94	INTRUST BANK, NATIONAL ASSOCIATION
7	BANK OF NEW YORK MELLON, THE	95	FIRST SECURITY BANK
8	CAPITAL ONE, NATIONAL ASSOCIATION	96	FIRST MERCHANTS BANK, NATIONAL ASSOCIATION
9	STATE STREET BANK AND TRUST COMPANY	97	CENTENNIAL BANK
10	HSBC BANK USA, NATIONAL ASSOCIATION	98	RENASANT BANK
11	BRANCH BANKING AND TRUST COMPANY	99	MIZUHO CORPORATE BANK (USA)
12	SUNTRUST BANK	100	UNION FIRST MARKET BANK
13	REGIONS BANK	101	NEVADA STATE BANK
14	FIFTH THIRD BANK	102	SANDY SPRING BANK
15	NORTHERN TRUST COMPANY, THE	103	BANK OF THE OZARKS
16	UNION BANK, NATIONAL ASSOCIATION	104	JOHNSON BANK
17	BMO HARRIS BANK NATIONAL ASSOCIATION	105	AMALGAMATED BANK
18	KEYBANK NATIONAL ASSOCIATION	106	SABADELL UNITED BANK, NATIONAL ASSOCIATION
19	MANUFACTURERS AND TRADERS TRUST COMPANY	107	WOODFOREST NATIONAL BANK
20	DISCOVER BANK	108	COMMUNITY TRUST BANK, INC.
21	COMPASS BANK	109	AMARILLO NATIONAL BANK
22	COMERICA BANK	110	UNITED BANK
23	BANK OF THE WEST	111	BUSEY BANK
24	HUNTINGTON NATIONAL BANK, THE	112	REPUBLIC BANK & TRUST COMPANY
25	CITY NATIONAL BANK	113	FIRST BANK
26	BOKF, NATIONAL ASSOCIATION	114	SOUTHSIDE BANK
27	BANCO POPULAR DE PUERTO RICO	115	OCEAN BANK
28	SYNOVUS BANK	116	MECHANICS BANK
29	FIRST TENNESSEE BANK NATIONAL ASSOCIATION	117	CENTURY BANK AND TRUST COMPANY
30	ASSOCIATED BANK, NATIONAL ASSOCIATION	118	WASHINGTON TRUST COMPANY OF WESTERLY, THE
31	FROST BANK	119	COMMUNITY BANK
32	COMMERCE BANK	120	LAKE CITY BANK
33	SILICON VALLEY BANK	121	AMERIS BANK
34	FIRST-CITIZENS BANK & TRUST COMPANY	122	FIRST NATIONAL BANK ALASKA
35	SUSQUEHANNA BANK	123	LAKELAND BANK
36	ZIONS FIRST NATIONAL BANK	124	CITY NATIONAL BANK OF WEST VIRGINIA
37	BNY MELLON, NATIONAL ASSOCIATION	125	BANKERS TRUST COMPANY
38	WELLS FARGO BANK NORTHWEST, NATIONAL ASSOCIATION	126	HUDSON VALLEY BANK, N.A.
39	FIRST HAWAIIAN BANK	127	HANMI BANK
40	VALLEY NATIONAL BANK	128	FIRST AMERICAN BANK
41	FIRSTMERIT BANK, N.A.	129	BREMER BANK, NATIONAL ASSOCIATION
42	UMB BANK, NATIONAL ASSOCIATION	130	BROADWAY NATIONAL BANK
43	PROSPERITY BANK	131	FIRST FINANCIAL BANK, NATIONAL ASSOCIATION
44	FIRST NATIONAL BANK OF OMAHA	132	FIVE STAR BANK

Appendix A: list of commercial banks used in the exercise - part II

45 BANK OF HAWAII
46 BANCORPSOUTH BANK
47 RABOBANK, NATIONAL ASSOCIATION
48 ARVEST BANK
49 AMEGY BANK, NATIONAL ASSOCIATION
50 FIRSTBANK
51 FIRST NATIONAL BANK OF PENNSYLVANIA
52 UMPQUA BANK
53 CALIFORNIA BANK & TRUST
54 CATHAY BANK
55 ISRAEL DISCOUNT BANK OF NEW YORK
56 INTERNATIONAL BANK OF COMMERCE
57 TRUSTMARK NATIONAL BANK
58 MB FINANCIAL BANK, NATIONAL ASSOCIATION
59 OLD NATIONAL BANK
60 FULTON BANK, NATIONAL ASSOCIATION
61 GREAT WESTERN BANK
62 NATIONAL PENN BANK
63 FIRST MIDWEST BANK
64 FIRST INTERSTATE BANK
65 COMMUNITY BANK, NATIONAL ASSOCIATION
66 BANCO SANTANDER PUERTO RICO
67 MERCANTIL COMMERCEBANK NATIONAL ASSOCIATION
68 UNITED COMMUNITY BANK
69 PLAINSCAPITAL BANK
70 HANCOCK BANK
71 PARK NATIONAL BANK, THE
72 FIRST FINANCIAL BANK, NATIONAL ASSOCIATION
73 FIRST BANK
74 CITIZENS BUSINESS BANK
75 BOSTON PRIVATE BANK & TRUST COMPANY
76 WESBANCO BANK, INC.
77 NBT BANK, NATIONAL ASSOCIATION
78 SCOTIABANK DE PUERTO RICO
79 FIRST COMMONWEALTH BANK
80 CHEMICAL BANK
81 ROCKLAND TRUST COMPANY
82 BANK LEUMI USA
83 SCBT
84 FARMERS AND MERCHANTS BANK OF LONG BEACH
85 UNITED BANK, INC.
86 WESTAMERICA BANK
87 CITY NATIONAL BANK OF FLORIDA
88 NATIONAL BANK OF ARIZONA
133 WILSHIRE STATE BANK
134 MAINSOURCE BANK
135 AMERICANWEST BANK
136 MORTON COMMUNITY BANK
137 UNION BANK AND TRUST COMPANY
138 BURKE AND HERBERT BANK AND TRUST COMPANY
139 CAPITAL CITY BANK
140 COBIZ BANK
141 BELL STATE BANK & TRUST
142 TRI COUNTIES BANK
143 TIB THE INDEPENDENT BANKERSBANK
144 FREMONT BANK
145 CAMDEN NATIONAL BANK
146 VECTRA BANK COLORADO, NATIONAL ASSOCIATION
147 FIDELITY BANK
148 TOTALBANK
149 ALPINE BANK
150 BANK OF COLORADO
151 UNIVEST BANK AND TRUST CO.
152 BANKPLUS
153 AMERICAN NATIONAL BANK OF TEXAS, THE
154 FIRST UNITED BANK AND TRUST COMPANY
155 FIRST BANK
156 CENTIER BANK
157 MANUFACTURERS BANK
158 AMBOY BANK
159 STANDARD BANK AND TRUST COMPANY
160 SEACOAST NATIONAL BANK
161 BANK OF STOCKTON
162 STOCK YARDS BANK & TRUST COMPANY
163 INTER NATIONAL BANK
164 LONE STAR NATIONAL BANK
165 FIRST NATIONAL BANK OF LONG ISLAND, THE
166 HILLS BANK AND TRUST COMPANY
167 SIMMONS FIRST NATIONAL BANK OF PINE BLUFF
168 ANB BANK
169 OLD SECOND NATIONAL BANK
170 PARKWAY BANK AND TRUST COMPANY
171 AMERICAN NATIONAL BANK
172 CITY BANK
173 SOUTHERN BANK AND TRUST COMPANY
174 BRYN MAWR TRUST COMPANY, THE
175 WEST SUBURBAN BANK
176 GERMAN AMERICAN BANCORP

Appendix B: list of macroeconomic variables

Name	Description	Source	Transformation
GDP	Real Gross Domestic Product, SA	Fed St.Louis	diff log
URATE	Unemployment Rate, SA	Fed St.Louis	diff
PMI Manuf	ISM Manufacturing: PMI Composite Index, SA	Fed St.Louis	diff
C&I Loans	Commercial & Industrial Loans, Quarterly, SA	Fed St.Louis	diff log
Consumer Credit	Total Consumer Credit Owned and Securitized, Outstanding, SA	Fed St.Louis	diff log
Corporate profits	Corporate Profits After Tax (without IVA and CCAdj), SA	Fed St.Louis	diff log
CPI	Consumer Price Index for All Urban Consumers: All Items, SA	Fed St.Louis	diff log
Core CPI	Core Consumer Price Inflation	Fed St.Louis	diff log
HP California	All Transactions House price index for California	Fed St.Louis	diff log
SP500	S&P 500 index	Fed St.Louis	diff log
EER	Effective Exchange Rate, NSA	Fed St.Louis	diff log
FFR	Effective Federal Funds Rate, NSA	Fed St.Louis	diff
SPREAD 3MTBILL-AAACORP	Spread between the 3 months Treasury Bill and the Moody's seasoned AAA Corporate bond yield	Authors´calculation	diff
MUNI INDEX	State and local bonds - Bond buyer Go 28-Bond Municipal Bond Index	Fed St.Louis	diff
MORT RATE	30-Year Conventional Mortgage Rate	Fed St.Louis	diff
CAP UTIL	Capacity Utilization: Total Industry, SA	Fed St.Louis	diff log
BANKR AM	N° of Bankruptcies - Business only	Dept. Of Justice	diff
DEBT TO INCOME	Household Debt Service Payments as a Percent of Disposable Income	Fed St.Louis	diff
DIFF IND	Diffusion Index	Fed St.Louis	diff
OILP	Spot Oil Price: West Texas Intermediate NSA	Fed St.Louis	diff log
HOUSING PERMITS	New Private Housing Units Authorized by Building Permits, SA	Fed St.Louis	diff
FRED_MAC_INDEX	Freddie Mac House Price Index	Freddie Mac	diff log
GOLDP	Gold Fixing Price 10:30 AM (London Time) in London Bullion Market, based in USD	Fed St.Louis	diff log
REAL_CONS	Real Personal Consumptions Expenditures SA	Fed St.Louis	diff log
CREDIT_FED	Total aggregate credit in circulation, SA	Authors´calculation	diff log
BANK TA	Total assets US commercial banks, NSA	Fed St.Louis	diff log
MBS_AGENCY_OUTSTANDING	Outstanding Mortgage Backed Securities Issuances, NSA	SIFMA	diff log
SPREAD3M10Y	Spread between the 3 months and 10 years US treasury bonds (constant maturity rate)	Authors´calculation	diff
DEL_FED	Delinquencies on All Loans, All Commercial Banks, NSA	Fed St.Louis	diff
USNPTL	Non performing loans (past due 90+ plus nonaccrual for all US comm. Banks), NSA	Fed St.Louis	diff
DRIWCIL	Net percentage of domestic Banks reporting increased willingness to make consumer installment loans	Fed St.Louis	diff
all ROAs	Return on Assets, NSA	Fed Chicago, FDIC	raw

Chapter 3

Dissecting Banks' Responses to a Monetary Policy Shock: What are the Mechanisms at Work?

1. Introduction

Modelling the sensitivity of banks' profits to changes in interest rates is a key aspect for central banks and supervisors. Central banks are concerned with the effectiveness of the mechanism of propagation of monetary policy to the real economy. Mishkin (1996) discusses the existence of a bank lending transmission channel, where an expansionary monetary policy increases deposits and hence lending, boosting investment and consumer spending as consequence. Gambacorta and Marques-Ibanez (2011) observe that bank-specific characteristics played an important role in the functioning of the lending channel, in particular during the latest financial crisis. One important aspect of the effectiveness of the bank lending transmission channel can be observed in the lending spread, a proxy of which is the net interest margin (NIM hereinafter). Moreover, if the effects of a monetary policy shock are detected in the NIM, it may also provide further insights into other channels of monetary policy, such as the traditional interest rate channel, given the role of banks in transferring the costs of a change in interest rates to market participants.

While central banks look at macro dynamics of monetary policy shocks, supervisors aim to reduce the impact of sudden changes in interest rates on the profitability of the banking sector, as it may harm the capability of a bank to generate profits and triggers risks for financial stability. English (2002) describes the potentially large impact deriving from improper management of interest rate risks. The author identifies a series of shocks to interest rates that have created havoc to the balance sheet of banks: the secondary banking crisis of the 1970s in the United Kingdom and the early 1980s crisis in the United States, characterized by a yield curve inversion, are among these episodes. In the United States this event led to negative NIM. Overall, historical evidence teaches us that the impact of interest rates dynamics on banks' profitability cannot be neglected. In particular, in a low interest rates environment as the current one, the impact of a monetary policy shock is specifically relevant (see e.g. Bednar and Elamin, 2014).

A combined approach is then required when modelling the impact of a monetary policy shock, while capturing the dynamics of the underlying variables at the microeconomic level and eventually assess the effects on the banking sector. This analysis tackles this issue in a comprehensive framework that encompass micro and macro information and originates forecasts for net interest margins of banks. The approach adopted in this study is fit for application to stress tests, where macroeconomic variables react to the monetary policy shock in a scenario-driven output. In fact, understanding the transmission channels between the banking sector, the real economy and financial markets is a key element of the modelling framework of macro stress tests[21], as mentioned by the Bank of England (2007), the Bank for International Settlements (2011) as well as the European Central Bank (2013). Indeed, stress testing models should be informative and robust (see Alfaro and Drehmann, 2009) at the macro *and* microeconomic levels. As a consequence, banks' responses should contain micro information for policy makers and risk modellers to be able to draw inference from the stress test results.

This study investigates impulse-response functions (IRF hereinafter) generated by a dynamic factor model (DFM hereinafter) in a monetary policy shock scenario for the US commercial banks[22], observed between 1988 and 2015. The IRFs generated by the DFM are defined as the difference between the conditional and unconditional forecasts, following the procedure defined in Banbura, Giannone and Lenza (2014). NIM and a risk-adjusted version of it (NIMRSK hereinafter) represent the banking ratios of choice for the exercises. NIM is chosen as it is widely used in the literature and by practitioners to capture the difference between interest rate earned on assets and the interest expenses on the funding sources. Hence it is also a good measure of the sensitivity of banks' profitability to movements of interest rates.

Besides the raw NIM, the analysis also makes use of a risk-adjusted measure of NIM, NIMRSK, which addresses the increase in credit risk usually triggered by a change in the monetary policy stance. Borio (2015) and Noizet (2016) describe the reasons behind the idea of an adjusted indicator for NIM, mostly related to the fact that interest rate dynamics entail changes in the strategy of banks' lending. When interest rates are low, banks tend to engage in riskier lending activities to improve their profitability, *ceteris paribus*.

[21] Macro stress tests are "[...] techniques (*which*) have been employed to test the stability of groups of financial institutions that, taken together, can have an impact on the economy as a whole" see Borio, *et al.* (2012).

[22] It is referred to commercial banks as all institutions reporting that filed a reporting form 041 (call report) to the Federal Financial Institutions Examination Council (www.ffeic.gov) during the period considered in this study.

This triggers, with some delay, higher levels of non-performing loans and require usually higher levels of provisions for losses on loans. This process leads eventually to a distorted assessment of NIM, as this measure does not account for the increased level of riskiness of loans. Ultimately, the aim of the paper is to answer the following research questions:

1. Which characteristics of banks explain the differences in NIMs' and NIMRSK's impulse-response functions to a monetary policy shock?
2. Does the informational content of the impulse-response functions change across the sample and over time?

The estimation period for the exercises spans from 1988:Q1 until 2015:Q2. This timeline encompasses three US recessionary episodes (i.e. July 1990, March 2001 and December 2007) and at least two US banking crises (i.e. the end of the Savings and Loans crisis and the Subprime-Lehman crisis). Moreover, it includes several recessions and banking crises worldwide that may have directly or indirectly affected the banking business in the US (e.g. the Scandinavian Banking Crisis of the early 90s', the Asian Financial Crisis of 1997 and the European Sovereign Debt Crisis that began at the end of 2009, among others)[23].

The results of this study contribute to the debate on the transmission channel of monetary policy shock. The study brings forward new evidence to the mechanisms at work within the banking sector as it highlights the presence of a large heterogeneity in the responses of banks to a monetary tightening. In fact, the results illustrate that the modelling setup based on a DFM captures non-trivial effects in NIM responses. In addition, it underlines that interest rate shocks to NIMs are better described by the use of indicators of maturity mismatch, such as the Income Gap. Moreover, it illustrates that when adjusting NIMs for risk, the statistical significance of explanatory variables changes. Other variables related to solvency and liquidity risk become significant. This is supporting evidence that the model captures additional aspects of banks that are mostly related to credit risk. At last, it indicates that the methodology is suitable for applications to stress tests as risk factors of banks can shed light on the shapes of IRFs, hence helping supervisors to detect ailing banks.

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[23] See the Federal Deposit Insurance Corporation website (www.fdic.gov) regarding the dating of banking crises in the US and the National Bureau of Economic Research's website (www.nber.org) for a comprehensive analysis concerning US recessionary episodes.

The paper is structured as follows: section 2 discusses the literature, section 3 introduces the dataset used. Section 4 is dedicated to the description of the modelling framework while section 5 describes the exercises, the impact of the modelling framework and the choices of the dependent variables. Section 6 illustrates the findings of the regressions and the policy implications. Section 7 concludes.

2. Literature

2.1 Transmission Channels of Monetary Policy: Another View of the Bank Lending Channel

The existence and the mechanism at work in the transmission channel of monetary policy and the role of the banking sector have been investigated by several authors. Most authors focused their attention on the relationship between monetary policy and bank lending, e.g. Bernanke and Blinder (1992), Romer and Romer (1993), Hubbard (1995) and Peek and Rosengren (1995). They all discuss and/or provide supporting evidence of the existence of a bank lending channel. Kashyap and Stein (2000) analyse the effects of monetary policy on bank lending using micro-level data. The authors argue that focusing on individual banks' behaviour is beneficial to reduce issues related to the possible alternative interpretations of the bank lending channel. Their study provides supporting evidence of a bank lending channel in the US and that heterogeneity is present in the responses of banks to monetary policy shocks.

Recently, Peek and Rosengren (2013) discuss the bank lending channel and the impact of the Great Recession on the efficacy of the transmission mechanism. Their findings stress that recent evidence indicate that a liquidity crunch, such as the one experienced during the latest crisis, may also distort the lending channel. Characteristics related to deposit funding and capital levels seem to have played a role in determining the impact on lending, as described in Cornett et al. (2011) as well as in Gambacorta and Marques-Ibanez (2011). Gambacorta (2001), considering Italian banks, find that liquidity plays an important role and interact with lending in the responses of banks to a monetary policy shock. At last, Brissimis and Delis (2009) investigate in detail the different characteristics of the responses of banks to a monetary policy shock. The authors identify three characteristics of banks that shape their responses to a monetary policy shock, i.e. capitalization, credit risk and profitability. In particular, with respect to profitability, the findings highlight that a link exists between capital, profitability (here measured by RoA) and a monetary policy shock and this effect is positive for well capitalized banks and negative when capital levels are low. Moreover, a substantial difference exists between Euro-area and US banks.

2.2 Interest Rates and NIM

The effects of interest rate shocks on banks, in general and on banks' profitability in particular have been discussed by Flannery (1980), Genay and Podjasek (2014), Wheelock (2016), Landier *et al.* (2013) as well as Borio, *et al.* (2015). Flannery (1980) argues that bank revenues and costs adjust at different speed to market interest rate movements. Flannery's findings, investigating 75 US banks from 1961 to 1978, highlight that volatility of interest rates has virtually no impact on profits while levels are more important. Moreover, he finds that bank size matters for the speed of response to interest rate shocks. Thus, while larger banks adjust more quickly neutralizing the effect of a shock to their profits, particularly in the short run, smaller banks seem more sensitive to an increase of market rates. Genay and Podjasek (2014) investigate the impact of a 3M T-bill interest rate and yield curve combined shock, which equals to an increase of 1% to banks' NIM. The authors find that NIM rises following this shock, with noticeable differences between smaller (i.e. greater impact on NIM) and larger (i.e. smaller impact on NIM) banks.

Bednar and Elamin (2014.a, 2014.b) also analyse the impact of interest rate risk on US banks in two different studies. In their first analysis they assess the evolution of interest rate risk in US commercial banks by constructing a maturity mismatch ratio which weights assets and liabilities according to their expected sensitivity to an increase in market interest rates. Their findings highlight that interest rate risk has raised in the US commercial banking sector over time, despite the use of interest rate derivatives; smaller banks are the most significant contributors to this increase in interest rate risk. In a second study, the same authors look closely to the maturity mismatch in US banks and find that, while larger banks swapped their holdings from loans into securities, smaller banks turned their exposures to short-term loans into securities characterized by longer maturities (i.e. 5 years or more), since the subprime crisis. At last, Landier, *et al.* (2013) investigate the sensitivity of bank profits to interest rates and the impact on lending by means of an Income Gap (ICG hereinafter) measure. Their results indicate that the response of bank holding companies to a monetary policy shock depends on their income gap. More specifically, banks characterized by a larger income gap experience a larger increase in total earnings, when interest rates increase.

Borio, *et al.* (2015) investigate in an empirical cross-country analysis how monetary policy rates affect banks' profitability, focusing on RoA and NIM. In particular, they test if a positive and concave relationship exists between RoA or NIM, the level of interest rates and the slope of the yield curve. The authors make use of a panel regression, including several macroeconomic indicators amongst the explanatory variables (i.e. GDP growth, stock index, house prices, short term rates, etc.) on a large sample of international banks. Their results highlight that a concave relationship between NIM and interest exists as the quadratic term for NIM has negative coefficient, while NIM is positive, both being significant at the 1% confidence level.

Wheelock (2016) argues that the impact of an increase in interest rates on NIMs is ambiguous as banks are affected on both side of the balance sheet by movement in interest rates. For this latter reason, the combined effect on both sides of banks' balance sheet can be difficult to ascertain. To support this view, Wheelock shows that during episodes of large declins of the yield on Treasuries in the recessionary episodes of 1990-91, 2001 and 2007-2009, NIMs increased substantially. Summarizing, the bulk of the existing research points to the following effects of an interest rate shock on NIM:

1. An increase in interest rates (i.e. both market and policy rates) has empirically shown a positive effect on NIM, but this relationship is not stable over time.
2. The evolution in the composition of maturities of the loans and securities' portfolios of US banks is likely to have an impact on their responses to interest rate shocks, while the overall effects are not yet clearly outlined.

3. Larger and smaller banks display rather different behaviours and responses to interest rate shocks, due to their different maturity mismatch characteristics.

3. Dataset Description

This analysis investigates US commercial banks by making use of information collected from the Consolidated Report of Condition and Income[24]. The dataset is available since 1976:Q2 at the Federal Reserve Bank of Chicago and also at the Federal Financial Institutions Examination Council since 2001. The study focuses on a subset of banks with more than 1 bn. USD of total assets in any given quarter during the reporting period. Due to limitations and amendments to the reporting scheme, the indicators used in the analysis can only be estimated starting 1988:Q1. In addition, only the top 176 banks ranked by total assets as of 2015:Q2 that report without interruptions for the whole estimation period are retained. This is necessary as the DFM does not allow for missing values at this stage.

In addition, keeping the sample constant in its composition allows for comparisons over time[25]. As regards the NIM, it is provided directly by US Commercial Banks in the report FFEIC031 as RIAD4074. NIMRSK is calculated as below:

$$NIMRSK_b = \frac{(NIM_b - Prov_b)}{TA_b} \tag{1}$$

The above formula is derived from Noizet (2016) and is also used by commercial banks in their official reporting scheme[26]. In the above formula, *prov* indicates provisions for losses on loans and *TA* stands for total assets. NIMRSK allows for a better understanding of the underlying dynamics of NIM. Indeed, as explained by Noizet (2016), NIM suffers from a compression effect in times when the interest rates decrease below a defined

[24] This report is known also as Call report or Federal Financial Institutions Examination Council form n. 031, see also www.ffeic.gov.
[25] The exercise could have been run using an alternative approach, selecting the set of largest banks by total assets at the end of each estimation period. The results of the exercise run according to this assumptions are available upon request and confirm by and large the approach used in this study. In this latter case, the DFM and the conclusions concerning the evolution of the sign and significance of the explanatory variables are only partly affected by changes in composition and size of the sample.
[26] See e.g. the Quarterly Supplement of Wells Fargo for 2011:Q1 and Barclays' presentation of UK Retail and Business Banking, 30th May 2012.

threshold. This creates incentives for banks to lend at higher premium in times when interest rates are low and macroeconomic conditions are stressful. For this reason, NIM can increase even when interest rates are decreasing. Overall, the measurement of an efficient risk-adjusted NIM is difficult and NIMRSK only provides one of the possible alternatives that can be thought to counterbalance this issue.

Furthermore, the analysis focuses on the US commercial banks reporting scheme that collects information on activities in the US, hence it is better suited to investigate domestic macroeconomic shocks to the US banking sector. US commercial banks include most of the largest banks in the US by total assets and are broadly representative for the main business models and risk profile of US banks. At last, the DFM makes use of a set of macroeconomic variables, listed in appendix A for the model estimation. These variables are selected as they are the main financial and real economic variables for the US and should enable the DFM to capture the underlying dynamics in the US economy and in the US financial markets.

4. Modelling Framework

4.1 The Model

The modelling approach of this study is based on a dynamic factor model (DFM hereafter), as defined in Stock and Watson (2002) and Forni et al. (2000). The model is chosen as it is considered suitable for studying jointly micro and macroeconomic variables in a macro stress testing framework[27]. Hence, it allows to simulate a shock and observe both, a macroeconomic scenario and a micro-economic response (the IRFs), simultaneously. The model is described by two sets of equations for the micro and macro variables ($Y_{i,t}$, *i=1…N)*:

$$Y_{i,t} = \lambda_i f_t + \xi_{i,t} \tag{2}$$

[27] For more details on the model's settings used, see Lenza and Stragiotti (2015). In this exercise investigating NIMs and NIMRSKs, the set of macroeconomic variables is adapted to focus on interest rates' dynamics; hence it includes two extra variables, namely Monetary Base (M3) and the TED Spread. See appendix A for the variables used and the applied transformations.

$$f_t = A(L)f_{t-1} + e_t \quad (3)$$

The common component ($\lambda_n f_t$) collects the bulk of the correlation among variables and depends on the product of the r-dimensional vector of common factors f_t and the $N*r$ matrix of factor loadings $\Lambda = [\lambda_1{'}\ldots\lambda_N{'}]$. The dynamics of the common factors is described by a vector autoregression. The idiosyncratic component of each generic variable i is allowed to be mildly cross-correlated. The model is estimated by means of the two-steps approach described in Doz et al. (2011). All data is transformed into stationary time series, when necessary. The setup of the model allows for three common factors in all exercises since one additional factor explains roughly 5% of the total panel variance. Overall, the three factors account for more than 70% of the total panel variance over time.

A shock is then applied to one or more macroeconomic variables included in the dataset, according to the settings below:

$$y_{b,t+h}^{CX} = E_t\left(y_{b,t+h} | I_t, X_{t+1}\right) \quad (4.1)$$

I_t is the whole set of macro and micro variables at time t and X_{t+1} represents the selected variable(s), shocked at time t+1. y^{CX} is the conditional forecast at time t+h, for each bank b. The model produces also an unconditional forecast y^{UX} according to the below equation:

$$y_{b,t+h}^{UX} = E_t\left(y_{b,t+h} | I_t\right) \quad (4.2)$$

The exercise focuses on a simulated monetary policy shock. The variable measuring the monetary policy stance used in the exercise is a Shadow Monetary Policy Rate (SMPR hereinafter), chosen to address the impact of the zero-lower bound of the Federal Funds' Rate in the sample horizon[28]. To allow the model to capture the effects of a monetary policy shock, the model is identified as follows:

$$y_{b,t+h}^{CX} = E_t\left(y_{b,t+h} | X_{t+1}, Y_{t+1}^{UX-real}\right) \quad (4.3)$$

[28] The shadow monetary policy rate is constructed using the methodology described in Lombardi and Zhu (2014).

X_{t+1} represents the selected variable(s), shocked at time t+1 while $Y^{UX\text{-}real}$ is the set of the unconditional forecast at t+1 for real economy variables present in the dataset[29]. Y^{CX} and Y^{UX} are then used to construct an impulse-response function, as described in Banbura, Giannone and Lenza (2014). $IRF^{H}_{b,t+h}$ is then defined according to:

$$IRF^{H}_{b,t+h} = y^{CX}_{b,t+h} - y^{UX}_{b,t+h} \tag{4.4}$$

$IRF^{H}_{b,t+h}$ is then used to produce two indicators of the cycle-generated response (IC) of each bank to a specific shock in the macroeconomic environment. The indicators are defined by the following equations[30]:

$$ICT1^{H}_{b} = IRF^{H}_{b,t+1} \tag{5.1}$$

and

$$ICHP^{H}_{b} = \frac{[Peak(Trough)^{H}_{b,t} - IRF^{H}_{b,t+1}]}{Dur^{H}_{b}} \tag{5.2}$$

ICT1 measures the value of an IRF at t+1, while ICHP adopts an approach inspired from Harding and Pagan (1999). The latter authors, while discussing methodologies for describing an economic cycle, introduce what they define as the *triangle approximation to the cumulative movements* of the business cycle; this indicator can be approximately described as the area of the triangle described by the duration from peak to trough and the amplitude of the business cycle[31]. The approach used here differs from the Harding and Pagan's measure as the conditional and unconditional forecasts obtained by means of DFM are in levels. To circumvent this issue, the difference from peak to the IRF at t+1 is divided by the duration to peak/trough. The measure obtained is ultimately the slope of the curve of the IRFs. Eventually, ICHP allows for testing of IRFs' ability to include an

[29] See appendix A for more details.

[30] The model allows for any choice of horizon (H); the proposed values are matching the horizons used in previous stress testing exercises, see Lenza and Stragiotti (2015).

[31] In order to provide for further insight and validation regarding the approach used, other indicators and other forecasting horizons (H) were used: results are available upon request.

important component of interest rate risk in banking, i.e. the duration of balance sheet exposures.

4.2 Identification Scheme

This study focuses on the determinants of NIM's IRFs to a quarterly raise of the SMPR. To capture the common features of a Monetary Policy shock, the analysis adopts the standard recursive identification assumptions that the shock has no effect contemporaneously on the DFM's real economic variables, while financial markets' variables are allowed to respond.

These assumptions partly reflect previous identification strategies aiming to integrate a causal ordering among the variables used in the model as e.g. Bernanke, Boivin and Eliasz (2005), which differentiate between slow and fast-moving variables. Their settings allows fast-moving variables to respond contemporaneously to a monetary policy shock, while slow-moving variables respond with a delay. In a proper DFM framework, Forni and Gambetti (2010), adopt similar identification settings. The identification scheme is hence defined as:

$$y_{t+1}^{MC} = E_t(\mathrm{y}_{t+1}^{MU}|\mathrm{R}_t) \tag{6}$$

Where y^{MC}_{t+1} and y^{MU}_{t+1} are, respectively, the conditional and unconditional response of the macroeconomic variable y to the monetary policy shock at time t=1 and R_t is the subset of real macroeconomic variables that are assumed to respond to the shock with a delay. The financial variables that are included in the model are instead left free to react to the shock, as well as NIMs and NIMRSKs.

4.3 Determinants of the Shapes of the IRFs

The last step of the exercise focuses on the identification of the determinants of the characteristics of the IRFs. The study is based on a series of linear regressions using robust, White heteroskedasticity-corrected standard errors. The goal of this section is to assess if IRFs capture characteristics of risks and business models of US Commercial banks. To achieve this goal, several explanatory variables for risk, RF[32], are defined, combining several aspects of risk in banking. *ICs* enter then the below equations as dependent variable:

$$IC_b^H = c + \beta RF_b^m + \varepsilon_b \qquad \varepsilon_b \sim N(0,\sigma) \tag{7}$$

IC_b^H represents the IRF's indicator at the selected horizon for each bank, $RF^m{}_b$ indicates the means of a set of banks' risk factors, calculated during the estimation period, c is the constant and ε_b is the error term. In addition, as pointed out by several authors[33], larger and smaller banks may experience different behaviours in their responses to shocks, hence the sample is split in two subsamples of the top 30 banks and the remaining 146 banks according to the size of their balance sheet at the end of 2015Q3. At end of each estimation period, the top 30 banks encompass 90% of the total assets of the entire sample of banks considered for the exercise.

5. Least Squares Regression Exercises

5.1 Explanatory Variables Used in the Exercises

The current theory broadly supports the use of risk factors (RF) based on the concepts of maturity mismatch and duration to investigate interest rate sensitivities of banks. Banks are exposed to interest rate risk by the nature of their business. While a certain degree of mismatch is embedded in banks' business models, its magnitude changes due to the risk profile of each bank. As discussed above, Landier, *et al.* (2013) measure the exposure of US bank holding companies to interest rates shocks using the ICG, that measures the difference between the amounts of assets and liabilities that reprice within a one year horizon. This ratio represents a proxy for the sensitivity of profits to interest rate movements. Moreover, Bednar and Elamin (2014.a) discuss the effects of rising interest rates on US banks' profits, measuring the impact by means of an indicator which assigns different weights to the various asset classes according to their maturity.

[32] The variables used are discussed and defined in section 3.
[33] See Kashyap and Stein (1999) but also Bednar and Elamin (2014.a).

The income gap indicator, developed by Landier, *et al.* (2013), acts as foundation for the construction of the regressor for the Monetary Policy shock[34]. Due to differences in the reporting scheme used, the measure for the ICG is included in equations (7) as:

$$ICG_b = \left[\frac{AM_b<3M - LM_b<3M}{TA_b}\right] \tag{8}$$

AM < 3M are assets and liabilities, respectively, with remaining maturity or next re-pricing date up to three months and TA stands for total assets. The asset side includes loans and securities with a remaining maturity of three months while on the liabilities side, deposits with a re-pricing date below three months are reported. On both sides of the balance sheet, the ratio assumes all repurchase agreements and federal funds to mature within three months. This latter assumption is coherent with business practices, as described in Baklanova, *et al.* (2015) and in Maerowitz (1981) for both type of operations. The above ratio can be considered a proxy of the maturity mismatch gap as it measures the cash flow at risk from changes in interest rates. According to the results of Landier et al. (2013), ICG should have a general positive impact on ICs. Differences in magnitude of ICG depend on the indicator used, as defined in equations 5.1 and 5.2 as the unfolded scenario shapes the IRFs along the forecasting horizons. The sign and magnitude of the responses differ due to a number of effects that may have an impact on the relationship between ICG and NIM. Among these effects, the frequency of the re-pricing of assets, the roll-over cost of debt, which can be different from the short rate and relate to the funding structure of the bank, can be observed.

The maturity mismatch of assets and liabilities is important to assess the impact of an increase in interest rates, as described by Bednar and Elamin (2014.a). Hence, the ability of a bank to adjust its loan book to the new interest rate environment is a critical factor in controlling the magnitude of the impact of a monetary policy shock. Aiming to take into account the

[34] Alas, the reporting scheme for US commercial banks does not fully reflect the maturity gap between all assets and liabilities, but the coverage is large enough to allow constructing an indicator that mimics the income gap ratio developed by these authors. Moreover, while this latter ratio focuses on all items maturing within one year, the study look closely at maturities of up to 3 months, which seems more apt to capture the shock in the sample at a quarterly frequency.

duration of the loan book, a Weighted Maturity Gap Ratio (WMG)[35] is included among the regressors:

$$WMG_b = \left[\frac{(Weighted\ Assets)_b - (Weighted\ Liabilities)_b}{(Weighted\ Assets)_b + (Weighted\ Liabilities)_b}\right] \quad (9)$$

In the above formula, weights are assigned to both assets and liabilities according to their expected maturity and normalized. This ratio aims at capturing the maturity profile of each bank by comparing the duration of the assets and liabilities of a bank. This ratio is expected to have similar effects on ICs as ICG.

In addition, two ratios which are extensively used in studies related to banking as proxies for solvency and for liquidity, respectively Tangible Common Equity (TCE) and Loan to Deposit ratio (LTD), are also included. These indicators should in principle be able to capture features which are more related to macroeconomic conditions, TCE in particular and to the funding profile of banks, in the case of LTD. They are calculated according to:

$$TCE_b = \left[\frac{Equity_b - (Intangible\ Assets)_b - Goodwill_b - (Preferred\ Stock)_b}{TA_b}\right] \quad (10)$$

and,

$$LTD_b = \left[\frac{(Total\ Gross\ Loans)_b}{(Total\ Deposits)_b}\right] \quad (11)$$

The last two ratios focus on the two major interest rates' sensitive areas of the asset side of the balance sheet: securities and lending. An indicator of duration of the securities' portfolios should capture the sensitivity of bonds to changes in interest rates. The duration is measured as a weighted average of exposures, according to:

[35] See appendix B for more details on the weights used in the construction of the ratio.

$$DSEC_b = \left[\frac{(Sec<3M)_b*3+(Sec<12M)_b*6+(1Y<Sec<5Y)_b*30+(Sec>5Y)_b*60}{(Total\ Securities)_b}\right] \quad (12)$$

Sec indicates securities maturing before respectively 3 months, 1 year, between 1 and 5 years and after 5 years, according to the reporting scheme. The expected duration of the loan book is also important as it indicates how fast a bank can react to changes in the interest rates' environment. The duration of the loan book is measured as:

$$DLEN_b = \left[\frac{(Lns<3M)_b*3+(Lns<12M)_b*6+(1Y<Lns<5Y)_b*30+(Lns>5Y)_b*60}{(Total\ Gross\ Loans)_b}\right] \quad (13)$$

Lns indicates Loans maturing before respectively 3 months, 1 year, between 1 and 5 years and after 5 years.

The duration of the securities' portfolio and of the loan book are also important for the definition of shocks originating from the interest rate environment. Shorter maturities should have a general positive impact on NIM when interest rates are increasing as banks may swiftly reprice the assets at higher rates. Table 1 provides selected descriptive statistics on the explanatory variables used in the analysis.

Table 1: descriptive statistics for the variables used in the exercise.

	NIM	ICG	TCE	LTD	WMG	DSEC	DLEN
Mean	0.009	0.189	0.081	0.805	0.296	35.849	19.849
Standard Error	0.001	0.004	0.001	0.007	0.005	0.465	0.289
Median	0.957	0.182	0.079	0.801	0.317	36.246	20.035
Standard Deviation	0.102	0.041	0.006	0.072	0.049	4.878	3.039
Sample Variance	0.001	0.002	0.00004	0.005	0.002	23.796	9.238
Kurtosis	-1.355	-1.265	0.059	-0.822	-0.934	-1.414	-0.421
Skewness	-0.098	0.205	0.656	0.208	-0.631	0.048	0.414
Range	0.004	0.131	0.025	0.281	0.182	15.196	11.549
Minimum	0.007	0.125	0.069	0.685	0.189	28.393	15.024
Maximum	0.011	0.256	0.095	0.966	0.371	43.588	23.573
Count	110	110	110	110	110	110	110

The table reports the main statistics for the explanatory and dependent variables used in the regressions.

The major difference between the findings of this study and results of the studies previously mentioned resides in the setup of the exercises. While most of these analyses use least squares or panel regressions to make inference about the impact of explanatory variables on NIM, this study takes a different approach. The DFM model generates a scenario triggered by a shock on the SMPR, which shapes the forecasts of macro and microeconomic variables. A decrease in the Federal Funds Rate (i.e. a component of the SMPR) is likely to affect the forecasts of the general macroeconomic environment (e.g. non-performing loans, credit, inflation), defined by the paths of the variables included in the model. The resulting paths of NIMs are consequently affected by the forecasted variables which may have conflicting effects on the target variable.

5.2 Choice of the Estimation Periods and its Impact on NIMs, NIMRSKs and CIs

The first set of regressions aims at analysing if a relationship exists between the set of explanatory variables identified in chapter 4.1 and the ICs defined in equations 4.1 to 4.4 and generated by the DFM according to the framework described in chapter 2.1. The estimated ICs are then regressed upon the set of explanatory variables (namely, ICG, TCE, LTD, WMG, DSEC and DLEN). The following exercises are performed:

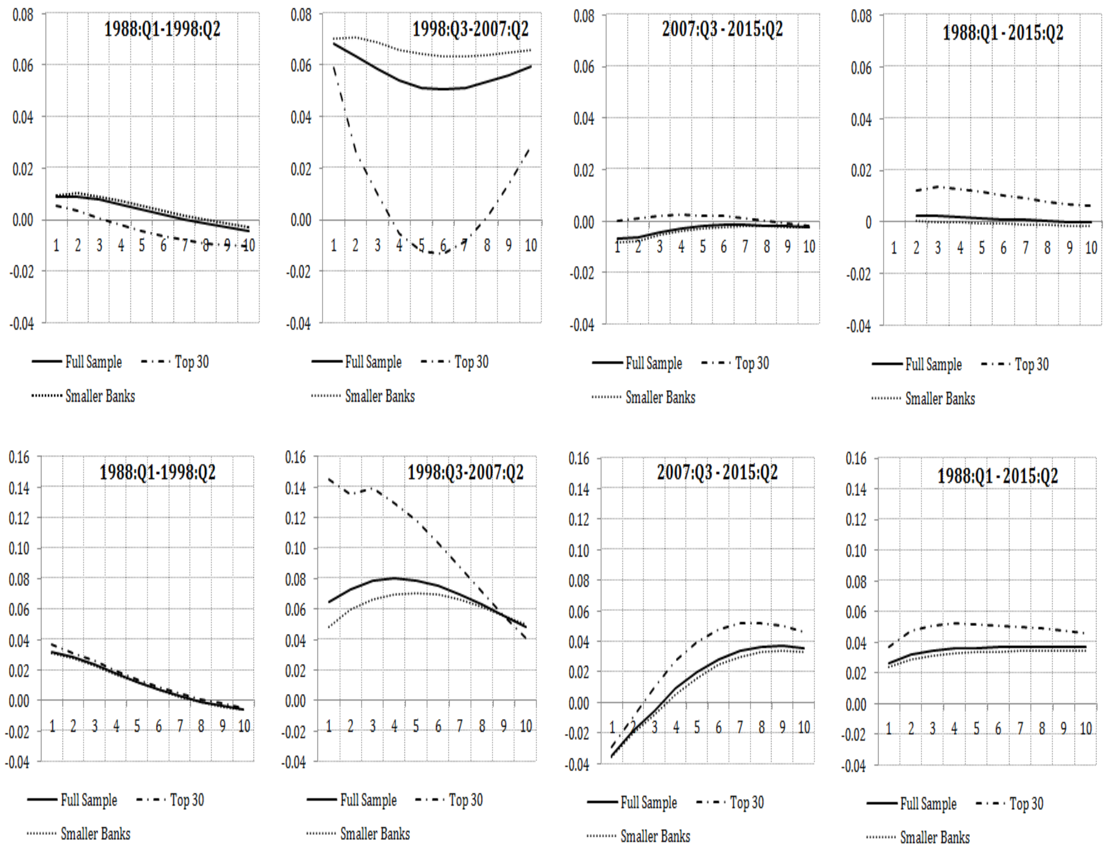
1. Over three non-overlapping periods: 1988:Q1 to 1998:Q2, 1998:Q3 to 2007:Q2 and 2007:Q3 to 2015:Q2 and
2. Over the full sample period, from 1988:Q1 until 2015:Q2.

The periods are selected for a number of reasons. These periods:

1. Are representative for different macroeconomic conditions and interest rates' environments: from rather high interest rates in the late 80s' to the recent zero-lower bound years,
2. Include different recessionary episodes: the early 90s' recession for the first period, the internet bubble for the second and the Lehman crisis for the last one,
3. Encompass different accounting and regulatory (i.e. Basel) frameworks, that have an impact on the microeconomic variables,
4. Are balanced in terms of number of quarters that makes them suitable for modelling by means of DFM.

Hence, the use of non-overlapping periods and the comparison with a longer period allows for testing the informational content of the model in different economic conditions. In fact, different regulatory and structural changes took place in the US banking sector between 1988 and 2015, e.g. Basel I, II and the originate-to-distribute, securitization-based business model[36] and its fall in the aftermath of the Lehman crisis, among others.

Figure 1: average NIM IRFs (upper row) and NIMRSK IRFs (lower row)



The charts indicate the average impulse-responses for the whole sample and the two subsets of banks selected for the exercises. In the x axis the numbers indicate quarters while the y axis reports NIM (in the upper line) and NIMRSK (in the lower line) values. Each chart illustrates the average of the impulse-responses for the selected horizons of the analysis. The last column on the right hand side reports the value over the whole horizon of the analysis (1988-2015). Values in the axis are reported in thousands for reader´s convenience.

An increase in the SMPR has heterogeneous effects on banks' NIMs, depending on the size of the banks as well as to the periods of reference for

[36] For more information on the rise of the originate-to-distribute business model, see Bord and Santos (2012).

the exercise. Understanding ICs' differences is functional to assess the impact of the explanatory variables in the OLS regressions run in this study and to support the validity of the model to capture NIM's general behaviour in a monetary policy shock. Figure 1 illustrates this aspect. As regards NIMs and NIMRSKs, the findings highlight that overall, a monetary policy shock has a positive effect on the margins, supporting existing evidence on the topic (e.g. Genay and Podjasek, 2014) and validating indirectly the use of the DFM as tool for modelling NIMs' responses to shocks.

Table 2: monetary policy shock, average ICT1 and ICHP for NIM and NIMRSK under the specifications outlined in equations 5.1 and 5.2

		NIM		
H=1	*1988 - 1998*	*1998 - 2007*	*2007 - 2015*	*1988 - 2015*
Full Sample ICT1	0.009	0.069	-0.007	0.002
Top 30 ICT1	0.006	0.059	0.000	0.012
Remaining ICT1	0.010	0.070	-0.008	0.000
H=10	*1988 - 1998*	*1998 - 2007*	*2007 - 2015*	*1988 - 2015*
Full Sample ICHP	-0.028	0.313	0.108	0.019
Top 30 ICHP	-0.149	-0.555	0.054	0.042
Remaining ICHP	-0.004	0.491	0.119	0.015

		NIMRSK		
H=1	*1988 - 1998*	*1998 - 2007*	*2007 - 2015*	*1988 - 2015*
Full Sample ICT1	0.032	0.065	-0.035	0.026
Top 30 ICT1	0.037	0.015	-0.029	0.037
Remaining ICT1	0.031	0.048	-0.036	0.024
H=10	*1988 - 1998*	*1998 - 2007*	*2007 - 2015*	*1988 - 2015*
Full Sample ICHP	-0.211	0.679	0.879	0.262
Top 30 ICHP	-0.249	-0.139	1.123	0.369
Remaining ICHP	-0.203	0.847	0.829	0.240

The table reports the average values of ICT1 and ICHP for the three periods under consideration and for the whole horizon of the exercise, for both NIM and NIMRSK. The average values are split by subsamples. Values reported in thousands for reader´s convenience.

While the response of NIMs is the basis for the understanding of the impact of the monetary policy shock, this study focuses on two ICs to describe NIMs' behaviour and makes use of these ICs as dependent variables in the regressions. Table 2 illustrates the average ICs for NIMs' IRFs at the end of each estimation period. While the interpretation of ICT1 is rather straightforward, ICHP integrates the dimension of duration and the persistence from t+1 to the peak/trough.

Positive and large values of ICHP indicate a steep sloping curve, potentially signalling that a bank's NIM is fast in responding to the shock. On average and on the full sample horizon, i.e. from 1988 to 2015, the ICs are positive in sign, indicating that a positive shock to the SMPR triggers a positive response on NIM. Alas, this is not always true for the subsets' horizons. ICHP is in fact mostly negative on average in the periods 1988-1998 and 1998-2007. In addition, ICT1 and ICHP often diverge in signs, highlighting a broad heterogeneity in the IRFs of the banks included in the sample, hinting to differences in business models and risk profiles across banks.

6. Results for NIMs and NIMRSKs

The results of the OLS regressions are illustrated in table 3.a to 3.d below[37] for NIM and NIMRSK. One important result emerges from the observation of the significance levels of the explanatory variables: ICG is overall the most important RFs among the ones shaping the impulse-response functions generated by the DFM. When NIM is the dependent variable, ICG emerges as statistically significant at least at the 0.05 significance level in more than 60% of the 24 regressions run, often at the 0.001 significance level. The sign of the coefficient is positive in the large majority of cases and mostly when ICG is also statistically significant. WMG, TCE and LTD are also significant but at lower levels and in fewer cases.

Overall, ICG and LTD emerge as the most informative variables defining the contemporaneous response of NIM to a monetary policy shock as measured by ICT1. ICG is informative on the whole sample as well as on small banks and carries mostly negative sign, which indicates that, in a tightening of monetary policy scenario, an increase of the income gap reduces NIM at t=1. Overall, the results show that between 1988 and 2007, the relationship between NIM and ICG, following a monetary policy shock was positive on ICT1. The findings indicate that higher levels of interest rates increase NIM for banks with larger ICG in the aftermath of the increase in the SMPR.

[37] For a comprehensive analysis of the results of the OLS regressions, see appendix C and D.

Table 3.a: statistical significance of explanatory variables for NIM in OLS regressions. Dep. Var. = ICT1.

Full Sample (176 Banks) - Estimates are White Heteroscedastic Consistent - Dependend Variable ICT1 - H=1

1988:Q1 - 1998:Q2				1998:Q3 - 2007:Q2			2007:Q2 - 2015:Q2			1988:Q1 - 2015:Q2		
R-sq. adj.	0.0235			R-sq. adj.	-0.0077		R-sq. adj.	0.067		R-sq. adj.	0.1832	
Variable	Coeff.	t-stat.	t-prob.	Coeff.	t-stat.	t-prob.	Coeff.	t-stat.	t-prob.	Coeff.	t-stat.	t-prob.
Cnst	-0.009	-0.915	0.361	0.050	0.454	0.651	0.037	1.807	0.073	0.039	1.605	0.110
ICG	0.042	2.486	0.014 *	0.014	0.084	0.933	-0.084	-2.727	0.007 **	-0.161	-4.516	0.000 ***
LTD	-0.002	-0.245	0.807	-0.012	-0.163	0.871	0.005	0.446	0.656	0.040	2.505	0.013 *
TCE	0.026	0.417	0.677	-0.453	-1.083	0.281	-0.196	-2.288	0.023 *	-0.194	-2.384	0.018 *
WMG	0.020	1.248	0.214	0.021	0.150	0.881	-0.088	-3.145	0.002 **	-0.049	-1.559	0.121
DSEC	0.000	0.991	0.323	0.002	1.365	0.174	0.000	1.647	0.101	0.000	1.090	0.277
DLEN	0.000	-1.079	0.282	-0.001	-0.520	0.604	0.000	-0.430	0.668	-0.001	-1.893	0.060

Top 30 Sample (30 Banks) - Estimates are White Heteroscedastic Consistent - Dependend Variable ICT1 - H=1

R-sq. adj.	-0.0426			R-sq. adj.	0.1484		R-sq. adj.	0.0238		R-sq. adj.	0.0483	
Variable	Coeff.	t-stat.	t-prob.	Coeff.	t-stat.	t-prob.	Coeff.	t-stat.	t-prob.	Coeff.	t-stat.	t-prob.
Cnst	-0.021	-1.214	0.237	-0.256	-1.003	0.326	0.016	0.714	0.482	0.036	1.296	0.208
ICG	0.076	2.115	0.045 *	1.350	2.325	0.029 *	-0.055	-1.373	0.183	-0.159	-2.575	0.017 *
LTD	0.003	0.137	0.892	-0.610	-3.198	0.004 **	-0.016	-0.616	0.544	0.077	2.987	0.007 **
TCE	-0.021	-0.170	0.866	-0.533	-0.311	0.758	-0.111	-0.551	0.587	-0.279	-1.840	0.079
WMG	0.049	1.484	0.151	-0.212	-0.431	0.671	-0.127	-2.995	0.006 **	-0.002	-0.038	0.970
DSEC	0.000	-0.309	0.760	0.016	2.360	0.027 *	0.001	1.548	0.135	0.000	0.105	0.917
DLEN	0.000	0.075	0.941	0.000	0.041	0.968	0.001	0.695	0.494	-0.002	-1.199	0.243

Remaining Sample (146 Banks) - Estimates are White Heteroscedastic Consistent - Dependend Variable ICT1 - H=1

R-sq. adj.	0.01			R-sq. adj.	-0.0049		R-sq. adj.	0.0609		R-sq. adj.	0.1709	
Variable	Coeff.	t-stat.	t-prob.	Coeff.	t-stat.	t-prob.	Coeff.	t-stat.	t-prob.	Coeff.	t-stat.	t-prob.
Cnst	-0.005	-0.415	0.679	0.087	0.631	0.529	0.039	1.102	0.273	0.041	0.999	0.320
ICG	0.039	2.143	0.034 *	-0.130	-0.786	0.433	-0.106	-2.957	0.004 **	-0.168	-4.365	0.000 ***
LTD	-0.005	-0.415	0.679	0.057	0.618	0.537	0.008	0.427	0.670	0.036	1.448	0.150
TCE	0.000	0.003	0.997	-0.745	-1.749	0.083	-0.166	-1.683	0.095	-0.137	-1.048	0.296
WMG	0.007	0.352	0.726	0.065	0.410	0.682	-0.077	-1.903	0.059	-0.032	-0.551	0.583
DSEC	0.000	1.362	0.176	0.001	0.359	0.720	0.000	0.625	0.533	0.000	0.253	0.800
DLEN	0.000	-0.815	0.416	-0.001	-0.380	0.704	0.000	-0.850	0.397	-0.001	-1.941	0.054

**** denotes significance at the 0.1%, ** significance at the 1% and * at the 5% levels. The results are reported for ICT1 (three top rows) and ICHP (three bottom rows). Coefficient values are reported in thousands for the reader´s convenience.*

Table 3.b: statistical significance of explanatory variables for NIM in OLS regressions. Dep. Var. = ICHP.

Full Sample (176 Banks) - Estimates are White Heteroscedastic Consistent - Dependend Variable ICHP - H=10

1988:Q1 - 1998:Q2				1998:Q3 - 2007:Q2			2007:Q2 - 2015:Q2			1988:Q1 - 2015:Q2		
R-sq. adj.	0.0774			R-sq. adj.	0.0836		R-sq. adj.	0.0201		R-sq. adj.	0.0227	
Variable	Coeff.	t-stat.	t-prob.	Coeff.	t-stat.	t-prob.	Coeff.	t-stat.	t-prob.	Coeff.	t-stat.	t-prob.
Cnst	-0.058	-0.347	0.729	-3.200	-1.156	0.249	-0.411	-1.985	0.049 *	0.013	0.055	0.956
ICG	0.806	3.514	0.001 ***	11.784	3.816	0.000 ***	0.761	2.227	0.027 *	-0.521	-1.159	0.248
LTD	-0.194	-1.208	0.229	-0.820	-0.347	0.729	0.212	1.543	0.125	0.307	1.452	0.148
TCE	0.651	0.614	0.540	11.564	1.573	0.118	1.281	1.316	0.190	-0.838	-1.145	0.254
WMG	0.343	1.264	0.208	2.834	0.943	0.347	0.794	2.769	0.006 **	-0.080	-0.261	0.794
DSEC	-0.004	-1.151	0.251	-0.029	-1.123	0.263	-0.003	-1.557	0.121	-0.002	-0.659	0.511
DLEN	-0.002	-0.459	0.647	0.072	1.434	0.153	0.000	0.047	0.962	0.001	0.117	0.907

Top 30 Sample (30 Banks) - Estimates are White Heteroscedastic Consistent - Dependend Variable ICHP - H=10

R-sq. adj.	0.024			R-sq. adj.	0.1564		R-sq. adj.	0.1959		R-sq. adj.	0.1711	
Variable	Coeff.	t-stat.	t-prob.	Coeff.	t-stat.	t-prob.	Coeff.	t-stat.	t-prob.	Coeff.	t-stat.	t-prob.
Cnst	0.285	0.934	0.360	-1.042	-0.300	0.767	0.022	0.071	0.944	0.348	1.685	0.106
ICG	0.012	0.014	0.989	-9.387	-1.246	0.225	0.267	0.504	0.619	-1.313	-1.966	0.062
LTD	-0.783	-1.811	0.083	5.098	1.753	0.093	0.701	2.463	0.022 *	0.840	2.821	0.010
TCE	3.441	1.162	0.257	24.634	1.214	0.237	0.642	0.212	0.834	-3.151	-1.747	0.094
WMG	-0.692	-1.808	0.084	6.398	0.999	0.328	0.679	1.266	0.218	-0.800	-1.191	0.246
DSEC	0.001	0.249	0.806	-0.187	-2.067	0.050	-0.015	-3.101	0.005 **	-0.004	-0.724	0.476
DLEN	0.010	0.649	0.523	0.137	1.124	0.273	-0.008	-0.550	0.587	-0.011	-0.825	0.418

Remaining Sample (146 Banks) - Estimates are White Heteroscedastic Consistent - Dependend Variable ICHP - H=10

R-sq. adj.	0.0551			R-sq. adj.	0.1664		R-sq. adj.	0.0169		R-sq. adj.	0.0046	
Variable	Coeff.	t-stat.	t-prob.	Coeff.	t-stat.	t-prob.	Coeff.	t-stat.	t-prob.	Coeff.	t-stat.	t-prob.
Cnst	-0.171	-0.861	0.391	-2.061	-0.607	0.545	-0.480	-1.401	0.164	0.011	0.029	0.977
ICG	0.887	3.930	0.000 ***	15.094	4.401	0.000 ***	0.993	2.491	0.014 *	-0.489	-0.996	0.321
LTD	-0.090	-0.488	0.626	-2.638	-0.942	0.348	0.178	0.834	0.406	0.248	0.822	0.412
TCE	0.445	0.371	0.711	7.988	0.982	0.328	0.950	0.902	0.369	-0.638	-0.607	0.545
WMG	0.369	1.057	0.292	-2.495	-0.773	0.441	0.853	2.115	0.036 *	0.068	0.134	0.893
DSEC	-0.003	-0.636	0.526	0.015	0.588	0.558	-0.001	-0.391	0.697	-0.003	-0.733	0.465
DLEN	-0.003	-0.475	0.635	0.082	1.520	0.131	0.001	0.169	0.866	0.001	0.148	0.882

**** denotes significance at the 0.1%, ** significance at the 1% and * at the 5% levels. The results are reported for ICT1 (three top rows) and ICHP (three bottom rows). Coefficient values are reported in thousands for the reader´s convenience.*

On the whole sample and during the Great Recession of 2008 the sign of the coefficient turns negative. The change in sign and the overall results may be explained by the impact of the unconventional monetary policy stance of the Federal Reserve and by the zero-lower bound interest rates environment. The results of the regressions on ICHP highlight the role played by ICG in the amplification of the monetary policy shock on NIM.

Larger ICGs trigger larger increases in NIM following a monetary policy tightening and supporting the view of Landier *et al.* (2013). Small banks seem to drive the overall results while larger banks are mostly sensitive to LTD, WMG and DSEC to their response to a monetary policy tightening. The liquidity crunch observed in 2008 played a role in our results as LTD and DSEC are reported jointly statistically significant only in the latest period.

Table 3.b presents the results of the same exercise on NIMRSK. While ICG is mostly informative regarding NIMs' ICs, it is relatively less informative for NIMRSKs. NIMRSKs' ICs are more sensitive to LTD and TCE. A potential explanation could be that the risk adjustment factor (i.e. provisions for losses on loans) embeds macroeconomic information in NIMs. This aspect is therefore captured by the DFM and mirrored in the IRFs. The shapes of the IRFs and the derived ICs appear to be more sensitive to micro indicators capturing business models (such as LTD) and more cyclical in nature such as solvency (as in the case of TCE).

An informative result emerges from the observation of ICG in the regression for NIMRSK when looking at ICHP, the slope of the responses. Over larger and for smaller banks the results are statistically significant and the coefficient highlights a positive relationship between ICG and NIMRSK, i.e. steeper responses for larger values of ICG. The relationship is less informative for larger banks, but the sign is negative. Potentially, the use of mitigating factors such as derivatives, which are more commonly used by larger banks, played a role in the results. Another valid argument could refer to the better diversification of larger bank holding companies, as illustrated in Demsetz and Strahan (1997). Overall, when NIM is corrected for credit risk more heterogeneity is observed in the results.

Table 3.c: statistical significance of explanatory variables for NIMRSK in OLS regressions. Dep. Var. = ICT1.

Full Sample (176 Banks) - Estimates are White Heteroscedastic Consistent - Dependend Variable ICT1 - H=1

1988:Q1 - 1998:Q2				1998:Q3 - 2007:Q2			2007:Q2 - 2015:Q2			1988:Q1 - 2015:Q2		
R-sq. adj.	0.0255			R-sq. adj. 0.0101			R-sq. adj. 0.0826			R-sq. adj. 0.0789		
Variable	Coeff.	t-stat.	t-prob.	Coeff.	t-stat.	t-prob.	Coeff.	t-stat.	t-prob.	Coeff.	t-stat.	t-prob.
Cnst	0.025	0.725	0.469	-0.089	-0.612	0.541	0.047	0.934	0.352	-0.025	-0.800	0.425
ICG	0.061	1.275	0.204	0.112	0.458	0.648	-0.275	-2.799	0.006 **	0.050	0.921	0.359
LTD	-0.007	-0.304	0.762	0.109	1.243	0.215	0.007	0.185	0.854	0.093	3.834	0.000 ***
TCE	-0.476	-2.984	0.003 **	0.013	0.019	0.985	-0.273	-1.338	0.183	-0.176	-1.746	0.083
WMG	-0.037	-0.810	0.419	-0.132	-0.797	0.427	-0.158	-2.837	0.005 **	0.092	1.945	0.053
DSEC	0.001	2.002	0.047 *	0.001	0.405	0.686	0.001	1.686	0.094	-0.001	-1.243	0.216
DLEN	0.001	0.551	0.582	0.002	0.926	0.356	-0.001	-1.126	0.262	-0.001	-1.303	0.194

Top 30 Sample (30 Banks) - Estimates are White Heteroscedastic Consistent - Dependend Variable ICT1 - H=1

R-sq. adj.	0.2954			R-sq. adj. -0.0716			R-sq. adj. 0.2504			R-sq. adj. 0.3877		
Variable	Coeff.	t-stat.	t-prob.	Coeff.	t-stat.	t-prob.	Coeff.	t-stat.	t-prob.	Coeff.	t-stat.	t-prob.
Cnst	-0.120	-2.181	0.040 *	-0.422	-1.632	0.116	0.001	0.022	0.983	-0.036	-1.034	0.312
ICG	0.448	3.646	0.001 **	1.246	2.137	0.043 *	-0.050	-0.511	0.614	-0.095	-1.205	0.240
LTD	-0.170	-3.429	0.002 **	-0.231	-1.292	0.209	-0.128	-2.370	0.027 *	0.103	2.784	0.011 *
TCE	0.511	1.165	0.256	-0.049	-0.029	0.977	-0.368	-1.165	0.256	0.131	0.608	0.549
WMG	0.102	0.970	0.342	0.162	0.299	0.768	-0.401	-5.599	0.000 ***	-0.006	-0.074	0.942
DSEC	0.001	1.139	0.266	0.008	1.201	0.242	0.003	3.518	0.002 **	0.000	0.153	0.880
DLEN	0.007	2.286	0.032 *	0.008	0.931	0.361	0.004	2.503	0.020 *	0.000	-0.316	0.755

Remaining Sample (146 Banks) - Estimates are White Heteroscedastic Consistent - Dependend Variable ICT1 - H=1

R-sq. adj.	0.0285			R-sq. adj. 0.0028			R-sq. adj. 0.0903			R-sq. adj. 0.0518		
Variable	Coeff.	t-stat.	t-prob.	Coeff.	t-stat.	t-prob.	Coeff.	t-stat.	t-prob.	Coeff.	t-stat.	t-prob.
Cnst	0.056	1.249	0.214	-0.112	-0.622	0.535	0.019	0.225	0.822	-0.024	-0.529	0.597
ICG	0.017	0.320	0.749	-0.068	-0.259	0.796	-0.322	-2.661	0.009 **	0.054	0.916	0.361
LTD	0.005	0.145	0.885	0.198	1.821	0.071	0.040	0.706	0.482	0.087	2.681	0.008 **
TCE	-0.659	-3.251	0.001 **	0.201	0.259	0.796	-0.164	-0.642	0.522	-0.138	-1.114	0.267
WMG	-0.103	-1.785	0.076	0.042	0.218	0.827	-0.097	-1.189	0.237	0.123	1.907	0.059
DSEC	0.001	2.085	0.039 *	-0.001	-0.531	0.596	0.001	1.271	0.206	-0.001	-1.415	0.159
DLEN	0.001	0.707	0.480	0.000	0.161	0.872	-0.002	-1.456	0.148	-0.001	-1.398	0.164

**** denotes significance at the 0.1%, ** significance at the 1% and * at the 5% levels. The results are reported for ICT1 (three top rows) and ICHP (three bottom rows). Coefficient values are reported in thousands for the reader´s convenience.*

Table 3.d: statistical significance of explanatory variables for NIMRSK in OLS regressions. Dep. Var. = ICHP.

Full Sample (176 Banks) - Estimates are White Heteroscedastic Consistent - Dependend Variable ICHP - H=10

1988:Q1 - 1998:Q2				1998:Q3 - 2007:Q2			2007:Q2 - 2015:Q2			1988:Q1 - 2015:Q2		
R-sq. adj.	0.0416			R-sq. adj.	0.039		R-sq. adj.	0.1051		R-sq. adj.	0.1151	
Variable	Coeff.	t-stat.	t-prob.	Coeff.	t-stat.	t-prob.	Coeff.	t-stat.	t-prob.	Coeff.	t-stat.	t-prob.
Cnst	-1.172	-2.503	0.013 *	0.175	0.074	0.941	-0.743	-0.931	0.353	-0.572	-2.179	0.031 *
ICG	1.599	2.557	0.011 *	7.050	2.476	0.014 *	4.565	2.993	0.003 **	1.204	2.373	0.019 *
LTD	0.145	0.353	0.724	-1.330	-0.875	0.383	0.753	1.182	0.239	0.358	1.750	0.082
TCE	6.613	3.220	0.002 **	0.415	0.037	0.971	1.202	0.245	0.807	0.500	0.317	0.752
WMG	0.282	0.401	0.689	1.055	0.407	0.684	1.586	1.667	0.097	-0.009	-0.022	0.982
DSEC	-0.007	-0.870	0.386	0.005	0.213	0.832	-0.016	-1.291	0.198	0.004	0.992	0.322
DLEN	0.007	0.541	0.589	-0.007	-0.183	0.855	0.020	1.024	0.307	0.007	1.092	0.276

Top 30 Sample (30 Banks) - Estimates are White Heteroscedastic Consistent - Dependend Variable ICHP - H=10

R-sq. adj.	0.1267			R-sq. adj.	0.1677		R-sq. adj.	0.5097		R-sq. adj.	0.455	
Variable	Coeff.	t-stat.	t-prob.	Coeff.	t-stat.	t-prob.	Coeff.	t-stat.	t-prob.	Coeff.	t-stat.	t-prob.
Cnst	-0.300	-0.293	0.772	1.736	0.359	0.723	0.657	0.802	0.431	-0.716	-1.621	0.119
ICG	-2.379	-1.409	0.172	-18.947	-2.111	0.046 *	-0.443	-0.305	0.763	-0.587	-0.532	0.600
LTD	0.852	1.183	0.249	0.636	0.212	0.834	3.584	3.388	0.003 **	0.621	1.351	0.190
TCE	5.957	1.336	0.195	45.521	2.443	0.023 *	7.969	1.191	0.246	7.994	2.368	0.027 *
WMG	-1.629	-1.606	0.122	-15.268	-2.274	0.033 *	2.824	1.638	0.115	-1.701	-1.499	0.147
DSEC	-0.009	-0.675	0.506	0.010	0.124	0.903	-0.045	-2.592	0.016 *	0.007	0.741	0.466
DLEN	0.008	0.161	0.874	0.049	0.390	0.700	-0.083	-2.488	0.021 *	0.011	0.608	0.549

Remaining Sample (146 Banks) - Estimates are White Heteroscedastic Consistent - Dependend Variable ICHP - H=10

R-sq. adj.	0.0585			R-sq. adj.	0.1362		R-sq. adj.	0.0796		R-sq. adj.	0.0685	
Variable	Coeff.	t-stat.	t-prob.	Coeff.	t-stat.	t-prob.	Coeff.	t-stat.	t-prob.	Coeff.	t-stat.	t-prob.
Cnst	-1.464	-2.653	0.009 **	2.072	0.790	0.431	-0.547	-0.428	0.669	-0.397	-1.221	0.224
ICG	2.260	3.468	0.001 ***	10.150	3.478	0.001 ***	5.027	2.558	0.012 *	1.271	2.364	0.019 *
LTD	-0.058	-0.133	0.895	-2.953	-1.622	0.107	0.384	0.416	0.678	0.210	0.853	0.395
TCE	7.590	2.850	0.005 **	-10.652	-1.085	0.280	-0.074	-0.015	0.988	-0.575	-0.435	0.664
WMG	0.696	0.705	0.482	-1.680	-0.635	0.526	1.593	1.255	0.212	0.096	0.259	0.796
DSEC	-0.003	-0.314	0.754	0.014	0.702	0.484	-0.015	-1.084	0.280	0.004	0.864	0.389
DLEN	0.002	0.164	0.870	0.017	0.400	0.689	0.025	1.096	0.275	0.006	0.862	0.390

**** denotes significance at the 0.1%, ** significance at the 1% and * at the 5% levels. The results are reported for ICT1 (three top rows) and ICHP (three bottom rows). Coefficient values are reported in thousands for the reader´s convenience.*

The correction for risk used to construct NIMRSK (i.e. deduction of provisions for losses on loans, see equation 6) is important in the statistical significance of the variables in estimation periods characterized by the occurrence of recessions featuring high levels of delinquencies in the US banking sector[38]. This may be partly explained by the fact that provisions are usually high during recessions. This effect is likely to influence the ICs and hence the results of the regressions. This latter result supports the hypothesis that the model's IRFs embed non-negligible information of the dynamics of NIMRSKs.

7. Conclusions

This study discusses the ability of an application of the DFM to capture microeconomic information related to NIMs and NIMRSKs in a monetary policy shock scenario. The shock is then analyzed by means of an OLS regression framework, using a set of micro-based explanatory variables and a set of composite indicators as dependent variables. Overall, it emerges that proxies for banks maturity mismatches capture non-trivial effects in NIMs' responses, while these responses are heterogeneous and depending on banks' business models and risk profiles. TCE and LTD are both statistically and economically significant, as previously emerged in the context of studies related to banks' profitability.

The findings are overall informative of the presence of a bank lending transmission channel of monetary policy. The presence of a statistically significant relationship between ICG and the impulse response of NIM to a monetary policy shock supports the view that banks transmit the monetary policy shock via NIM to clients. The pass-through mechanism is heterogeneous and depends from some specific characteristics of banks, such as their maturity mismatch and their solvency levels and size. More, the findings for NIMRSK highlight that other features of banks, e.g. their level of credit risk measured by provisioning, affect the degree and sensitivity to which banks respond to a change in the monetary policy stance. What gives room for further investigation is to what extent a monetary policy shock is transferred from banks to clients.

[38] As observed in the 1988-1998 and the 2007-2015 estimation periods. For more information see: https://fred.stlouisfed.org/series/DRALAQBS.

In addition, the findings highlight that ICG and other indicators of maturity mismatches influence the duration and the magnitude of the responses of banks to a monetary policy shock. Furthermore, signs and statistical significance of ICG change over time and across the sample. Large banks' responses can be captured by a larger set of explanatory variables, while for smaller banks ICG seems to be the main variables of interest. Taking credit risk into account in the model by using NIMRSK as microeconomic variable in the DFM adds insights to the investigation, while confirming the previous results. NIMRSKs regressions indicate that during recessionary episodes characterized by high levels of banks' delinquent loans, the responses of banks are defined by a larger set of explanatory variables, mainly related to solvency, as TCE or to business model, as in the case of LTD. This finding definitely deserves further research.

Finally, the results indicate that the signs of the coefficients of the regressions are evolving over time, indicating that the impact of the variables changes in correspondence with the macroeconomic environment. In addition, the current environment characterized by low interest rates calls for a deeper investigation of the consequences of a potential increase of interest rates and on the effects on the banking sector's profitability. These effects have been neglected so far but their impact might be significant as the results of this study highlights.

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Appendix A: list of macroeconomic variables used in the Dynamic Factor Model and applied transformations

Variable	*Description*	*Mon. Pol. Shock.*	*Applied Transform.*	*Source*
GDP	Nominal GDP of the US	Real	Log Diff	Fred St.Louis
URATE	Unemployment Rate	Real	Diff	Fred St.Louis
PMI Manuf	PMI Manufacturing Index	Real	Diff	Fred St.Louis
C&I Loans	Commercial and Industrial Loans	Real	Log Diff	Fred St.Louis
Real Estate Loans	Real Estate Loans	Real	Log Diff	Fred St.Louis
Consumer Credit	Consumer Credit	Real	Log Diff	Fred St.Louis
Corporate profits	Corporate profits	Real	Log Diff	Fred St.Louis
CPI	Core Price Index	Real	Log Diff	Fred St.Louis
M3	Monetary Aggegrate (M3)	Real	Log Diff	Fred St.Louis
HP California	House Price Index for California	Real	Log Diff	Fred St.Louis
SP500	Standard and Poors' 500 Index	Financial	Log Diff	Fred St.Louis
EER	Effective Exchange Rate	Financial	Log Diff	Fred St.Louis
SMPR	Shadow Monetary Policy Rate	Financial	Diff	Author's Calculation
SPREAD 3MTBILL-AAACORP	Spread 3M Treasury Bill vs. AAA Corporate Bond	Financial	Diff	Author's Calculation
VIX	VIX volatility Index	Financial	raw	Fred St.Louis
MORT RATE	Mortgage Rate	Financial	Diff	Fred St.Louis
CAP UTIL	Capacity Utilitzation	Real	Log Diff	Fred St.Louis
DEBT TO INCOME	Debt to Income Ratio	Real	Diff	Fred St.Louis
DIFF IND	Diffusion Index	Real	Diff	Fred St.Louis
OILP	Oli Price	Real	Log Diff	Fred St.Louis
HOUSING PERMITS	Housing Permits in the US	Real	Diff	Fred St.Louis
FRED_MAC_INDEX	Freddie Mac House Price Index	Real	Log Diff	Fred St.Louis
GOLDP	Gold Price	Real	Log Diff	Fred St.Louis
CREDIT_FED	Aggregate Credit in the US	Real	Log Diff	Fred St.Louis
TED	TED Spread	Financial	Diff	Author's Calculation
MBS_AGENCY_OUTSTANDING	MBS Agency Outstanding Debt	Real	Log Diff	SIFMA
SPREAD3M10Y	Spread 3M vs 10 Y Treasury Bills	Financial	Diff	Author's Calculation
DEL_FED	Delinquencies of US Commercial Banks	Real	Diff	Fred St.Louis
USNPTL	Non-Performing Loans of US Commercial Banks	Real	Diff	Fred St.Louis
DRIWCIL	Loan Officer Survey of the Federal Reserve	Real	Diff	Fred St.Louis
NIM / NIMRAD	Net Interest Margin / Net Interest Margin - Risk Adjusted	n/a	raw	FFEIC - Fed Chicago

Appendix B: Weighted Maturity Gap

Assets		*Weight*	*Liabilities*	*Weight*
Loans and Securities	Maturing before 3 months	1	Capital	13
	Mat. between 3 and 12 months	3	Repurchase Agreements	1
	Mat. between 1 and 5 years	7	Deposits	1
	Mat. over 5 years	13	Other Liabilities	13
Repurchase Agreements		1		
Cash		1		
Intangibles, Fixed Assets and Other Assets		13		

Chapter 4

Solvency to Liquidity Channel in the US Banking Sector Before, During and After the Subprime Crisis

1. Introduction

The interaction between liquidity and solvency played an important role in the Lehman Crisis in the US. Since the end of the *Great Recession*, several studies highlighted that the dynamics at work before, during and after the outbreak of the 2008 banking crisis pinpointed to these two risks and their interlinkages as pivotal factors to understand the unfolding of the events that led to the bankruptcy of Lehman Brothers (Cornett et al., 2011). The relationship between solvency and liquidity does not only play havoc to banks' financial soundness, by exposing banks to default risk (Pierret, 2015), but has severe repercussions to the capacity of banks to lend to the real economy (Ivashina and Scharfstein, 2010).

The channel solvency-liquidity is central for banks. In fact, the capacity of banks to extend loans depends on the ability to transform liquid deposits into illiquid loans (Diamond and Dybvig, 1983). While this transformation takes place, banks are exposed to bank runs, which require banks to maintain a liquidity buffer to face sudden and unforeseen withdrawals from depositors. The migration of risk from liquidity to solvency, when capital shortfalls occur, may eventually have an impact on banks' lending capacity.

In addition, since the introduction of Basel I the lending capacity of a bank depends on its capital resources. The system of weights designed by Basel obliges a bank to set aside capital according to the perceived riskiness of counterparties; the higher the risk, the larger the capital requirement. The interaction of capital requirements, capital shortfalls and liquidity constraints adds up to worsen the capacity of a bank to extend loans to the real economy. Henceforth the capacity of a bank to increase lending depends on its capital and liquidity risk profiles, jointly. The practical implications of the interaction between capital and liquidity are clearly outlined by Farag, Harland and Nixon (2013).

The transmission of a banking crisis' effects to the real economy may be seen as a justification for central banks and regulators[39] to focus on gaining a better understanding of the solvency and liquidity nexus. This latter

[39] See e.g. Madigan, F. B. "Bagehot's Dictum in Practice: Formulating and Implementing Policies to Combat the Financial Crisis" Speech given at the Federal Reserve Bank of Kansas City's Annual Economic Symposium, Jackson Hole, Wyoming, August 21st, 2009 and Rosengren, E. S. "Liquidity and Systemic Risk" at the Federal Reserve Bank of Richmond's 2008 Credit Markets Symposium, Charlotte, North Carolina, April 18th, 2008.

relationship plays a key role in macro stress tests[40]. Borio, Drehmann and Tsatsaronis (2012) assess the strengths and weaknesses of stress tests, indicating the link between solvency and liquidity as a critical issue, difficult to address in a modelling framework and hence in need of further analysis. Bookstaber et al. (2013) discuss a number of issues related to the design of the stress testing exercises run in the US, namely the Federal Reserve's Supervisory Capital Assessment Program and the later Comprehensive Capital Analysis & Review exercises. In particular, the authors highlight the need for a joint solvency-liquidity modelling approach to stress testing and the lack of a proper understanding of banks' responses to macro & microeconomic shocks, which encompass the solvency-liquidity interlinkages. In addition, in an attempt to infer that stress tests have become less informative over time, Glasserman and Tangirala (2015) illustrate how the recent stress tests in the US could have been improved by reducing what they define as predictability of the regulatory stress tests' exercises. Among the idea outlined in their study, they also pinpoint to the solvency-liquidity link as one of the paths for further research.

The importance of understanding the solvency-liquidity channel is outlined also in the 2012 final report of the US Monetary Policy Forum on macro-prudential principles for stress testing[41]. The report highlights that: "...banks have to be sufficiently solvent to avert runs", adding to the point that: "...the “run point” of a systemic bank often entails significantly higher capital than the bare solvency point". In addition, it is mentioned the need to integrate fire-sales in stress testing scenarios, concluding that "...liquidity rules, in addition to capital requirements, should be part of the overall framework of macro-prudential oversight". These recommendations condensate some of the major aspects related to the solvency-liquidity channel. Finally, the importance of solvency and liquidity risk has emerged in the design of regulatory frameworks worldwide, with Basel III and in the US, with the Frank-Dodd Act. While these reforms attempt to integrate solvency and liquidity in a framework to prevent future crisis, the interactions between liquidity and capital is still largely unexplored yet pivotal to understand the effects of the new regulatory requirements on banks.

[40] A macro stress test can be defined as: "... various techniques used by financial firms to gauge their potential vulnerability to exceptional but plausible events. [...], a stress test can be either a stress test scenario or a sensitivity stress test”, The Bank for International Settlements, 2000.

[41] See Greenlaw, Kashyap, Shoenholtz and Shin: "Stressed Out: Macroprudential Principles for Stress Testing" (2012).

The study focuses on one of the potentially relevant aspects of the solvency-liquidity channel, namely in understanding the chain of transmission between a number of markers of the solvency of a bank and three aspects related to liquidity risk, i.e. funding costs and the withdrawals of deposits and wholesale funding. The analysis exploits the US reporting scheme FR Y 9-C for bank holding companies, spanning from 1986 until 2014. The time spans allows us to cover three US recessionary episodes[42] (the 1990's, the 2001 and the 2008 recessions); In addition, the dataset captures at least three severe episodes of distress in the US banking sector, namely the less developed countries, the savings and loans and the subprime crisis. Furthermore, the depth of the is used to construct a number of indicators of solvency and liquidity risk, across the sample and over time, which allows exploring the dynamics of the banking sector during recessions and crises.

The findings indicate that a solvency to liquidity channel is present in the data, while signs and significance of the explanatory variables change during the observed horizon. In particular, it emerges that IMPP play an important role in the withdrawal of deposits, but are less relevant in collateralized transactions such as repurchase agreements. Eventually, funding costs are driven mostly by credit risk and the interest rate environment. The paper is structured as follows: section two discusses the literature and section three illustrates the dataset. Section four identifies triggers for solvency risk, while section five describes the variables used. The last two sections present the econometric approach and comment on the obtained results. Section seven concludes.

2. Literature

In their seminal work, Diamond and Dybvig (1983) identify the structural weakness which make bank runs a disruptive phenomenon for banks, that is the holding of illiquid assets financed by liquid liabilities (deposits). When depositors run to the bank, afraid that the bank can fail, they force the bank to sell illiquid assets to fund the withdrawals. This usually generates fire-sale losses which may trigger a bank failure. The authors define a classical view on bank runs' triggers, which takes place when the bank's assets are no

[42] For a detailed list and discussion of recessionary episodes in the US, see http://www.nber.org/cycles.html

longer able to cover the nominal value of the bank's liabilities. The authors do not define a proper trigger for bank runs, referring to changes in expectations in the general public[43].

Gauthier, Souissi and Liu (2014) present a model where liquidity and credit risk interact in a stress testing framework. They provide an analytical underpinning for the interlinkages between liquidity and credit risk. The solvency issues are originating by losses on the credit book, triggered by deteriorating macroeconomic conditions. They further develop an inter-temporal approach, where losses in the banking book and the liquidity buffer interact to define when/if a bank becomes insolvent. If the bank is insolvent, a bank runs takes place and the bank defaults. In their simulation exercise, the authors find that leveraged institutions are vulnerable to the combination of low cash holdings and the prevalence of short-term debt funding.

From an applied perspective, De Haan and Van den End (2011) propose a panel vector autoregression which takes heterogeneity of banks by allowing for fixed effects, where intercepts differ from bank to bank. The authors run a model estimated by means of generalized method of moments on three scenarios based on wholesale funding liquidity shock: reduced lending, fire sales and liquidity hoarding where macro and micro variables interact. Their results are coherent with a number of theoretical models of banks. Another study looking into liquidity risk is De Graeve and Karas (2014). The authors make use of a panel structural vector autoregression with restrictions to investigate bank runs in the Russian banking industry over the period 2002-2012. They tests two theoretical approaches to bank runs: the fundamental and the panic view. Their findings confirm that the panic view is more important than the information-based theory.

The integration of solvency and liquidity in a consolidated framework can be also found in the study of Aikman et al. (2009) that takes a central bank perspective. It includes an early attempt to integrate solvency and liquidity within the same framework. In their model (RAMSI), a funding run is triggered by a set of indicators reaching a danger zone. Their model represents an early work where the solvency-liquidity nexus is integrated in stress tests. Barnhill Jr. and Schumacher (2011) develops a methodology for

[43] They make reference to bad earnings news, run taking places in other banks, etc.

calculating equity capital levels needed to forestall a solvency and liquidity crisis from a systemic perspective to a target level set by means of a simulation technique. Their results indicate a strong correlation between solvency ratios and liquidity runs.

As regards recent studies, the BIS (2015) published a study where the interaction between liquidity and solvency is investigated from a regulatory perspective in an empirical setting. The results hint to the fact that regulatory solvency ratios and bank funding costs are determined simultaneously. Aymanns et al. (2016) investigate the sensitivity of bank funding cost to solvency measures in the US banking sector. They find that solvency matters for determining funding cost of banks, but its impact is limited in magnitude while this relationship appear to be nonlinear at times. At last, Schimtz et al. (2017) investigate the solvency-funding channel and illustrate that this relationship is more material than previously thought with important effects on banks' solvency.

3. Dataset

The study is build on the dataset of the Federal Reserve Bank of Chicago on bank holding companies (BHC hereinafter), the FR Y9-C reporting scheme. The report has quarterly frequency and data are collected at the consolidated level, which is consistent with the goal of studying liquidity and solvency risks that are mostly set at the group levels[44]. All collected data focuses on BHCs reporting total assets larger than 1 billion USD at least once between 1986:Q3 and 2014:Q1. The final sample consists of 1361 banks and 111 quarters[45].

The analysis investigates the historical evolution of capital, liquidity and risk indicators in four non-overlapping periods. The reasons behind this approach relate to the different economic environments and regulatory frameworks spanning through the almost 30 years that the dataset encompasses. For instance, since the end of the savings and loans crisis the

[44] Due to changes in accounting rules (introduction of fair value/mark-to-market accounting practices) in 03-1995 some items in the time series have a structural break. The time series are reconstructed according to several Federal Reserve guidelines; to ensure consistency in our time series we refer to the instructions of the Federal Reserve Bank of Chicago, available at: https://www.chicagofed.org/banking/financial-institution-reports/bhc-data.

[45] In order to eliminate bank holding companies created for specific purposes, for instance for merger and acquisition, the sample is reduced by selecting only bank holding companies which report for more than 20 quarters. See Avraham *et al.* (2012) "A structural view of U.S. Bank Holding Companies", Federal Reserve Bank of New York.

management of capital and liquidity risks in banks was influenced by the implementation of the new capital requirements, i.e. the Basel I capital regulatory framework; more, as suggested by Cornett et al. (2011) banks changed their approach to liquidity risk management before and after the subprime crisis. The exercises are therefore performed over the periods listed below:

1. From 1986:Q2 to 1992:Q4. This period is characterized by the occurrence of the LDC, the Savings and Loans (S&L hereinafter) Crisis, a series of regional banking crises and the 1990s' recession, which spans according to the NBER from July 1990 to March 1991. Moreover, at the end of 1992 the US adopted the capital regulation standards set by Basel I.
2. From 1993:Q1 to 2001:Q3. This was a period of sustained growth, featuring only one short-lasted recession, in the early 2000s, triggered by the burst of the so-called "dot-com bubble". Aoki and Nikolov (2012) characterize this crisis as related to an asset bubble and hence not significantly affecting banks, to the contrary of previous recessionary episodes.
3. From 2001:Q4 to 2007:Q2. These years were characterized by weak growth and rising unemployment[46].
4. From 2007:Q3 to 2014:Q2. This period includes the subprime crisis and a severe recession for the US. Moreover, it includes the period of phase-in of new regulatory requirements defined by the BIS, namely Basel III and the following modifications.

Overall, the large number of banks present in the sample and their size, global presence and activities encompass enough business models ensuring that the main risk profiles, management styles, etc. are included in the analysis.

4. Choice of Variables

4.1 Dependent Variables

[46] for more details see: http://www.cbpp.org/research/how-robust-was-the-2001-2007-economic-expansion.

Three dependent variables are used in the study, namely a ratio of funding cost to total liabilities, the nominal growth of deposits and of short-term funding. These variables are selected as they should capture the transmission of solvency issues to liquidity. Table 1 below illustrates the formulas used for the three above-mentioned variables:

Table 1: dependent variables

Code	Name of Variable	Description
FNDC	Funding Cost	Interest Paid on Liabilities / Total Liabilities (excl. Equity)
DEP	Deposit Funding	log (Retail, Corporate and State Deposits at t=1) - log (Retail, Corporate and State Deposits at t=0)
STF	Short-Term Funding	log (Repurchase Agreements and Commercial Papers at t=1) - log (Repurchase Agreements and Commercial Papers at t=0)

The nominal growth of retail and wholesale deposits as well as short-term funding is expected to be able to integrate events linked to "bank runs" as described in the theory of Diamond and Dybvyg (1983). This analysis focuses on nominal changes as changes in nominal values of deposits and short-term funding as these variables are deemed to identify a reduction of funds more efficiently than e.g. a ratio of deposits to total assets. Indeed, this latter can remain high even in a case of bank run due to stickiness of deposits vis-à-vis other sources of funding.

4.2 Explanatory Variables

The analysis performed in this study is based on a number of explanatory variables that are chosen because of their efficacy in capturing a particular aspect of funding and solvency risk in banking or due to their widespread use in other studies. As proxy for solvency issues the analysis adopts a tangible common equity ratio, which is a conservative indicator of solvency and it is well known by practitioners. Besides solvency risk, profitability plays an important role in the solvency of a bank. Losses affect a bank's capital position and hence they increase the risk of default. To encompass this aspect, the analysis includes an indicator for the impact of profitability, according to the formulas below:

$$\mathrm{IMPP_b} = \begin{cases} \mathrm{IMPP_b} \ \rightarrow \left[\frac{(\mathrm{PROFITS}_{t=1} - \mathrm{PROFITS}_{t=0})}{\mathrm{TA}_{t=0}}\right] < 0\% \\ 0 \ \rightarrow \left[\frac{(\mathrm{PROFITS}_{t=1} - \mathrm{PROFITS}_{t=0})}{\mathrm{TA}_{t=0}}\right] > 0\% \end{cases} \tag{1}$$

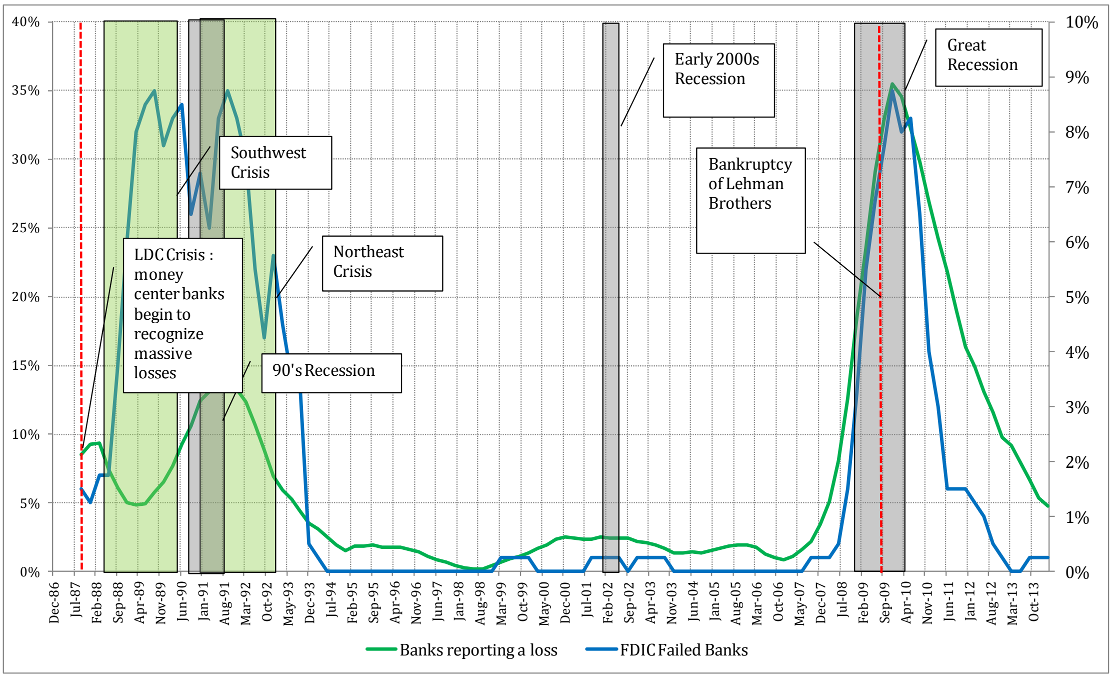
Figure 1 supports the idea that the above indicators capture solvency risk: the number of banks with negative IMPP increases during the main episodes of crisis in the US defined in the literature. In particular, it emerges clearly that during the less developed countries and the savings and loans crises and the default of Lehman Brothers, the number of banks reporting a profit loss increase significantly[47]. In addition, during the 2001 recession, which had a minor impact on the banking sector, the number of banks identified by IMPP remains low, hence further reinforcing the assumption that this variable represents valid proxies for solvency risk.

Eventually, a further check regarding the goodness of the indicators to signal solvency problems is performed. 172 banks closed or were purchased by another banking institution and stopped reporting according to the information provided by the FFIEC. The information collected from the press also confirmed that these banks had solvency issues which ended in liquidation or a sale.

Eventually, IMPP identifies 4607 occurrences of profitability issues. These figures represent 6.8% of the total data points for the overall period. Although it can be argued that losses weaken the bank solvency situation, it is difficult to quantify a direct relationship between failure and losses, as in several occasions banks experiencing difficulties in the market are purchased by competitors, so failure and the following liquidation only represent one among the possible solution for regulators. Hence, while the use of IMPP allows us to better identify solvency problems, the possibility of false positives could arise from this identification strategy. It may occur that a bank with a high level of capital can better absorb a profit loss due to a larger capital buffer. This shortcoming while difficult to address is not critical for the analysis as the impact of "bad news" on the behaviour of investors and IMPP captures anyhow these situations of stress.

[47] The number of banks which failed during the savings & loans crisis is in fact higher that the number captured in our dataset. The main reason is the threshold chosen for the reporting (1 bn. USD) that drops from the sample a significant number of small savings banks that were affected by the crisis. Moreover, it may be that not many savings banks chose to establish themselves as a bank holding company.

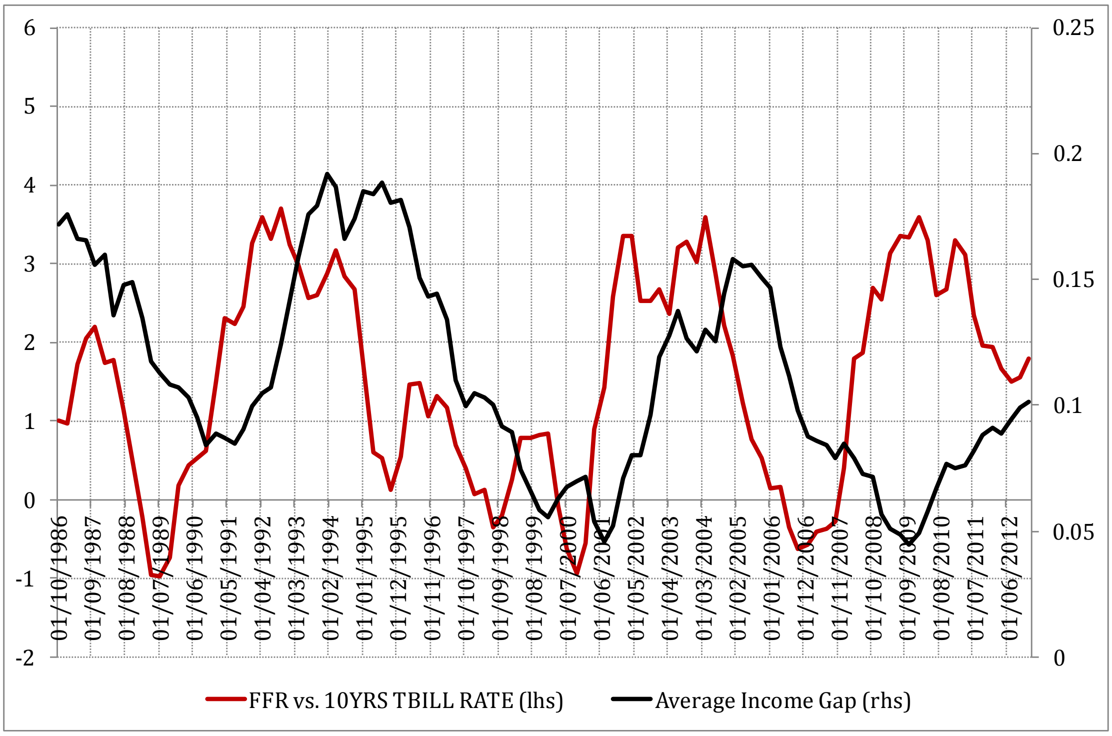
Figure 1: percentage of bank holding companies reporting losses in a quarter (lhs) and declared failed by the FDIC (rhs)



All figures are yearly moving averages. The axis report the percentage of banks reporting a loss (lhs) and failed (rhs) with respect to the total number of reporting banks in that specific quarter. Shaded areas represent episodes of crisis as reported by the Federal Deposit Insurance Corporation and Recessionary episodes as defined by the National Bureau of Economic Research.

In addition, the regressions include the income gap, which can be considered a proxy of the maturity mismatch gap as it measures the cash flow at risk from changes in interest rates and captures the capacity of the bank to extend new lending when interest rates rise. The behaviour of this indicator has been explained in details by Landier *et al.* (2013) that use it to investigate the sensitivity of banks to changes in interest rates and on the impact on profitability. In the analysis this variable captures the impact of the maturity structure of asset and liabilities on lending. In addition, the income gap on aggregate follows closely the behaviour of the spread between the Federal Funds Rate and the 10 Years US Treasury Rate, as illustrated in the figure two.

Figure 2: Income gap vs. 10 Years US T-Bill Rate.

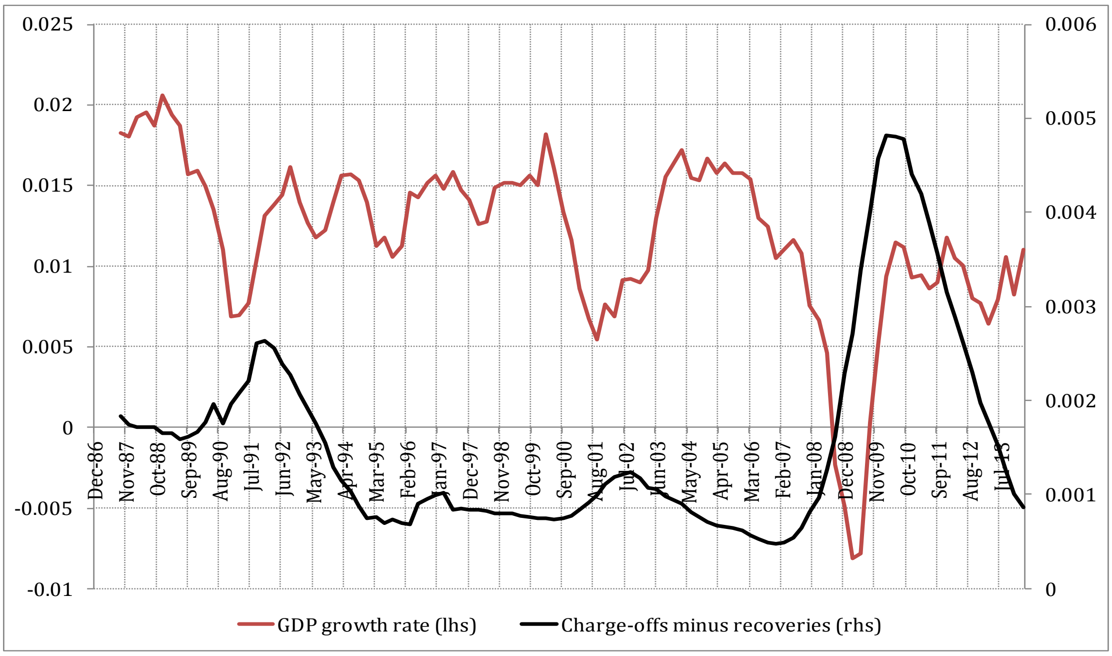


The chart illustrates the path of the spread between the Federal Funds rate and the 10 years Treasury Bill rate on the left hand side and the quarterly average income gap on the risgh hand side for the whole sample.

Furthermore, a ratio of charge-offs minus recovery to total gross loans (COREC) is included. This is necessary to be able to assess the amount of credit risk taken by each bank as well as the underlying macroeconomic conditions, as this ratio, on aggregate, is cyclical and strongly correlated with recessionary episodes[48]. The rationale for including COREC is based on the idea that liquidity and solvency are also connected via the funding costs arising from the liabilities of banks, that is depending on market rates as well as the bank's credit rating. Hence a worsening of the credit risk of a bank could reverberate in an increase of its funding costs with consequences for its cost of debt and its liquidity position. Figure three illustrates the cyclicality of COREC.

[48] Furlong, F. and Knight, Z. (2010) discuss charge-offs and provisioning in banks. They argue that banks under-provisioning is triggered by constrained accounting rules. This motivates also our preference for the charge-off indicator for credit risk.

Figure 3: Charge-offs minus recoveries vs. US GDP growth rate (4 quarters moving average)



The chart illustrates the path of the GDP growth rate, calculated using quarterly logarithmic-differences on the left-hand side and the average quarterly difference between charge-offs and recoveries over the whole sample on the right hand side.

In addition, the role of securities is central when investigating changes in wholesale funding of banks, as repurchase agreements are collateralized transactions and securities are pledged in exchange for cash. In order to encompass this effect, securities are therefore included in the regression investigating the relationship between short-term funding and solvency.

Eventually, the analysis integrates one variable capturing the evolution of the business model of banks in the US and its role played during the subprime crisis, i.e. the volume of non-government agency asset-backed securities (ABS) in each bank's balance sheet[49]. This variable allows taking into account the rise of the originate-to-distribute business model that affected the lending activity of banks from the nineties onwards.

[49] HABS excludes the securities issued by Government Sponsored Agencies, such as Fannie Mae and Freddie Mac Bonds.

Table 2: names of variables and related description.

Code	Name of Variable	Description
TCE	Tangible Common Equity	(Total Equity - Intangible Assets - Goodwill - Preferred Stocks) / Total Assets
SEC	Securities to Total Assets	Total Investment Securities (before 1992:Q4) and Total Available for Sale and Held-to-Maturity Securities Marked-to-Markets (after 1992:Q4)
CASH	Cash Holdings	Cash and balances due from depository institutions / Total Assets
COREC	Charge Offs minus Recoveries	(ChargeOffs - Recoveries on Losses on Loans) / Total Gross Loans
ICG	Income Gap	Total Assets Maturing < 3 Months / Total Liabilities Maturing < 3 Months
ABS	High Risk Asset Backed Securities	Asset Backed Securities (excl. US Govt. Sponsored Agencies) / Total Assets

Since it is a common business practice for banks to purchase asset-backed securities issued by vehicles sponsored by the bank, the volumes of the financial instruments purchased partly reflects the volumes of lending originated by the bank. Given the opacity in the evaluation and the liquidity risk attached to these financial instruments, large holdings of asset-backed securities may signal a bank at higher risk of failure. Hence, it can be expected that investors request higher premia for risk or withdraw their funds as a precautionary measure, in particular during the subprime crisis. The indicators included as explanatory variables in the regressions used in this study are reported in table two. Appendix A provides information on sample statistics and correlations for the variables used in the exercises.

5. Econometric Approach

The analysis focuses on testing a number of theories regarding the link between market information, as in this case related to balance sheet figures, and solvency and liquidity issues. The tests performed aim to detect if these theories hold in practice and what is the magnitude of the impact. Hence, the study makes use of the explanatory variables described in section four, assuming that "bad news" concerning the financial soundness affect the solvency and liquidity levels of a bank. The identification of a solvency issue and the timing of the unfolding events is achieved by using IMP as markers for a quarter when the bank is hit by a negative rumour in the market. The estimation of these effects is obtained in steps.

At first, the study adopts a panel regression analysis, which is used as baseline. This procedure allows establishing the main relationships between solvency and liquidity. Alas, the panel regression model used in this study does not allow for missing data. Banks that fail, stop reporting their data to the Federal Reserve, generating a discontinued time series and dropping out of the dataset. Since failed banks are mostly affected by solvency or liquidity issues, or both, this issue is likely to create a bias in the data. Nevertheless, since the failure does not always occur shortly after the solvency issue starts, we can observe a number of banks over the four horizons set in the exercise.

This panel regression approach is defined according to the following equation for fixed effects:

$$y_{b,t} = x_{b,t}^{'}\beta^{lq} + c_b + \varepsilon_{b,t} \qquad \varepsilon_{b,t} \sim N(0,\sigma) \tag{2.a}$$

And the below equation for random effects, both in the specification described in Greene (2003):

$$y_{b,t} = x_{b,t}^{'}\beta^{lq} + (\alpha + u_i) + \varepsilon_{b,t} \; \varepsilon_{b,t} \sim N(0,\sigma) \tag{2.b}$$

Where $y_{b,t}$ is a vector of quarterly dependent variables (i.e. FNDC, DEP or STF), β^{lq} is the vector of parameters and $x_{b,t}$ is a matrix collecting the micro banking ratios listed in table two measuring liquidity or solvency risk, or both. Furthermore, c_b is a vector of time invariant fixed effects for each bank *b*. At last $\varepsilon_{b,t}$ is a vector of i.i.d. error terms. To mitigate the potential issue of endogeneity of the effects observed in the analysis, a system of contemporaneous and lagged explanatory variables is used to capture the evolution of the dependent variables. The choice of model, i.e. fixed vs. random effects, is based on the Hausman test using a threshold of 0.1 for the selection between fixed (below the threshold) and random (above the threshold) effects.

From a modelling perspective, this study closely follows the panel approach used by Cornett et al. (2011). Similarities in the econometric approach can be found related to the type of variables used in the analysis, i.e. mostly capital and liquidity-related ratios, and the duration and characteristics of the dataset, i.e. US banks during a crisis episode. Furthermore, a number of econometric challenges arise from the use of panel data methods for time series analysis. One major issue in the analysis originates from the choice of panel data specification. For instance, the fixed effect approach allows capturing individual effects which are specific to each bank.

Overall, while a number of biases in the estimation may be present, these issues are mitigated by applying fixed or random effects and using heteroskedasticity autocorrelation corrected standard errors, as suggested by Arellano (2003) which is applicable to the dataset of this study, characterized by large n and small T. At last, a number of regressions is run to test for specific effects related to the solvency and liquidity channel that are important for understanding the dynamics of stress tests, in particular during the subprime crisis. Hence the analysis includes squares of COREC and IMPP to check for non-linear behaviours as well as liquidity-related explanatory variables, namely CASH and ABS, to validate assumptions on the specification of the model during the subprime crisis.

Finally, while it is common practice to control for year effects in panel regressions, splitting the sample in four periods characterized by similar macroeconomic conditions allows for equally efficient regressions, without loss of degree of freedoms. In the end, when running tests on the basic regressions of the exercises performed in this study, time effects did not significantly alter the signs and statistical significance of the explanatory variables.

6. Discussion of Results

6.1 Funding Costs and the Solvency-Liquidity Channel

Table 3.a to 3.c discuss the coefficients and the p-values of the explanatory variables illustrated in equations 2.a and 2.b for FNDC as dependent variable. Funding costs are assumed to be partly exogenous, as they are taken by banks from the interest rate environment. They should also be partly affected by the risk profiles that are idiosyncratic to each bank. Hence, at first, the study tests the assumption that credit risk influences the funding

cost using COREC as proxy for credit risk and ICG as variable describing the dynamics of interest rates. To this model specification, TCE is added to investigate how solvency issues play a role in the cost of funding. In addition, IMPP substitutes TCE in the regression to validate if the magnitude and the identification of issues at the capital and profitability levels also are statistically significant in this specification. Eventually, as argued e.g. by Drehmann, Patton and Sorensen (2007), credit risk variables may be characterized by a non-linear behaviour. To capture this potential aspect, squares of selected explanatory variables are added to the basis regressions. The results are reported in table three a. to c. for the four periods listed in section three.

ICG emerges as the most informative variable and the sign is negative at t=0 and positive at lags in the majority of tests. ICG closely follows the pattern of the spread between short and long-term interest rates in the US, as highlighted in figure two, with a lag. The statistical significance indicates that FNDC is closely correlated with ICG, and an increase in this latter variable drives a reduction of FNDC. This is related to the informational content of the ICG, which signals that banks can reprice a larger share of their assets at the current interest rates, increasing their net interest margin hence improving their profitability (see Landier et al. 2013). It can be noticed that ICG loses part of its explanatory power during the subprime crisis. This may be partly explained, as highlighted in figure two, by the disrupted relationship between ICG and the spread between the Federal Funds Rate and the 10 years T-Bill after 2007.

COREC is statistically significant in most occurrences, often at lags, but its sign changes over time. During the first two periods (1986-2001), an increase in COREC highlights a deterioration of credit risk in a bank, with consequences to its funding costs. This behaviour is reflected in a negative coefficient. The presence of statistical significance at lags supports the informational hypothesis that "bad news" on a bank's credit risk profile trigger and increase in FNDC. This relationship changes as during periods of growth of the US economy COREC's sign turns positive.

Table 3.a: funding cost as dependent variable, recession of the 90s and roaring 90s.

	RECESSION 90									ROARING 90s								
Coefficient	eq. 1	eq. 2	eq. 3	eq. 4	eq. 5	eq. 6	eq. 7	eq. 8	eq. 9	eq. 1	eq. 2	eq. 3	eq. 4	eq. 5	eq. 6	eq. 7	eq. 8	eq. 9
const	0.014	0.016	0.014	0.015	0.017	0.015	0.015	0.016	0.014	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010
COREC	0.033	0.023	0.035	0.012	0.004	0.017	-0.003	0.023	0.037	0.104	0.107	0.115	0.134	0.136	0.137	0.246	0.106	0.115
ICG	-0.003	-0.003	-0.003	-0.004	-0.004	-0.004	-0.013	-0.003	-0.003	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002
TCE	...	-0.023	...	...	-0.016	...	...	-0.028	...	...	0.005	...	...	0.027	...	...	0.002	...
IMPP	...	...	0.000	...	...	0.000	...	...	0.001	...	...	-0.004	...	...	-0.001	...	...	-0.005
COREC (t-1	...	...	...	-0.070	-0.083	-0.069	...	...	...	...	...	...	-0.008	-0.007	0.000	...	...	...
ICG (t-1)	...	...	...	0.001	0.001	0.001	...	...	...	...	...	...	-0.001	-0.001	-0.001	...	...	...
TCE(t-1)	...	...	...	...	-0.017	...	...	...	...	...	...	...	...	-0.025	...	...	...	...
IMPP(t-1)	...	...	...	...	...	-0.001	...	...	...	...	...	...	...	...	-0.002	...	...	...
COREC_sq	...	...	...	...	...	...	2.407	...	...	...	...	...	...	...	...	-13.177	...	...
TCE_sq	...	...	...	...	...	...	...	0.034	...	...	...	...	...	...	...	...	0.016	...
IMPP_sq	...	...	...	...	...	...	...	...	-0.002	...	...	...	...	...	...	...	...	0.004
Hausmann	0.084	0.002	0.108	0.011	0.000	0.017	0.077	0.000	0.210	0.005	0.003	0.014	0.000	0.000	0.000	0.040	0.001	0.014
Stat. Signific.																		
const	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***
COREC							***			*	*	**	**	**	**	***	*	**
ICG	***	***	***	***	***	***		***	***	***	***	***	***	***	***	***	***	***
TCE		*												**				
IMPP																		
COREC (t-1				**	**	**												
ICG (t-1)				*	*	*							*	*	*			
TCE(t-1)														**				
IMPP(t-1)																		
COREC_sq																***		
TCE_sq																		
IMPP_sq																		

*The figures in the upper table indicate the average coefficients of the regressors of equation [2]. The lower table reports the statistical significance of the explanatory variables: *** denotes significance at the 0.1%, ** significance at the 1% and * at the 5% levels.*

Table 3.b: funding cost as dependent variable, lost decade of 2001 and subprime crisis of 2008.

	LOST DECADE OF 2001									SUBPRIME CRISIS OF 2008					
Coefficient	eq. 1	eq. 2	eq. 3	eq. 4	eq. 5	eq. 6	eq. 7	eq. 8	eq. 9	eq. 1	eq. 2	eq. 3	eq. 4	eq. 5	eq. 6
const	0.007	0.008	0.007	0.007	0.007	0.007	0.007	0.008	0.007	0.029	0.154	0.029	0.031	0.157	0.031
COREC	-0.213	-0.230	-0.216	-0.293	-0.300	-0.302	-0.002	-0.233	-0.219	1.251	2.905	1.276	1.432	3.091	1.467
ICG	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.299	-0.002	-0.002	-0.046	0.113	-0.046	-0.184	-0.042	-0.184
TCE	...	-0.018	...	...	-0.039	...	...	-0.011	...	...	-1.956	...	...	-1.019	...
IMPP	...	...	0.004	...	...	0.005	...	...	0.008	...	...	-0.001	...	...	-0.001
COREC (t-1)	...	...	...	-0.234	-0.238	-0.238	...	...	...	...	...	...	-0.478	0.855	-0.448
ICG (t-1)	...	...	...	0.000	0.000	0.000	...	...	...	...	...	...	0.143	0.230	0.143
TCE(t-1)	...	...	...	...	0.032	...	...	...	...	...	...	...	...	-1.085	...
IMPP(t-1)	...	...	...	...	...	0.001	...	...	...	...	...	...	...	...	-0.001
COREC_sq	...	...	...	...	...	...	0.916	...	...	...	...	...	...	...	...
TCE_sq	...	...	...	...	...	...	...	-0.018	...	...	...	...	...	...	...
IMPP_sq	...	...	...	...	...	...	...	...	-0.005	...	...	...	...	...	...
Hausmann	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.705	0.003	0.874	0.816	0.041	0.955

Stat. Signific.															
const	***	***	***	***	***	***	***	***	***						
COREC	***	***	***					***	***						
ICG													*		*
TCE		*													
IMPP			**			**									
COREC (t-1)				***	***	***									
ICG (t-1)															
TCE(t-1)															
IMPP(t-1)															
COREC_sq															
TCE_sq															
IMPP_sq															

*The figures in the upper table indicate the average coefficients of the regressors of equation [2]. The lower table reports the statistical significance of the explanatory variables: *** denotes significance at the 0.1%, ** significance at the 1% and * at the 5% levels.*

Table 3.c: funding cost as dependent variable, subprime crisis of 2008 with added ABS and CASH as explanatory variables

	SUBPRIME CRISIS OF 2008 (ABS and CASH as expl. variables)					
Coefficient	eq. 10	eq. 11	eq. 12	eq. 13	eq. 14	eq. 15
const	0.031	0.028	0.032	0.030	0.031	0.017
COREC	1.250	1.229	1.480	1.402	1.285	0.981
ICG	-0.044	-0.048	-0.182	-0.193	-0.042	-0.048
COREC (t-1)	...	...	-0.498	-0.498	...	...
ICG (t-1)	...	...	0.144	0.152	...	...
ABS	-0.144	...	0.017	...	-0.343	...
CASH	...	0.031	...	0.129	...	0.355
ABS(t-1)	...	...	-0.171	...	...	...
CASH(t-1)	...	...	...	-0.111	...	...
ABS_sq	...	...	...	...	0.722	...
CASH_sq	...	...	...	...	...	-1.005
Hausmann	0.869	0.844	0.949	0.945	0.877	0.934

Stat. Signific.						
const						
COREC						
ICG			*	***		
COREC (t-1)						
ICG (t-1)				***		
ABS						
CASH						
ABS(t-1)						
CASH(t-1)						
ABS_sq						
CASH_sq						

*The figures in the upper table indicate the average coefficients of the regressors of equation [2]. The lower table reports the statistical significance of the explanatory variables: *** denotes significance at the 0.1%, ** significance at the 1% and * at the 5% levels.*

A possible explanation could be that in normal macroeconomic conditions risk-taking of banks signal potential further incomes and henceforth financial markets evaluate this information as positive news for the bank. The non-linearity tests performed with a quadratic term on COREC indicate that this variable may be characterized by an inverted behaviour but during the "roaring 90s". This result may have two facets: on one side, the prolonged period of growth in the US may have altered the perception of risk in financial markets. In addition, the relatively low volume of charge-offs during the 90s' may indicate that this relationship is valid only for low levels of COREC.

IMPP is not often significant, while still carrying the expected sign, as an increase in the impact of a shock to profits or capital leads to a deterioration of solvency, hence to higher funding costs. In general, the results of the tests during the subprime crisis indicate that most variables are not statistically significant. This puzzling result may relate to the unconventional monetary policy operations of the Federal Reserve that played a role in influencing banks financial soundness as well as funding costs as discussed by Lambert and Ueda (2014). In addition, the systemic nature of the subprime crisis and its complexity adds to the difficulty in explaining the dynamics of funding costs using mostly microeconomic information, as in this exercise. The results described above support the findings of Aymanns et al. (2016) investigating the sensitivity of bank funding cost to solvency measures in the US banking sector. They find that solvency matters for determining funding cost of banks and this relationship appear to be nonlinear.

The overall results may also be explained by the accounting nature of the indicators used in the analysis. The increase in COREC and IMPP are likely to be follow rumours about a bank's credit risk. Hence the positive coefficient observed at t=0 is likely to indicate the realization of a relationship which originate at lags, but the accounting nature only materialize at lead. The quadratic term of COREC is statistically significant in only one regression: the negative sign of the coefficient indicates that this term act as counterbalancing factor, mitigating the effect of COREC. The relationship described is henceforth convex.

It can be observed that during period of growth in the US economy, the sign begins to revert to negative. This is possibly indicate that the relationship between credit risk and funding costs also depends on macroeconomic conditions: an increase in credit risk is likely correlated with higher profits in periods of growth, and this may translate into lower funding cost. Eventually, during the subprime crisis, the variable ABS is not statistically significant: it appears that presence of high-risk asset-backed securities in the balance sheet does not drove funding cost higher. This may be explained by the general increase of risk aversion that hit the whole banking sector and hence investors did not focus their attention on ABS volumes in banks' balance sheets.

6.2 Deposit Base, Short-Term Funding and the Solvency-Liquidity Channel

Deposit and short-term funding are sensitive to "bad news", as discussed in several studies. Both in the past and in recent times, it has been observed that negative communication concerning a bank may lead to a run on funding sources. Historical perspectives on episodes of bank runs are provided by Saunders and Wilson (1994), and, based on more recent episodes in the aftermath of the subprime crisis, Allen and Moessner (2011). These studies support the view that during episodes of banking crises, depositors' outflows were one of the important sources of liquidity risk. In particular, Saunders and Wilson (1994) highlight the importance of contagion effects among depositors during banking panic, which take place in the dataset used in this study.

Table 4.a: deposit base as dependent variable, yearly average coefficients of regressors

	RECESSION 90									ROARING 90s							
Coefficient	eq. 1	eq. 2	eq. 3	eq. 4	eq. 5	eq. 6	eq. 7	eq. 8	eq. 9	eq. 1	eq. 2	eq. 3	eq. 4	eq. 5	eq. 6	eq. 7	eq. 8
const	0.023	0.095	0.023	0.024	-0.005	0.024	0.022	0.080	0.023	0.028	0.080	0.028	0.029	0.034	0.028	0.027	0.076
COREC	0.007	0.008	0.006	0.806	-0.876	1.034	0.273	-0.194	0.601	1.623	1.705	2.047	2.359	1.901	2.459	3.326	1.730
ICG	0.246	-0.228	0.545	-0.032	-0.024	-0.033	0.007	0.008	0.006	-0.002	0.007	-0.002	-0.030	-0.024	-0.029	-0.002	0.007
TCE	...	-1.078	...	...	-7.094	...	...	-0.633	...	...	-0.699	...	...	-5.566	...	...	-0.588
IMPP	...	...	-0.078	...	...	-0.057	...	...	-0.119	...	...	-0.181	...	...	-0.188	...	...
COREC (t-1)	...	...	...	-3.066	-1.922	-2.939	...	...	...	...	...	...	-2.080	-2.293	-1.705	...	...
ICG (t-1)	...	...	...	0.040	0.036	0.040	...	...	...	...	...	...	0.031	0.027	0.030	...	...
TCE(t-1)	...	...	...	...	7.575	...	...	...	...	...	...	...	...	5.497	...	...	...
IMPP(t-1)	...	...	...	...	...	-0.002	...	...	...	...	...	...	...	...	-0.050	...	...
COREC_sq	...	...	...	...	...	...	-1.382	...	...	...	...	...	...	...	...	-176.954	...
TCE_sq	...	...	...	...	...	...	...	-3.063	...	...	...	...	...	...	...	...	-0.702
IMPP_sq	...	...	...	...	...	...	...	...	0.064	...	...	...	...	...	...	...	...
Hausmann	0.000	0.000	0.000	0.099	0.000	0.028	0.000	0.000	0.000	0.375	0.000	0.209	0.735	0.233	0.827	0.164	0.000

Stat. Signific.																	
const	***	***	***	***		***	***	*	***	***	***	***				***	***
COREC												*				*	
ICG				*		*											
TCE		***			***						***			***			
IMPP			***			***			***			*					
COREC (t-1)				***	***	***											
ICG (t-1)				*	*	*											
TCE(t-1)					***									***			
IMPP(t-1)																	
COREC_sq																*	
TCE_sq																	
IMPP_sq																	

*The figures in the upper table indicate the average coefficients of the regressors of equation [2]. The lower table reports the statistical significance of the explanatory variables: *** denotes significance at the 0.1%, ** significance at the 1% and * at the 5% levels.*

Table 4.b: deposit base as dependent variable, significance levels of regressors

	LOST DECADE OF 2001									SUBPRIME CRISIS OF 2008							
Coefficient	eq. 1	eq. 2	eq. 3	eq. 4	eq. 5	eq. 6	eq. 7	eq. 8	eq. 9	eq. 1	eq. 2	eq. 3	eq. 4	eq. 5	eq. 6	eq. 7	eq. 8
const	0.027	0.103	0.028	0.026	0.009	0.026	0.030	0.069	0.028	0.019	0.042	0.019	0.020	0.016	0.020	0.021	0.039
COREC	-1.769	-3.693	-2.716	-0.945	-1.259	-0.991	-5.502	-4.016	-2.688	-0.897	-1.208	-0.901	-0.506	-1.316	-0.510	-2.019	-1.184
ICG	-0.002	-0.002	-0.005	-0.010	-0.007	-0.010	-0.004	0.000	-0.005	-0.022	-0.015	-0.022	-0.024	-0.011	-0.024	-0.024	-0.015
TCE	...	-1.037	...	...	-4.530	...	...	-0.427 ...		...	-0.310 ...		...	-2.829	...	...	-0.217
IMPP	...	...	-0.021	...	...	-0.016	...	...	-0.062	...	...	0.000	...	...	0.000	...	...
COREC (t-1)	...	...	...	-0.417	-0.019	-0.544	...	...	...	...	...	...	-0.822	-0.335	-0.828	...	...
ICG (t-1)	...	...	...	0.018	0.014	0.018	...	...	...	...	...	...	0.003	-0.015	0.003	...	...
TCE(t-1)	...	...	...	...	4.761	...	...	...	...	...	...	...	...	2.909	...	...	...
IMPP(t-1)	...	...	...	...	...	-0.032	...	...	...	...	...	...	...	...	0.000	...	...
COREC_sq	...	...	...	...	...	...	29.509	...	...	...	...	...	...	...	...	49.766	...
TCE_sq	...	...	...	...	...	...	...	-1.556	...	...	...	...	...	...	...	...	-0.627
IMPP_sq	...	...	...	...	...	...	...	...	0.046	...	...	...	...	...	...	...	...
Hausmann	0.068	0.000	0.001	0.326	0.000	0.007	0.000	0.000	0.006	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Stat. Signific.																	
const	***	***	***			***	***	**	***	***	***	***	***	**	***	***	***
COREC										***	***	***		***		***	***
ICG										*		*				*	
TCE		**			***						**			***			
IMPP												*			**		
COREC (t-1)													**		**		
ICG (t-1)				*													
TCE(t-1)					***									***			
IMPP(t-1)																	
COREC_sq																*	
TCE_sq																	
IMPP_sq																	

*The figures in the upper table indicate the average coefficients of the regressors of equation [2]. The lower table reports the statistical significance of the explanatory variables: *** denotes significance at the 0.1%, ** significance at the 1% and * at the 5% levels.*

Table 4.c: deposit base as dependent variable, subprime crisis of 2008 with added ABS and CASH as explanatory variables

	SUBPRIME CRISIS OF 2008 (ABS and CASH as expl. variables)					
Coefficient	eq. 10	eq. 11	eq. 12	eq. 13	eq. 14	eq. 15
const	0.018	0.007	0.019	0.021	0.019	0.011
COREC	-0.880	-1.125	-0.502	-0.888	-0.899	-1.090
ICG	-0.022	-0.040	-0.024	-0.095	-0.022	-0.038
COREC (t-1)	...	...	-0.810	-0.951	...	...
ICG (t-1)	...	...	0.003	0.079	...	...
ABS	0.071	...	0.047	...	-0.049	...
CASH	...	0.229	...	0.955	...	0.108
ABS(t-1)	...	...	-0.007	...	...	...
CASH(t-1)	...	...	...	-0.986	...	...
ABS_sq	...	...	...	...	0.459	...
CASH_sq	...	...	...	...	...	0.454
Hausmann	0.000	0.000	0.000	0.000	0.000	0.000

Stat. Signific.						
const	***	**	***	***	***	**
COREC	***	***		***	***	***
ICG	*	***		***	*	***
COREC (t-1)			**	***		
ICG (t-1)				***		
ABS	*					
CASH		***		***		
ABS(t-1)						
CASH(t-1)				***		
ABS_sq					*	
CASH_sq						

*The figures in the upper table indicate the average coefficients of the regressors of equation [2]. The lower table reports the statistical significance of the explanatory variables: *** denotes significance at the 0.1%, ** significance at the 1% and * at the 5% levels.*

The authors bring forward the idea that depositors can discriminate between "good" and "bad" banks, but this ability is reduced during episodes of banking panic.

The results of the regressions provide evidence supporting the view that depositors are sensitive to "bad news" about the bank (see table 4.a and b). First, a strong statistically significant relationship emerges between COREC and DEPLN, which persist over the whole horizon. This relationship carries non-linear characteristic, as the significance of the quadratic term in two sub-periods, namely the roaring 90s' and the subprime crisis, indicates. The consistence of the negative sign over the whole horizon of the investigation supports the hypothesis that excessive credit risk and consequent "bad news" about a bank trigger a withdrawal of deposits. In addition, the average sign of the quadratic term is positive, indicating that the relationship linking COREC and IMPP with DEP is convex and the quadratic term competes with the linear term, reducing the overall effect.

The statistical significance of IMPP emerges mostly during the first and last periods, namely the recession of the 90s and the subprime crisis. This is an important result that stresses the relevance of the role of profitability during period characterized by banking distress. The negative sign indicates that larger losses trigger larger volumes of withdrawals of deposits. Both the signs and statistical significance of IMPP and COREC support the general theory of Diamond and Dybvyg on bank runs. The explanatory variable CASH, used as proxy for a liquid bank emerges as informative during the subprime crisis. The signs on equation 11 and 13 (see table 4.c) indicates that banks that were "cash-rich" attracted more deposits. TCE also emerges as significant and its coefficient carries different signs, i.e. negative at t=0 and positive at lags. The overall effect is related possibly to the accounting identity of the variable and is overall positive, potentially indicating that higher solvency overall favours deposit growth.

A last aspect emerging from the results relates to the overall low informational content of the explanatory variables during times of relative economic growth. The reason behind these results may be the fact that "bad news" mostly trigger withdrawals in times of crisis, while in normal times other factors may play a role, e.g. deposit-guarantee schemes, that refrain depositors from acting on negative information.

Tables 5.a to 5.c report the results for short-term funding. The regressions performed include repurchase agreements and commercial papers for the largest part. Given that repurchase agreements are specific transactions where collateral is the basis for this operation, SEC is added to the regressions to capture the availability of collateral by a bank. Without collateral is likely that a bank cannot enter a repurchase agreement and the model may not be correctly specified.

The findings highlight that COREC is significant over the horizon and the sign is consistent and positive for the regression coefficient, as expected. These results indicate that the presence of high levels of credit risk and losses trigger withdrawals of short-term funds but mostly at t=0: this may again relate to the presence of delay in the information channel between withdrawals and the materialization of the depletion of short-term funding sources by investors. The sensitivity of these funding sources is confirmed and the presence of collateral does emerge as mitigating factor; SEC carries positive sign over the whole horizon. Moreover, the presence of non-linearity is confirmed only seldom as the quadratic terms are statistically significant only in equations 7, 8 and 14 for TCE, COREC and ABS respectively.

Table 5.a: short-term funding as dependent variable, yearly average coefficients of regressors

	RECESSION 90									ROARING 90s								
Coefficient	eq. 1	eq. 2	eq. 3	eq. 4	eq. 5	eq. 6	eq. 7	eq. 8	eq. 9	eq. 1	eq. 2	eq. 3	eq. 4	eq. 5	eq. 6	eq. 7	eq. 8	eq. 9
const	-0.005	-0.011	-0.004	0.018	0.004	0.017	-0.004	-0.036	-0.003	-0.136	0.019	-0.136	-0.078	-0.136	-0.080	-0.136	0.017	-0.136
COREC	-4.658	-4.503	-3.999	-3.218	-6.318	-1.485	-5.291	-4.289	-3.809	0.475	-0.732	1.105	-7.147	-7.783	-6.498	0.411	-0.725	1.114
ICG	0.038	0.039	0.038	0.216	0.233	0.214	0.038	0.038	0.038	0.065	0.096	0.065	0.340	0.355	0.341	0.065	0.095	0.065
SEC	0.120	0.116	0.116	0.222	0.225	0.217	0.119	0.112	0.114	0.672	0.670	0.672	3.654	3.500	3.650	0.672	0.670	0.672
TCE	...	0.102	...	...	-13.548	...	...	0.844	...	...	-2.040	...	...	-17.056	...	...	-2.011	...
IMPP	...	...	-0.126	...	...	0.045	...	...	-0.226	...	...	-0.221	...	...	-0.587	...	...	-0.253
COREC (t-1	...	...	...	-6.991	-4.895	-6.269	...	...	...	...	...	...	-1.961	-1.808	-0.403	...	...	...
ICG (t-1)	...	...	...	-0.210	-0.218	-0.210	...	...	...	...	...	...	-0.375	-0.382	-0.375	...	...	...
SEC(t-1)	...	...	...	-0.146	-0.152	-0.146	...	...	...	...	...	...	-3.093	-2.958	-3.089	...	...	...
TCE(t-1)	...	...	...	...	13.859	-0.286	...	...	...	...	...	...	...	17.838	...	...	...	...
IMPP(t-1)	...	...	...	...	...	-0.286	...	...	...	...	...	...	...	...	-0.220	...	...	...
COREC_sq	...	...	...	...	...	...	36.683	...	...	...	...	...	...	...	...	5.878	...	...
TCE_sq	...	...	...	...	...	...	...	-4.865	...	...	...	...	...	...	...	...	-0.187	...
IMPP_sq	...	...	...	...	...	...	...	...	0.156	...	...	...	...	...	...	...	...	0.069
Hausmann	0.249	0.304	0.416	0.953	0.612	0.995	0.368	0.438	0.577	0.000	0.000	0.000	0.001	0.002	0.005	0.000	0.000	0.000
Stat. Signific.																		
const										***		***	**	***	**	***		***
COREC	*	*						*										
ICG														*				
SEC	***	***	***				***	**	***	***	***	***	***	***	***	***	***	***
TCE											***			***				
IMPP															***			
COREC (t-1																		
ICG (t-1)													*	*	*			
SEC(t-1)													***	***	***			
TCE(t-1)														***				
IMPP(t-1)																		
COREC_sq																		
TCE_sq																		
IMPP_sq																		

*The figures in the upper table indicate the average coefficients of the regressors of equation [2]. The lower table reports the statistical significance of the explanatory variables: *** denotes significance at the 0.1%, ** significance at the 1% and * at the 5% levels.*

Table 5.b: Short-term funding as dependent variable, significance levels of regressors

	LOST DECADE OF 2001									SUBPRIME CRISIS OF 2008							
Coefficient	eq. 1	eq. 2	eq. 3	eq. 4	eq. 5	eq. 6	eq. 7	eq. 8	eq. 9	eq. 1	eq. 2	eq. 3	eq. 4	eq. 5	eq. 6	eq. 7	eq. 8
const	-0.075	0.035	-0.075	-0.013	0.026	0.040	-0.073	0.074	-0.076	-0.041	-0.045	-0.041	-0.025	-0.033	-0.025	-0.034	-0.055
COREC	-8.954	-10.644	-9.000	-14.047	-9.435	-8.867	0.047	-10.255	0.047	-4.783	-4.690	-4.586	-2.624	-4.267	-2.485	-9.055	-4.450
ICG	0.046	0.053	0.046	0.087	0.087	0.077	-11.906	0.051	-9.248	0.011	0.010	0.010	0.259	0.310	0.254	0.013	0.011
SEC	0.511	0.615	0.513	2.153	2.190	2.021	0.513	0.624	0.516	0.141	0.139	0.141	1.531	1.758	1.514	0.135	0.139
TCE	...	-1.833	...	...	-11.033	...	...	-2.581	...	...	0.054	...	...	-6.654	...	...	0.255
IMPP	...	...	0.057	...	...	0.082	...	...	0.423	...	...	-0.008	...	...	-0.007	...	...
COREC (t-1)	...	...	...	2.533	7.482	5.973	...	...	...	...	...	...	-5.661	-4.236	-5.500	...	...
ICG (t-1)	...	...	...	-0.075	-0.099	-0.088	...	...	...	...	...	...	-0.267	-0.317	-0.264	...	...
SEC(t-1)	...	...	...	-1.862	-2.159	-1.985	...	...	...	...	...	...	-1.430	-1.658	-1.413	...	...
TCE(t-1)	...	...	...	...	11.212	...	...	...	...	...	...	...	...	6.823	...	...	...
IMPP(t-1)	...	...	...	...	...	-0.461	...	...	...	...	...	...	...	...	-0.002	...	...
COREC_sq	...	...	...	...	...	...	31.454	...	...	...	...	...	...	...	...	211.854	...
TCE_sq	...	...	...	...	...	...	...	1.893	...	...	...	...	...	...	...	...	-0.680
IMPP_sq	...	...	...	...	...	...	...	...	-0.407	...	...	...	...	...	...	...	...
Hausmann	0.004	0.000	0.008	0.493	0.178	0.646	0.005	0.000	0.011	0.049	0.062	0.092	0.814	0.745	0.905	0.136	0.078
Stat. Signific.																	
const	***		***				***	*	***	***	***	***				***	***
COREC	**	**	**					**		***	***	***				***	***
ICG									**								
SEC	***	***	***	***			***	***	***	***	***	***				***	***
TCE		***			***			***									
IMPP												***					
COREC (t-1)																	
ICG (t-1)																	
SEC(t-1)				***													
TCE(t-1)					*												
IMPP(t-1)																	
COREC_sq																*	
TCE_sq								*									
IMPP_sq																	

*The figures in the upper table indicate the average coefficients of the regressors of equation [2]. The lower table reports the statistical significance of the explanatory variables: *** denotes significance at the 0.1%, ** significance at the 1% and * at the 5% levels.*

Table 5.c: Short-term funding as dependent variable, subprime crisis of 2008 with added ABS and CASH as explanatory variables

	SUBPRIME CRISIS OF 2008 (ABS and CASH as expl. variables)					
Coefficient	eq. 10	eq. 11	eq. 12	eq. 13	eq. 14	eq. 15
const	-0.112	-0.028	-0.024	-0.014	-0.108	-0.026
COREC	-3.413	-4.595	-2.389	-2.449	-3.524	-4.545
ICG	0.082	0.026	0.249	0.291	0.078	0.026
SEC	0.403	0.135	1.468	1.366	0.399	0.135
COREC (t-1)	...	...	-5.708	-5.416	...	...
ICG (t-1)	...	...	-0.262	-0.287	...	...
SEC(t-1)	...	...	-1.372	-1.272	...	...
ABS	0.437	...	1.618	...	-0.228	...
CASH	...	-0.221	...	-0.512	...	-0.292
ABS(t-1)	...	...	-1.484	...	...	...
CASH(t-1)	...	...	...	0.331	...	...
ABS_sq	...	...	...	...	2.547	...
CASH_sq	...	...	...	...	...	0.219
Hausmann	0.043	0.092	0.922	0.894	0.018	0.140

Stat. Signific.						
const	***	***			***	*
COREC	*	***			*	***
SEC	***	***			***	***
ICG						
COREC (t-1)						
ICG (t-1)						
SEC(t-1)						
ABS	*					
CASH		***				
ABS(t-1)						
CASH(t-1)						
ABS_sq					***	
CASH_sq						

*The figures in the upper table indicate the average coefficients of the regressors of equation [2]. The lower table reports the statistical significance of the explanatory variables: *** denotes significance at the 0.1%, ** significance at the 1% and * at the 5% levels.*

The positive signs and the large coefficients of the quadratic terms may indicate that these latter act as amplifying factor, emphasizing the non-linear effect. IMPP is also confirmed as a relevant factor for short-term withdrawals, but it is only significant during the subprime crisis and the roaring 90s' indicating that this variable carries less sensitive information on the solvency risk of the bank, at least according to wholesale investors.

Eventually TCE is also statistically significant, mostly at t=0, indicating that lower levels of solvency are an important trigger of withdrawal of short-term funds. Overall, and given the cyclicality of COREC and IMPP, the findings may also be indicating a more general phenomenon: i.e. when credit risk increases overall, the volume of repurchase agreements is reduced as general deterioration of macroeconomic conditions trigger and increase in counterparty risk. In particular, this latter argument would support the hypothesis brought forward by Gorton and Metrick (2009) that explain the reasons behind the run on the repo market of 2007-2008.

7. Conclusions

This study investigates the solvency to liquidity channel in the US banking sector over a prolonged horizon, spanning over several banking and macroeconomic crises. The mechanisms of transmission of solvency to liquidity risk and vice-versa are very important for the outcome of stress tests. In fact, the interactions between solvency and liquidity heavily influence the dynamics of feedback effects which can significantly deteriorate the financial soundness of a bank.

The findings highlight new supporting evidence of the existence of a solvency to liquidity channel. Overall, credit and interest rate risks materialize as leading factors for explaining the dynamics of the funding cost of banks, as expected. The identifiers used for profitability and capital shortfall play a minor role in this context, while they emerge as important for deposits, that appear more sensitive to "bad news". Short-term funds are affected mostly by the availability of collateral as well as by credit conditions, at the macro and micro levels.

In addition, stickiness may play a role in the behaviours of the variables, in particular of deposits and short-term withdrawals. While this aspect may be particularly relevant in the identification of the magnitude of the shock, i.e. the duration of the bank run is also important for the measures that a bank can put in place to counterbalance these withdrawals, e.g. do contingency funding plan mitigate the effects of bank run? what is the role of central banks? The dynamics of bank run would particularly benefit from further investigations.

Finally, the analysis could benefit from further research by using interaction effects among the explanatory variables. The potential advantage of using interactions derives from the likely differences in the transmission of solvency issues to liquidity, depending on the characteristics of banks with respect to credit risk and business models. These aspects in particular should be investigated in more details to have a better understanding of feedback effects in stress tests.

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Appendix A: Sample statistics and correlation

	TCE	*DEPLN*	*STFLN*	*FNDC*	*ABS*	*COREC*	*ICG*	*SEC*	*IMP*
Mean	0.074	0.024	0.024	0.013	0.009	0.001	0.111	0.237	1.460
Standard Error	0.001	0.001	0.009	0.004	0.001	0.001	0.004	0.003	1.252
Median	0.073	0.025	0.007	0.009	0.008	0.001	0.102	0.233	0.004
Standard Deviation	0.007	0.015	0.094	0.037	0.007	0.008	0.040	0.033	13.128
Sample Variance	0.000	0.000	0.009	0.001	0.000	0.000	0.002	0.001	172.336
Kurtosis	-1.073	3.253	0.248	93.637	-1.229	105.234	-0.877	5.599	107.874
Skewness	0.242	0.829	0.130	9.450	0.242	-10.143	0.370	1.281	10.345
Range	0.027	0.107	0.530	0.381	0.023	0.084	0.148	0.236	137.246
Minimum	0.060	-0.018	-0.244	0.000	0.000	-0.078	0.044	0.175	0.000
Maximum	0.087	0.090	0.286	0.382	0.023	0.006	0.192	0.411	137.246
Sum	8.087	2.690	2.674	1.440	0.992	0.088	12.178	26.059	160.593
Count	110.000	110.000	110.000	110.000	110.000	110.000	110.000	110.000	110.000

	TCE	*DEPLN*	*STFLN*	*FNDC*	*ABS*	*COREC*	*ICG*	*SEC*	*IMP*
TCE	1.000								
DEPLN	0.010	1.000							
STFLN	0.136	0.092	1.000						
FNDC	-0.196	0.000	-0.109	1.000					
HABS	0.165	0.236	0.106	-0.127	1.000				
COREC	-0.035	0.075	0.033	0.071	0.012	1.000			
ICG	0.176	0.083	0.182	-0.183	-0.296	0.028	1.000		
SEC	0.360	0.061	0.179	-0.144	-0.430	0.062	0.516	1.000	
IMPP	-0.075	-0.119	-0.098	-0.016	-0.066	0.048	-0.128	-0.126	1.000

Chapter 5

Lending During the Subprime Crisis: a Quasi-Natural Experiment

(Joint work with Leonardo Iania)

1. Introduction

The measures undertaken by the US Government and by the Federal Reserve System (the Fed hereinafter) in the aftermath of the subprime crisis have highlighted that early intervention measures may be implemented when risks to financial stability materialize. For instance, the Capital Purchase Program (CPP), part of the Troubled Asset Relief Program (TARP), provided funds to US banks in the form of capital injections while the Credit Market Programs created incentives "to restart the flow of credit to meet the critical needs of small businesses and consumers[50]". Other measures included the support for borrowers in distress, via the Making Home Affordable (MHA) program, and the bailouts of, respectively, the automobile industry by means of the Auto-industry Financing Program and of American International Group.

In parallel to the US Government, The Fed also implemented a series of measures aimed to counteract the effects of the subprime crisis. First, by means of the Term Auction Facility (TAF), aiming to "ensure that liquidity provisions can be disseminated efficiently even when the unsecured interbank markets are under stress[51]". In addition, under the Emergency Economic Stabilization (EES) Act of 2008 the Fed started paying interest on reserves; this measure proved important for monetary policy to achieve the federal funds rate targeted by the Fed[52], while also affecting the allocation of liquidity in the US banking sector.

Furthermore, by means of unconventionally monetary policy measures (also known as Large Scale Asset Purchase Program - LSAP or quantitative easing, QE hereinafter) the Fed intervened in financial markets with three different QE programs of assets purchases in the secondary market, whose aims were to "put downward pressure in yields of [...] longer term securities, support mortgage markets, and promote a stronger economic recovery[53]". At last, after almost nine years from the beginning of the subprime crisis,

[50] For more information on the TARP and on the specific programs: https://www.treasury.gov/initiatives/financial-stability/TARP-Programs/credit-market-programs/Pages/default.aspx and for an analysis of the usage of the funds, see https://www.stlouisfed.org/publications/central-banker/fall-2013/the-troubled-asset-relief-programfive-years-later for an analysis of the programs and the overall distribution

[51] See https://www.federalreserve.gov/monetarypolicy/files/TAFfaq.pdf

[52] Walter J. R. and Courtois R. (2009) "The Effect of Interest on Reserves on Monetary Policy", The Federal Reserve Bank of Richmond, Economic Brief, EB09-12.

[53] www.federalreserve.gov/faqs/what-were-the-federal-reserves-large-scale-asset-purchases.htm

the efficacy of the TARP and of the measures implemented by the Fed on the US financial sector and on the US economy in general is still debated[54].

Taylor (2011) expressed some criticism in his written testimony to the US Senate concerning the TARP. He argued that the measures of the TARP had no stabilizing effects on the US economy and that it may have actually exacerbated the crisis due to its "chaotic rollout". To the contrary, Berger, Makaew and Roman (2014) find evidence that the TARP improved economic conditions on the markets where more banks participating in the program operated. Other authors find diverging results while focusing on lending (Li, 2010, Puddu and Wälchli, 2015 and Montgomery and Takahashi, 2014). Eventually, several studies on the impact and efficacy of the TARP have been conducted but have not clarified to what extent the interventions of the US Government were effective to stall the subprime crisis.

The actions of the Fed also raised doubts and criticism on their effects on financial markets and on the US economy. The effects of QE on the balance sheet of banks have been debated in several studies and articles. For instance, Montecino and Epstein (2014) find weak evidence of an increase of lending associated with QE. Choulet (2015) provides evidence that the Fed's QE operations increased liabilities of US banks to customers through deposits of bank customers participating in the LSAP. At the same time, the share of loans shrunk vis-à-vis deposits due to the underlying unfavourable macroeconomic conditions and the simultaneous increase in excess reserves driven by QE. In addition, and to retain better control of the federal funds rate, the Fed started paying interests of 25 basis points on excess reserves.

Some authors argue that the payment of interests on voluntary reserves created an incentive for banks to deposit funds with the Fed rather than lending to risky counterparties (Craig and Koepke, 2015 and more critically, Stiglitz and Rashid, 2016). In addition, these specific measures took place during a period of macroeconomic stress, characterized by an increase in bankruptcies and counterparty risk (Sarkar, 2009) and low demand for loans.

To the contrary, some believe the actions of the Fed had no impact on lending. Keister and McAndrews (2009) explain why the creation of excess

[54] See http://web.stanford.edu/~johntayl/Taylor%20TARP%20Testimony.pdf for more details on the efficacy of the measures implemented with the TARP.

reserves is merely a side-effect of the unconventional monetary policies of the Fed. Accordingly, the authors support the view that these policies halted the lending crunch and kept banks lending. What academics agree to a large extent is that the combined effects of capital injections and liquidity measures played a role in the lending behaviour of banks during the Great Recession, as illustrated e.g. by Ennis and Wolman (2015). The solvency-liquidity channel emerges also here as important, affecting the provision of loans to the real economy.

This study aims to investigate the effects of the TARP on bank lending, in particular the CPP. The analysis focuses on micro behaviours of US bank holding companies making use of a quasi-natural experiment over the recessionary period following the default of Lehman. First, banks are clustered by size and analyzed by least square regressions. In a second step, banks are randomly sampled from two subsets of banks participating or declining the CPP, which are engineered to carry similar characteristics in terms of business and risk profiles. In addition, the analysis exploits interactions of TARP with a set of liquidity risk indicators to capture the effects of QE on banks. The spirit of the exercise is similar to the studies of Gropp, Mosk, Ongena and Wix (2016) and Jimenez, Ongena, Peydrò and Saurina (2013), which attempt to exploit policy measures, i.e. the 2011 European Banking Authority capital exercise and the dynamic provisioning in the Spanish banking sector between the year 2000 and 2008, respectively, to analyze the effects of these measures on individual banks.

The findings of this study highlight that a difference exists before and after the self-selection bias is removed from the exercise. In the baseline regressions, where all banks are included, the TARP dummy seems to carry some information regarding lending, with a positive influence. In particular, when using interactions and capital in the regressions, the TARP variable is more informative. When the bias is removed and the samples are comparable in terms of risk profiles and bank characteristics, the TARP dummy loses informative power. Other indicators of liquidity risk that are capturing the effects of the QE, such as reserves to deposits and indicators of liquidity stress carry more important information on the behaviour of bank lending during the subprime crisis. While in the baseline equations interactions are often statistically significant, in the quasi-natural experiment mostly the role of liquidity indicators emerges as important for lending.

These results carry relevant policy insights concerning the effects of government interventions on banks and the potential interactions with other crisis measures.

2. Literature

2.1 The Subprime Crisis, a Quasi-Natural Experiment

Natural (and Quasi-Natural) experiments can be largely defined as "...studies where there is a transparent exogenous source of variation in the explanatory variables that determine the treatment assignment[55]". The main feature of the exercise is the lack of random assignment to the treatment or control groups. This study follows the approach suggested by Meyer (1994) and Goldfarb and Tucker[56] (2014) in applying a quasi-natural experiment framework to the analysis. In particular, their recommendations are applied concerning the construction of the dataset, the definition of potential threats to internal and external validity of the results and the use of techniques and shortcomings that allow us to adopt a quasi-natural experimental framework for the exercise.

The presence of endogeneity in our research question, i.e. the relationship between capital and lending, can be mitigated by relying on an exogenous force in the form of a crisis or a regulatory intervention or both. In this case, the subprime crisis and the following US Government and Fed policy measures are exploited. The bankruptcy of Lehman Brothers has been widely assessed as a severe shock that affected the US economy and potentially worsened the magnitude and duration of the crisis (Mishkin, 2010). Due to the impact of the shock on the US banking sector, the Fed and the US Government had to intervene to mitigate the effects of the crisis with monetary policy and regulations interventions as well as bailout measures (Ball, 2016).

In particular, the analysis investigates two of these interventions, namely the TARP and the Financial Services Regulatory Relief Act, that allow us to

[55] Meyer, B. (1994) NBER Technical Working Paper No. 170, cited, page 1.

[56] While the study of the cited authors is designed for marketing academics, we believe that it provides a clear and well structured procedure for consistently building an appropriate quasi-natural experiment and we take into account most of their suggestions in the construction of the dataset and in the setup of the analysis in this section.

reduce the issue of identification to a quasi-natural experiment. Overall the use of crisis or policy interventions as identification strategy in finance has been previously attempted by Gropp, Mosk, Ongena and Wix (2016) in an exercise where the authors investigate the effects of higher capital requirements and on bank lending.

2.2 The TARP, its Effects on Lending and the Role of Liquidity Risk

Calomiris and Khan (2015) highlight that the Fed and the US Treasury became convinced that a comprehensive response would be needed to avert a systemic collapse of the US banking sector and to ensure that US banks could continue lending to the real economy. This argument supports the view that the default of Lehman was a systemic event and, as a result, the solvency risk of the whole banking sector increased significantly. Hence, the TARP can be considered a systemic bailout of the US banking sector.

Li (2010) discusses the effects of the TARP intervention on bank loan growth. The author finds that banks that accepted the TARP funds increased lending by an annualized rate of 6.41% for all classes of loans. Moreover, Li finds evidence that banks having connections with the Fed or ties with local representatives are significantly correlated with the probability of receiving TARP funds. Montgomery and Takahashi (2014) find no supporting evidence that the TARP improved lending and, while looking at the CAP program, actually reduced loan growth. Puddu and Wälchli (2015) also investigate the effects of TARP on lending focusing on bank loan activities in the community where the banks are located. Their findings support the view that TARP was effective but the local macroeconomic conditions also played a role in the lending activities.

Using the results of the above mentioned authors as baseline, this study contributes to the understanding of the relationship between TARP and lending by integrating liquidity considerations in the analysis. In fact, the measures implemented by the Fed in terms of liquidity, such as the EES Act[57] and the TAF, may have distorted the appetite for lending of US banks. With the EES, the Fed offered the possibility to deposit cash at a risk-free

[57] This measure was in fact decided before the outburst of the subprime crisis, with the Financial Services Regulatory Relief Act of 2006. The Emergency Economic Stabilization Act merely allowed the Federal Reserve to start paying interests on reserves at an earlier stage.

interest rate of 0.25% without any need to set aside capital (since under Basel II, central banks claims rated AAA to AA- carry zero capital risk weight[58]). Suddenly banks experienced a deterioration of counterparty credit risk, as it is the case in most recessions, combined with a shortage of capital due to losses in the balance sheet and a risk-free opportunity to invest in cash proceeds with positive interest rates.

The incentive scheme for banks to extend new loans may have changed with the introduction of these measures, as discussed also by Wheelock (2010) as well as Craig and Koepke (2015). While some authors describe these measures as neutral or beneficial in terms of bank lending (Keister and McAndrews, 2009), other authors are more critical of this policy (Stiglitz and Rashid, 2016). Ennis and Wolman (2015) disentangle the effects of the increase of excess reserves on the balance sheet of US banks. They conclude that excess reserves added to liquidity buffers of banks and substituted liquidity needs of banks in the interbank markets. More, they found that excess reserves did not hamper the capacity of banks to lend. Overall, a clear empirical evidence is missing on the interaction between the Fed's policies and the TARP in the aftermath of the subprime crisis. The above considerations call for the introduction of liquidity variables in the analysis as both, the liquidity squeeze and the intervention of the Fed with the EES Act, affected the willingness of banks to lend to the real economy.

3. Choice of Variables

The analysis makes use of indicators that are designed to capture the effects of the policies of the US Government and of the Fed on the balance sheets of US banks. Their construction is inspired by the literature and by previous works on the subject. To identify a bank participating in TARP this analysis makes use of one dummy variable. The dummy captures the quarter when a bank receives TARP funds, hence it is pivotal in the definition and measurement of the other variables in terms of lags and leads. The dummy, DTRP, is constructed according to the below formula:

[58] This was the case for the US at the time of the crisis. For more details on the system of weights of Basel II, we refer the reader to: www.bis.org/publ/bcbs128b.pdf

$$DTRP = \begin{cases} 1 \rightarrow [Participate] \\ 0 \rightarrow [Decline] \end{cases} \tag{1}$$

To fulfil the aim of the study we also integrate a series of variables that encompass the effects of the QE program as well as the other measures of the Fed, e.g. the setting of positive interest rates for excess reserves. Hence, this study makes use of the ratio of reserves to deposits (RSDP), which targets the increase of excess reserves described in the work of Ennis and Wolman (2015), Craig and Koepke (2015) and Choulet (2015) following the beginning of QE. Moreover, the ratio of high-risk asset-backed securities to total assets (ABS) is also included. Only asset-backed securities not issued by Government Sponsored Agencies, such as Fannie Mae and Freddie Mac Bonds are included in the formula. This variable allows us to take into account the rise of the originate-to-distribute business model that affected the lending activity of banks from the nineties onwards. Since it was a common business practice for banks to purchase asset-backed securities issued by vehicles sponsored by the bank, their volumes partly reflects the lending originated by the bank. The analysis focuses on higher risk asset-backed securities since these securities were identified as the culprit of the liquidity crunch during the subprime crisis.

Ivashina and Scharfstein (2010), Berrospide (2012) and Cornett *et al.* (2011) emphasize the role played by off-balance sheet credit commitments during the subprime crisis in reducing lending. To observe these effects the ratio of undrawn committed credit lines to total assets (OBS) is added to the explanatory variables. In addition, to capture the effects of the precautionary liquidity hoarding that followed the default of Lehman, the model makes use of a high-quality liquid assets ratio (HQLA). This ratio is composed of high-quality liquid assets (i.e. US Treasuries as well as US States and Political Subdivisions Bonds), cash and repurchase agreements, which compose the "liquidity buffer". Short-term borrowing and pledged assets are deducted from this latter. The ratio is normalized by total assets.

Liquidity and lending are also connected via the funding cost (FNDC). The idea behind this ratio is that the funding costs arising from the liabilities of banks are depending on market rates as well as the bank's credit rating. Hence a worsening of the credit risk of a bank could reverberate in an increase of its funding costs with consequences on its liquidity position. During the subprime crisis a series of downgrades hit the US banking sector[59], with repercussions on their refinancing costs, hence FNDC should enable us to identify the differences in the soaring funding costs of banks.

The analysis also makes use of the income gap (ICG), which can be considered a proxy of the maturity mismatch gap as it measures the cash flow at risk from changes in interest rates and captures the capacity of the bank to extend lending when interest rates rise. The behaviour of this indicator has been explained in details by Landier *et al.* (2013) that use it to investigate the sensitivity of the profitability of banks to changes in interest rates. At last a ratio of charge-offs minus recovery to total gross loans (COREC) is added as explanatory variable. This is necessary to capture the level of credit risk taken by each bank as well as the macroeconomic conditions, as this ratio is cyclical and strongly correlated with recessionary episodes[60].

Table 1: names of variables and related description.

Code	Name of variable	Description
TGL	Total Gross Loans	Total Gross Loans / Total Assets
CCR	Committed Credit Lines	Committed Credit Lines / Total Assets
CAP	Capital to Assets	Total Equity / Total Assets
HQLA	High Quality Liquid Assets Ratio	[Cash (excl. Obligatory and Voluntary Reserves) + Repurchase Agreements + US Treasury Bills + US States and Pol. Subs. Bonds] / [Federal Funds Purchased and Securities Sold under Agreements to Repurchase + Commercial Papers + Debt Maturing < 1 year]
RSDP	Reserve to Deposits	(Obligatory + Voluntary Reserves at the Federal Reserve System) / Total Assets
FNDC	Funding Cost	Interest Paid on Liabilities / Total Liabilities (excl. Equity)
COREC	Charge Offs minus Recoveries	(Charge Offs - Recoveries on Losses on Loans) / Total Gross Loans
ICG	Income Gap	Total Assets Maturing < 3 Months / Total Liabilities Maturing < 3 Months
RCPS	Regulatory Capital Surplus	Tier I - Minimum Regulatory Tier I requirements
ABS	High Risk Asset Backed Securities	Asset Backed Securities (excl. US Govt. Sponsored Agencies) / Total Assets
OBS	Undrawn Commitments and Guarantees	Total Undrawn Commitments and Guarantees / Total Assets

[59] See e.g. https://www.ft.com/content/ef5c9074-cdf7-11dd-8b30-000077b07658 and http://www.cnbc.com/id/28310479 for a list of downgrades of large banks in the aftermath of the Lehman failure.
[60] Furlong, F. and Knight, Z. (2010) discuss charge-offs and provisioning in banks. They argue that banks under-provisioning is triggered by constrained accounting rules. This motivates also the preference for the charge-off indicator for credit risk.

Finally, a number of interaction terms are added to the regressions. As previously discussed, the US Government and the Fed implemented different measures to mitigate the adverse effects of the bankruptcy of Lehman, in particular to strengthen the liquidity and solvency levels of the US banking sector. It is therefore a matter of interest to understand if and how these measures played a role in the stabilization of US banks. Hence, liquidity ratios (i.e. RSDP, HQLA and FNDC) are interacted with DTRP in a separate set of regressions.

In a second step, the analysis aims to define two sets of banks that are similar regarding their risk profiles and business models to run a quasi-natural experiment. To further ensure the subsets are comparable, a variable defined as surplus over the regulatory requirements set by capital Tier I and Tier II instruments (RCSP) is added. This variable measures the difference between the minimum capital requirements[61] and the sum of Tier I and II instruments available. The obtained difference measures the capacity of the bank to create new loans without recurring to issuances of new capital. Since the CPP offered to inject capital in US banks, it is likely that considerations concerning the amount of "free" capital available played a role in the choice of accepting or declining the TARP funds. It is therefore important to include this variable in the methodology for the construction of comparable samples for the random sampling exercise.

Moreover, return on equity (RoE) and capital over total assets (CAP) are also included as an indicator of profitability and for accounting capital, respectively. Since profitability is important to build-up capital, banks with different levels of profitability and capital may have evaluated differently the need for capital injections in the aftermath of the subprime crisis. Eventually, the dependent variables used in the regression are total gross loans over total assets (TGL) and committed credit lines over total assets (CCR). These variables are extensively used in previous exercises to model bank lending behaviour. The indicators included as explanatory variables in the regressions used in this study are reported in table 1. Appendix A collects correlation and sample statistics for the above-listed explanatory variables.

[61] In the US at the time of the Lehman Crisis, the Tier I and II minimum capital requirements were set at a cumulative rate of 8% for Total Regulatory Capital / Risk-weighted Assets.

4. Dataset of the Quasi-Natural Experiment

Overall, 234 of the 635 reporting banks as at 2008:Q3 received funds from the TARP, in the form of capital injections (CPP and the Community Development Capital Initiative) and/or loans[62]. The dataset used in this analysis covers 93% of the funds allocated via the TARP and it is therefore comprehensive and exhaustive of the breadth and scope of the Government intervention. While a large number of US banks accepted TARP funds, many BHCs declined the Government intervention. 164 banks were identified by means of information found in newspapers, in the official communication of the bank (i.e. annual reports, Security Exchange Commission filings) or in the internet[63]. In addition, 48 banks failed or experienced severe solvency issues in the recession periods following the default of Lehman, while 68 banks were discarded as subsidiaries of foreign entities or of other bank holding companies and therefore not eligible to the program. A small number of banks participated in the TARP and did not receive capital but other forms of subsidies, i.e. the Small Business Lending Program and for the MHA Program. At last, for 106 banks no information related to their participation to the TARP or to other US Government programs could be found.

Table 2: Characteristics of the sample.

Capital Purchase Program	234
Did not participate	164
Failed Banks	48
Subsidiaries pf Bank Holding Co.	38
Subisidiaries of Foreign Banking Groups	28
Small Business Lending Program	9
Financial Instruments for Home Loan Modification Program	7
No information	106

[62] The sample includes the 8 largest US banks, that agreed to receive capital injections (Goldman Sachs Group, Morgan Stanley, J.P. Morgan Chase, Bank of America Corporation, Citigroup Inc., Wells Fargo, Bank of New York Mellon and State Street Corporation). We drop from the dataset all subsidiaries of foreign banking groups that were not eligible for TARP funds as well as banks which were themselves subsidiaries of US banking groups. All the information concerning the TARP allocation of funds can be found in the website https://project.propublica.org/bailout.

[63] A number of them provided explicitly some explanation for this refusal, others were mentioned as having rejected the funds without further information.

Table 2 illustrates the composition of the sample and Appendix B highlights the different distribution of a number of widely used ratios to describe business models and risk profiles of banks.

Li (2010) and Montgomery and Takahashi (2014) highlight that the TARP funds may have been allocated according to the presence of key Congress members in the districts where banks were headquartered. Moreover, banks which were identified as more systemically relevant may have been pressured to receive funds to forestall the US banking sector and reduce risks to financial stability[64]. Eventually and more importantly, it is likely that a self-selection bias affects our sample. Entering the TARP entailed a number of limitations for participants, some of these to the potential detriment of existing shareholders and of the management[65]. For this reason, it can be argued that only banks in need of capital would request to enter the program, while better capitalized banks would decline to participate. This assumption is somehow confirmed by the data. A major difference is that, on average, banks participating in the TARP have higher regulatory capital surplus and capital ratios. It appears that the participation to the TARP was indeed largely driven by capital considerations. The other variables seem to be largely comparable among the two groups (i.e. "participate", the treatment group and "decline", the control group) in terms of their distributions (see Appendices B and D for sample statistics).

Acknowledged the presence of the above-mentioned biases, a number of measures deemed necessary to mitigate these risks are implemented in the analysis. At first, the eight largest banks that agreed to receive TARP funds[66] are removed from the sample. Discarding the largest banks allows for limiting to a minimum the share of lending that is granted to foreign counterparties, as this concerns mostly the largest banks. Loans granted by foreign subsidiaries of large US banks to foreign clients may be driven by more favourable macroeconomic conditions outside the US at the time of the subprime crisis that may render the groups difficult to compare. Second, it appears that the size of banks may have an impact on the lending, in

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[64] see e.g. https://www.theguardian.com/business/blog/2008/oct/15/banking or http://www.judicialwatch.org/press-room/weekly-updates/20-banks-forced-bailout/

[65] The terms and conditions of the TARP foresaw that the US Treasury would receive a 5% cumulative dividend for the first 5 years and 9% per year afterwards. Moreover, participants had to accept a number of restrictions on the payment of bonuses and other form of remunerations to the management. For more information, see: www.treasury.gov/initiatives/financial-stability/about-tarp/Pages/default.aspx

[66] For the sake of clarity, the Capital Assistance Program and the Supervisory Capital Assessment Program are not affecting our exercise as the banks involved are removed from the sample due to constraints of size and characteristics.

particular concerning the impact of policy measures (see Kishan and Opiela, 2000). Hence all banks whose total assets as at 2008:Q3 are larger than 5% of the largest observed bank declining TARP are dropped from the sample of TARP participants. Furthermore, the analysis focuses on the bias originating from the regulatory capital surplus (RCPS), which certainly plays an important role in the choice to participate or not in the TARP. To make the two groups comparable, all the banks reporting RCPS above and below the 80th and 20th percentiles as at 2008:Q3, respectively, are removed from the sample of declining and participating banks. This allows us to obtain a treatment and a control group composed respectively of 149 and 124 banks.

Once the potential bias of banks characterized by high and low levels of RCPS and TGL is controlled for, the groups can be considered homogeneous and the participation in the TARP cannot be clearly justified by the underlying main financial conditions of the banks. The distributions of a selected set of business and risk-related ratios across the two groups are rather similar, supporting the assumption of homogeneity of banks according to a number of relevant financial indicators.

It is likely that other aspects, potentially related to opportunity-cost rationales and different perspectives on US macroeconomic developments may have played a role in the decision to participate or decline access[67] to the TARP while the characteristics of the banks falling into the two groups was similar. Eventually, the relatively large number of banks and the distribution of the variables supports the assumption that most business models of US banks are represented in both groups. Appendices C and D illustrate the resulting samples obtained from the above-described procedure.

To further enforce comparability, this study performs a random sampling exercise with replacement, i.e. a bootstrapping procedure. In 100 repeated trials with repetition, 100 banks are drawn from our full sample of banks, 56 and 41 banks respectively from the two groups of participants and declining banks. This proportion maintains the original ratio of participant and declining banks observed in the dataset. The random samples are deemed representative of the main possible combinations of business models and

[67] Among others, these issues were associated with participating or declining access to the TARP, e.g. stigma attached to participating institutions, cost-opportunity of accessing capital in a stressful period, lending opportunities and strategic plans of banks, fear of hostile take-over by better capitalized banks, etc.

risk profiles in our sample. The main obstacle to external validity of our results rests on the size of the banks included in the exercise. It has been argued (see e.g. Leuven, Ratnowski and Tong, 2014 and Regehr and Sengupta, 2016) that size is an important variable for the behaviour of banks: size affects several aspects of the banking business and risks, e.g. competition, systemic relevance, cost efficiency, etc.

The exercise focuses on banks of medium to small size. The choice of the focus on those type of banks is driven by the setup of the TARP and by the US Government structure of the intervention, which forced the largest banks to accept capital injections, hence excluding them from the possibility to decline the TARP. To get a clearer understanding of the impact of capital and liquidity, regressions (2.a) to (2.c) are run again and used as baseline, including all banks receiving the TARP funds as well as all the banks rejecting (including the ones for which no information is available). These results are eventually compared with those of the quasi-natural experiment.

5. Least Squares Regression and Setup of the Exercise

The sample of banks is observed from Q3:2008 to Q4:2009, i.e. from the aftermath of the default of Lehman to two quarters after the end of the recessionary episode as defined by the National Bureau of Economic Research[68]. The purpose of this setup is to be able to observe the response of banks to a capital injection over the selected horizons. The issue of identification is largely reduced for capital, as the US Government provides the information about the timing and the amount of the intervention. In addition, the effects of a capital injection on lending may appear with a delay, which the analysis captures by using an average of the dependent variable over two or four quarters following the occurrence of the capital shortfall.

Several regressions are then run to capture the different aspects of the effects of capital on lending and the interactions between capital and liquidity risk. At first the analysis relies on a baseline regression of lending on different set of explanatory variables defined in section 3 for different

[68] For more information on recessionary episodes see http://www.nber.org/cycles.html

subsets of the sample. These combinations of subsets and variables are defined as follows:

1. Full sample, including all banks participating and declining TARP,
2. A sample of the largest 100 banks by total assets as at Q4:2008,
3. A sample of the smallest 100 banks by total assets as at Q4:2008.
4. A sample including all banks used in the random sampling exercise, participating and declining the TARP.

It may have occurred that in the aftermath of the subprime crisis, both banks accepting and declining the TARP, increased their capital for different reasons (e.g. change of mind about the TARP, high levels of non-performing loans, mergers or acquisitions, etc.). The capital addendum may affect the results of our regression since the levels of lending may now depend from an action occurring after the TARP. For these reasons an interaction term is added as follows:

$$itcDC_b = CAP(after\,TARP)_b * DTRP_b \qquad (2.a)$$

CAP enters the above interaction term only at leads, and only for periods subsequent the entrance of a bank in a TARP agreement. This setup should capture in principle the major changes in lending of banks that received TARP funds and partly correct for cases of recapitalization "on the run". The other interaction terms are constructed using liquidity-related explanatory variables as:

$$itcDHQ_b = HQLA_b * DTRP_b \qquad (2.b)$$

$$itcDRS_b = RSDP_b * DTRP_b \qquad (2.c)$$

$$itcDFC_b = FNDC_b * DTRP_b \qquad (2.d)$$

The aim of these explanatory variables is defining potential relationships between banks participating or declining the TARP. As DTRP can only take on values equal to 0 or 1, the interaction terms can be interpreted as the sum of the effects of the coefficient of the liquidity variable jointly with the choice of participating or declining the TARP aid. The exercises are performed over different horizons, for H=2 and H=4[69]. The regressions performed in this study are based on the equations below:

$$\bar{y}_b = c + \bar{x}_b'\beta^{lq} + DTRP_b\beta^d + \varepsilon_b \qquad \varepsilon_b \sim N(0,\sigma) \tag{2.e}$$

$$\bar{y}_b = c + \bar{x}_b'\beta^{lq} + \bar{w}_b'\beta^{rp} + DTRP_b\beta^d + \varepsilon_b \qquad \varepsilon_b \sim N(0,\sigma) \tag{2.f}$$

$$\bar{y}_b = c + \bar{x}_b'\beta^{lq} + \bar{z}_b'\beta^{itc} + DTRP_b\beta^d + CAP_b\beta^{cap} + itcDC_b\beta^{itc} + \varepsilon_b \qquad \varepsilon_b \sim N(0,\sigma) \tag{2.g}$$

$$\bar{y}_b = c + \bar{x}_b'\beta^{lq} + \bar{w}_b'\beta^{rp} + DTRP_b\beta^d + CAP_b\beta^{cap} + itcDC_b\beta^{itc} + \varepsilon_b \qquad \varepsilon_b \sim N(0,\sigma) \tag{2.h}$$

In the above regressions, *y* is the average of TGL or UCCR, *c* is the constant, *x* is a vector of liquidity risk indicators, *w* is a vector of ratios capturing the risk profile of banks. In addition, *z* collects interactions terms defined by equations 2.b to 2.d. CAP is the capital to assets ratio, while itcDC is the interaction term for banks adding further capital after the TARP takes place described in equation 2.a.

All regressions are corrected for heteroskedasticity using White-robust standard errors. The dependent variables included in equation 2.e to 2.h represent the averages across H quarters of the respective ratios, as described below:

$$\bar{y}_b = \sum_{t=0}^{T=H} \frac{y_{b,t} + \cdots + y_{b,T}}{T} \tag{2.i}$$

$$\bar{x}_b = \sum_{t=0}^{T=H} \frac{x_{b,t} + \cdots + x_{b,T}}{T} \tag{2.j}$$

$$\bar{w}_b = \sum_{t=0}^{T=H} \frac{w_{b,t} + \cdots + w_{b,T}}{T} \tag{2.k}$$

This arrangement is justified to mitigate the issues of endogeneity in the relationship between capital and lending and to capture the longer term dynamics of the banking business. In this exercise, the dummy sets without ambiguity the moment when a capital injection is taking place. Moreover, all observations occurring before the TARP intervention are dropped from the

[69] The same set of regressions was run also for H=2, with small differences in the results.

sample while lending and the other explanatory variables are observed over a changing horizon.

6. Results of the Baseline Exercise

The results of the baseline regressions, illustrated in tables 3.a to 3.d, indicate that overall, DTRP and the interaction variables related to it are significant in a number of regressions. When looking at the impact of the CPP in the several regressions run, the results of DTRP provide mixed insight. When comparing the results for the whole sample and the subsets of largest and smallest banks, it emerges that DTRP is not often significant when entering the equation alone, but its importance increases when interactions are added.

The regressions on TGL highlight that DTRP is more significant for larger banks and in the aggregate sample, while on the shorter horizon, smaller banks seem to benefit the most from the TARP. This latter effect may be related to the fact that smaller banks have limited access to capital markets, in particular during a crisis period. When itcDC is added, the sign of DTRP changes to negative and the interaction term is statistically significant and carries a positive sign but it makes the interpretation of the effects less straightforward.

For banks receiving CPP (DTRP=1) the negative effect of CAP on TGL is overall mitigated. Once other interaction terms are added, itcDC retains the statistical significance while reducing the economic effect of CAP while providing supporting evidence of a positive impact of CPP. The negative sign of CAP may signal its use to manage the banking book of banks under Basel II, i.e. by reducing risk-weighted assets to keep control of the regulatory capital ratio (see Calomiris 2012). The observation of small banks indicates that once we include interactions to the regressions, these added explanatory variables are not statistically significant. The interpretation of the impact of DTRP on TGL is more complex as CAP is a continuous variable. For CAP equals to 10%, the impact of TARP is positive and equals, on average across regressions 2.g and 2.h for H= 2 and H=4, an increase of lending by 1.7% points. Overall, the value of CAP for which the impact of DTRP is zero equals 7.7%, when the average CAP in the four quarters after the default of Lehman is around 9%. While using TGL as dependent variable, liquidity ratios are flagged as important in most regressions, with HQLA, FNDC and RSDP often statistically significant. HQLA seems to be more important for lending of large banks, while smaller banks are seldom sensitive to this variable. HQLA and itcDHQ both carry a positive sign, indicating that banks that had a high quality liquidity buffer benefit the most from receiving TARP funds. The sign of the coefficient supports the idea that banks characterized by large liquidity buffer were more likely to lend during the subprime crisis.

FNDC carries positive sign and is associated with high levels of lending while in normal conditions we would expect higher funding costs associated with lower levels of lending. This puzzling result can be explained as FNDC and TGL decrease after the shock. While the US Government and the Fed interventions stabilized the financial markets in the aftermath of the default of Lehman, reducing the cost of funding of banks, at the same time lending to the real economy suffered from stressful macroeconomic conditions ("credit crunch") and declined. The sign and significance of FNDC capture therefore mostly the deterioration of macroeconomic conditions combined with a simultaneous improvement of the funding costs.

COREC is statistically significant and the results highlight a positive relationship with lending. This may be explained by the worsening of macroeconomic conditions and counterparty risk in the aftermath of the subprime crisis; hence an increase in lending would be linked to higher levels of COREC. The relationship between lending and COREC, a more conservative measure of non-performing loans is particularly relevant to explain the behaviour of banks. Indeed, the TARP intervention took place during a period when the incentive to lend for banks would be very low, given the steep increase of counterparty risk as discussed by Sarkar (2009). This would explain why the provision of loans to the real economy during the subprime crisis and in particular in the aftermath of the default of Lehman may have indeed been correlated with high levels of COREC. Moreover, the measure chosen for the regression, i.e. COREC, focuses on the realization of a loan loss and not on the probability of a loan defaulting. This makes this measure more conservative and less forward-looking. The positive coefficient may therefore be related to the time necessary for COREC to adjust to the deteriorating macroeconomic conditions.

Table 3.a: baseline least squares analysis, all banks, largest and smallest 100 banks by total assets as at 2008:Q3 - TGL as dependent variable, H=2.

All banks (Including Large 8)				**Largest 100**			**Smallest 100**		
Regression 2.e									
Variable	Coeff.	T-stat.	p-value	Coeff.	T-stat.	p-value	Coeff.	T-stat.	p-value
Int	0.742	57.777	0.000 ***	0.582	8.014	0.000 ***	0.625	13.311	0.000 ***
HQLA	0.275	5.586	0.000 ***	0.340	3.759	0.000 ***	0.183	1.820	0.072
FNDC[a]	-0.002	-2.233	0.026 *	32.836	3.926	0.000 ***	19.732	2.757	0.007 **
RSDP	-0.182	-1.896	0.059	-1.068	-4.572	0.000 ***	-0.610	-2.320	0.023 *
DTRP	0.030	2.843	0.005 **	0.044	1.599	0.113	0.042	2.105	0.038 *
R-sq. adj.	0.159			0.436			0.152		
Regression 2.f									
Variable	Coeff.	T-stat.	p-value	Coeff.	T-stat.	p-value	Coeff.	T-stat.	p-value
Int	0.720	43.035	0.000 ***	0.548	6.198	0.000 ***	0.453	6.365	0.000 ***
HQLA	0.190	4.004	0.000 ***	0.235	2.723	0.008 **	0.025	0.276	0.783
FNDC[a]	-0.003	-11.086	0.000 ***	32.588	3.153	0.002 **	29.895	3.804	0.000 ***
RSDP	-0.207	-2.524	0.012 *	-0.719	-3.420	0.001 ***	-0.589	-2.277	0.025 *
COREC	4.431	4.405	0.000 ***	-0.742	-0.243	0.808	5.616	1.597	0.114
ABS	-2.938	-7.055	0.000 ***	-2.289	-4.222	0.000 ***	-2.976	-4.492	0.000 ***
OBS	0.085	1.431	0.153	0.055	0.734	0.465	0.646	3.171	0.002 **
ICG	-0.006	-0.145	0.885	0.128	1.399	0.165	0.079	1.410	0.162
DTRP	0.022	2.268	0.024 *	0.035	1.287	0.201	0.038	2.236	0.028 *
R-sq. adj.	0.288			0.520			0.321		
Regression 2.g									
Variable	Coef.	T-stat.	p-value	Coef.	T-stat.	p-value	Coef.	T-stat.	p-value
Int	0.830	45.928	0.000 ***	0.634	9.131	0.000 ***	0.575	5.635	0.000 ***
HQLA	0.300	4.623	0.000 ***	0.359	3.474	0.001 ***	0.112	0.755	0.453
FNDC[a]	0.002	1.328	0.185	32.003	4.433	0.000 ***	26.430	2.712	0.008 **
RSDP	-0.115	-2.403	0.017 *	0.083	0.155	0.877	-0.915	-2.091	0.039 *
DTRP	-0.081	-2.053	0.041 *	0.180	1.635	0.106	0.177	1.407	0.163
itcDHQ	0.065	0.774	0.439	0.095	0.655	0.514	0.158	0.844	0.401
itcDRS	-1.007	-4.521	0.000 ***	-1.526	-2.570	0.012 *	0.499	0.909	0.366
itcDFC	13.150	2.760	0.006 **	-15.553	-1.411	0.162	-18.743	-1.315	0.192
CAP	-0.957	-8.697	0.000 ***	-0.739	-7.938	0.000 ***	0.114	0.179	0.859
itcDC	0.838	3.774	0.000 ***	0.147	0.279	0.781	-0.212	-0.273	0.785
R-sq. adj.	0.332			0.603			0.135		
Regression 2.h									
Variable	Coef.	T-stat.	p-value	Coef.	T-stat.	p-value	Coef.	T-stat.	p-value
Int	0.820	47.307	0.000 ***	0.727	12.479	0.000 ***	0.474	5.062	0.000 ***
HQLA	0.225	5.079	0.000 ***	0.330	4.150	0.000 ***	0.036	0.414	0.680
FNDC[a]	0.001	1.815	0.070	23.431	3.602	0.001 ***	29.854	3.589	0.001 ***
RSDP	-0.221	-2.784	0.006 **	-0.873	-4.149	0.000 ***	-0.623	-2.395	0.019 *
COREC	4.521	3.757	0.000 ***	0.641	0.272	0.787	5.384	1.525	0.131
ABS	-2.932	-7.733	0.000 ***	-2.123	-4.096	0.000 ***	-2.980	-4.154	0.000 ***
OBS	0.053	1.021	0.308	-0.021	-0.523	0.602	0.656	3.115	0.002 **
ICG	0.048	1.504	0.133	0.183	2.510	0.014 *	0.087	1.556	0.123
DTRP	-0.060	-3.198	0.001 **	-0.042	-1.020	0.310	0.037	0.766	0.446
CAP	-1.008	-10.793	0.000 ***	-0.890	-8.865	0.000 ***	-0.220	-0.427	0.670
itcDC	0.873	4.174	0.000 ***	0.697	1.984	0.050	-0.085	-0.134	0.894
R-sq. adj.	0.392			0.673			0.309		

*a) The difference in the results as regards FNDC between the full sample regression and the regressions for the largest and smallest banks is related to the presence of outliers. The other coefficients are not significantly affected by the outliers. When these outliers are removed from the sample the values of the coefficient of FNDC are closer to the one reported in the other regressions. These results are available upon request. The subset of smaller banks is reduced to 99 entries due to a missing value. ***, ** and * indicates statistical significance at respectively the 0.1, 1 and 5% levels.*

Table 3.b: baseline least squares analysis, all banks, largest and smallest 100 banks by total assets as at 2008:Q3 - TGL as dependent variable, H=4.

All banks (Including Large 8)				**Largest 100**			**Smallest 100**		
Regression 2.e									
Variable	Coeff.	T-stat.	p-value	Coeff.	T-stat.	p-value	Coeff.	T-stat.	p-value
Int	0.735	59.171	0.000 ***	0.586	9.364	0.000 ***	0.621	13.851	0.000 ***
HQLA	0.281	5.781	0.000 ***	0.379	4.250	0.000 ***	0.229	2.338	0.021 *
FNDC[a]	-0.003	-2.175	0.030 *	35.884	4.427	0.000 ***	21.186	2.764	0.007 **
RSDP	-0.206	-2.222	0.027 *	-1.023	-4.690	0.000 ***	-0.464	-1.873	0.064
DTRP	0.027	2.637	0.009 **	0.042	1.519	0.132	0.033	1.697	0.093
R-sq. adj.	0.165			0.452			0.143		
Regression 2.f									
Variable	Coeff.	T-stat.	p-value	Coeff.	T-stat.	p-value	Coeff.	T-stat.	p-value
Int	0.711	42.913	0.000 ***	0.553	6.971	0.000 ***	0.447	6.560	0.000 ***
HQLA	0.209	4.503	0.000 ***	0.277	3.150	0.002 **	0.062	0.632	0.529
FNDC[a]	-0.004	-12.694	0.000 ***	35.038	3.544	0.001 ***	32.595	3.984	0.000 ***
RSDP	-0.223	-3.044	0.002 **	-0.827	-4.380	0.000 ***	-0.376	-1.401	0.165
COREC	3.430	3.869	0.000 ***	1.056	0.430	0.668	3.193	1.027	0.307
ABS	-3.500	-6.719	0.000 ***	-2.060	-3.487	0.001 ***	-3.747	-3.194	0.002 **
OBS	0.100	1.638	0.102	0.036	0.493	0.623	0.663	3.358	0.001 **
ICG	-0.001	-0.020	0.984	0.129	1.437	0.154	0.094	1.498	0.138
DTRP	0.019	2.043	0.042 *	0.029	1.074	0.286	0.031	1.798	0.076
R-sq. adj.	0.286			0.521			0.294		
Regression 2.g									
Variable	Coef.	T-stat.	p-value	Coef.	T-stat.	p-value	Coef.	T-stat.	p-value
Int	0.821	47.802	0.000 ***	0.619	9.594	0.000 ***	0.604	6.162	0.000 ***
HQLA	0.303	4.815	0.000 ***	0.373	4.051	0.000 ***	0.179	1.236	0.220
FNDC[a]	0.004	1.442	0.150	35.227	4.701	0.000 ***	26.710	2.513	0.014 *
RSDP	-0.120	-2.762	0.006 **	0.241	0.520	0.605	-0.499	-1.329	0.187
DTRP	-0.047	-1.249	0.212	0.283	2.707	0.008 **	0.133	1.127	0.263
itcDHQ	0.091	1.091	0.276	0.190	1.373	0.173	0.130	0.711	0.479
itcDRS	-0.936	-4.725	0.000 ***	-1.669	-3.184	0.002 **	-0.076	-0.155	0.877
itcDFC	13.271	2.647	0.008 **	-16.568	-1.416	0.160	-19.509	-1.289	0.201
CAP	-0.955	-8.809	0.000 ***	-0.743	-8.935	0.000 ***	-0.204	-0.325	0.746
itcDC	0.596	2.380	0.018 *	-0.510	-0.906	0.368	0.316	0.418	0.677
R-sq. adj.	0.336			0.619			0.128		
Regression 2.h									
Variable	Coef.	T-stat.	p-value	Coef.	T-stat.	p-value	Coef.	T-stat.	p-value
Int	0.811	46.936	0.000 ***	0.717	11.887	0.000 ***	0.517	5.748	0.000 ***
HQLA	0.244	5.707	0.000 ***	0.370	4.338	0.000 ***	0.074	0.795	0.429
FNDC[a]	0.003	1.906	0.057	26.833	3.824	0.000 ***	30.988	3.598	0.001 ***
RSDP	-0.234	-3.310	0.001 **	-0.909	-4.301	0.000 ***	-0.434	-1.630	0.107
COREC	3.020	2.565	0.011 *	0.952	0.448	0.655	2.815	0.901	0.370
ABS	-3.462	-6.820	0.000 ***	-1.964	-3.701	0.000 ***	-4.034	-3.467	0.001 ***
OBS	0.068	1.281	0.201	-0.025	-0.557	0.579	0.634	3.104	0.003 **
ICG	0.054	1.636	0.103	0.175	2.376	0.020 *	0.109	1.690	0.095
DTRP	-0.055	-2.360	0.019 *	-0.009	-0.164	0.870	-0.012	-0.219	0.827
CAP	-0.988	-10.267	0.000 ***	-0.835	-7.922	0.000 ***	-0.606	-1.161	0.249
itcDC	0.809	3.224	0.001 **	0.326	0.649	0.518	0.490	0.718	0.475
R-sq. adj.	0.388			0.660			0.287		

*a) The difference in the results as regards FNDC between the full sample regression and the regressions for the largest and smallest banks is related to the presence of outliers. The other coefficients are not significantly affected by the outliers. When these outliers are removed from the sample the values of the coefficient of FNDC are closer to the one reported in the other regressions. These results are available upon request. The subset of smaller banks is reduced to 99 entries due to a missing value. ***, ** and * indicates statistical significance at respectively the 0.1, 1 and 5% levels.*

RSDP emerges as an important explanatory variable for lending. It carries negative sign and is statistically significant in most regressions but it appears not to be as important for smaller banks. This fact supports the findings of Ennis and Wolman (2015) that mostly large banks hold excess reserves with the Federal Reserve. More, itcDRS is also significant, which supports the idea that the effect of RSDP on lending for banks that received TARP funds is larger in magnitude, i.e. 10 times larger than for banks not receiving TARP. Further insights come from the observation of itcDRS. This interaction term is statistically significant at high levels and carries negative sign as RSDP. The remaining explanatory variables are also informative as regards TGL. First, ABS is consistently strongly statistically significant in regressions 2.f. and 2.h, with negative coefficient. Holdings of ABS had a negative effect on lending in the US. A potential explanation of the sign and significance of this variable might be related to the high losses experienced by banks with large holdings of ABS. The effects of these losses on the capital of banks may have reduced their lending capacity. Undrawn credit commitments and guarantees (OBS) are mostly statistically significant for smaller banks and carry different sign when compared to larger banks. The results underline the different nature of the lending business across the sample.

The impact of DTRP on CRR is mostly emerging on larger banks and on the aggregate sample, it is positive and is equal to a 1.6% increase when CAP is equal to 10%. Overall the interaction effects are statistically significant at very high levels at both horizons. For banks participating in TARP, the effects of the liquidity ratios are inverted to the no-TARP banks. A higher liquidity buffer has a positive effect on CCR but not for TARP banks, for which the effect is negative and larger in magnitude and funding costs are lower for TARP banks. RSDP indicates that TARP banks carry a positive relationship, while the basic no-TARP relationship is negative. At last COREC; OBS and ICG are not particularly relevant for the analysis.

Table 3.c: baseline least squares analysis, all banks, largest and smallest 100 banks by total assets as at 2008:Q3 - CCR as dependent variables, H=2.

All banks (Including Large 8)				**Largest 100**			**Smallest 100**		
Regression 2.e									
Variable	Coeff.	T-stat.	p-value	Coeff.	T-stat.	p-value	Coeff.	T-stat.	p-value
Int	0.008	7.105	0.000 ***	0.028	4.132	0.000 ***	0.019	6.203	0.000 ***
HQLA	-0.008	-1.443	0.150	-0.009	-0.574	0.567	0.014	2.250	0.027 *
FNDC[a]	0.000	-0.457	0.648	-4.280	-3.653	0.000 ***	-1.074	-2.557	0.012 *
RSDP	0.001	0.186	0.853	0.077	1.651	0.102	-0.034	-1.709	0.091
DTRP	0.007	4.384	0.000 ***	0.022	4.752	0.000 ***	-0.001	-0.890	0.376
R-sq. adj.	0.041			0.171			0.099		
Regression 2.f									
Variable	Coeff.	T-stat.	p-value	Coeff.	T-stat.	p-value	Coeff.	T-stat.	p-value
Int	-0.003	-0.888	0.375	-0.002	-0.193	0.848	0.007	1.625	0.108
HQLA	-0.005	-1.007	0.315	-0.026	-1.674	0.098	0.008	1.116	0.267
FNDC[a]	0.000	0.372	0.710	-2.015	-1.422	0.158	-0.440	-0.958	0.341
RSDP	-0.015	-1.930	0.054	0.082	1.424	0.158	-0.026	-1.339	0.184
COREC	0.024	0.149	0.881	-0.128	-0.270	0.788	0.055	0.190	0.850
ABS	0.056	0.809	0.419	-0.080	-0.612	0.542	-0.034	-0.474	0.637
OBS	0.067	3.258	0.001 **	0.060	2.163	0.033 *	0.049	3.248	0.002 **
ICG	0.008	2.003	0.046 *	0.032	1.734	0.086	0.001	0.211	0.833
DTRP	0.005	3.904	0.000 ***	0.015	3.252	0.002 **	-0.002	-1.073	0.286
R-sq. adj.	0.2916			0.3187			0.1541		
Regression 2.g									
Variable	Coef.	T-stat.	p-value	Coef.	T-stat.	p-value	Coef.	T-stat.	p-value
Int	0.011	11.918	0.000 ***	0.027	4.659	0.000 ***	0.019	2.601	0.011 *
HQLA	0.003	0.819	0.413	0.008	0.773	0.442	0.015	1.664	0.100
FNDC	0.000	1.477	0.140	-1.924	-2.645	0.010 **	-1.215	-2.007	0.048 *
RSDP	-0.004	-2.143	0.033 *	-0.016	-0.305	0.761	-0.046	-1.698	0.093
DTRP	0.007	1.523	0.128	0.000	-0.003	0.997	-0.004	-0.511	0.611
itcDHQ	-0.030	-2.473	0.014 *	-0.035	-1.108	0.271	-0.003	-0.251	0.803
itcDRS	0.106	3.357	0.001 ***	0.113	1.662	0.100	0.022	0.563	0.575
itcDFC	-4.001	-4.838	0.000 ***	-4.814	-2.682	0.009 **	0.615	0.729	0.468
CAP	-0.013	-2.753	0.006 **	-0.031	-4.382	0.000 ***	0.014	0.293	0.771
itcDC	0.194	4.944	0.000 ***	0.346	3.556	0.001 ***	-0.023	-0.411	0.682
R-sq. adj.	0.224			0.228			0.058		
Regression 2.h									
Variable	Coef.	T-stat.	p-value	Coef.	T-stat.	p-value	Coef.	T-stat.	p-value
Int	-0.002	-0.436	0.663	0.002	0.151	0.880	0.002	0.319	0.750
HQLA	-0.004	-0.806	0.421	-0.027	-1.676	0.097	0.008	1.156	0.251
FNDC	0.000	0.790	0.430	-2.408	-1.575	0.119	-0.259	-0.593	0.555
RSDP	-0.013	-1.795	0.073	0.109	2.120	0.037 *	-0.026	-1.357	0.178
COREC	0.018	0.119	0.905	-0.112	-0.247	0.805	0.046	0.164	0.870
ABS	0.049	0.750	0.454	-0.131	-1.035	0.304	-0.006	-0.070	0.945
OBS	0.063	3.150	0.002 **	0.054	2.012	0.047 *	0.053	3.729	0.000 ***
ICG	0.007	1.639	0.102	0.031	1.696	0.093	0.001	0.204	0.839
DTRP	-0.003	-1.357	0.176	-0.009	-0.948	0.346	0.004	0.967	0.336
CAP	-0.005	-0.759	0.448	-0.017	-1.021	0.310	0.045	0.939	0.351
itcDC	0.111	3.023	0.003 **	0.259	2.426	0.017 *	-0.082	-1.492	0.139
R-sq. adj.	0.308			0.339			0.150		

*a) The difference in the results as regards FNDC between the full sample regression and the regressions for the largest and smallest banks is related to the presence of outliers. The other coefficients are not significantly affected by the outliers. When these outliers are removed from the sample the values of the coefficient of FNDC are closer to the one reported in the other regressions. These results are available upon request. ***, ** and * indicates statistical significance at respectively the 0.1, 1 and 5% levels.*

Table 3.d: baseline least squares analysis, all banks, largest and smallest 100 banks by total assets as at 2008:Q3 - CCR as dependent variables, H=4.

All banks (Including Large 8)				**Largest 100**			**Smallest 100**		
Regression 2.e									
Variable	Coeff.	T-stat.	p-value	Coeff.	T-stat.	p-value	Coeff.	T-stat.	p-value
Int	0.007	7.048	0.000 ***	0.030	4.316	0.000 ***	0.019	6.459	0.000 ***
HQLA	-0.009	-1.650	0.100	-0.008	-0.519	0.605	0.013	2.107	0.038 *
FNDC[a]	0.000	-1.580	0.115	-4.856	-3.495	0.001 ***	-1.232	-2.771	0.007 **
RSDP	0.000	-0.040	0.968	0.037	1.011	0.314	-0.033	-1.675	0.097
DTRP	0.007	4.402	0.000 ***	0.021	4.599	0.000 ***	-0.002	-0.987	0.326
R-sq. adj.	0.317			0.311			0.175		
Regression 2.f									
Variable	Coeff.	T-stat.	p-value	Coeff.	T-stat.	p-value	Coeff.	T-stat.	p-value
Int	-0.003	-0.973	0.331	0.001	0.061	0.951	0.007	1.603	0.112
HQLA	-0.006	-1.408	0.160	-0.025	-1.660	0.100	0.007	0.948	0.345
FNDC[a]	0.000	-0.392	0.695	-2.500	-1.747	0.084	-0.613	-1.270	0.207
RSDP	-0.018	-2.902	0.004 **	0.050	1.177	0.242	-0.022	-1.157	0.251
COREC	0.049	0.351	0.726	-0.278	-0.599	0.551	0.177	0.786	0.434
ABS	0.057	0.852	0.395	-0.094	-0.900	0.370	-0.048	-0.545	0.587
OBS	0.071	3.117	0.002 **	0.062	2.177	0.032 *	0.052	3.641	0.000 ***
ICG	0.009	2.199	0.028 *	0.027	1.587	0.116	0.000	0.089	0.930
DTRP	0.005	3.667	0.000 ***	0.016	3.148	0.002 **	-0.002	-0.996	0.322
R-sq. adj.	0.042			0.162			0.101		
Regression 2.g									
Variable	Coef.	T-stat.	p-value	Coef.	T-stat.	p-value	Coef.	T-stat.	p-value
Int	0.010	11.512	0.000 ***	0.026	4.563	0.000 ***	0.022	3.044	0.003 **
HQLA	0.003	0.847	0.397	0.008	0.764	0.447	0.016	1.847	0.068
FNDC	0.000	-0.157	0.875	-1.985	-2.629	0.010 *	-1.494	-2.236	0.028 *
RSDP	-0.004	-2.091	0.037 *	-0.017	-0.369	0.713	-0.032	-1.296	0.198
DTRP	-0.002	-0.270	0.788	-0.010	-0.598	0.551	-0.007	-0.844	0.401
itcDHQ	-0.042	-3.313	0.001 ***	-0.046	-1.391	0.168	-0.007	-0.558	0.578
itcDRS	0.080	2.891	0.004 **	0.100	1.595	0.114	0.002	0.037	0.970
itcDFC	-4.433	-4.606	0.000 ***	-5.777	-2.791	0.006 **	0.675	0.747	0.457
CAP	-0.011	-2.334	0.020 *	-0.029	-4.751	0.000 ***	-0.013	-0.294	0.769
itcDC	0.255	4.355	0.000 ***	0.428	3.169	0.002 **	0.010	0.188	0.851
R-sq. adj.	0.224			0.236			0.057		
Regression 2.h									
Variable	Coef.	T-stat.	p-value	Coef.	T-stat.	p-value	Coef.	T-stat.	p-value
Int	-0.002	-0.633	0.527	0.004	0.275	0.784	0.004	0.693	0.490
HQLA	-0.006	-1.422	0.156	-0.030	-1.766	0.081	0.008	1.042	0.300
FNDC	0.000	-0.224	0.823	-2.881	-1.856	0.067	-0.499	-1.067	0.289
RSDP	-0.016	-2.636	0.009 **	0.085	2.070	0.041 *	-0.019	-0.975	0.332
COREC	0.080	0.573	0.567	-0.039	-0.092	0.927	0.204	0.912	0.364
ABS	0.047	0.720	0.472	-0.128	-1.193	0.236	-0.026	-0.259	0.796
OBS	0.067	3.014	0.003 **	0.053	1.955	0.054	0.055	4.039	0.000 ***
ICG	0.008	1.951	0.052	0.031	1.884	0.063	0.000	0.097	0.923
DTRP	-0.006	-1.618	0.106	-0.019	-1.523	0.131	0.003	0.701	0.485
CAP	-0.005	-0.631	0.528	-0.025	-1.522	0.131	0.026	0.586	0.559
itcDC	0.130	2.444	0.015 *	0.345	2.516	0.014 *	-0.058	-1.095	0.276
R-sq. adj.	0.330			0.339			0.163		

*a) The difference in the results as regards FNDC between the full sample regression and the regressions for the largest and smallest banks is related to the presence of outliers. The other coefficients are not significantly affected by the outliers. When these outliers are removed from the sample the values of the coefficient of FNDC are closer to the one reported in the other regressions. These results are available upon request. ***, ** and * indicates statistical significance at respectively the 0.1, 1 and 5% levels.*

7. Results of the Quasi-Natural Exercise

Table 4.a to 4.d illustrate the results of the quasi-natural experiment. The main relationships between the explanatory variables and lending are confirmed, both in terms of statistical significance and signs with the exception of DTRP. As regards TGL, when the two samples of participating and declining banks are considered jointly in our regressions, DTRP is significant only when itcDC and CAP are added to the equation and once for H=2 in regression 2.f. The joint effect on lending is hence negative and statistically significant.

The main finding of the analysis of the random sampling exercise is that DTRP is very seldom significant and carries a slightly negative sign. It is possible to interpret the results in a probabilistic way. Once the self-selection bias and other major sources of bias (i.e. size, business models, risk profiles) are mitigated, there is low probability of an incentive effect of TARP funds. In the few cases of statistical significance, TARP banks seem to have decreased lending, vis-à-vis the banks declining government help. RSDP carries negative signs and it is statistically significant for most of the regressions, indicating that higher RSDP are related to reduced levels of lending. In regression 2.g, including the interaction term, RSDP is not statistically significant, potentially indicating that participating in TARP had no effect on RSDP: the negative sign is hence most likely independent from DTRP.

The other major relationships are largely confirmed, e.g. for HQLA and FNDC while ICG is now more informative on lending, possibly due to the fact that this variable captures differences across the sample that were not observed in the previous exercise. When controlling for other explanatory variables, ABS, OBS carry the expected signs. ABS, in particular, has highly probable and negative effect on lending. This confirms previous findings in this subject, such as described by Carbò-Valverde, Degryse and Rodriguez-Fernandez (2016). In addition, this effect may be partly related to the interactions between the amount of ABS in the balance sheet and the difficulty for banks exposed to ABS to refinance in the financial market, lacking eligible collateral. The Term Asset-Backed Securities Loan Facility of the Fed may have played a role in the results, which deserve further investigation.

Table 4.a: quasi-natural exp. - participating vs. declining banks using the sample of comparable banks, H=2.

Dependent variable: TGL

Regression 2.e

Variable	Coeff.	T-stat.	p-value
Int	0.719	39.450	0.000 ***
HQLA	0.288	7.419	0.000 ***
FNDC	12.156	4.014	0.000 ***
RSDP	-0.453	-3.447	0.001 ***
DTRP	-0.010	-0.969	0.333
R-sq. adj. 0.2102			

Regression 2.f

Variable	Coeff.	T-stat.	p-value
Int	0.681	25.644	0.000 ***
HQLA	0.251	6.618	0.000 ***
FNDC	15.406	4.936	0.000 ***
RSDP	-0.594	-4.577	0.000 ***
COREC	3.587	2.621	0.009 **
ABS	-2.045	-4.490	0.000 ***
OBS	0.082	1.139	0.256
ICG	0.096	3.214	0.001 **
DTRP	-0.018	-1.925	0.055
R-sq. adj.	0.3091		

Regression 2.g

Variable	Coef.	T-stat.	p-value
Int	0.758	16.714	0.000 ***
HQLA	0.312	5.902	0.000 ***
FNDC	15.751	3.897	0.000 ***
RSDP	-0.268	-1.362	0.174
DTRP	-0.009	-0.155	0.877
itcDHQ	-0.023	-0.296	0.767
itcDRS	-0.287	-1.066	0.287
itcDFC	-11.461	-1.864	0.063
CAP	-0.721	-1.859	0.064
itcDC	0.847	1.916	0.057
R-sq. adj.	0.2394		

Regression 2.h

Variable	Coef.	T-stat.	p-value
Int	0.764	18.236	0.000 ***
HQLA	0.254	6.726	0.000 ***
FNDC	13.417	4.132	0.000 ***
RSDP	-0.602	-4.611	0.000 ***
COREC	2.841	2.078	0.039 *
ABS	-2.112	-4.742	0.000 ***
OBS	0.073	1.015	0.311
ICG	0.100	3.221	0.001 **
CAP	-0.839	-2.343	0.020 *
itcDC	0.851	2.154	0.032 *
DTRP	-0.085	-2.771	0.006 **
R-sq. adj.	0.3267		

Dependent variable: CCR

Regression 2.e

Variable	Coef.	T-stat.	p-value
Int	0.019	8.273	0.000 ***
HQLA	-0.001	-0.311	0.756
FNDC	-1.463	-3.752	0.000 ***
RSDP	0.024	0.753	0.452
DTRP	0.001	0.461	0.645
R-sq. adj.	0.0495		

Regression 2.f

Variable	Coef.	T-stat.	p-value
Int	0.007	1.351	0.178
HQLA	-0.001	-0.171	0.864
FNDC	-0.582	-1.331	0.184
RSDP	0.010	0.428	0.669
COREC	0.198	1.531	0.127
ABS	0.109	1.588	0.113
OBS	0.036	1.982	0.049 *
ICG	0.004	1.297	0.196
DTRP	0.001	0.683	0.495
R-sq. adj.	0.2101		

Regression 2.g

Variable	Coef.	T-stat.	p-value
Int	0.026	6.968	0.000 ***
HQLA	-0.002	-0.221	0.825
FNDC	-1.865	-4.487	0.000 ***
RSDP	-0.028	-1.021	0.308
DTRP	-0.015	-2.719	0.007 **
itcDHQ	0.002	0.219	0.827
itcDRS	0.081	1.700	0.090
itcDFC	0.584	0.781	0.435
CAP	-0.053	-1.871	0.062
itcDC	0.141	3.745	0.000 ***
R-sq. adj.	0.0988		

Regression 2.h

Variable	Coef.	T-stat.	p-value
Int	0.008	1.456	0.147
HQLA	0.000	0.104	0.917
FNDC	0.199	1.531	0.127
RSDP	-0.679	-1.538	0.125
COREC	0.014	0.608	0.544
ABS	-0.004	-1.554	0.121
OBS	0.107	1.557	0.121
ICG	0.034	1.972	0.050 *
CAP	0.003	0.862	0.389
itcDC	-0.006	-0.263	0.793
DTRP	0.067	1.996	0.047 *
R-sq. adj.	0.226		

****, ** and * indicates statistical significance at respectively the 0.1, 1 and 5% levels. The two columns report the results of the four regressions using TGL as dependent variables, on the left hand side, and CCR on the right hand side, respectively.*

Table 4.b: quasi-natural exp. - participating vs. declining banks using the sample of comparable banks, H=4.

Dependent variable: TGL

Regression 2.e

Variable	Coeff.	T-stat.	p-value	
Int	0.709	38.933	0.000	***
HQLA	0.289	7.098	0.000	***
FNDC	13.380	4.130	0.000	***
RSDP	-0.425	-3.333	0.001	***
DTRP	-0.010	-1.045	0.297	
R-sq. adj.	0.2068			

Regression 2.f

Variable	Coeff.	T-stat.	p-value	
Int	0.669	26.619	0.000	***
HQLA	0.256	6.344	0.000	***
FNDC	17.422	5.302	0.000	***
RSDP	-0.569	-4.338	0.000	***
COREC	2.598	2.289	0.023	*
ABS	-2.858	-4.356	0.000	***
OBS	0.095	1.422	0.156	
ICG	0.101	3.016	0.003	**
DTRP	-0.018	-1.950	0.052	
R-sq. adj.	0.295			

Regression 2.g

Variable	Coef.	T-stat.	p-value	
Int	0.749	16.964	0.000	***
HQLA	0.310	5.327	0.000	***
FNDC	17.237	3.959	0.000	***
RSDP	-0.184	-1.050	0.295	
DTRP	0.016	0.271	0.786	
itcDHQ	-0.024	-0.306	0.760	
itcDRS	-0.418	-1.747	0.082	
itcDFC	-13.705	-2.096	0.037	*
CAP	-0.776	-2.104	0.036	*
itcDC	0.679	1.582	0.115	
R-sq. adj.	0.2518			

Regression 2.h

Variable	Coef.	T-stat.	p-value	
Int	0.768	19.033	0.000	***
HQLA	0.260	6.658	0.000	***
FNDC	14.776	4.201	0.000	***
RSDP	-0.599	-4.657	0.000	***
COREC	1.638	1.414	0.159	
ABS	-2.836	-4.253	0.000	***
OBS	0.086	1.297	0.196	
ICG	0.109	3.219	0.001	**
CAP	-0.972	-2.882	0.004	**
itcDC	0.835	2.140	0.033	*
DTRP	-0.084	-2.630	0.009	**
R-sq. adj.	0.3227			

Dependent variable: CCR

Regression 2.e

Variable	Coef.	T-stat.	p-value	
Int	0.018	8.935	0.000	***
HQLA	-0.005	-0.955	0.341	
FNDC	-1.583	-4.079	0.000	***
RSDP	0.007	0.241	0.810	
DTRP	0.000	0.412	0.681	
R-sq. adj.	0.0519			

Regression 2.f

Variable	Coef.	T-stat.	p-value	
Int	0.007	1.407	0.161	
HQLA	-0.004	-0.968	0.334	
FNDC	-0.676	-1.541	0.124	
RSDP	-0.007	-0.301	0.763	
COREC	0.200	1.517	0.130	
ABS	0.076	0.954	0.341	
OBS	0.036	1.946	0.053	
ICG	0.004	1.213	0.226	
DTRP	0.001	0.617	0.537	
R-sq. adj.	0.2135			

Regression 2.g

Variable	Coef.	T-stat.	p-value	
Int	0.027	6.626	0.000	***
HQLA	-0.003	-0.363	0.717	
FNDC	-2.004	-4.551	0.000	***
RSDP	-0.045	-1.791	0.075	
DTRP	-0.019	-3.172	0.002	**
itcDHQ	-0.006	-0.594	0.553	
itcDRS	0.082	1.905	0.058	
itcDFC	0.560	0.743	0.458	
CAP	-0.059	-1.933	0.054	
itcDC	0.154	3.257	0.001	**
R-sq. adj.	0.0911			

Regression 2.h

Variable	Coef.	T-stat.	p-value	
Int	0.008	1.431	0.154	
HQLA	-0.004	-0.983	0.326	
FNDC	-0.766	-1.711	0.088	
RSDP	-0.004	-0.168	0.867	
COREC	0.222	1.657	0.099	
ABS	0.073	0.937	0.350	
OBS	0.035	1.929	0.055	
ICG	0.003	1.004	0.316	
CAP	-0.011	-0.429	0.668	
itcDC	0.079	1.942	0.053	
DTRP	-0.006	-1.697	0.091	
R-sq. adj.	0.2244			

****, ** and * indicates statistical significance at respectively the 0.1, 1 and 5% levels. The two columns report the results of the four regressions using TGL as dependent variables, on the left hand side, and CCR on the right hand side, respectively.*

Table 4.c: quasi-natural exp. - participating vs. declining banks - random sampling exercise, H=2.

TGL dep. var.	*	**	***	Sum of %	Average coeff.
Regression 2.e					
Int	0%	0%	100%	100%	0.723
HQLA	3%	20%	76%	99%	0.288
FNDC	28%	25%	16%	69%	11.668
RSDP	24%	23%	19%	66%	-0.495
DTRP	8%	2%	0%	10%	-0.009
Regression 2.f					
Int	0%	0%	100%	100%	0.673
HQLA	5%	26%	68%	99%	0.258
COREC	15%	12%	10%	37%	3.551
FNDC	16%	32%	49%	97%	15.888
RSDP	18%	23%	47%	88%	-0.645
DTRP	10%	6%	1%	17%	-0.017
ABS	15%	24%	36%	75%	-2.008
ICG	12%	12%	5%	29%	0.127
OBS	25%	15%	6%	46%	0.093
Regression 2.g					
Int	0%	0%	90%	90%	0.762
HQLA	17%	13%	34%	64%	0.280
FNDC	18%	20%	14%	52%	14.503
RSDP	5%	2%	1%	8%	-0.176
DTRP	2%	0%	0%	2%	-0.015
itcDHQ	1%	0%	0%	1%	0.011
itcDRS	7%	6%	0%	13%	-0.358
itcDFC	10%	7%	0%	17%	-9.986
CAP	15%	7%	2%	24%	-0.782
itcDC	12%	7%	1%	20%	0.923
Regression 2.h					
Int	0%	0%	94%	94%	0.738
HQLA	6%	25%	62%	93%	0.241
COREC	12%	4%	1%	17%	2.325
FNDC	18%	29%	36%	83%	15.481
RSDP	19%	27%	27%	73%	-0.583
DTRP	23%	12%	3%	38%	-0.086
ABS	13%	22%	50%	85%	-2.184
ICG	20%	14%	7%	41%	0.203
OBS	17%	21%	3%	41%	0.101
CAP	20%	12%	2%	34%	-0.939
itcDC	17%	9%	0%	26%	0.877

CCR dep. var.	*	**	***	Sum of %	Average coeff.
Regression 2.e					
Int	0%	3%	96%	99%	0.018
HQLA	3%	0%	0%	3%	-0.002
FNDC	21%	39%	12%	72%	-1.421
RSDP	2%	0%	0%	2%	0.017
DTRP	3%	0%	0%	3%	0.001
Regression 2.f					
Int	15%	8%	4%	27%	0.001
HQLA	3%	0%	0%	3%	0.000
COREC	6%	0%	1%	7%	0.191
FNDC	11%	1%	0%	12%	-0.145
RSDP	0%	0%	0%	0%	-0.001
DTRP	4%	0%	0%	4%	0.001
ABS	18%	5%	1%	24%	0.129
ICG	3%	1%	64%	68%	0.056
OBS	5%	2%	0%	7%	0.003
Regression 2.g					
Int	6%	16%	60%	82%	0.026
HQLA	4%	1%	0%	5%	-0.004
FNDC	16%	23%	23%	62%	-1.818
RSDP	7%	2%	0%	9%	-0.041
DTRP	15%	10%	5%	30%	-0.015
itcDHQ	2%	0%	0%	2%	0.006
itcDRS	11%	4%	2%	17%	0.070
itcDFC	6%	1%	2%	9%	0.715
CAP	15%	6%	3%	24%	-0.059
itcDC	18%	22%	12%	52%	0.142
Regression 2.h					
Int	14%	3%	2%	19%	0.002
HQLA	1%	0%	0%	1%	0.001
COREC	5%	2%	0%	7%	0.203
FNDC	6%	4%	0%	10%	-0.189
RSDP	5%	1%	0%	6%	0.001
DTRP	5%	4%	0%	9%	-0.003
ABS	9%	3%	2%	14%	0.117
ICG	2%	1%	65%	68%	0.057
OBS	3%	0%	0%	3%	0.002
CAP	2%	0%	0%	2%	-0.006
itcDC	12%	5%	0%	17%	0.053

*The table reports the percentage of occurrences for which each explanatory variable was statistically significant in 100 regressions run. The column "sum of %" illustrates the cumulative sum of occurrences for which an explanatory variable has been found statistically significant, with p-values below 0.05 or below. The column "average coefficient" indicates the average of the coefficient for each explanatory variable obtained in repeated trials. ***, ** and * indicates statistical significance at respectively the 0.1, 1 and 5% levels.*

Table 4.d: quasi-natural exp. - participating vs. declining banks - random sampling exercise, H=4.

TGL dep. var.	*	**	***	Sum of %	Average coeff.
Regression 2.e					
Int	0%	0%	100%	100%	0.710
HQLA	2%	23%	74%	99%	0.292
FNDC	36%	16%	21%	73%	13.139
RSDP	20%	19%	18%	57%	-0.407
DTRP	5%	2%	1%	8%	-0.009
Regression 2.f					
Int	0%	0%	100%	100%	0.652
HQLA	5%	18%	75%	98%	0.260
COREC	21%	10%	7%	38%	2.861
FNDC	8%	29%	60%	97%	18.290
RSDP	22%	22%	32%	76%	-0.545
DTRP	12%	5%	2%	19%	-0.017
ABS	14%	31%	45%	90%	-2.899
ICG	11%	17%	3%	31%	0.171
OBS	29%	9%	3%	41%	0.094
Regression 2.g					
Int	0%	0%	90%	90%	0.765
HQLA	7%	12%	47%	66%	0.294
FNDC	16%	25%	10%	51%	14.757
RSDP	7%	4%	1%	12%	-0.264
DTRP	0%	0%	0%	0%	-0.010
itcDHQ	3%	0%	0%	3%	0.008
itcDRS	5%	3%	1%	9%	-0.273
itcDFC	12%	3%	0%	15%	-10.959
CAP	12%	2%	2%	16%	-0.773
itcDC	12%	3%	0%	15%	0.881
Regression 2.h					
Int	0%	0%	94%	94%	0.733
HQLA	4%	10%	78%	92%	0.254
COREC	10%	5%	7%	22%	2.850
FNDC	15%	37%	31%	83%	15.518
RSDP	19%	25%	32%	76%	-0.603
DTRP	22%	8%	3%	33%	-0.080
ABS	9%	20%	53%	82%	-2.118
ICG	21%	15%	11%	47%	0.207
OBS	29%	23%	7%	59%	0.105
CAP	24%	8%	3%	35%	-0.878
itcDC	12%	3%	2%	17%	0.792

CCR dep. var.	*	**	***	Sum of %	Average coeff.
Regression 2.e					
Int	0%	1%	99%	100%	0.018
HQLA	3%	2%	0%	5%	-0.006
FNDC	31%	26%	26%	83%	-1.562
RSDP	7%	1%	0%	8%	-0.007
DTRP	7%	0%	0%	7%	0.000
Regression 2.f					
Int	15%	17%	10%	42%	0.003
HQLA	4%	0%	0%	4%	-0.004
COREC	14%	5%	0%	19%	0.265
FNDC	11%	9%	2%	22%	-0.389
RSDP	13%	1%	0%	14%	-0.018
DTRP	5%	0%	0%	5%	0.000
ABS	8%	1%	0%	9%	0.080
ICG	3%	2%	54%	59%	0.050
OBS	8%	2%	1%	11%	0.004
Regression 2.g					
Int	6%	22%	56%	84%	0.028
HQLA	6%	2%	0%	8%	-0.007
FNDC	19%	21%	28%	68%	-2.109
RSDP	10%	4%	2%	16%	-0.058
DTRP	21%	20%	7%	48%	-0.021
itcDHQ	4%	0%	0%	4%	0.000
itcDRS	18%	10%	4%	32%	0.081
itcDFC	3%	5%	1%	9%	0.896
CAP	15%	6%	4%	25%	-0.069
itcDC	26%	20%	7%	53%	0.162
Regression 2.h					
Int	5%	9%	0%	14%	0.002
HQLA	3%	0%	0%	3%	-0.003
COREC	7%	4%	0%	11%	0.255
FNDC	9%	3%	0%	12%	-0.245
RSDP	6%	2%	0%	8%	-0.008
DTRP	6%	3%	0%	9%	-0.004
ABS	8%	6%	0%	14%	0.124
ICG	3%	1%	66%	70%	0.058
OBS	2%	2%	1%	5%	0.002
CAP	1%	1%	0%	2%	-0.004
itcDC	5%	4%	0%	9%	0.055

*The table reports the percentage of occurrences for which each explanatory variable was statistically significant in 100 regressions run. The column "sum of %" illustrates the cumulative sum of occurrences for which an explanatory variable has been found statistically significant, with p-values below 0.05 or below. The column "average coefficient" indicates the average of the coefficient for each explanatory variable obtained in repeated trials. ***, ** and * indicates statistical significance at respectively the 0.1, 1 and 5% levels.*

The results of the regressions on CCR highlight that the model is less informative. The only statistically significant explanatory variables are FNDC and ICG. Overall DTRP emerges as more informative for CCR, but the impact on CCR cannot easily be disentangled as it has to be estimated as the combined effects of the interaction terms and DTRP. The results indicate that an increase in the income gap signals an increase in credit commitments, while the opposite is true for FNDC. The role of ICG may be signalling that an increase in the gap between short term assets and liabilities allows banks to extend CCRs. Since CCRs will become on-balance sheet assets, once drawn, it is possible that banks characterized by higher ICG, i.e. that are faster to reprice their assets to changes in interest rates, are willing to extend more CCRs. FNDC is likely related to the fact that an increase in funding costs discourages banks from extending CCRs, as it could be expected.

At last, we run a set of repeated random trials for robustness check. The results of tables 4.c and 4.d support by and large the previous findings that CCR and TGL carry significant differences. Overall, the results can be interpreted as a probability analysis to the regressions and strengthen the findings of the previous analysis. The liquidity indicators are identified as statistically significant in the large majority of regressions for TGL, while ABS, OBS and ICG are confirmed as informative for lending. The TARP dummy is not often statistically significant, as previously.

7. Conclusions

This study investigates the effects of the TARP and in particular of the CPP on bank lending and their interactions with other measures mostly affecting the liquidity of US bank holding companies. We make use of both on- and off-balance sheet ratios to investigate this issue and we include a number of liquidity ratios and interaction terms to investigate how these effects are joint and depend on common movements of the explanatory variables.

First, the analysis investigates a broad sample of banks including banks that accepted the CPP either voluntarily or not. We find important differences between larger and smaller banks. The former are more sensitive to the measures of QE (RSDP) implemented by the Fed, as expected. The results also indicate that for larger banks the TARP led to an increase in TGL, although the evidence is weak when interactions are added. Moreover, it appears that DTRP is significant mostly for shorter horizons, i.e. H=2. Hence the effects of TARP seemed to be short-lasting on TGL. CAP has the expected negative sign and supports the theory of Calomiris (2012), where capital is used to adjust lending in a risk-weighted asset framework. When using CCR as dependent variable, DTRP is statistically significant and positive when using baseline equations. When interactions are added, the interaction between the capital ratio and the DTRP becomes significant. This may signal that banks receiving TARP funds which also increased further capital increased their CCRs.

In a second step, we try to remove the self-selection bias that taint the analysis when considering banks that accepted the TARP experience lower regulatory capital surplus, which affect their lending behaviour. Once the sample shrinks to exclude this bias, the results indicate that while liquidity still plays a significant role in shaping bank lending, the TARP measures emerge as less relevant overall, as DTRP, the dummy variable used in the study to identify TARP participants is seldom significant.

The difference in results between the baseline and the comparable sample analysis might be explained as evidence that the biases removed from the second exercise drive the results of the first analysis. This carries a first important policy message. The efficacy of the TARP intervention was most likely influenced by the characteristics of the banks receiving funds: banks with lower regulatory surpluses, lower lending volumes and higher funding costs (i.e. the banks that were removed in the comparable sample exercise) that received the TARP seem to have increased lending, while banks that received TARP funds but had no need for it, accepted the funds likely as a precautionary measure. This highlights the importance for the policy maker to define accurately the conditions for accessing the funds to avoid unnecessary costs.

Another lesson that can be drawn from the analysis focuses on the role of potentially diverging policy measures (such as in our case, the Fed payment of interests on reserves and the CPP of the US Government). The results indicate that the measures may have obtained diverging effects on lending as RSDP is often statistically significant in most regressions. While there is likely no causal relationship between reserves and lending, as explained by Keister and McAndrews (2009), it is likely that positive interests on reserves have created wrong incentive for banks to lend to the real economy. This might have been exacerbated by the stressful macroeconomic conditions present in the US after the default of Lehman. In this respect, policy makers should play particular attention in setting measures that have potential interaction effects and that can be affected by the macroeconomic environment.

Other factors play a significant role in defining lending. ABS is statistically significant with negative sign, by and large confirming that the opacity of risky asset-backed securities played a significant and negative role in lending to the real economy. This study focuses on micro-behaviours of banks and hence do not consider other macroeconomic aspects that have played a role in lending in the US in the aftermath of the subprime crisis and that could be therefore investigated more in depth.

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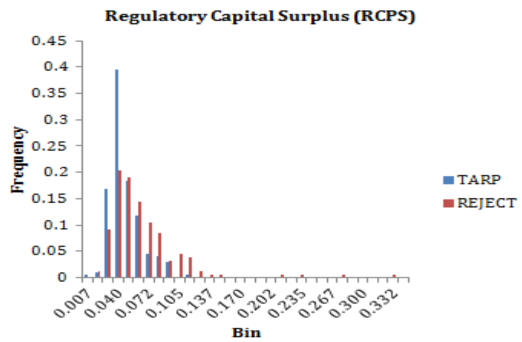
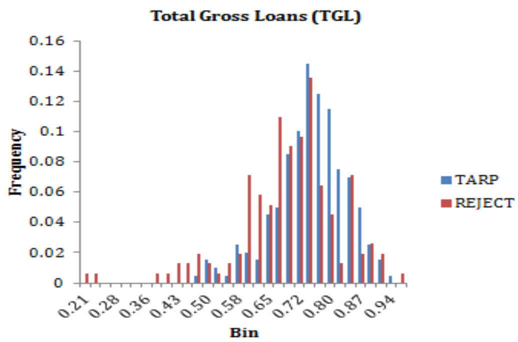
Appendix A: Sample Statistics and Correlations

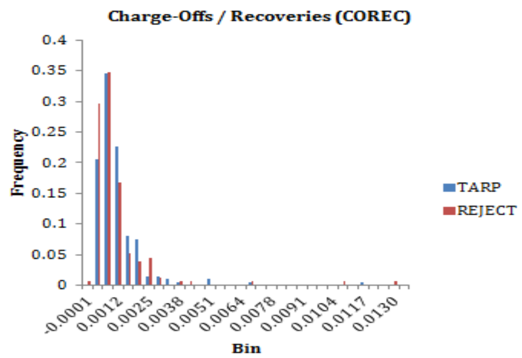
	ABS	*ROE*	*COREC*	*RSDP*	*RSCP*	*CAP*	*FNDC*	*HQLA*	*ICG*	*TGL*	*UCCR*	*CCR*
Mean	0.004	0.229	-0.005	0.087	0.000	0.089	0.056	-0.185	0.057	0.666	-0.006	0.012
Standard Error	0.001	0.301	0.010	0.023	0.000	0.002	0.042	0.006	0.008	0.005	0.001	0.001
Median	0.000	0.007	0.003	0.037	0.002	0.088	0.005	-0.164	0.054	0.688	-0.005	0.006
Standard Deviati	0.013	7.270	0.230	0.565	0.012	0.048	1.006	0.143	0.184	0.132	0.036	0.017
Sample Variance	0.000	52.854	0.053	0.319	0.000	0.002	1.013	0.020	0.034	0.018	0.001	0.000
Kurtosis	96.048	575.369	584.211	502.215	22.995	67.553	512.507	6.549	0.893	4.999	255.917	35.451
Skewness	8.256	23.883	-24.162	21.802	-2.675	5.323	22.236	-1.612	-0.112	-1.754	9.051	4.818
Range	0.189	184.093	5.631	13.206	0.174	0.796	23.544	1.343	1.253	0.909	1.055	0.195
Minimum	0.000	-9.048	-5.563	0.000	-0.090	-0.034	-0.005	-1.212	-0.570	0.028	-0.379	0.000
Maximum	0.189	175.045	0.068	13.206	0.084	0.762	23.539	0.131	0.683	0.937	0.675	0.195
Sum	2.129	134.207	-2.694	51.180	-0.110	52.071	32.767	-108.249	33.273	389.721	-3.445	6.785

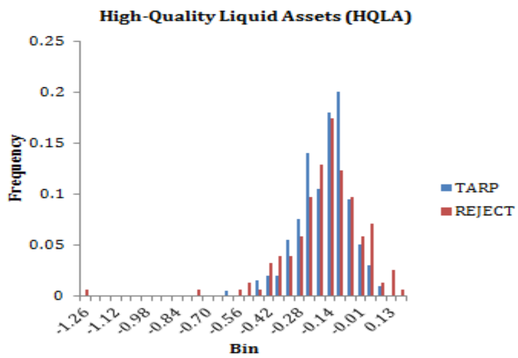
	ABS	*ROE*	*COREC*	*RSDP*	*RSCP*	*CAP*	*FNDC*	*HQLA*	*ICG*	*TGL*	*UCCR*	*CCR*
ABS	1.000											
ROE	-0.013	1.000										
COREC	0.004	-0.996	1.000									
RSDP	-0.007	-0.001	0.003	1.000								
RSCP	-0.123	-0.197	0.191	0.013	1.000							
CAP	-0.049	-0.077	0.080	-0.069	0.299	1.000						
FNDC	-0.015	-0.002	0.004	0.001	0.014	0.254	1.000					
HQLA	-0.216	-0.106	0.102	-0.092	0.023	0.113	-0.021	1.000				
ICG	0.076	-0.064	0.068	0.186	0.137	0.200	0.018	-0.099	1.000			
TGL	-0.283	-0.054	0.051	-0.271	-0.090	-0.220	-0.044	0.356	-0.123	1.000		
UCCR	0.059	-0.015	0.000	-0.039	0.024	-0.031	0.005	0.078	-0.157	0.008	1.000	
CCR	0.114	-0.001	0.004	-0.021	0.126	0.100	-0.025	-0.055	0.271	-0.076	-0.012	1.000

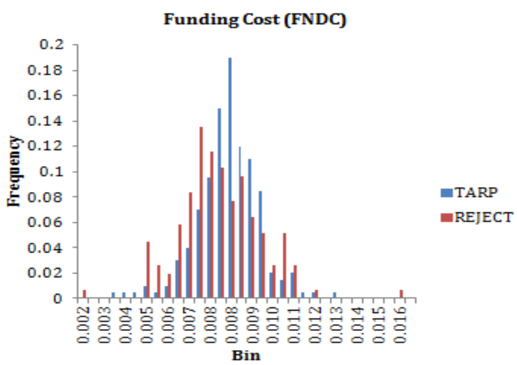
Appendix B: distributions of selected ratios for baseline sample of banks

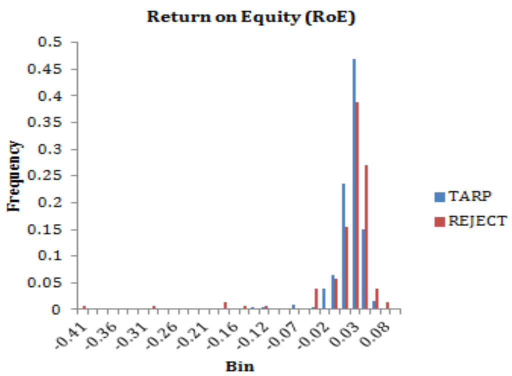


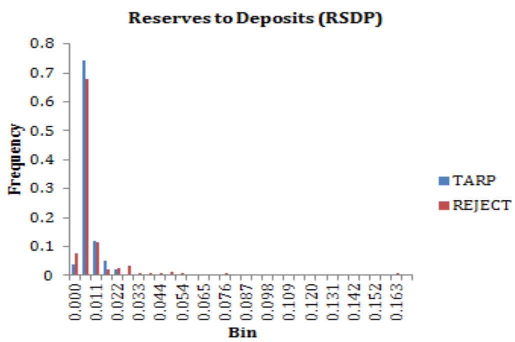


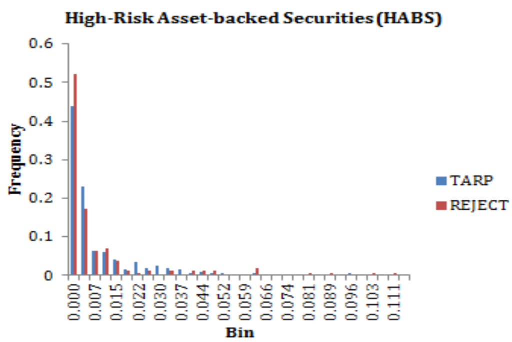


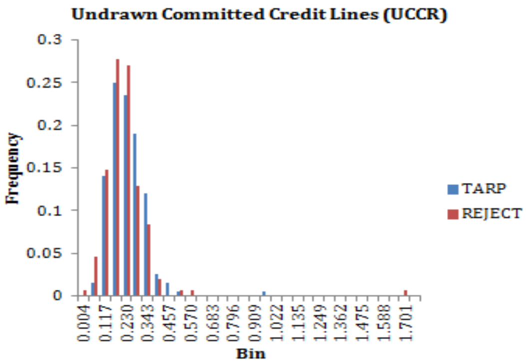


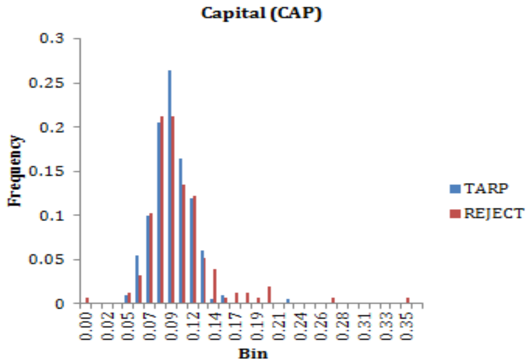


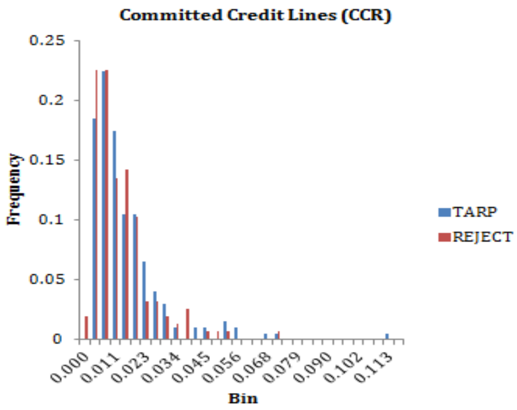


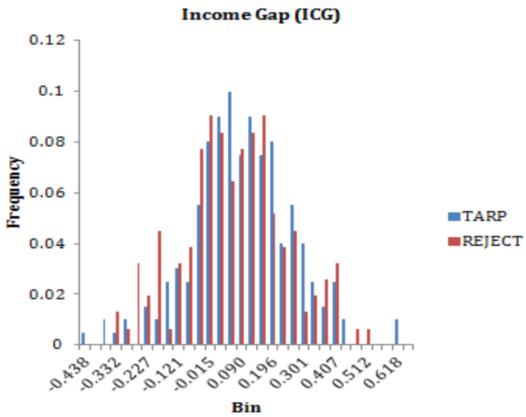




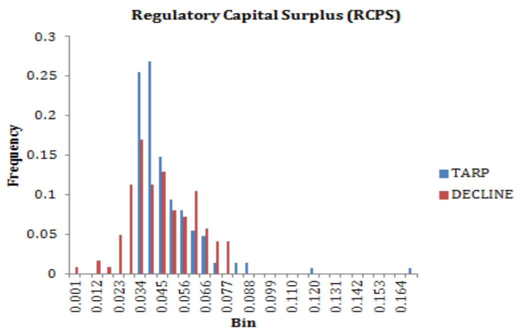


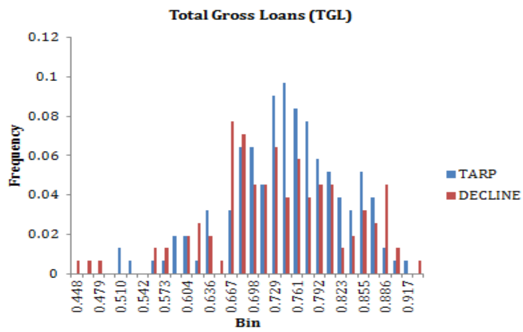


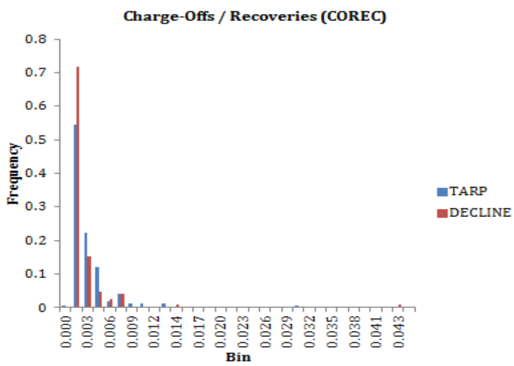


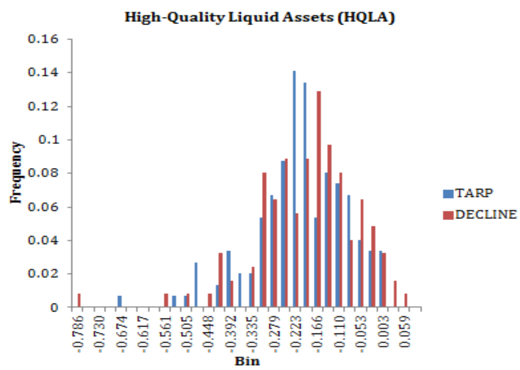


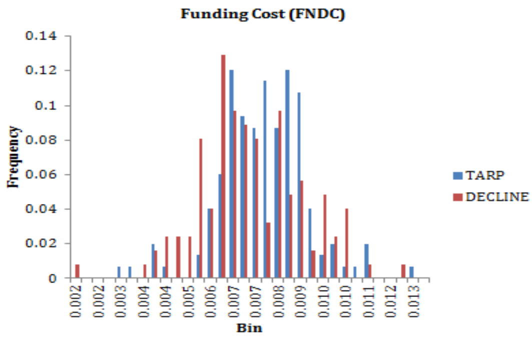
Appendix C: distributions of selected ratios for adjusted sample of banks

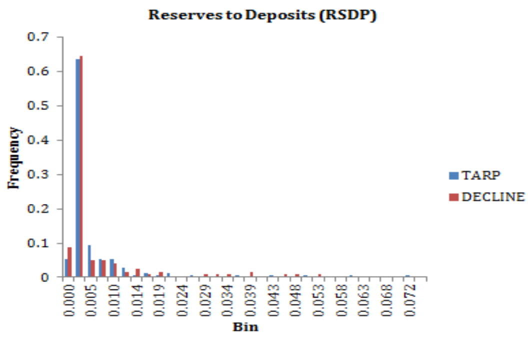


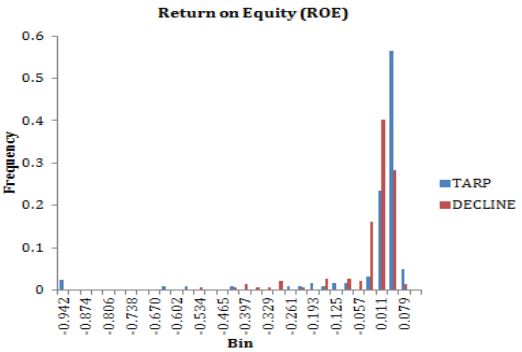


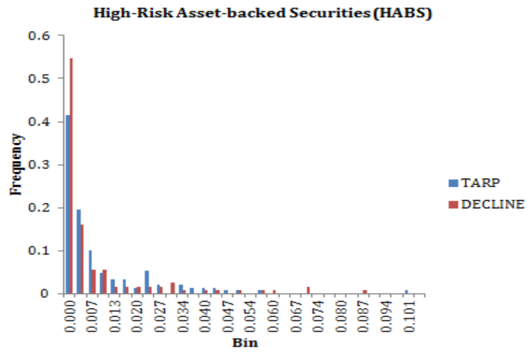


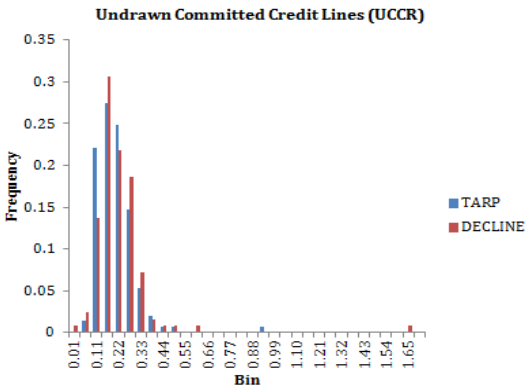


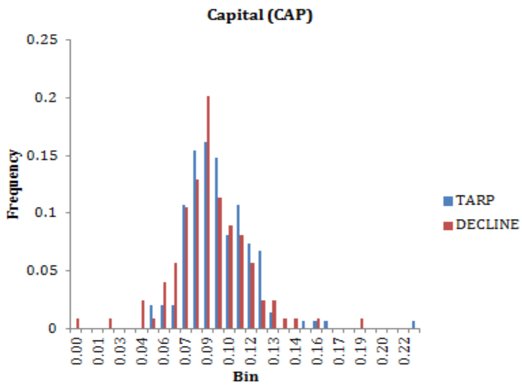

Funding Cost (FNDC)
Frequency
Bin
TARP
DECLINE

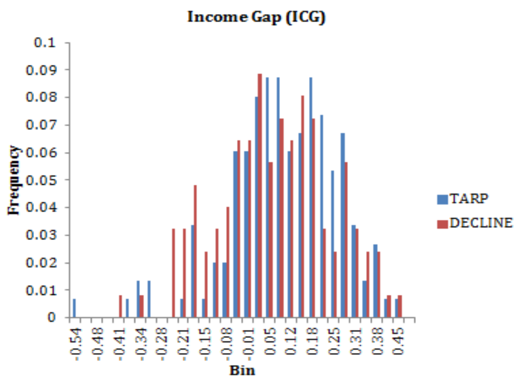

Reserves to Deposits (RSDP)
Frequency
Bin
TARP
DECLINE

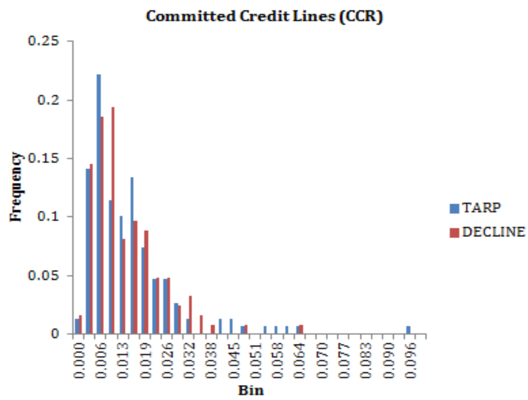

Return on Equity (ROE)
Frequency
Bin
TARP
DECLINE


High-Risk Asset-backed Securities (HABS)
Frequency
Bin
TARP
DECLINE


Undrawn Committed Credit Lines (UCCR)
Frequency
Bin
TARP
DECLINE


Capital (CAP)
Frequency
Bin
TARP
DECLINE


Income Gap (ICG)
Frequency
Bin
TARP
DECLINE


Committed Credit Lines (CCR)
Frequency
Bin
TARP
DECLINE

Appendix D: sample statistics of the random sampling exercise

FULL SAMPLE

Participating Banks

	RCPS	CAP	TGL	CCR	HQLA	FNDC	RSDP	COREC	ABS	OBS	ICG	ROE
average	0.042	0.089	0.737	0.013	-0.190	0.008	0.004	0.0009	0.007	0.205	0.077	0.015
St. Dev.	0.017	0.021	0.087	0.014	0.117	0.001	0.010	0.0011	0.013	0.096	0.171	0.023
Kurtosis	2.237	6.397	0.657	15.170	0.828	1.624	47.386	39.1207	12.393	16.599	0.809	15.809
Skewness	1.374	1.215	-0.644	3.151	-0.639	-0.248	6.030	5.1505	2.992	2.548	-0.065	-3.170

Declining Banks

	RCPS	CAP	TGL	CCR	HQLA	FNDC	RSDP	COREC	ABS	OBS	ICG	ROE
average	0.062	0.098	0.685	0.011	-0.189	0.008	0.006	0.0009	0.008	0.194	0.048	0.012
St. Dev.	0.042	0.038	0.123	0.011	0.171	0.002	0.017	0.0015	0.019	0.149	0.176	0.056
Kurtosis	15.941	14.512	2.176	6.130	9.594	2.221	52.344	37.6470	12.175	68.134	-0.176	28.678
Skewness	3.365	2.830	-0.955	2.073	-1.925	0.465	6.307	5.5670	3.370	6.924	0.029	-4.877

COMPARABLE SAMPLE

Participating Banks

	RCPS	CAP	TGL	CCR	HQLA	FNDC	RSDP	COREC	ABS	OBS	ICG	ROE
average	0.044	0.091	0.739	0.013	-0.222	0.008	0.004	0.0022	0.008	0.182	0.079	-0.035
St. Dev.	0.017	0.022	0.080	0.014	0.118	0.001	0.010	0.0032	0.014	0.097	0.168	0.102
Kurtosis	19.684	6.749	0.471	10.502	1.312	1.686	21.691	38.0144	13.226	23.519	1.071	9.125
Skewness	3.532	1.626	-0.551	2.691	-0.785	-0.109	4.364	5.1383	3.044	3.442	-0.716	-3.003

Declining Banks

	RCPS	CAP	TGL	CCR	HQLA	FNDC	RSDP	COREC	ABS	OBS	ICG	ROE
average	0.042	0.085	0.728	0.012	-0.206	0.007	0.005	0.0017	0.007	0.200	0.045	-0.019
St. Dev.	0.016	0.024	0.094	0.010	0.129	0.002	0.010	0.0042	0.016	0.157	0.175	0.135
Kurtosis	-0.517	2.764	0.273	4.722	2.803	0.349	9.686	81.1328	9.049	59.295	-0.414	23.651
Skewness	0.165	0.314	-0.329	1.766	-1.011	0.120	3.119	8.3642	2.960	6.620	-0.152	-4.545

Chapter 6

Conclusions

Macro stress tests have become popular amongst investors and supervisors, but their role is still debated. Some argue that it is mostly a tool to inform investors and hence full disclosure of results to financial markets should always be preferred; some others see macro stress tests as a supervisory tool that should be used to address potential shortcomings in the banking sector. Macro stress tests have generated debates and controversies but their role to identify weaknesses in the banking sector cannot easily be replaced. Given the relevance of stress tests in financial markets, it is therefore a duty for academic and practitioners to strengthen their framework, to isolate them from political pressures and to develop robust methodologies enabling stress tests to fulfil their role for micro and macro supervision.

This study investigated several aspects related to macro stress tests and the behaviours of banks in times of crisis. The idea behind this analysis lies mostly on the fact that macroeconomic crises offer many insights on a feature that is major in stress testing: the identification of a severe but plausible scenario. Past episodes of macroeconomic stress are often used as references to construct hypothetical scenarios to be applied to stress testing exercises. Understanding the dynamics of these past occurrences is then critical to the modelling and to the interpretation of the results of stress tests. In this respect, the richness of the dataset allowed for an extensive coverage of different crisis episodes as well as aspects of risk and business of banks, including regulatory aspects and its evolution (e.g. from pre-Basel until Basel II). Hence, while the analysis focuses on the US banking sector, its external validity is larger and can be extended to the major OECD banking sectors.

The findings highlight the importance of profitability in developing sound stress testing methodologies. First, the study brings forward the importance of profits for a sound banking sector. The joint analysis of profitability and stress testing has been rather neglected so far, both at academic and practitioner levels. The results of this study demonstrate that low profitability both at individual and aggregate bank levels is the "canary in the mine" of broader issues and should attract closer supervisory scrutiny. More, sound practices for stress testing should always integrate risks to profitability, also given the impact of losses on solvency and liquidity.

The analysis attempts to develop a methodology, based on a dynamic factor model, that integrates measures of profitability into a comprehensive stress testing framework. The model, while investigating return on assets and its subcomponents, proves to be fit for stress testing purposes and it is flexible enough to be able to define several scenarios, which can be applied to forecast profitability indicators under stress. The study further demonstrates that these forecasts capture important macro and microeconomic information concerning the business models and risk profiles of banks.

The model developed has several practical applications, as it can be implemented to assess the impact of a predefined macroeconomic scenarios, or in a more parsimonious way, where the stress tester has specific expectations concerning one or more macroeconomic variables. In addition, when investigating the responses of banks to a specific shock, the model allows to identify weaker banks; hence, supervisors can focus resources on those banks that are more vulnerable.

The solvency and liquidity channel emerges as important for the transmission of shocks, as expected. The findings illustrate the importance of solvency risk in the transmission of shocks to liquidity indicators. While supporting existing theories on the solvency-liquidity nexus, the results highlight also that these effects are not constant and depend on the underlying macroeconomic conditions. At last, while investigating specific crisis triggers, i.e. the default of Lehman Brothers, the analysis sheds some light on the interactions between the different policy interventions of the Federal Reserve and of the US Government. The results indicate that the quantitative easing operations of the Federal Reserve and the Troubled Asset Relief Program of the US Government created some diverging incentive in the US banking sector. In particular, when reducing the self-selection bias in a quasi-natural framework, the effects of the capital injections on bank lending is weak.

Several aspects related to macro stress test have not been discussed in this study, and remain open to further investigation. A number of studies provide with lists of shortcomings to which academics and practitioners should pay more attention in their design of stress tests. In particular, episodes of crisis trigger responses in micro and macroeconomic variables that are non-linear in their behaviour. These effects are particularly relevant in stress test, since these exercises are assumed to model the dynamics of micro and macroeconomic variables in times of stress, when non-linear dynamics are likely to occur. In addition, contagion effects among banks and other financial markets' players (e.g. the shadow banking sector) have been identified as a key feature whose dynamics are still largely unexplored, particularly due to the globalized system of relationships that requires a wide access to data for in-depth analysis.

Eventually, and possibly the most important shortcoming lies outside of stress tests and relates to the efficacy of the policies implemented as results of stress testing exercises. This study, along with few others, reflects on the effectiveness of policy interventions that are often the outcome of stress tests, i.e. recapitalization of banks. As stress tests can be improved, so can our understanding of how public money is used for interventions aimed to restore financial stability.

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Franco STRAGIOTTI

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UNIVERSITE CATHOLIQUE DE LOUVAIN

Louvain School of Management

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du grade de Docteur
en sciences économiques et de gestion

Membres du Jury :

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