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Strategic complementarity in banks' funding liquidity choices and financial stability

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Abstract

This paper examines whether banks' liquidity and maturity mismatch decisions are affected by the choices of competitors and the impact of these coordinated funding liquidity policies on financial stability. Using a novel identification strategy where interactions are structured through decision networks, I show that banks do consider their peers' liquidity choices when determining their own. This effect is asymmetric and not present in bank capital choices. Importantly, I find that these strategic funding liquidity decisions increase both individual banks' default risk and overall systemic risk. From a macroprudential perspective, the results highlight the importance of explicitly regulating systemic liquidity risk.

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Keywords: funding liquidity risk, financial stability, macroprudential policy

1. Introduction

Until very recently the funding liquidity risk of financial institutions has received very little attention from regulators and policymakers, even though excessive maturity and liquidity mismatches were one of the main causes of the recent global financial crisis (Tirole, 2011). In fact, by funding their lending activities using a much broader range of liabilities, banks became fragile not only to bank runs (Diamond and Dybvig, 1983), but also to the risk of a drying up of funds in wholesale markets (Huang and Ratnovski, 2011). The problem was further exacerbated by higher interconnectedness and common exposures on both the asset and liability sides of their balance-sheets which resulted in idiosyncratic shocks propagating to the entire financial system (Farhi and Tirole, 2012). Ultimately, due to increased complexity of the banking system, liquidity risk is now inherently systemic since funding arrangements connect banks with other financial institutions and the non-financial sector i.e., one agent's liquid asset is another agent's liquid liability (Hardy and Hochreiter, 2014).

To confront this issue, an adequate regulatory mechanism should be in place to prevent banks from being "too interconnected to fail" and thus reduce the likelihood of a system-wide liquidity strain occurring. However, the recently proposed liquidity rules such as the Basel III Liquidity Coverage Ratio (LCR) and Net Stable Funding Ratio (NSFR) may only play a limited role in addressing such systemic liquidity risk problems as they target individual banks and abstract from the additional risk of simultaneous liquidity shortfalls due to interconnections between them (IMF, 2011). In addition, despite the prominent theoretical literature on the consequences that excessive liquidity risk may have for the economy (e.g., Diamond and Rajan, 2001, 2005; Allen and Gale, 2004a, 2004b), as well as the adverse effects that strategic risk-taking behavior and common exposures may entail for financial stability (e.g., Ratnovski, 2009; Allen et al., 2012; Farhi and Tirole, 2012; Vives, 2014), there is surprisingly little empirical evidence on this issue. This paper aims to fill this gap in the literature by assembling a unique bank ownership database, using this distinctive source of information to provide a rigorous econometric treatment for the endogeneity of peer effects, and examining (i) the extent to which banks' liquidity and maturity transformation activities are affected by the respective choices of their direct competitors, and (ii) the impact of these potentially strategic and coordinated funding liquidity policies on financial stability.

The institutional and regulatory environment specific to the banking sector and to banks' liquidity policies provides a unique setting to study peer influence. First, overall maturity and liquidity mismatch decisions remain, to a large extent, unregulated until the Basel III NSFR rules come into force in 2018. This makes it more likely for social multiplier effects to occur as there are no boundaries or thresholds on what banks can do. In addition, because of the implicit or explicit commitment of the Lender of Last Resort (LOLR) to bailout financial institutions in case of distress, individual banks may have incentives to engage in collective risk-taking strategies (Ratnovski, 2009; Farhi and Tirole, 2012). In fact, if there is a shock and several banks are at risk, the LOLR has little choice but to intervene in order to prevent contagion. This "too-many-to-fail" problem (Acharya and Yorulmazer, 2007) leads to time-inconsistent, imperfectly targeted support to distressed banks and makes their balance-sheet choices strategic complements i.e., a given bank may be willing to take more funding liquidity risk when other banks competing in the same market are pursuing a similar policy. Nonetheless, common exposures may not necessarily be driven by distorted bank incentives due to the desire of extracting rents from government guarantees. For instance, Morrison and Walther (2016) show that correlated investments can arise to resolve a time-inconsistency problem specific to the banking sector: individual banks would prefer to commit not to rescue a distressed competitor, but interbank lenders prefer to renegotiate ex-post. As a result, the optimal commitment is only achieved if a bank ensures that its financial performance is sufficiently correlated with that of its peers.[1]

Ultimately, common bank exposures may have a tremendous adverse impact on the stability of the financial system due to higher correlation of defaults and amplification of the impact of liquidity shocks (e.g., Allen et al., 2012). In addition, excessive funding liquidity risk due to abnormally high maturity and liquidity transformation activities may also make individual banks less resilient from a default risk perspective (Hong et al., 2014; Berger and Bouwman, 2015). This may increase the probability of bank failures that can generate costly crises associated with sharp recessions, prolonged recoveries and large increases in government debt. In this regard, Acharya and Yorulmazer (2008) also highlight the importance of examining the ex-ante drivers of bank fragility and systemic risk, of which the extent of banks' mimicking behavior may play an important role since it affects the likelihood that all banks fail altogether. Most of these conclusions are nevertheless based on theoretical results that lack empirical support. In fact, while there is some evidence of peer effects in bank lending policies (Rajan, 1994; Uchida and Nakagawa, 2007), or even bank liquidity choices (Van den End and Tabbae, 2012; Bonfim and Kim, 2014)[2], to the best of my knowledge no study explicitly examines and quantifies the impact of banks' correlated balance-sheet decisions on the stability of the financial system.

While theoretically intuitive, identifying peer effects in banks' funding liquidity decisions is empirically challenging because of the reflection problem (Manski, 1993). More specifically, if competitors' balance-sheet choices affect the respective decisions of a particular bank, the decision of this bank may also in turn affect the choice made by the peers. To overcome this reverse causality problem, I use a novel identification strategy based on Bramoullé et al. (2009) framework where bank interactions are structured through a social (decision) network. In such a network, an agent's friend's friend may not be a direct friend of

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[1] Banks' correlated balance-sheet choices can also be rationalized on other grounds which may still lead to inefficient outcomes with fully rational agents. Complementarity in financial decisions may, for instance, arise from learning motives i.e., free-riding in information acquisition. In such case, a certain bank, particularly if small, may be unsure about its optimal funding liquidity risk management policy and thus may consider the decisions of its competitors as informative for its own. In other words, the actions of the peers explicitly enter in the bank's objective function. In fact, banks may rationally put more weight on the choices of others than on their own information (Banerjee, 1992), particularly when other banks are perceived as having greater expertise (Bikhchandani et al., 1998). On a different view, reputation concerns and the reward structures of bank managers may also give them incentives to mimic their competitors since this restricts responsibility in case of collective failure (e.g., Devenov and Welch, 1996).

[2] Using a sample of Dutch banks during the period between 2003 and 2009, Van den End and Tabbae (2012) show that bank liquidity choices became increasingly dependent during the global financial crisis. Bonfim and Kim (2014) analyze the behavior of European and North-American banks from 2002 to 2009 and find strong evidence of "herding" in liquidity risk management decisions. Both studies are silent in relation to the consequences this effect may have on the stability of the financial system.

that agent. Therefore, one can use the intransitivity in network connections as an exclusion restriction to identify different social interaction effects. In brief, heterogeneity in peer group choice allows us to use the liquidity holdings of the "peer's peer" as a relevant instrument that is orthogonal to the peer banks' liquidity policies, thus extracting the exogenous part of its variation. This identification strategy is particularly appealing when studying funding liquidity risk since large cross-border banking groups tend to manage liquidity on a global scale (e.g., Cetorelli and Goldberg, 2012a, 2012b; Galema et al., 2016). As a result, the funding liquidity risk profile of a parent bank-holding group based in a foreign country y can be viewed as an instrument for all banks operating in country x that belong to the peer group of its foreign subsidiary.

I find that individual banks do take into consideration the liquidity and maturity mismatch policies of their respective competitors when determining their own. In other words, the funding liquidity decisions of a specific bank, captured by either the Berger and Bouwman (2009) Liquidity Creation measure or the Basel III NSFR, are positively and highly statistically associated with the respective choices of its peers. Furthermore, banks' liquidity choices are in large part direct responses to the liquidity decisions of their respective peers and, to a much lesser extent, their other characteristics e.g., competitors' size, capital or profitability. This suggests that the results are not being driven by shared characteristics between a certain bank and its respective peers. Importantly, the coefficient estimates indicate that the economic impact is large and consistent with coordinated and complementary behavior where each bank constantly adjusts to each other's policies e.g., a one standard deviation change in the peer banks' liquidity creation (0.089 to 0.103) is associated with a change in the liquidity creation of bank i of 0.040 to 0.069 (where the mean of liquidity creation is 0.421 and standard deviation is 0.184). This finding is robust to the use of multiple peer group sizes and definitions, different bank, peer and country-level controls, alternative liquidity risk measures, as well as an alternative instrument based on market data as in Leary and Roberts (2014).

In addition, I show that peer effects in banks' funding liquidity policies are generally concentrated in commercial banks with high credit risk, high share of wholesale funding, low share of deposits as a percentage of balance-sheet size and with low efficiency. While there are no discernible differences between low vs. high capitalized banks, these peer effects are generally higher in magnitude for banks with low profits. This is consistent with strategic behavior being driven by the incentive of improving profitability (e.g., Ratnovski, 2009) and indicates that higher levels of liquidity risk are not being compensated with higher capital ratios. Furthermore, different falsifications tests confirm the a priori assumptions when defining peer groups (i.e., commercial banks of similar size operating in the same country and year) and show that the results are not likely to be driven by shared omitted factors not controlled for in the model. First, I find that individual banks funding liquidity policies are not sensitive to that of banks of similar size that operate in all other OECD countries. This is consistent with the fact that within-country banks are expected to have higher incentives to mimic their peers. Second, I find that while large banks' liquidity decisions are highly sensitive to their large counterparts and small banks' liquidity choices are also strongly affected by small banks, neither large banks mimic small banks, nor small banks follow large ones. The latter result specifies that the size of competitors is indeed a crucial determinant for individual banks decision-making and suggests that the "too-many-to-fail" problem (Acharya and Yorulmazer, 2007; Farhi and Tirole, 2012) may in fact be one of the main drivers of correlated exposures and mimicking behavior in banks' balance-sheet choices.

Interestingly, in a falsification test I find no evidence of strategic complementarity and peer effects in banks' capital choices. This indicates that the lack of explicit regulation on maturity and liquidity mismatches of financial institutions may enable such collective risk-taking behavior in funding liquidity policies. In fact, while liquidity rules aimed at constraining systemic liquidity risk-taking are to a large extent non-existent, bank capital has been heavily regulated for a considerable period of time, both from a micro and macroprudential perspectives. This imposes considerable limits on banks and bank managers' capital decision possibilities. As distinctly argued by Allen (2014), while there has been a comprehensive academic and policy debate on capital regulation, "with liquidity regulation, we do not even know what to argue about".

Finally, and more importantly, I find that strategic complementarity in banks' funding liquidity risk management policies significantly affect the stability of the financial system. In order to examine the direction in which these peer effects operate, I first show that the response of individual banks to the funding liquidity choices of competitors is asymmetric. In other words, individual banks mimic their respective peers strongly when these competitors are increasing funding liquidity risk rather than decreasing it. I then show explicitly that these correlated maturity and liquidity mismatch decisions increase both individual banks' default risk and overall systemic risk. The results are robust across multiple model specifications, alternative funding liquidity risk indicators, and for various financial stability measures: (i) the Z-Score to capture individual banks' financial stability; and (ii) Marginal Expected Shortfall and SRISK (Acharya et al., 2012; Engle et al., 2015) to capture systemic risk. This effect is both statistically and economically significant. For instance, a change in the peer effect in liquidity creation from one standard deviation below the mean to one standard deviation above the mean (0.10 to 0.15) is associated with a decrease in the Z-score of 12% to 17% (where mean of Z-score is 3.67 and standard deviation 1.35). Similarly, a one standard deviation increase in the peer effect in funding liquidity choices captured by either funding liquidity risk measure (0.04 to 0.09) is associated with a 3-9% and 8-14% increase from the mean MES and SRISK, respectively.

The contribution of this paper is twofold. First, to the best of my knowledge, this is the first study to explicitly analyze the impact of strategic balance-sheet decisions on either individual banks' financial stability or overall systemic risk. In fact, previous empirical research is silent on the existence of asymmetries in such behavior and on the consequences of these risk-taking strategies on the stability of the financial system. This issue is particularly relevant after the 2007-2009 global financial crisis, with both academics and policymakers questioning the extent to which the recent regulatory reforms are sufficient to deter banks' excessive risk-taking behavior. In this regard, this paper delivers a detailed analysis that is beneficial to regulators and supervisory agencies, particularly concerning the macroprudential regulation of liquidity risk. While broadly consistent with the literature analyzing the direct effects of implicit bailout guarantees on the risk of individual banks (e.g., Dam and Koetter, 2012), the results in this paper show that moral-hazard is not necessarily restricted to banks exogenously engaging in excessive risk-taking. Instead, as theoretically conjectured by Farhi and Tirole (2012), banks also create aggregate (systemic) risk by mimicking each other's balance-sheet structures and behaving strategically. In addition, the framework I use avoids relying on potentially noisy credit rating agency expectations of government support to construct bank-specific bail-out probabilities, and does not restrict collective risk-taking behavior to be driven only by government bailout incentives (e.g., Gropp et al., 2011; Mariathasan et al., 2014).[3]

Finally, this paper also complements the recent and growing literature showing that competitors do have a significant role on individual firm's decision-making. Empirical evidence on peer effects in corporate actions suggest that competitors affect capital structure choices (Leary and Roberts, 2014), bank credit policies (Rajan, 1994; Uchida and Nakagawa, 2007), stock splits (Kaustia and Rantala, 2015), investment decisions (Foucault and Fresard, 2014), among other domains.[4] In a related study, Bonfim and Kim (2014) find strong evidence of peers affecting banks' liquidity risk management policies. My paper however differs from theirs in several dimensions. First, I provide a rigorous econometric treatment for the endogeneity of peer effects. More specifically, I explore systematic variation in peer group composition to capture and identify the effect of interest, thus solving the reflection problem (Manski, 1993) and minimizing the potential bias from weak instruments (Angrist, 2014). Second, I disentangle whether banks are reacting to peers' liquidity risk management policies per se or, instead, simply responding to chances in other peer characteristics such as size, profitability or capitalization. The latter issue is particularly important as we could observe common liquidity choices because banks share similar characteristics rather than by true strategic behavior. More importantly, unlike Bonfim and Kim (2014) I examine whether coordinated banks' funding liquidity risk policies significantly affect financial stability.

The remainder of the paper is organized as follows. Section 2 describes the identification strategy to detect and quantify peer effects and to examine their impact on financial stability. The data, sample and descriptive statistics are presented in section 3. Section 4 discusses the empirical results and section 5 concludes and provides policy recommendations.

[3] Gropp et al. (2011) examine the effects of bailout commitments on banks' risk-shifting behavior in the cross-section i.e., considering the year 2003 only in 30 OECD countries. The authors show that competitive distortions due to government guarantees to peer banks (and not the bank itself) significantly decrease individual banks' liquidity and capital ratios. Mariathasan et al. (2014) obtain somehow different results when analyzing a panel covering 90 countries over 2001-2013. First, they show that banks tend to hold both less capital and liquidity when the individual banks themselves are perceived as being more likely to benefit from government support. Finally, they find that expected support to competitors is associated with lower capital ratios of individual banks, but has no significant effect on liquidity ratios. None of the studies analyses systemic risk.

[4] Survey evidence also indicates that a significant number of CFOs consider important the financing decisions of the competitors when determining their own (Graham and Harvey, 2001). Similarly, Bizjak et al. (2011) explore the change in the US Securities and Exchange Commission (SEC) proxy disclosure rules introduced in 2006 that require firms to report the peer groups they use to set managerial compensation (as long as the use of peer groups is material in determining pay) and find that 69% of the firms in their sample report the composition of their compensation peer groups to the SEC.

2. Identification strategy

I employ a two-step method in order to examine whether financial stability is affected by common exposures and potential strategic behavior of banks in their funding liquidity choices. First, I investigate and quantify the influence of competitor banks' liquidity decisions on individual banks' liquidity choices, providing a rigorous econometric treatment for the endogeneity of peer effects by using a novel identification strategy based on Bramoullé et al. (2009) social network framework. I then analyze the impact of peer effects in funding liquidity choices on individual banks' and system-wide stability by making use of the panel structure of the data and allowing the relationship between the funding liquidity risk profile of a certain bank and that of its peers to vary across countries and time.

2.1. Methodology to capture and quantify peer effects

In order to empirically assess whether the competitors funding liquidity risk decisions matter for individual banks' liquidity choices, I specify the following baseline model:

$$LIQ_{i,j,t} = \omega + \beta \overline{LIQ}_{-i,j,t} + \lambda' \bar{X}_{-i,j,t-1} + \gamma' X_{i,j,t-1} + \eta' Z_{j,t-1} + \mu_i + v_t + \varepsilon_{i,j,t} \qquad (1)$$

where the indices i, j, and t correspond to bank, country, and year, respectively. The dependent variable $LIQ_{i,j,t}$ is a measure of bank's funding liquidity (see section 3.2). $\overline{LIQ}_{-i,j,t}$ denotes peer banks' average liquidity in year t within country j. Because bank i is excluded, this variable does not only vary across countries and over time, but also across banks within each country-year combination. I use a contemporaneous measure as banks can observe each other's liquidity needs in the interbank market and because (i) it limits the amount of time for banks to respond to one another, thus making more difficult to identify mimicking behavior; and (ii) it mitigates the scope for confounding effects by reducing the likelihood of other financial structure changes (Leary and Roberts, 2014). $\bar{X}_{-i,j,t-1}$ are average peer bank characteristics other than liquidity to ensure that the parameter β is capturing the direct response to peer liquidity choices, rather than their other characteristics such as size, capital or profitability. The vectors $X_{i,j,t-1}$ and $Z_{j,t-1}$ contain lagged firm-specific and country-specific factors. μ_i and v_t represent bank and year fixed-effects to control for unobserved heterogeneity and account for average differences across banks and time that are not captured by the other exogenous variables. Finally, $\varepsilon_{i,j,t}$ is the residual term that is assumed to be heteroskedastic and correlated within banks. As a result, I use robust standard errors clustered at the bank level in all specifications. Under model (1), the peer effects of interest are captured by the coefficient β which measures the influence of peer banks' liquidity choices on the funding liquidity risk management decisions of bank i.

The above naïve empirical specification however suffers from a clear endogeneity problem that leads to biased and inconsistent estimates of the parameters in the model: if peers' liquidity choices affect the liquidity decisions of a specific bank, the decision of this bank may also in turn affect the choice made by the peers. In fact, I posit that banks take into consideration their peers' liquidity policies when determining their own, which implicitly means that each bank in a peer group constantly adjusts to each other's decisions. This reverse causality problem, commonly referred to as the reflection problem (Manski, 1993), arises from the fact that one is using the average peer liquidity measure as an explanatory variable in the regression. In other words, the peer firm average liquidity is an endogenous explanatory variable in (1) since it is determined simultaneously with the outcome variable.

To resolve this reflection problem, I use a novel identification strategy based on Bramoullé et al. (2009) extended version of the linear-in-means model where interactions between entities are structured through a social network. In such network, an agent's friend's friend may not be a (direct) friend of that agent, and thus one can use the intransitivity in network connections as an exclusion restriction to identify different social interaction effects. Intuitively, heterogeneity in peer group choice (i.e., different peer groups for the different banks in the sample) allows to use the liquidity holdings of the "peer's peer" as a relevant instrument to capture the peer group liquidity holding of any given bank. This identification strategy is particularly attractive when studying funding liquidity risk of financial institutions since, as shown by Cetorelli and Goldberg (2012a, 2012b) and Galema et al. (2016), large cross-border banking groups tend to manage liquidity on a global scale. As a result, it is reasonable to assume that in addition to the funding liquidity choices of its direct competitors, foreign-owned subsidiaries also take into consideration the funding liquidity risk management policies of their respective parent bank-holding group when determining their own. Consequently, the funding liquidity risk profile of a parent bank-holding group based in country p can be viewed as an instrument for all banks operating in country j that belong to the peer group of its foreign subsidiary. This instrument meets both the relevance and exclusion conditions and thus solves the reflection problem described in Manski (1993). In addition, systematic variation in group composition causes the potential bias from weak instruments to fall away (Angrist, 2014).

To illustrate this identification strategy, consider the following scenario presented in Figure 1. Bank A is a foreign-owned subsidiary of a Bank X. Bank A's major competitors are Bank C1, C2, C3 and C4. These banks interact as follows: (i) Bank A's peer group includes Bank X, its parent bank-holding company, and Banks C1, C2, C3 and C4 that compete in the same country and have similar size and business models; (ii) Bank C1 peer group only includes Bank A, C2, C3 and C4, not bank X. Thus, the liquidity holdings of Bank X can be viewed as an instrument for Bank C1 that meets both the relevance and exclusion conditions. Indeed, the liquidity holdings of Bank X is both (i) relevant for Bank C1 liquidity holdings, because it influences the performance of Banks C1's direct peer, i.e., Bank A, and (ii) exclusive, because it achieves its effect on Bank C1 liquidity holdings only through the Bank C1's peer group. The same analogy can be used for Banks C2, C3 and C4. The identifying assumption is therefore that the foreign parent bank-holding group only affects individual domestic banks indirectly through its effect on its subsidiary.

[Figure 1 here]

2.2. Criteria to form peer groups

The definition of peer groups for a given population of agents is key to any analysis of peer effects (Manski, 1993). Following previous literature (e.g., Leary and Roberts, 2014; Berger and Bouwman, 2015), information sources used by practitioners (e.g., Bankscope, SNL Financial) and supervisory and regulatory practice, competitors are defined as other banks in the same size class, local market and area of specialization.

First, following the theoretical arguments in Ratnovski (2009) and Farhi and Tirole (2012), among others, within-country banks are expected to have higher incentives to mimic their peers since they share the same LOLR. Similarly, peer influence for learning motives (Banerjee, 1992; and Bikhchandani et al., 1998) or reputation concerns and reward structures (Devenov and Welch, 1996) is more likely to occur within borders where information for bank managers is more accessible. As a result, peer groups are first defined as commercial banks operating in the same country in the same year.[5] To further incorporate heterogeneity in peer group choice, peer groups are also constructed based on bank size. In fact, given their systemic importance, large banks face a higher probability of a collective bailout during a crisis than their small counterparts. This criteria is in line with, for instance, the Federal Financial Institutions Examination Council (FFIEC) in the US that differentiates banks according to their asset size and splits them into more than 10 different peer groups.[6] The peer group of a certain commercial bank i (its competitors) is then defined as other commercial banks with similar size operating in the same country j in the same year t.

To ensure that the results are not driven by a particular choice of peer group size, I report results throughout the paper based on size groups of a maximum of 10, 20 and 30 banks i.e., each bank operating in a certain country in a certain year has 9, 19 and 29 competitors, respectively. Peer groups are formed in every time period so that a bank can change a peer group from one period to the other e.g., due to an acquisition. The same set of criteria to define peer groups is also proposed by Berger and Bouwman (2015). As with the mechanism described in this paper, the authors suggest a benchmarking exercise to executives and financial analysts in which a bank would compare its liquidity creation to that of its peers in order to increase performance. The choice of peer group size (between 10 and 30 banks) is also consistent with Bizjak et al. (2011) and Kaustia and Rantala (2015). The former study finds that the average size of the peer group when setting executive compensation is around 17.3 for S&P 500 firms and 15.8 for non-S&P firms. They also show that majority of firms in the peer group come from the same industry, and a vast proportion come for the same industry-size classification. Kaustia and Rantala (2015) computes peer groups based on analyst-following, three-digit SIC codes and six-digit GICS codes and indicates that the average peer group size is of 11.7, 15.8 and 23.5 firms, respectively, when looking at NYSE-listed entities.

[5] Since only commercial banks are included in the sample, peer groups are also implicitly defined based on their business model i.e., area of specialization.

[6] The inter-agency body reports publicly-available data for all commercial banks supervised by the Board of Governors of the Federal Reserve System, Federal Deposit Insurance Corporation or the Office of the Comptroller of the Currency on these bank peer groups once call reports become available.

2.3. Methodology to examine the impact of peer effects on financial stability

In the second step of the analysis, I investigate whether peer effects in banks' funding liquidity risk management decisions affect financial stability. Based on the identification strategy described above to identify peer effects after adequately having dealt with the reflection problem, I use the following regression specification to capture time and country-varying peer effects in liquidity decisions:

<u>Step 1</u>: $$LIQ_{i,j,t} = \omega + \beta_{j,t}\overline{LIQ}_{-i,j,t} + \lambda'\bar{X}_{-i,j,t-1} + \gamma' X_{i,j,t-1} + \eta' Z_{j,t-1} + \mu_i + v_t + \varepsilon_{i,j,t} \quad (2)$$

where the indices i, j, and t correspond to bank, country, and year, respectively. Compared to model (1), the relationship between liquidity of bank i and liquidity of its peers, $\beta_{j,t}$, is now allowed to vary across countries and over time. As before, the dependent variable $LIQ_{i,j,t}$ is a measure of bank's funding liquidity risk, $\overline{LIQ}_{-i,j,t}$ denotes the peer firms' average liquidity excluding firm i in year t within country j, and $\bar{X}_{-i,j,t-1}$ and $X_{i,j,t-1}$ are average peer bank characteristics and bank-specific factors, respectively.

In practice, I make use of the panel structure of the data and estimate model (2) for each country-year combination by shocking the average peer effect in the overall sample with two indicator variables specifying the country and year such that:

$$LIQ_{i,j,t} = \omega + [\beta_0 + (\beta_1 \times I_{country} \times I_{year})]\overline{LIQ}_{-i,j,t} + \lambda'\bar{X}_{-i,j,t-1} + \gamma' X_{i,j,t-1} + \eta' Z_{j,t-1} + \mu_i + v_t + \varepsilon_{i,j,t}$$

The estimated coefficient on the peer effect of interest in model (2), $\hat{\beta}_{j,t}$, is then used to run the following specification to gauge the impact of peer effects in liquidity choices on financial stability:

<u>Step 2</u>: $$STA_{i,j,t} = \kappa + \delta\hat{\beta}_{j,t} + \gamma' X_{i,j,t-1} + \eta' Z_{j,t-1} + \mu_i + v_t + u_{i,j,t} \quad (3)$$

where the dependent variable $STA_{i,j,t}$ is a measure of financial stability of bank i in country j in year t, $\hat{\beta}_{j,t}$ is the country and time-varying peer effect estimated in (2) and $X_{i,j,t-1}$ and $Z_{j,t-1}$ contain lagged bank and country-specific characteristics, respectively. As before, I also include bank and year fixed-effects (μ_i and v_t) to control for unobserved heterogeneity and account for average differences across banks and time not captured by the other exogenous variables.

I analyze the consequences of these peer effects on both individual banks' financial stability (default risk of individual institutions) and their contribution to the risk of the financial system as a whole (systemic risk). Strategic complementarity in banks' funding liquidity risk management policies is hypothesized to decrease individual banks' financial stability and increase systemic risk. Thus, I expect $\delta < 0$ when considering the Z-score as the dependent variable (i.e., peer effects decrease individual bank's solvency risk) and, in contrast, $\delta > 0$ when analyzing systemic risk (i.e., peer effects increase their contribution to systemic risk).

3. Sample and Descriptive Statistics

3.1. Data

3.1.1. Bank and country-level data

Given that the main objective of this study is to investigate the impact of strategic behavior in banks' funding liquidity choices and that these peer effects are hypothesized to vary not only over time but also by country, I consider a heterogeneous sample of commercial banks operating in 32 OECD countries before, during and after the global financial crisis i.e., from 1999 to 2014.[7] Information on banks' balance-sheets and income statements are obtained from Bankscope, a database compiled by Fitch/Bureau Van Dijk from publicly-available data and adjusted to ease international comparison of banks' financial statements. Following Gropp et al. (2011), among others, to avoid double-counting within a single institution and have financial information at the most disaggregated level possible, I discard consolidated entries if banks report information at the unconsolidated level.[8] I also restrict the coverage to the largest 100 commercial banks in each country, thus excluding smaller (mostly regional) banks in the US and Japan and hence limiting the over-representation of these two countries in the sample.[9] While most bank-specific variables are expressed in ratios, all variables in levels (e.g., total assets) are also adjusted for inflation and converted into millions of US dollars.

[7] Out of the 34 OECD members, Iceland and Israel are not included in the sample because of the very limited number of foreign-owned commercial banks (if any) that would not allow to identify the peer effects of interest for banks operating in these two countries – see Section 2.1.

[8] I go to great lengths to (i) identify duplicate observations in a given country/year and thus avoid capturing spurious peer effects; and (ii) check whether the bank specialization reported in Bankscope is accurate i.e., if a commercial bank is indeed engaged in financial intermediation activities. First, besides discarding consolidated entries if banks report information at the unconsolidated level, I also look for banks having for instance the same address, nickname, website or phone and drop the respective duplicates e.g., banks reporting information according to different financial standards in the same year. Second, I cross-check the specialization codes in Bankscope with those reported in Claessens and van Horen (2015) and adjust them accordingly. Since many Bank Holding Companies in Bankscope are actually subsidiaries of investment banks or private banking and asset management companies, all bank holding companies are excluded from the sample. Finally, to further ensure that the sample only includes commercial banks (typically defined as institutions that make commercial loans and issue transaction deposits e.g., Berger and Bouwman, 2015), I exclude bank-year observations for which customer deposits do not exceed 5% of liabilities, and for which loans do not exceed 5% of total assets.

[9] In practice, a commercial bank is excluded from the sample if and only if it is not in the Top 100 in terms of assets in the country it operates in all the years it is active. I also exclude branches of foreign banks since they generally do not report individual information and are not covered by the LOLR of the country where they operate.

I obtain daily stock prices and number of shares outstanding from Thomson Reuters Datastream which includes stock market information on over 200,000 active and delisted firms worldwide. Bankscope and Datastream are matched on the basis of the International Securities Identification Number (ISIN) for the listed banks. With respect to the country-level variables, I collect GDP per capita, GDP growth rate, imports and exports of goods and services and the Consumer Price Index (CPI) from the World Bank's World Development Indicators (WDI) Database and the Federal Reserve Economic Data (FRED). The date of inception of explicit deposit insurance arrangements is obtained from Demirgüç-Kunt et al. (2015). Country-specific banking sector equity market indices are from FTSE Russell. Finally, information on whether a country has binding quantitative regulatory liquidity requirements in place in a certain year is collected from Bonner et al. (2015), the IMF country-level reports on "Detailed Assessment of Observance of Basel Core Principles for Effective Banking Supervision" and the websites of the individual national central banks and the European Systemic Risk Board (ESRB). The final sample yields a panel of 19,125 bank-year observations corresponding to 2,047 commercial banks in the 32 OECD countries from 1999 to 2014.

3.1.2. Ownership data

Ownership information for all commercial banks in the sample is manually collected using various sources including Bureau van Dijk ownership database, banks and national central banks' websites, and newspaper articles obtained from Factiva. In fact, although the Bureau van Dijk's ownership database has historical data on banks' ownership structures, this information (i) is only partially recorded for a considerable number of banks in many of the countries analyzed and (ii) is only available from 2002. This data is further cross-checked with the Claessens and van Horen (2015) bank ownership database. Compared to the latter, the database compiled in this paper is however unique in a number of important ways. First, while the Claessens and van Horen (2015) database indicates whether a certain bank is foreign-owned and the respective home country of the parent bank, I obtain information on who the actual owner of this foreign-owned bank is and the respective Bankscope identifier.[10] Further, while Claessens and van Horen (2015) report the country of ownership based on direct ownership, I obtain information and consider throughout the paper the ultimate bank owner based on a 50% threshold. While more limited in terms of coverage, the data collected for this paper is therefore considerably more detailed and provides a distinctive and novel source of information.

3.2. Funding liquidity risk indicators

[10] Consider the US as a practical example. While the Claessens and van Horen (2015) bank ownership database only indicates the home country of the majority shareholder of HSBC Bank USA (the UK), the database I construct specifies who it is (HSBC Holdings Plc) and respective BvD (GB00617987) and Bankscope identifiers (47424; 34727). With this information in hand, one can then compute the liquidity position of the parent bank in order to construct the main instrumental variable of interest - see Section 2.1.

Financial intermediaries perform maturity and liquidity transformation by issuing liquid, short-term liabilities while holding illiquid, longer-term assets. This arrangement is beneficial for banks when compared to situations in which these activities are performed separately, and is particularly valuable to investors who face uncertainty about the timing of their liquidity needs (Kashyap et al., 2002). However, the intermediaries' role of liquidity providers and the combination of deposit-taking and loan-making activities has an inherent fragility problem. In fact, such structure is highly vulnerable to market shocks, bank runs and breakdowns in wholesale funding markets, particularly when banks' rely less on own capital raising and traditional deposits-taking activities. This funding liquidity risk played a prominent role in the recent global financial crisis.[11]

Given that banks hold liquidity on their asset side and provide liquidity through their liabilities, liquidity risk management is ultimately a joint decision over both assets and liabilities. As a result, I use two distinct, though complementary, structural funding mismatch indicators to capture funding liquidity risk: (i) the Berger and Bouwman (2009) Liquidity Creation measure, and (ii) the Basel III Net Stable Funding Ratio (BCBS, 2014). By considering and assigning weights to every item on both sides of banks' balance-sheets, these indicators account for both asset liquidity and liability liquidity and thus provide a broad picture of the overall maturity and liquidity mismatch of each institution. While Liquidity Creation is an inverse indicator of current liquidity, the NSFR captures what the liquidity would be under a stress scenario.

In detail, the Berger and Bouwman (2009) Liquidity Creation measure is constructed as follows: in the first step, all bank assets and liabilities are classified as liquid, semi-liquid, or illiquid according to their category. Liquidity is only created by the coexistence of demand and supply and by funding illiquid assets with liquid liabilities. Ceteris paribus, a bank creates \$1 of liquidity by investing \$1 of liquid liabilities into \$1 of illiquid assets. Similarly, a bank destroys \$1 of liquidity by investing \$1 of illiquid liabilities or equity into \$1 of liquid assets. As a result, liquid, semi-liquid, and illiquid liabilities are then assigned a weight of 0.5, 0, and -0.5, respectively, and liquid, semi-liquid, and illiquid assets a weight of -0.5, 0, and 0.5. In the final step, a weighted average of the liquidity scores across different assets classes is calculated for each bank, where all components are scaled by total assets.[12] Since some accounting items are reported differently in Bankscope when compared to the US Call Reports used in Berger and Bouwman (2009), I adapt the classifications based on those of the authors and the categories defined in their more recent work when using a supervisory bank-

[11] The literature provides two different (although interconnected) concepts of liquidity: funding and market liquidity. Whereas the former is generally defined as the ability to meet obligations as they come due, the latter refers to the ability to sell a certain asset without disrupting its market price. For the purpose of this study, I focus my attention in banks' maturity and liquidity transformation activities and associated funding liquidity risk (i.e., the risk that a financial agent will be unable to meet obligations at a reasonable cost as they come due) as well as on systemic liquidity risk, defined as the risk that multiple institutions face simultaneous liquidity problems due to widespread dislocations of money and capital markets (IMF, 2011).

[12] Berger and Bouwman (2009) consider four different measures of liquidity creation: with and without off-balance-sheet items, and by combining activities other than loans by either product category or maturity. Although the "cat fat" measure (i.e., with off-balance items and by combining activities by category) is more comprehensive, Bankscope does not have the necessary data to compute it. Hence, I use the "cat nonfat" measure (i.e., without off-balance positions and by combining activities by category) in all specifications.

level dataset for Germany (Berger et al., 2016). The classification and weights for each bank balance-sheet item are in Table A1 in appendix. In short, the higher the Liquidity Creation measure is, the higher the bank's maturity and liquidity mismatch and associated funding liquidity risk.

The Basel III Net Stable Funding Ratio (NSFR), which is expected to enter into effect in January 2018, aims to encourage banks to hold more stable and longer term funding against their less liquid assets, thus reducing maturity and liquidity transformation risk. This measure is defined as the ratio of the available amount of stable funding (ASF) to the required amount of stable funding (RSF) over a one-year horizon. Banks will have to meet a regulatory minimum of 100 percent. Table A1 in appendix displays the weights of assets and liabilities for the ASF and RSF. These are given according to the final calibrations provided by the Basel Committee in October 2014 (BSCS, 2014) and adapted to the granularity of Bankscope data. All assumptions are applied uniformly and consistently across the various categories, and, where applicable, items are treated relatively conservatively e.g., all loans are assumed to have a maturity of more than 1 year and hence a RSF weight of 85 percent. Following Distinguin et al. (2013), among others, I use the inverse of the NSFR throughout the paper (NSFRi = RSF/ASF) so that this indicator is directly comparable to the Liquidity Creation measure i.e., a higher value indicates higher illiquidity.

Figure 2 illustrates the evolution of banks' funding liquidity risk between 1999 and 2014 as measured by the Liquidity Creation measure and the inverse of the NSFR. To ensure comparability across countries, both measures are calculated for each bank in a given year and subsequently averaged by country on a yearly basis. The figure shows a steady increase in Liquidity Creation between 1999 and 2007 and sharp decrease afterwards, suggesting that banks were indeed creating too much liquidity in the period that led to the 2007-2009 financial crisis. Berger and Bouwman (2015), for instance, looks at US banks from 1984 to 2014 and find that Liquidity Creation tends to be high before crises and then fall during these crises. The same decreasing trend can be observed when looking at the NSFRi measure. Furthermore, Figure 2 shows that the two measures are in fact highly, though not perfectly, correlated as they measure slightly different components of illiquidity risk – the correlation coefficient between the two variables is 48.9%. This is consistent with Berger and Bouwman (2015) that compare the Liquidity Creation measure with the NSFR and the LCR and find that despite the lack of consistently large correlations between Liquidity Creation and the LCR, the correlation between NSFR and Liquidity Creation is sizeable, particularly for small and medium banks.[13]

[Figure 2 here]

[13] This study does not consider the Basel III Liquidity Coverage Ratio (LCR) in the analysis for several reasons. First, the LCR is designed to gauge whether banks have an adequate stock of unencumbered high-quality liquid assets to overcome liquidity stress over 30 days, while this paper aims to examine banks' overall maturity and liquidity mismatch. This requires a more structural measure that captures both sides of their balance-sheet. Second, detailed information regarding the LCR is only available to bank insiders (e.g., net cash outflows over the next 30 days) and it is therefore extremely challenging to empirically compute reliable estimates (IMF, 2011). Finally, even assuming that one could obtain this type of private information, a more high-frequency dataset (e.g., using monthly data) is required to compute the LCR (Distinguin et al., 2013).

3.3. Financial stability indicators

Following the literature standard (e.g., Dam and Koetter, 2012; Beck et al., 2013; Kick and Prieto, 2015; Berger et al., 2016), I use the Z-score to capture of individual bank's default risk. This measure can simply be interpreted as the number of standard deviations by which returns would have to fall from the mean to eliminate all the equity of a certain bank i.e., a lower Z-score implies a higher probability of default. The Z-score (distance-to-default) of bank i at time t is then defined as the sum of return-on-assets (ROA) and the equity to assets ratio, all divided by the standard deviation of the ROA. I use a three and five-year rolling window to compute the standard deviation of ROA. This approach avoids the variation in Z-scores within banks over time to be exclusively driven by variation in levels of profitability and capital. Furthermore, by not relying on the full sample period, the denominator is no longer computed over different window lengths for different banks. Given that the Z-score is highly skewed, I use its natural logarithm to allow for a more uniform distribution.

From a regulatory perspective of ensuring the stability of the financial system, the correlation in the risk-taking behavior of banks is increasingly more relevant than the absolute level of risk-taking in any individual institution (Anginer et al., 2014). As a result, I analyze not only the consequences of peer effects in funding liquidity choices on individual banks' financial stability (i.e., the solvency risk of individual financial institutions), but also on its contribution to the risk of the financial system as a whole.

I use two different measures to capture systemic risk. The first, MES - Marginal Expected Shortfall (Acharya et al., 2012) is defined as the bank i's expected equity loss (in %) per dollar in year t conditional on the market experiencing one of its 5% lowest returns in that given year. MES is computed using the opposite of the returns such that the higher a bank's MES is, the higher its systemic risk contribution. The market is defined as the country-specific banking sector equity market. The second, Systemic Capital Shortfall - SRISK (Acharya et al., 2012; Engle et al., 2015) corresponds to the expected bank i's capital shortage (in US$ billion) during a period of system distress and severe market decline. Following Acharya et al. (2012), the long-run MES is approximated as $1\text{-exp}(-18 \times \text{MES})$ where MES is the one day loss expected if market returns are less than −2%. Unlike MES, SRISK is a also function of the bank's book value of debt, its market value of equity and a minimum capital ratio that bank firm needs to hold. To ensure comparability across countries, I follow Engle et al. (2015) and set this prudential capital ratio to 4% for banks reporting under IFRS and to 8% for all other accounting standards, including US GAAP.

Figure 3 depicts the evolution of individual banks' default risk (upper figure) and systemic risk (lower figure) between 1999 and 2014. All measures are first calculated for each bank i in each year t and subsequently averaged by country on a yearly basis to give equal weight to each country. The time-series pattern is very similar to that shown in previous research. Both Z-score indicators show a stable increase in distance-to-defaults up to 2007 and a sharp decline during the global financial crisis, though recovering afterwards to their pre-crisis levels. Similarly, systemic risk peaked in 2008 during global financial crisis, decreased slightly afterwards but jumped again in 2011-2012 during the European sovereign debt crisis. However, while both systemic risk measures show a considerable improvement in system-wide stability in recent years, systemic risk did not yet reach its pre 2007-2008 levels.

[Figure 3 here]

3.4. Descriptive Statistics

I consider a large set of bank-specific and country-level indicators that previous literature consistently show that impact banks' financial decisions (e.g., Berger and Bouwman, 2009; Beltratti and Stulz, 2012; Ellul and Yerramilli, 2013; Beck et al., 2013; Anginer et al., 2014). Bank-level controls include the bank size (total assets), capital ratio (capital to assets), return on assets (ROA), deposits to assets, provisions (loan loss provisions to total assets), cost to income ratio, non-interest revenue share (non-interest income in total income), share of wholesale funding (share of money market funding in money market funding and total deposits) and foreign owned (dummy variable that equals 1 if a bank is foreign-owned and 0 otherwise). I winsorize all variables at the 1st and 99th percentile levels. Country-level controls include the natural logarithm of GDP per capita to measure economic development, the standard deviation of the GDP growth rate over the past 5 years to capture macroeconomic instability, imports plus exports of goods and service divided GDP to measure global integration, and local banking market concentration as measured by the Herfindahl index. The dummy IFRS accounts for potential reporting jumps at the time of a bank's accounting standards change (occurring mostly in 2005). Finally, I also control for the existence of country-specific (i) explicit deposit insurance schemes and (ii) binding quantitative regulatory liquid assets requirements similar to the Basel III's LCR i.e., a dummy variable that equals 1 if a quantitative liquidity requirement is in place in country j in year t, and 0 otherwise. All control variables are lagged by one period to mitigate concerns of reverse causality.

Table 1 reports descriptive statistics for the different variables used in the paper. In the sample, an average bank is creating liquidity (0.42) and complies with the regulatory NSFR (101%). It has a distance-to-default of 3.33 to 3.67, Marginal Expected Shortfall (MES) of 2.33% and an expected capital shortage of 2.65 US$ billion during a period of system distress (SRISK). 19.7% of the observations in the sample correspond to listed banks, and 30.9% to foreign-owned banks. This numbers are consistent with Claessens and van Horen (2015) when restricting their bank ownership database to commercial banks operating in the 32 OECD countries considered here. All the remaining controls are also comparable to those in previous studies. The table also shows the distribution of the sample across years. The sample varies from 1,341 bank-year observations in 1999 to 1,047 in 2014 and it is also fairly well distributed across the 32 OECD countries considered.

[Table 1 here]

4. Results

4.1. Peer effects in banks' funding liquidity choices

In this section I examine whether the funding liquidity decisions of a specific bank, captured by either the Liquidity Creation measure or the inverse of the NSFR, are associated with the respective choices of its competitors. While previous research indicates that banks do actively manage their liquidity (e.g., DeYoung and Jang, 2016), it may be the case that this decision is not made strictly at the individual level but collectively due to the LOLR commitment to bailout banks in case of a systemic crisis, because of learning motives since the optimal liquidity risk management policy is uncertain, or simply as a result of reputation concerns and reward structures which may give bank managers incentives to mimic their competitors as this restricts responsibility in case of collective failure.

Table 2 presents the coefficient estimates of model (1) when using Berger and Bouwman (2009) Liquidity Creation measure as dependent variable. Under (1), the peer effects of interest are captured by the coefficient β which measures the influence of competitors' actions on bank *i's* funding liquidity risk profile. The peer groups are defined as commercial banks operating in the same country in the same year and grouped into 10 banks (Columns 1 and 2), 20 banks (Columns 3 and 4) or 30 banks (Columns 5 and 6) according to their size (total assets). Columns 1, 3 and 5 show the 2SLS coefficient estimates when including key firm-specific, peer characteristics and country-level controls (all lagged) while columns 2, 4 and 6 include the full set of lagged bank, peer and country-level controls in the regression. All specifications contain year and bank fixed-effects, as well as robust standard errors clustered at the bank-level.

[Table 2 here]

The table shows that the liquidity created by each individual bank is indeed positively associated with that of its competitors. The coefficients are both statistically and economically significant in all specifications and robust to the use of different controls and peer group sizes, thus suggesting that banks do follow their competitors when making funding liquidity risk management decisions. The estimated 2SLS coefficients on the peer effect of interest range from 0.385 (when using the full set of controls, bank and year fixed-effects, and a peer group of 10 banks) to 0.770 (when using the key set of controls, year and country, and a peer group of 30 banks). This effect is underestimated, though still significant, when using OLS regressions - see Table IA.2 in the internet appendix. While the funding liquidity risk level of each bank (the bank *i* liquidity creation) is mostly driven by direct responses to the respective decisions of its competitors (the peer banks' liquidity creation), some other peer characteristics such as size and capitalization also matter for its determination. Nevertheless, their joint effect on individual banks' liquidity decisions is relatively small, suggesting that the results are not being driven by shared characteristics between a certain bank and its respective peers.

Furthermore, liquidity creation is in general negatively associated with bank size, capital ratio, deposit-to-assets ratio and non-interest revenue share, and positively related with the share of wholesale funding, degree of global integration and the concentration of the local banking sector. The direction of the different coefficients is broadly consistent with previous studies on the determinants of banks liquidity creation and associated funding liquidity risk (e.g., Berger and Bouwman, 2009, 2015; Berger et al., 2016). Kashyap et al. (2002) also show a strong effect of bank size on liquidity in the US, with smaller banks being more liquid and thus having lower funding liquidity risk due to capital market access constraints. A relationship between capital and liquidity is also to be expected. Berger and Bouwman (2009), for instance, show a positive correlation between capital and liquidity creation for large banks and negative for small banks. As in Gropp and Heider (2010) and Bonfim and Kim (2014) regarding what drives capital and liquidity ratios, respectively, a large part of the variation in the liquidity creation measure is attributable to unobserved time-invariant bank characteristics captured by the bank fixed-effect. This is also consistent with Fahlenbrach et al. (2012) that show that there is a bank fixed-effect in risk management since banks that had greater losses in 2008 were those that also suffered the most severe losses in 1998.

Finally, the relevance condition requires the IV to be significantly correlated with peer banks' average liquidity creation (the endogenous variable). This assumption is testable and the results in Table 2 show that this is indeed the case i.e., the instrument is always significant at the 1% level in the 1st stage of the 2SLS estimation for all specifications. The Kleibergen-Paap F-statistic also reject the hypothesis that this is a weak instrument. Identification threats thus come from a correlation between the instrument used and omitted or mismeasured bank *i* funding liquidity determinants that are being captured by the residual term. Nevertheless, the exclusion condition cannot be formally tested because the regression error term is unobservable. Against this setting, it is important to emphasize that the scope for potential identification problems is limited to the fraction of variation remaining after conditioning on (i) observable bank, peer and country-specific variables and on (ii) bank and time (year) fixed-effects used to further mitigate the likelihood that omitted/mismeasured bank *i* liquidity determinants that may be correlated with the IV are being captured by the residual term. The estimates can also be biased due to an omitted characteristic of competitors that is relevant for bank *i*'s funding liquidity choices. However, the results suggest a very limited role for other peer bank characteristics, implying that any remaining bias is likely to be very small.

Table 3 reports the results when using the inverse of the NSFR (NSFR*i*) to analyze the relationship between the funding liquidity choices of a specific bank and the decisions of its competitors. The table follows the same structure of Table 2 (see above). The 2SLS estimated coefficients of model (1) corroborate the previous findings: (i) the first-stage regression coefficient estimates and the Kleibergen-Paap F-statistic show that the instrument is relevant and not weak; (ii) the estimates on the coefficient of interest, Peer Banks' NSFR*i*, show that the relationship between funding liquidity risk levels of bank *i* and those of its peers is both positive and highly statistically significant in all specifications.

[Table 3 here]

Together, the evidence in Tables 2 and 3 suggest that banks do take into consideration the funding liquidity choices of their respective competitors when determining their own.

Furthermore, banks' liquidity decisions are in large part direct responses to the liquidity choices of their respective peers and, to a much lesser extent, their other characteristics (e.g., competitors' size, capital or profitability). Importantly, the coefficient estimates also suggest that the economic impact is large and consistent with coordinated and complementary behavior where each bank constantly adjusts to each other's funding liquidity decisions. A one standard deviation change in the peer banks' liquidity creation (0.089 to 0.103) is associated with a change in the liquidity creation of bank i of 0.040 to 0.069 (mean of liquidity creation is 0.421 and standard deviation is 0.184). Similarly, a one standard deviation change in the peer banks' NSFRi (0.204 to 0.253) is associated with a change in the NSFRi of bank i of 0.118 to 0.142, where the mean of the inverse of the NSFR is 0.986 and the standard deviation is 0.527.

4.2. Robustness and falsification tests

I conduct a battery of tests to ensure that previous findings are robust. First, Tables IA.3 and IA.4 in the internet appendix repeat the previous analysis when considering the Net Stable Funding Difference (required amount of stable funding - available amount of stable funding/total assets) and the standard Liquidity Ratio (liquid assets/total assets) as dependent variables, respectively. While the former is a simple reparametrization of the NSFR, the latter aims to capture liquidity risk just in the asset-side of banks' balance-sheet. Focusing on the substitutability of minimum regulatory capital and liquid asset requirements, Calomiris et al. (2015) suggest that liquid asset holdings reduce incentives for bank runs, increase inter-bank liquidity risk-sharing and mitigate managerial moral-hazard incentives. In brief, all the main conclusions also hold when considering these alternative liquidity risk measures.

Second, given that in the benchmark case each bank i in country j in year t belongs to a certain peer group of up to 30 banks based on their size, bank 30 and 31 in a size rank, for instance, would never interact with each other as they belong to different size groups. Besides, bank 30 would give equal weight to the liquidity profile of banks 1, 2,…, 29, even if there is a substantial difference between the size of bank 1 and bank 29. To address this issue, I construct peer weighted-averages based on the size similarity (inverse of the Euclidean distance) between all banks operating in country j in year t i.e., the smaller the distance between two banks, the more weight it has. The peer influence weight between bank i and p operating in the same country in the same year is then defined as

$$Weight_{Size-Similarity_{i-p,j,t}} = \frac{\max(TA_{j,t}) - |TA_{i,j,t} - TA_{p,j,t}|}{\sum_{p=1}^{N} \max(TA_{j,t}) - |TA_{i,j,t} - TA_{p,j,t}|} \quad (4)$$

where $\max(TA_{j,t}) - |TA_{i,j,t} - TA_{p,j,t}|$ is the inverse of the Euclidean distance between bank i and p in country j in year t, and $\sum_{p=1}^{N} \max(TA_{j,t}) - |TA_{i,j,t} - TA_{p,j,t}|$ is the sum of all the inverse size distances in country j in year t. By construction, the sum of weights in each country j in each year t is equal to 1. Columns (1) to (4) of Table 4 present the results. No matter the specification used and what variable is employed to capture funding liquidity risk, the estimated coefficients show that banks do follow their competitors when making funding liquidity risk management decisions.

[Table 4 here]

Third, to ensure that the results are not being driven by the choice of instrument used to identify peer banks' funding liquidity choices (our endogenous variable of interest), Columns (5) to (8) of Table 4 show the results when re-running the analysis with an alternative instrumental variable. In detail, following the identification strategy in Leary and Roberts (2014), the funding liquidity choices of competitors are now instrumented with the lagged idiosyncratic component of peer banks' equity returns. Intuitively, one extracts the idiosyncratic variation in stock returns using a traditional asset pricing model augmented by a factor to purge common variation among peers. The residual from this model is then lagged by one year and used to extract the exogenous variation in peer banks' liquidity choices – see in appendix a detailed description of the return shock construction. Due to the bank-specific nature of idiosyncratic stock returns and the vast asset pricing literature aimed at isolating this component, the instrument is unlikely to affect individual bank's liquidity decisions directly. Besides, stock returns are relatively free from manipulation and impound most, if not all, value-relevant events (Leary and Roberts, 2014). Finally, the instrument must be correlated with liquidity decisions of peers and there is a substantial literature linking banks' funding liquidity policies to stock returns. Beltratti and Stulz (2012), for instance, find that a higher proportion of deposits in banks' assets had an economically and statistically significant positive impact on share price performance during the financial crisis of 2007-2009. Compared to the main identification strategy used in this paper, however, this instrument requires the use of market data and thus only allows to identify a limited sub-set of publicly-listed banks in the sample. Nevertheless, the main conclusions remain unchanged.

Table 5 presents the results of a falsification test where the analysis is done under the assumption that individual commercial banks follow other financial institutions of similar size and business model, but not from their country of origin. This test is particularly important since the previous results may be attributed to banks simply sharing common characteristics and/or macroeconomic factors that are not controlled for in the model and that can ultimately lead to spurious peer effects. In practice, I first rank all banks in the sample according to their size (total assets), split them into 20, 50 or 100 groups, and then construct the peer averages for each bank accordingly while excluding bank *i*. These splits are performed each year which implies that banks can switch size groups over time. Given that the number of observations in the sample in a given year varies from 1,047 and 1,341 (see Table 1), the average size group in this analysis is comparable to those in Tables 2 and 3. The results reported show no statistically significant results for both funding liquidity risk indicators and no matter the number of global size groups in a given year. In other words, individual banks funding liquidity policies are not sensitive to those of banks of similar size that operate in all other OECD countries. This is consistent with our a priori assumption when forming peer groups that within-country banks are expected to have higher incentives to mimic their peers, and shows that the results are not likely to be driven by shared omitted characteristics.

[Table 5 here]

Finally, Table 6 reiterates the previous analysis on strategic complementarity in banks' liquidity choices (Tables 2 and 3) but when instead looking at potential peer effects in bank capital choices. Columns (1) to (6) report the coefficient of interest when using the Capital Ratio (Equity/Total Assets) as the dependent variable. Columns (7) to (12) repeats the analysis when looking at the Tier 1 Capital Ratio that is only available for a limited number of banks. All specifications include bank, peer and country-level lagged controls (key or full set), as well as year and bank fixed-effects. The reported estimates show no statistically significant results for both bank capital measures, irrespective on how the peer groups are defined and the controls and specifications used. The results also hold when defining bank capital as common equity/total assets - see Table IA.5 in the internet appendix. These findings suggest that the lack of explicit regulation on maturity and liquidity mismatch decisions may indeed be one of the main drivers of collective risk-taking behavior in funding liquidity risk management policies. In fact, existing liquidity rules aimed at constraining banks' ability to take liquidity and maturity risk such as the Basel III NSFR will only start being implemented in 2018 and, nonetheless, may only play a limited role in addressing such systemic liquidity risk concerns (IMF, 2011). Instead, bank capital has been heavily regulated for much longer, both from a micro and macroprudential perspectives. These different capital regulations ultimately impose boundaries on what banks can do and limit their decision possibilities.

[Table 6 here]

4.3. Heterogeneity and strategic behavior

What type of banks mimic liquidity and maturity mismatch exposures of competitors? To examine whether a particular sub-set of banks within a country is more sensitive to their peers' funding liquidity policies, in Table 7 I explore the heterogeneity in the coefficient β from equation (1) using both liquidity creation and the NSFR*i* as the outcome variable of interest. In detail, for each country-year combination I split the sample by the lower and upper values of the within country-year distribution of lagged bank-specific measures of solvency, profitability, credit risk, funding structure, asset mix and efficiency i.e., capital ratio (equity-to-assets), return-on-assets, share of wholesale funding, deposits-to-assets and cost-to-income ratio, respectively. These sample splits are implemented each year and therefore banks in a given country can switch classes (low or high) over time. The reported β coefficients (the peer effect of interest) correspond to specifications (3) and (4) of Tables 2 and 3 where the key ("Key") or full ("All") set of bank, peer and country-level (lagged) controls are included in the regression, respectively, as well as year and bank fixed-effects. To avoid redundancy, the results reported are based on the benchmark peer group definition i.e., competitors are defined as other commercial banks operating in the same country in the same year and grouped into a network of 20 banks according to their size (total assets).

[Table 7 here]

The results presented in Table 7 show that peer effects in banks' funding liquidity policies are generally concentrated in banks with high credit risk, high share of wholesale funding, low share of deposits as a percentage of balance-sheet size and low cost-to-income ratio. While there are no discernible differences between low vs. high capitalized banks, these peer effects are generally higher in magnitude for banks with low profits. This is consistent with strategic behavior being driven by the incentive of improving profitability (Ratnovski, 2009, Farhi and Tirole, 2012) and indicates that higher levels of funding liquidity risk are not being compensated with higher capital ratios.

Table 8 examines more directly the potential channels driving these correlated balance-sheet exposures. In detail, banks are first classified as "Small" or "Large" by splitting the within country-year distribution of bank size into these two groups. The peer averages are then constructed based on the following four scenarios: (i) large banks mimicking large banks; (ii) large banks mimicking small banks; (iii) small banks mimicking small banks; and (iv) small banks mimicking large banks. This analysis is particularly useful to shed light on the potential mechanisms behind this type of mimicking behavior (e.g., LOLR expected support, learning motives) and understand whether these decisions are indeed likely to be strategic.

[Table 8 here]

Consistent with our a priori assumption when constructing peer groups, the results show that the bank size of competitors is indeed a crucial determinant for individual banks decision-making. In fact, Table 8 indicates that while large banks' liquidity decisions are highly sensitive to their large counterparts and small banks' liquidity choices are also strongly affected by small banks, neither large banks mimic small banks, nor small banks follow large ones. The results therefore suggest that learning (i.e., free-riding in information acquisition) is unlikely to play a major role in this setting since small banks' liquidity choices do not seem to be affected by the respective decisions of large banks. This differs from the findings of Leary and Roberts (2014) that consider a sample of US firms (excluding financial corporations) and show that peer firm relevance is driven by a leader–follower model in which small firms are sensitive to large firms, but not vice-versa. In contrast with other industries, however, the institutional framework (e.g., existence of government guarantees) and regulatory environment (e.g., strict regulations and guidelines on what the banks should do) make it less likely for such rational "herding" behavior driven by uncertainty regarding the optimal liquidity policy to occur. Instead, as theoretically conjectured by Ratnovski (2009) and Farhi and Tirole (2012), collective moral-hazard due to the LOLR bailout commitment (i.e., the "too-many-to-fail" problem) may in fact dominate and be the main driver of peer effects in banks' balance-sheet choices. In addition, small and large banks often operate in different market segments and have different business strategies which lead to different composition of assets and liabilities.

It is important to note that, while insightful, these results do not prove or reject a particular theory per se. In fact, it is not the aim of this paper to take a definite view on what may be driving this type of mimicking behavior – this issue is left for future research. Rather, it stresses the importance of these peer effects for the stability of the financial system and the need of having a macroprudential tool that minimizes the propensity for banks to collectively underprice liquidity risk and that therefore allows for a more efficient systemic liquidity risk management that would ultimately reduce the potential public burden.

4.4. Peer effects in banks' funding liquidity choices and financial stability

While the previous sections highlighted that individual banks do take into consideration their respective competitors' funding liquidity decisions when determining their own, I now examine the consequences of such behavior explicitly i.e., whether these correlated balance-sheet exposures have an adverse effect on both individual banks' default risk and overall systemic risk. Despite the theoretical literature being clear on the direction one should expect (e.g., Ratnovski, 2009; Allen et al., 2012), this is, to the best of my knowledge, the first study that analyzes this issue empirically.[14]

First, in order to investigate in which direction these peer effects operate, I start by examining whether the response of individual banks to the funding liquidity choices of competitors is likely to be asymmetric. In other words, this analysis aims to understand if this type of mimicking behavior is stronger when peers are on average increasing funding liquidity risk rather than decreasing it. In fact, if banks' follow competitors with the same intensity when is to decrease risk rather than increase it, the impact of such coordinated behavior on financial stability is likely to be small. In order to answer this question, I first split the sample into three groups according to the bank-specific difference of the peer banks' funding liquidity risk from periods *t-1* to *t*. I then augment model (1) with two interaction variables to account for the potential asymmetric responses to competitors' behavior: (i) peer banks' funding liquidity risk x dummy variable equal to 1 if peer banks' funding liquidity risk decreased considerably from periods *t-1* to *t*, a 0 otherwise; (ii) peer banks' funding liquidity risk x dummy variable equal to 1 if peer banks' funding liquidity risk increased considerably from periods *t-1* to *t*, and 0 otherwise. Table 9 reports the results. I find that these correlated liquidity and maturity transformation activities do work in an asymmetric fashion, thus suggesting that this behavior is indeed strategic. In fact, individual banks mimic their respective peers strongly when these competitors are increasing funding liquidity risk rather than decreasing it. This result holds no matter the peer group size chosen, the specification used, or the measure employed to capture funding liquidity risk.[15]

[Table 9 here]

This finding again highlights the importance of explicitly dealing with the systemic component of liquidity risk. In fact, banks have a tendency to collectively underprice liquidity

[14] In a different context, Cai et al. (2016) analyze syndicated loans for US firms and show that a larger overlap of banks' loan portfolio makes them greater contributors to systemic risk and that interconnectedness increases aggregate systemic risk during recessions.

[15] Performing sample splits instead of interactions points towards the same conclusion – see Table IA.6 in the internet appendix.

risk in good times when funding markets work well due to, among other reasons, the implicit or explicit commitment of the LOLR to intervene in times of stress which prevents their failure and limits the impact of liquidity shortfalls on other banks and the real economy. In addition, the results suggest and are the first indication that these peer effects may in fact lead to lower financial stability due to increased funding liquidity risk in the banking system. Diamond and Rajan (2001, 2005) and Allen and Gale (2004a, 2004b), for instance, argue that banks' maturity and liquidity transformation activities are a fundamental driver of financial instability and suggest that bank failures are more likely to occur when the level of liquidity creation is high. Empirical studies also show that banking crises in the US have been preceded by periods of abnormal liquidity creation (e.g., Berger and Bouwman, 2015) and that banks with weaker Net Stable Funding Ratios in the pre-crisis period were more likely to fail during the crisis (Vazquez and Federico, 2015). Similarly, Hong et al. (2014) show that systemic liquidity risk as measured by interbank interest rate (TED) spreads was a major predictor of bank failures in 2009 and 2010.

Table 10 analyses the main question of this paper directly by looking at the impact of peer effects in liquidity holding decisions on financial stability. The dependent variable is the Z-score (distance-to-default) when using a 3-year window to compute the standard deviation of ROA. This measure captures the default (solvency) risk of individual institutions so that a lower Z-score implies a higher probability of default. I use a set of firm-specific and country-level controls that previous literature (e.g., Ellul and Yerramilli, 2013; Beck et al., 2013; Anginer et al., 2014) consistently show to impact bank risk. These include bank-specific measures size (total assets), asset mix (deposits-to-assets), credit risk (provisions-to-assets), efficiency (cost-to-income), funding structure (non-interest revenue share, share of wholesale funding) and ownership (foreign owned), as well as country-level indicators of economic development (GDP per capita), economic stability (GDP growth volatility), concentration (Herfindahl index), global integration (imports plus exports of goods and services by GDP), and of the presence of (i) binding liquidity regulations similar to the Basel III LCR, (ii) IFRS accounting standards and (iii) explicit deposit insurance mechanisms.

[Table 10 here]

As initially hypothesized, peer effects in funding liquidity choices are strongly negatively (positively) associated with Z-scores (banks' default risk). The results are robust across multiple model specifications and when considering both the Berger and Bouwman (2009) Liquidity Creation measure and the inverse of the NSFR (NSFR*i*) to capture funding liquidity risk. Importantly, this effect is both statistically and economically significant. For instance, a change in the peer effect in liquidity creation from one standard deviation below the mean to one standard deviation above the mean (0.10 to 0.15) is associated with a decrease in the Z-score of 12% to 17% (where mean of Z-score is 3.67 and standard deviation 1.35). In other words, the number of standard deviations profits would have to drop before capital is depleted is reduced by 12-17% in such case.[16] The conclusions do not change and the estimates are both quantitatively and economically similar when using a five-year window to compute Z-scores (see Table IA.7 in the internet appendix) and when also controlling for the bank-specific levels of liquidity risk in the regressions using both the liquidity creation measure and the NSFR and liquidity ratios (see Table IA.8 in the internet appendix). In short, this economically significant increase in the default risk of individual banks provides evidence for the distressing effects of correlated balance-sheet exposures and liquidity/maturity mismatch decisions.

Tables 11 and 12 report the estimation results when looking at consequences of peer effects in funding liquidity choices on systemic risk as measured by the Marginal Expected Shortfall (MES) and Systemic Capital Shortfall (SRISK), respectively. MES (Acharya et al., 2012) is defined as the bank *i*'s expected equity loss (in %) per dollar in year *t* conditional on the market experiencing one of its 5% lowest returns in that given year - the higher a bank's MES (in absolute value), the higher is its contribution to the risk of the banking system. SRISK (Acharya et al., 2012; Engle et al., 2015) corresponds to the expected bank *i*'s capital shortage (in US$ billion) during a period of system distress and severe market decline.

[Tables 11 and 12 here]

The estimated coefficients from model (3) indicate that peer effects in funding liquidity choices are positively and significantly associated with overall systemic risk. This is consistent with Allen et al. (2012) that show that collective risk-taking behavior may have extremely adverse consequences on the stability of the financial system as it affects the likelihood that they fail altogether due to higher correlation of defaults. This effect is present even after controlling for the introduction of liquidity requirements similar to the Basel III LCR that Bonner and Eijffinger (2016) show to increase banks' demand for long-term loans. As before, the results are robust across multiple model specifications, systemic risk proxies and when considering either funding liquidity risk measure or peer group size.[17] It is important to note, however, that both MES and SRISK are based on market data and therefore the sample size is significantly reduced when compared to Table 10. But notwithstanding the potential power issues in the regressions, the estimated coefficients are still significant at conventional levels in all specifications. The magnitude of the estimates also suggests that this effect is economically significant: a one standard deviation increase in the peer effect in funding liquidity choices captured by either measure (0.04 to 0.09) is associated with an increase in MES of 0.07 to 0.20 (where mean of MES is 2.33 and standard deviation 2.07) and increase in SRISK of 0.20 to 0.36 (where mean of SRISK is 2.65 and standard deviation 11.40). This represents approximately a 3-9% and 8-14% increase from the mean MES and

[16] Similarly, a change in the peer effect in NSFR*i* from one standard deviation below the mean to one standard deviation above the mean (0.08 to 0.09) leads to a decrease in the Z-score of 5%. Note that since the outcome variable is the natural logarithm of the Z-score, the point estimates can be interpreted as semi-elasticities.

[17] As before, the conclusions do not change and the estimates are both quantitatively and economically similar, if not stronger, when also controlling for the bank-specific levels of liquidity risk in the regressions using both the liquidity creation measure and the NSFR and liquidity ratios - see Tables IA.9 and IA.10 in the internet appendix.

SRISK, respectively. Overall, Tables 10, 11 and 12 provide robust evidence that strategic complementarity in funding liquidity risk management policies decrease the stability of the financial system.

5. Conclusion

The global financial crisis distinctly exposed the consequences of excessive liquidity risk by financial institutions on financial stability and the macroeconomy. These outcomes were achieved in part through banks' common balance-sheet exposures. Ultimately, funding liquidity risk management decisions made by individual banks spilled over to other institutions and markets, contributing to further losses and exacerbating overall liquidity stress. This systemic liquidity risk was, judging by the extent of government intervention, clearly undervalued by both the private and public sectors.

In this regard, this paper examines the extent to which banks' liquidity and maturity transformation activities are affected by the respective choices of direct competitors and the impact of these strategic funding liquidity policies on the stability of individual banks and the financial system. Using a novel identification strategy where bank interactions are structured through decision networks and by incorporating a large sample of commercial banks operating in 32 OECD countries from 1999 to 2014, I find that financial institutions do take into consideration their peers' funding liquidity risk management decisions when determining their own. Individual banks' level of liquidity and maturity mismatches are in large part a direct response to the respective choices of their competitors and, to a much lesser extent, other peer characteristics. The estimates also indicate that the economic impact is large and in line with coordinated behavior where each bank constantly adjusts to each other's funding liquidity decisions. Consistent with collective moral-hazard behavior, I find that while large banks' liquidity decisions are highly sensitive to their large counterparts and small banks' liquidity choices are also strongly affected by small banks, neither large banks mimic small banks, nor small banks mimic large ones. Finally, falsification tests indicate that there are no peer effects in banks' capital choices. This suggests that the lack of explicit regulation on maturity and liquidity mismatches of financial institutions may enable such collective risk-taking behavior in funding liquidity policies.

With respect to the consequences of strategic behavior for the financial system, I first show that the response of individual banks to the funding liquidity choices of competitors is asymmetric: individual banks mimic their respective peers strongly when competitors are increasing funding liquidity risk rather than decreasing it. I then show explicitly that peer effects in financial institutions' funding liquidity risk management policies increase both individual banks' default risk and overall systemic risk. This effect is both statistically and economically significant which, from a macroprudential perspective, highlights the importance of dealing with and regulating the systemic component of funding liquidity risk for the stability of the financial system.

The Basel III liquidity requirements are a positive addition to banks' internal liquidity risk management and, combined with improved supervision, should help to strengthen their individual funding structure and thus enhance banking sector stability. Nevertheless, these standards are microprudential in nature and despite recent proposals for macroprudential liquidity regulation such as liquidity risk charges, time-varying LCR and NSFR ratios or a macroprudential liquidity buffer in which each bank would be required to hold systemically-liquid assets (see IMF, 2011 and Hardy and Hochreiter, 2014 for a review), policymakers and regulators have yet to establish a concise macroprudential framework that mitigates the possibility of a simultaneous liquidity need by financial institutions. In fact, since information spillovers are a defining characteristic of panics due to financial agents' imperfect knowledge regarding cross-exposures, and given that, as shown in this paper, these information spillovers between banks do occur, a static and time-invariant microprudential liquidity requirement that mainly depends on individual banks' idiosyncratic risk (rather than system-wide conditions) may not be suited to prevent a systemic liquidity crisis. As argued by Dewatripont et al. (2010), "a 1 percent probability of failure means either that 1 percent of the banks fail every year or, alternatively, that the whole banking system fails every hundred years - quite distinct outcomes. Therefore it is crucial for regulators to find ways of discouraging herding behavior by banks, or at least penalizing excessive exposure to the business cycle".

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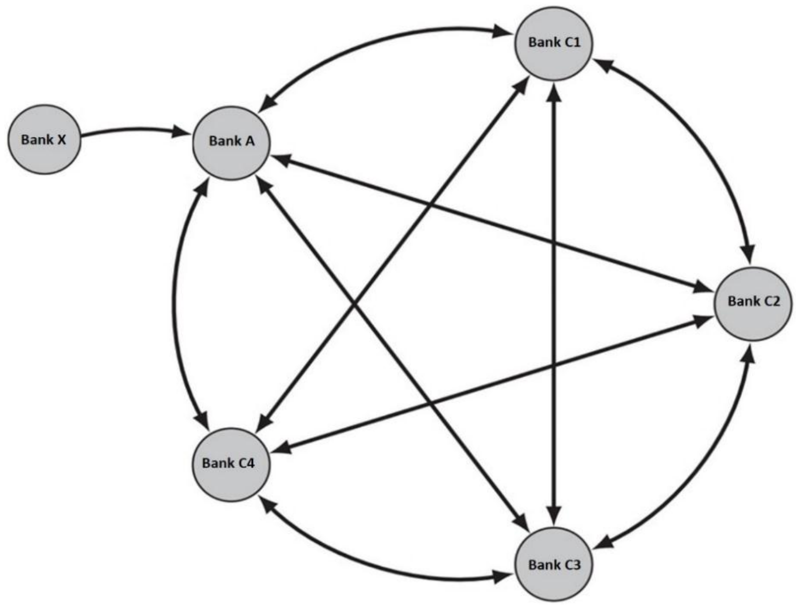

Figure 1. Example of simple network of banks.

This figure shows a "complete market structure" (Allen and Gale, 2000) with banks operating in country *j* in year *t* but with the presence of a cross-border banking-holding company based in country *p*, Bank X, that affects the decisions of Bank A - its foreign-owned subsidiary operating in country *p*. The different institutions interact as follows: (i) Bank A's peer group includes Bank X, its parent bank-holding company, and Banks C1, C2, C3 and C4 - its direct competitors (they all share similar size and business model, and all operate in country *j* in year *t).* (ii) Banks C1, C2, C3 and C4 respective peer groups include each other and Bank A, but not bank X (e.g., Bank C1 peer group contains Banks A, C2, C3 and C4).

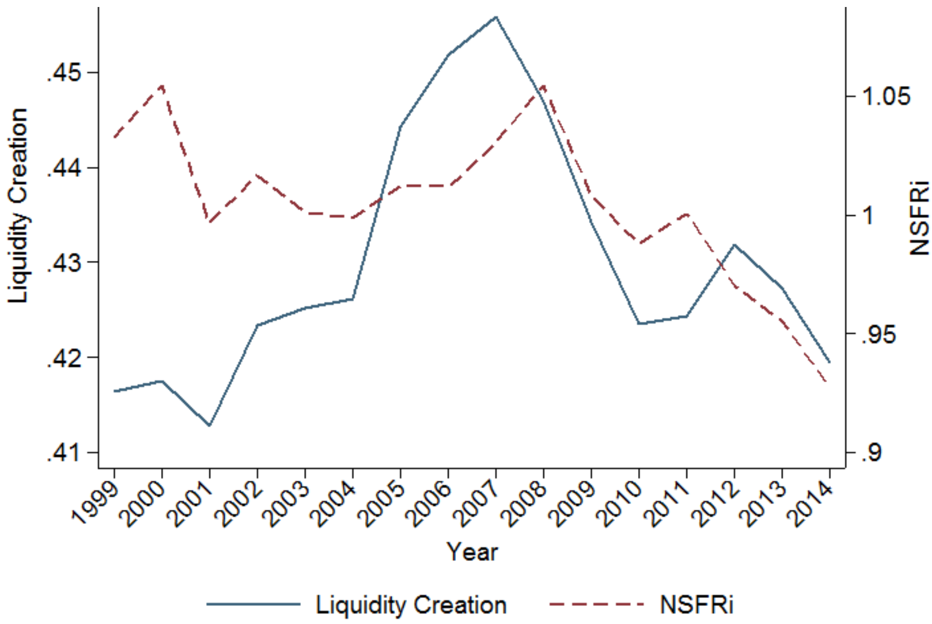

Figure 2. Evolution of funding liquidity risk indicators over time (1999-2014*).*

This figure shows the time-series pattern of the Liquidity Creation measure and the inverse of Net Stable Funding Ratio (NSFR*i*). Liquidity Creation is the Berger and Bowman (2009) "cat nonfat" measure i.e., on-balance-sheet liquidity creation when classifying activities by category. NSFR*i* is defined as the ratio of the required amount of stable funding (RSF) to the available amount of stable funding (ASF). The higher the Liquidity Creation and the NSFR*i* measure are, the higher the bank's maturity and liquidity mismatch and associated funding liquidity risk. Table A.1 in appendix presents the weights given to the different balance-sheet items when computing both measures. Both indicators are calculated for each bank in a given year and subsequently averaged by country on a yearly basis to give equal weight to each country. The full sample consists of 19,125 bank-year observations corresponding to 2,047 commercial banks operating in 32 OECD countries from 1999 to 2014.

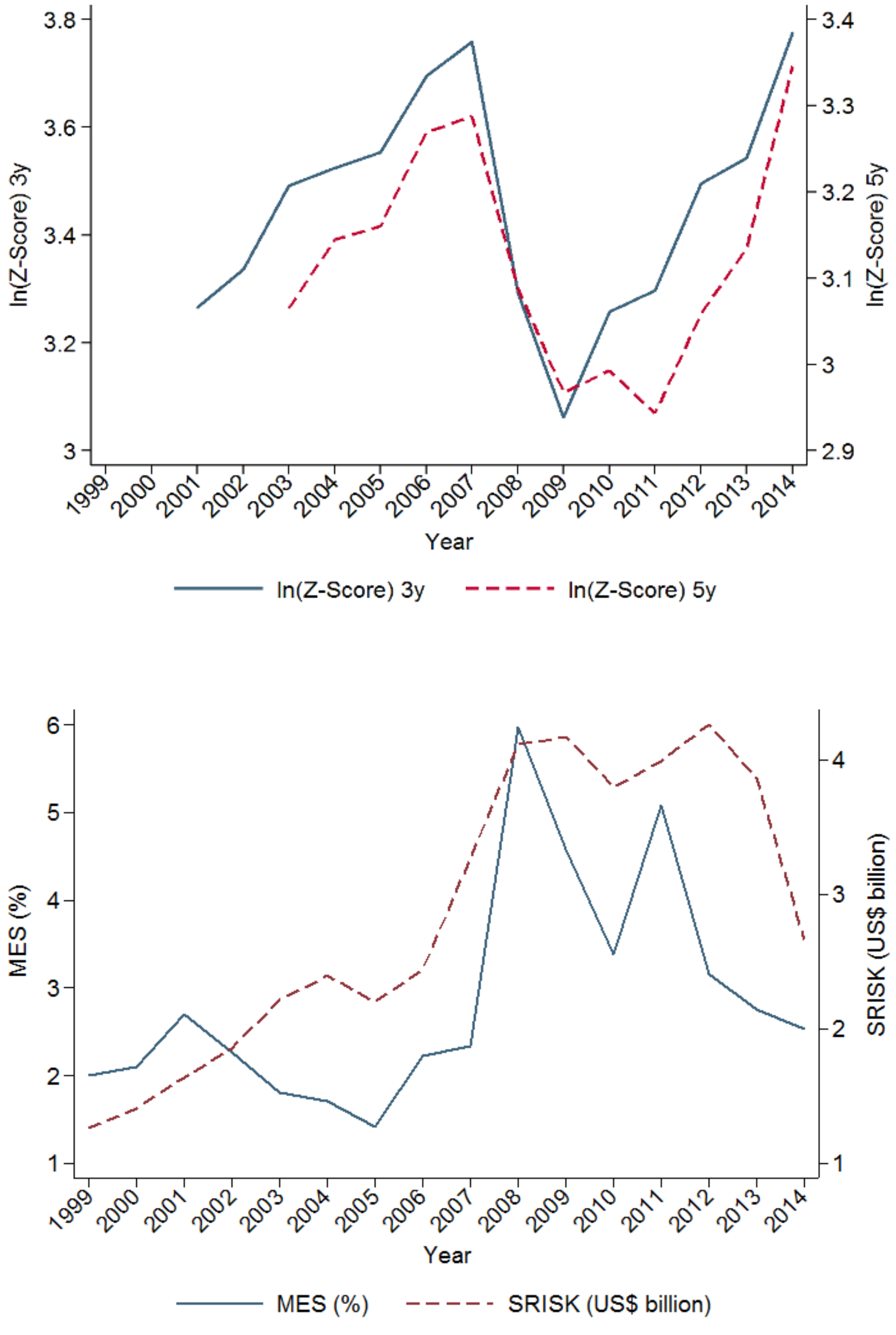

Figure 3. Evolution of financial stability over time (1999-2014).

This figure shows the time-series pattern of individual banks' financial stability (upper figure) and systemic risk (lower figure). The Z-score (distance-to-default) is defined as the sum of equity capital over total assets and return-on-assets (ROA), divided by either the three-year (3y) or five-year (5y) rolling standard deviation of ROA. A lower Z-score implies a higher probability of default. MES - Marginal Expected Shortfall (Acharya et al., 2012) is the bank *i*'s expected equity loss (in %) per dollar in year *t* conditional on the market experiencing one of its 5% lowest returns in that given year (the higher a bank's MES, the higher its contribution to systemic risk). SRISK - Systemic Capital Shortfall (Acharya et al., 2012; Engle et al., 2015) corresponds to the expected bank *i*'s capital shortage (in US$ billion) during a period of system distress and severe market decline. Unlike MES, SRISK is also function of the bank's book value of debt, its market value of equity and a minimum capital ratio that it needs to hold. All measures are calculated for each bank *i* in each year *t* and then averaged by country on a yearly basis to give equal weight to each country. The full sample consists of 19,125 bank-year observations corresponding to 2,047 commercial banks operating in 32 OECD countries from 1999 to 2014.

Table 1. Summary statistics

This table presents summary statistics for all the variables used in this study. Liquidity Creation is the Berger and Bowman (2009) "cat nonfat" measure i.e., on-balance-sheet liquidity creation when classifying activities by category. NSFR*i* (inverse of the Net Stable Funding Ratio) is defined as the ratio of the required amount of stable funding (RSF) to the available amount of stable funding (ASF). Table A.1 presents the weights given to the different balance-sheet items when computing both measures. Z-score is defined as the sum of equity capital over total assets and ROA, divided by either the three or five-year rolling standard deviation of ROA. Marginal Expected Shortfall (in %) corresponds to bank *i*'s expected equity loss per dollar in a certain year conditional on the market experiencing one of its 5% lowest returns in that given year. Similarly, Systemic Capital Shortfall (SRISK) measures the expected capital shortage (in billion US$) during a period of system distress when the market declines substantially. Bank-level controls include the bank size (total assets), capital ratio (capital to assets), return on assets (ROA), deposits to assets, provisions (loan loss provisions to total assets), cost to income ratio, non-interest revenue share (non-interest income in total income), share of wholesale funding (share of money market funding in money market funding and total deposits) and foreign owned (dummy variable that equals 1 if a bank is foreign-owned and 0 otherwise). All variables are winsorised at 1%. Country-level controls include the natural logarithm of GDP per capita, the standard deviation of the GDP growth rate over the past 5 years, global integration (imports plus exports of goods and service divided GDP), local market concentration (Herfindahl index), existence of explicit deposit insurance schemes, adoption of IFRS accounting standards, and presence of binding quantitative regulatory liquidity requirements. All control variables are lagged by one period to mitigate concerns of reverse causality. The full sample consists of 19,125 bank-year observations corresponding to 2,047 commercial banks operating in 32 OECD countries from 1999 to 2014.

Variables	N	Mean	SD	P25	P50	P75
Funding liquidity risk indicators						
Liquidity Creation	19,125	0.421	0.184	0.312	0.428	0.535
NSFR*i*	19,125	0.986	0.527	0.734	0.875	1.058
Financial stability indicators						
Ln(Z-score) – 3-year window	14,240	3.672	1.346	2.850	3.662	4.487
Ln(Z-score) – 5-year window	10,868	3.333	1.151	2.645	3.371	4.045
MES - Marginal Expected Shortfall (%)	3,765	2.326	2.070	0.870	1.946	3.145
S-RISK (bil US$)	3,664	2.650	11.40	0.000	0.278	1.338
Bank-level characteristics						
Ln(Total Assets)	19,125	8.249	2.164	6.577	8.143	9.802
Capital Ratio	19,125	0.100	0.083	0.053	0.078	0.116
Return-on-Assets	19,125	0.006	0.014	0.002	0.005	0.011
Deposits-to-Assets	19,125	0.598	0.233	0.447	0.634	0.786
Provisions	19,125	0.005	0.008	0.000	0.002	0.005
Cost-to-Income	18,382	0.674	0.271	0.529	0.640	0.758
Non-interest revenue share	18,489	0.367	0.232	0.199	0.333	0.500
Share of wholesale funding	19,125	0.244	0.246	0.048	0.160	0.372
Foreign Owned	19,125	0.309	0.462	0.000	0.000	1.000
Country-specific characteristics						
Ln(GDP per capita)	19,125	10.41	0.536	10.37	10.51	10.69
GDP growth volatility	19,125	0.018	0.012	0.009	0.015	0.024
Liquidity Regulation	19,125	0.318	0.466	0.000	0.000	1.000
Deposit Insurance	19,125	0.985	0.121	1.000	1.000	1.000
Concentration	19,125	0.200	0.148	0.070	0.163	0.282
Global Integration	19,125	0.774	0.603	0.469	0.581	0.925
IFRS	19,125	0.187	0.390	0.000	0.000	0.000

Year	N	Percent
1999	1,341	7.01
2000	1,308	6.84
2001	1,280	6.69
2002	1,255	6.56
2003	1,236	6.46
2004	1,211	6.33
2005	1,211	6.33
2006	1,180	6.17
2007	1,163	6.08
2008	1,129	5.90
2009	1,146	5.99
2010	1,175	6.14
2011	1,171	6.12
2012	1,155	6.04
2013	1,117	5.84
2014	1,047	5.47
Total	19,125	100

Table 2. Peer effects in banks' funding liquidity choices: liquidity creation

This table reports two-stage least squares (2SLS) coefficient estimates of model (1) when using the Berger and Bowman (2009) Liquidity Creation measure as the dependent variable i.e., on-balance-sheet liquidity creation when classifying activities by category. Table A.1 presents the balance-sheet weights given when computing this measure. Peer groups are defined as commercial banks operating in the same country in the same year grouped into a maximum of 10, 20 or 30 banks according to their size (total assets). The control variables (lagged) are defined in Table 1. Robust standard errors clustered at the bank level are in parentheses. *, ** and *** designate that the test statistic is significant at the 10%, 5% and 1% levels.

Dep. Variable: Liquidity Creation	Peer group size: 10 banks		Peer group size: 20 banks		Peer group size: 30 banks	
Peer Banks' Liquidity Creation	0.419**	0.385**	0.511***	0.459***	0.770***	0.708***
	(0.185)	(0.192)	(0.143)	(0.155)	(0.196)	(0.246)
ln(Total Assets)	-0.014**	-0.016**	-0.013**	-0.016***	-0.013**	-0.016***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Capital Ratio	-0.501***	-0.289***	-0.462***	-0.249***	-0.473***	-0.251***
	(0.055)	(0.066)	(0.053)	(0.063)	(0.052)	(0.063)
Return-on-Assets	0.078	-0.097	0.053	-0.142	0.079	-0.081
	(0.165)	(0.207)	(0.162)	(0.200)	(0.163)	(0.198)
Deposits-to-Assets	-0.089***	0.202***	-0.077***	0.200***	-0.082***	0.201***
	(0.021)	(0.037)	(0.020)	(0.035)	(0.020)	(0.035)
Provisions	-0.181	-0.191	-0.057	-0.044	-0.039	-0.020
	(0.281)	(0.298)	(0.273)	(0.285)	(0.269)	(0.285)
Cost-to-Income		-0.015		-0.018*		-0.015
		(0.010)		(0.010)		(0.010)
Non-interest revenue share		-0.044***		-0.039***		-0.039***
		(0.016)		(0.014)		(0.014)
Share of wholesale funding		0.291***		0.283***		0.288***
		(0.030)		(0.029)		(0.029)
Foreign Owned		0.021		0.018		0.016
		(0.014)		(0.013)		(0.012)
Peer Banks' ln(Total Assets)	0.002	0.000	0.005	0.005	0.007*	0.006
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Peer Banks' Capital Ratio	0.114	0.057	0.230**	0.251**	0.390***	0.308**
	(0.086)	(0.083)	(0.112)	(0.113)	(0.133)	(0.128)
Peer Banks' Return-on-Assets	0.410	0.248	0.223	-0.267	0.606	0.103
	(0.285)	(0.327)	(0.367)	(0.437)	(0.428)	(0.502)
Peer Banks' Deposits-to-Assets	0.011	0.012	-0.019	0.049	0.016	-0.014
	(0.027)	(0.054)	(0.037)	(0.063)	(0.042)	(0.077)
Peer Banks' Provisions	0.336	-0.004	0.155	-0.510	0.841	0.233
	(0.466)	(0.468)	(0.548)	(0.543)	(0.591)	(0.586)
Peer Banks' Cost-to-Income		-0.011		-0.034		-0.036
		(0.017)		(0.024)		(0.027)
Peer Banks' Non-interest revenue share		0.022		0.028		0.015
		(0.018)		(0.022)		(0.024)
Peer Banks' Share of wholesale funding		0.009		0.062		-0.037
		(0.054)		(0.060)		(0.084)
Peer Banks' Foreign Owned		0.004		0.006		0.020
		(0.012)		(0.017)		(0.021)
ln(GDP per capita)	0.070	0.007	0.059	0.015	0.019	-0.012
	(0.056)	(0.055)	(0.052)	(0.052)	(0.053)	(0.053)
GDP growth volatility	0.279	0.147	0.198	0.086	-0.023	-0.114
	(0.295)	(0.272)	(0.270)	(0.250)	(0.278)	(0.262)
Liquidity Regulation	0.002	0.014*	0.004	0.015**	0.005	0.013*
	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Deposit Insurance	0.013	0.010	0.009	0.008	0.002	0.001
	(0.026)	(0.024)	(0.024)	(0.022)	(0.025)	(0.022)
Concentration	0.128***	0.129***	0.108**	0.109**	0.066	0.072
	(0.048)	(0.047)	(0.042)	(0.042)	(0.044)	(0.046)
Global Integration		0.065**		0.051*		0.034
		(0.031)		(0.028)		(0.032)
IFRS		0.031***		0.029***		0.020
		(0.011)		(0.009)		(0.012)
No. observations	12,169	11,582	14,006	13,376	14,564	13,933
No. banks	1,489	1,438	1,573	1,522	1,619	1,568
R-squared	0.058	0.104	0.078	0.119	0.074	0.117
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap F-stat	77.04	68.52	166.7	129	95.30	58.20
IV	0.091***	0.085***	0.163***	0.139***	0.145***	0.108***
(1st stage)	(0.010)	(0.010)	(0.013)	(0.012)	(0.015)	(0.014)

Table 3. Peer effects in banks' funding liquidity choices: net stable funding ratio

This table reports two-stage least squares (2SLS) coefficient estimates of model (1) when using the inverse of the Net Stable Funding Ratio (NSFR*i*) as the dependent variable i.e., ratio of required amount of stable funding to the available amount of stable funding. Table A.1 presents the balance-sheet weights given when computing this measure. Peer groups are defined as commercial banks operating in the same country in the same year grouped into a maximum of 10, 20 or 30 banks according to their size (total assets). The control variables (lagged) are all defined in Table 1. Robust standard errors clustered at the bank level are in parentheses. *, ** and *** designate that the test statistic is significant at the 10%, 5% and 1% levels.

Dep. Variable: NSFR*i*	Peer group size: 10 banks		Peer group size: 20 banks		Peer group size: 30 banks	
Peer Banks' NSFR*i*	0.624***	0.668***	0.546**	0.558**	0.638**	0.696**
	(0.237)	(0.242)	(0.213)	(0.223)	(0.291)	(0.332)
ln(Total Assets)	-0.023	-0.031*	-0.023	-0.034**	-0.011	-0.022
	(0.017)	(0.018)	(0.016)	(0.017)	(0.015)	(0.017)
Capital Ratio	-1.254***	-0.947***	-1.297***	-1.000***	-1.322***	-1.016***
	(0.146)	(0.173)	(0.137)	(0.161)	(0.137)	(0.161)
Return-on-Assets	-0.176	-1.182*	-0.363	-1.265**	-0.309	-1.000*
	(0.404)	(0.614)	(0.389)	(0.559)	(0.385)	(0.558)
Deposits-to-Assets	-1.177***	-0.767***	-1.171***	-0.783***	-1.179***	-0.783***
	(0.064)	(0.109)	(0.060)	(0.097)	(0.060)	(0.097)
Provisions	-0.860	-1.482	-0.733	-1.229	-0.730	-1.108
	(0.839)	(0.918)	(0.753)	(0.815)	(0.731)	(0.802)
Cost-to-Income		-0.089***		-0.076***		-0.058**
		(0.030)		(0.027)		(0.026)
Non-interest revenue share		-0.024		-0.033		-0.021
		(0.048)		(0.045)		(0.045)
Share of wholesale funding		0.394***		0.386***		0.390***
		(0.088)		(0.078)		(0.076)
Foreign Owned		0.070**		0.061**		0.061**
		(0.031)		(0.028)		(0.026)
Peer Banks' ln(Total Assets)	0.011	0.008	0.023**	0.025**	0.009	0.012
	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)
Peer Banks' Capital Ratio	0.244	0.168	0.349	0.418	0.472	0.445
	(0.241)	(0.237)	(0.274)	(0.269)	(0.330)	(0.313)
Peer Banks' Return-on-Assets	0.695	1.546	0.397	0.925	1.205	1.403
	(0.760)	(1.013)	(0.880)	(1.165)	(0.971)	(1.304)
Peer Banks' Deposits-to-Assets	0.350**	0.323**	0.426*	0.552***	0.546*	0.560**
	(0.165)	(0.147)	(0.219)	(0.182)	(0.319)	(0.227)
Peer Banks' Provisions	0.352	0.983	0.113	0.462	0.838	0.990
	(1.120)	(1.222)	(1.259)	(1.320)	(1.359)	(1.432)
Peer Banks' Cost-to-Income		0.044		0.032		0.004
		(0.052)		(0.065)		(0.081)
Peer Banks' Non-interest revenue share		0.018		0.047		-0.003
		(0.047)		(0.055)		(0.066)
Peer Banks' Share of wholesale funding		-0.049		0.084		-0.077
		(0.129)		(0.179)		(0.240)
Peer Banks' Foreign Owned		0.008		-0.024		-0.026
		(0.028)		(0.047)		(0.062)
ln(GDP per capita)	-0.050	-0.030	0.023	0.065	-0.028	0.003
	(0.138)	(0.143)	(0.115)	(0.119)	(0.118)	(0.123)
GDP growth volatility	-0.181	-0.312	-0.219	-0.288	-0.329	-0.376
	(0.605)	(0.575)	(0.575)	(0.521)	(0.576)	(0.526)
Liquidity Regulation	-0.013	-0.007	-0.011	-0.003	-0.005	0.002
	(0.019)	(0.019)	(0.018)	(0.018)	(0.019)	(0.018)
Deposit Insurance	-0.019	-0.006	-0.012	0.005	-0.022	-0.008
	(0.040)	(0.039)	(0.037)	(0.036)	(0.037)	(0.036)
Concentration	0.064	0.050	0.124	0.123	0.096	0.094
	(0.116)	(0.122)	(0.099)	(0.102)	(0.097)	(0.100)
Global Integration		-0.043		-0.040		-0.049
		(0.087)		(0.082)		(0.081)
IFRS		0.008		0.013		0.004
		(0.022)		(0.020)		(0.021)
No. observations	12,169	11,582	14,006	13,376	14,564	13,933
No. banks	1,489	1,438	1,573	1,522	1,619	1,568
R-squared	0.098	0.097	0.167	0.177	0.165	0.169
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap F-stat	44.89	43.22	104.3	96.93	73.96	61.10
IV	0.053***	0.051***	0.070***	0.066***	0.062***	0.054***
(1st stage)	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)

Table 4. Peer effects in banks' funding liquidity choices - robustness tests: weighted peer averages based on size similarity and alternative instrument

This table reports two-stage least squares (2SLS) coefficient estimates of model (1) when using Liquidity Creation and NSFR*i* as dependent variables. Liquidity Creation is the Berger and Bowman (2009) "cat nonfat" measure i.e., on-balance-sheet liquidity creation when classifying activities by category. NSFR*i* (inverse of the Net Stable Funding Ratio) is defined as the ratio of the required amount of stable funding (RSF) to the available amount of stable funding (ASF). Table A.1 shows the weights given to the different balance-sheet items when computing both measures. Columns (1) to (4) present the results when using the benchmark IV as in Tables 2 and 3 but when computing peer weighted-averages based on the size similarity (inverse of the Euclidean distance) between all the commercial banks operating in country *j* in year *t*. The smaller the distance between two banks, the more weight it has. Specifications (5) to (8) use the benchmark peer group definition (i.e., commercial banks operating in the same country in the same year grouped into a maximum of 20 banks according to their size) but, following Leary and Roberts (2014), the peer banks' liquidity choices are now instrumented with the lagged idiosyncratic component of the peer banks' equity returns. All regressions include the same key ("Key") or full ("All") set of bank, peer and country-level (lagged) controls as in Tables 2 and 3, as well as year and bank fixed-effects. Robust standard errors clustered at the bank level are in parentheses. *, ** and *** designate that the test statistic is significant at the 10%, 5% and 1% levels.

	Liquidity Creation		NSFR*i*		Liquidity Creation		NSFR*i*	
Peer Banks' Liquidity Creation	0.845***	0.680*			1.256	0.994*		
	(0.285)	(0.374)			(1.484)	(0.573)		
Peer Banks' NSFR*i*			0.671***	0.598**			0.650*	0.730***
			(0.199)	(0.250)			(0.355)	(0.275)
No. observations	15,594	14,953	15,594	14,953	3,232	3,195	3,232	3,195
No. banks	1,687	1,636	1,687	1,636	323	317	323	317
R-squared	0.137	0.178	0.181	0.197	0.289	0.289	0.087	0.113
Bank Controls	Key	All	Key	All	Key	All	Key	All
Peers Controls	Key	All	Key	All	Key	All	Key	All
Country controls	Key	All	Key	All	Key	All	Key	All
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap F-stat	35.81	8.671	156.6	106.4	1.656	3.466	6.595	12.17
IV	0.151***	0.074***	0.135***	0.109***	0.016	0.024*	0.107**	0.147***
(1st stage)	(0.025)	(0.025)	(0.011)	(0.011)	(0.012)	(0.013)	(0.042)	(0.042)

Table 5. Peer effects in banks' funding liquidity choices - falsification test: peer groups defined globally

This table reports two-stage least squares (2SLS) coefficient estimates of model (1) when using Liquidity Creation and NSFR*i* as dependent variables. Liquidity Creation is the Berger and Bowman (2009) "cat nonfat" measure i.e., on-balance-sheet liquidity creation when classifying activities by category. NSFR*i* (inverse of the Net Stable Funding Ratio) is defined as the ratio of the required amount of stable funding (RSF) to the available amount of stable funding (ASF). Table A.1 shows the weights given to the different balance-sheet items when computing both measures. The peer (competitor) banks are now defined as other commercial banks of similar size operating in the same year, irrespective of the country of origin. In practice, I first rank banks according to their size, split them into 20, 50 or 100 size groups, and then construct the peer averages accordingly while excluding bank *i*. These splits are performed each year which implies that banks can switch size groups over time. All regressions include the same key ("Key") or full ("All") set of bank, peer and country-level (lagged) controls as in Tables 2 and 3, as well as year and bank fixed-effects. Robust standard errors clustered at the bank level are in parentheses. *, ** and *** designate that the test statistic is significant at the 10%, 5% and 1% levels.

	Liquidity Creation						NSFR*i*					
Peer Banks' Liquidity Creation	-0.033	0.123	-0.380	-0.129	-0.522	-0.362						
	(0.276)	(0.246)	(0.542)	(0.484)	(0.414)	(0.368)						
Peer Banks' NSFR*i*							-1.213	-1.940	0.432	0.668	0.538	0.625
							(1.998)	(1.535)	(0.485)	(0.490)	(0.382)	(0.383)
No. global size groups per year	20	20	50	50	100	100	20	20	50	50	100	100
No. observations	16,545	15,904	16,153	15,545	15,667	15,097	16,545	15,904	16,153	15,545	15,667	15,097
No. banks	1,732	1,681	1,712	1,662	1,697	1,649	1,732	1,681	1,712	1,662	1,697	1,649
R-squared	0.059	0.121	0.015	0.103	0.056	0.052	0.092	0.032	0.163	0.140	0.106	0.088
Bank Controls	Key	All	Key	All	Key	All	Key	All	Key	All	Key	All
Peers Controls	Key	All	Key	All	Key	All	Key	All	Key	All	Key	All
Country controls	Key	All	Key	All	Key	All	Key	All	Key	All	Key	All
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap F-stat	192.9	227.7	22.14	25.27	26.47	29.36	6.182	10.90	29.61	27.97	27.55	27.62
IV	0.121***	0.132***	0.034***	0.037***	0.031***	0.034***	0.015**	0.020***	0.032***	0.032***	0.026***	0.027***
(1st stage)	(0.009)	(0.009)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)

Table 6. Falsification test: peer effects in banks' capital choices

This table reports two-stage least squares (2SLS) coefficient estimates of model (1) when using the capital ratio (equity/total assets) and the Tier 1 Capital Ratio as dependent variables. As in the benchmark case, peer groups are defined as commercial banks operating in the same country in the same year grouped into a maximum of 10, 20 or 30 banks according to their size (total assets). All regressions include the same key ("Key") or full ("All") set of bank, peer and country-level (lagged) controls as in Tables 2 and 3, except that the "Capital Ratio" and "Peer Banks' Capital Ratio" are now removed as control variables, and the "Liquidity Ratio" (liquid assets to total assets) and "Peer Banks' Liquidity Ratio" are added instead. Robust standard errors clustered at the bank level are in parentheses. *, ** and *** designate that the test statistic is significant at the 10%, 5% and 1% levels.

	Capital Ratio (Equity/Assets)						Tier 1 Capital Ratio					
	Peer group size: 10 banks		Peer group size: 20 banks		Peer group size: 30 banks		Peer group size: 10 banks		Peer group size: 20 banks		Peer group size: 30 banks	
Peer Banks' Capital Ratio (E/A)	-0.277	-0.049	0.166	0.255	0.245	0.255						
	(0.510)	(0.428)	(0.302)	(0.273)	(0.255)	(0.230)						
Peer Banks' Tier 1 Capital Ratio							-0.182	0.019	-0.140	0.099	0.120	0.142
							(0.481)	(0.497)	(0.439)	(0.464)	(0.357)	(0.342)
No. observations	12,369	11,774	14,233	13,597	14,824	14,186	3,582	3,525	4,783	4,726	5,259	5,200
No. banks	1,506	1,454	1,603	1,551	1,648	1,596	637	627	721	712	747	738
R-squared	0.042	0.164	0.139	0.185	0.145	0.191	0.158	0.214	0.156	0.194	0.170	0.198
Bank Controls	Key	All	Key	All	Key	All	Key	All	Key	All	Key	Full
Peers Controls	Key	All	Key	All	Key	All	Key	All	Key	All	Key	Full
Country controls	Key	All	Key	All	Key	All	Key	All	Key	All	Key	Full
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap F-stat	9.433	11.99	29.08	36.12	60.91	78.40	7.576	6.585	14.05	12.43	26.56	27.41
IV	0.038***	0.042***	0.069***	0.072***	0.099***	0.106***	0.088***	0.082**	0.102***	0.096***	0.118***	0.119***
(1st stage)	(0.012)	(0.012)	(0.013)	(0.012)	(0.013)	(0.012)	(0.032)	(0.032)	(0.027)	(0.027)	(0.023)	(0.023)

Table 7. Peer effects in banks' funding liquidity choices: heterogeneity

This table reports the two-stage least square (2SLS) coefficient estimates of model (1) when using the Liquidity Creation measure and the inverse of the NSFR (NSFR*i*) as dependent variables and splitting the sample by the lower and higher (i.e., low vs. high) of the within country-year distribution of lagged values for bank-specific measures solvency, profitability, credit risk, funding structure, asset mix and efficiency i.e., capital ratio (equity to asset ratio), return on assets, share of wholesale funding (the share of money market funding in money market funding and total deposits), deposit-to-total assets and cost-to-income ratio, respectively. Liquidity Creation is the Berger and Bowman (2009) "cat nonfat" measure i.e., on-balance-sheet liquidity creation when classifying activities by category. NSFR*i* is defined as the ratio of the required amount of stable funding (RSF) to the available amount of stable funding (ASF). Table A.1 shows the weights given to the different balance-sheet items when computing both measures. Peer averages are constructed based on the benchmark peer group definition i.e., commercial banks operating in the same country in the same year grouped in a maximum of 20 banks according to their size. The reported β coefficients (i.e. the peer effect) correspond to specifications (3) and (4) of Tables 2 and 3 where the key ("Key") or full ("All") set of bank, peer and country-level (lagged) controls are included in the regression, respectively, as well as year and bank fixed-effects. Robust standard errors clustered at the bank level are in parentheses and the number of bank-year observations are in square brackets. *, ** and *** designate that the test statistic is significant at the 10%, 5% and 1% levels.

	Peer Effect: Liquidity Creation		Peer Effect: NSFR*i*	
Low Capital Ratio	0.646***	0.597***	0.625*	0.660*
	(0.174)	(0.201)	(0.365)	(0.394)
	[7,173]	[6,787]	[7,173]	[6,787]
High Capital Ratio	0.746***	0.672***	0.226	0.213
	(0.219)	(0.232)	(0.251)	(0.257)
	[6,610]	[6,368]	[6,610]	[6,368]
Low Profitability	0.601***	0.605***	0.813**	0.718*
	(0.192)	(0.210)	(0.388)	(0.399)
	[6,814]	[6,472]	[6,814]	[6,472]
High Profitability	0.577***	0.488**	0.376*	0.359*
	(0.207)	(0.225)	(0.204)	(0.213)
	[6,820]	[6,545]	[6,820]	[6,545]
Low provisions share	0.352*	0.326	0.400	0.462
	(0.195)	(0.233)	(0.306)	(0.345)
	[7,236]	[6,637]	[7,236]	[6,637]
High provisions share	0.671***	0.607***	0.723**	0.680**
	(0.208)	(0.207)	(0.334)	(0.341)
	[6,394]	[6,357]	[6,394]	[6,357]
Low share of wholesale funding	0.372**	0.232	0.132	0.089
	(0.175)	(0.202)	(0.126)	(0.125)
	[6,970]	[6,607]	[6,970]	[6,607]
High share of wholesale funding	0.739***	0.759***	0.833**	0.926**
	(0.209)	(0.225)	(0.404)	(0.427)
	[6,785]	[6,523]	[6,785]	[6,523]
Low deposit-to-assets ratio	0.753***	0.758***	0.755**	0.838**
	(0.214)	(0.238)	(0.382)	(0.404)
	[6,962]	[6,683]	[6,962]	[6,683]
High deposit-to-assets ratio	0.394**	0.291	0.147	0.042
	(0.189)	(0.214)	(0.118)	(0.120)
	[6,822]	[6,483]	[6,822]	[6,483]
Low Cost-to-Income ratio	0.722***	0.635***	0.744***	0.772***
	(0.219)	(0.221)	(0.261)	(0.277)
	[6,784]	[6,783]	[6,784]	[6,783]
High Cost-to-Income ratio	0.443**	0.354	0.292	0.244
	(0.219)	(0.235)	(0.359)	(0.345)
	[6,303]	[6,296]	[6,303]	[6,296]
Bank Controls	Key	All	Key	All
Peers Controls	Key	All	Key	All
Country controls	Key	All	Key	All
Year FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes

Table 8. Who is mimicking who?

This table reports two-stage least squares (2SLS) coefficient estimates of model (1) when using Liquidity Creation and NSFR*i* as dependent variables. Liquidity Creation is the Berger and Bowman (2009) "cat nonfat" measure i.e., on-balance-sheet liquidity creation when classifying activities by category. NSFR*i* (inverse of the Net Stable Funding Ratio) is defined as the ratio of the required amount of stable funding (RSF) to the available amount of stable funding (ASF). Table A.1 shows the weights given to the different balance-sheet items when computing both measures. Banks are classified as "Small" or "Large" by splitting the sample by the lower and higher (i.e., big vs. small) of the within country-year distribution of bank size. Peer averages are then constructed based on the following four scenarios: (i) large banks mimicking large banks; (ii) large banks mimicking small banks; (iii) small banks mimicking small banks; and (iv) small banks mimicking large banks. The reported β coefficients (i.e. the peer effect) correspond to specifications (3) and (4) of Tables 2 and 3 where the key ("Key") or full ("All") set of bank, peer and country-level (lagged) controls are included in the regression, respectively, as well as year and bank fixed-effects. Robust standard errors clustered at the bank level are in parentheses and the number of bank-year observations are in square brackets. *, ** and *** designate that the test statistic is significant at the 10%, 5% and 1% levels.

	Peer Effect: Liquidity Creation		Peer Effect: NSFR*i*	
Large banks mimicking Large banks & Small banks mimicking Small banks	0.782***	0.808***	0.705***	0.743***
	(0.118)	(0.124)	(0.240)	(0.268)
	[15,122]	[14,484]	[15,122]	[14,484]
Large banks mimicking Large banks	0.841***	0.825***	1.183*	1.286**
	(0.192)	(0.297)	(0.611)	(0.637)
	[6,473]	[6,134]	[6,473]	[6,134]
Small banks mimicking Small banks	0.855***	0.791***	0.642**	0.473*
	(0.199)	(0.202)	(0.289)	(0.279)
	[5,926]	[5,751]	[5,926]	[5,751]
Large banks mimicking Small banks & Small banks mimicking Large banks	0.275*	0.046	0.110	0.020
	(0.165)	(0.211)	(0.241)	(0.264)
	[15,122]	[14,484]	[15,122]	[14,484]
Large banks mimicking Small banks	0.240	0.126	0.178	0.382
	(0.203)	(0.213)	(0.416)	(0.426)
	[7,393]	[7,008]	[7,393]	[7,008]
Small banks mimicking Large banks	0.773**	1.108	1.106	1.479
	(0.375)	(1.069)	(0.716)	(1.142)
	[6,942]	[6,716]	[6,942]	[6,716]
Bank Controls	Key	All	Key	All
Peers Controls	Key	All	Key	All
Country controls	Key	All	Key	All
Year FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes

Table 9. Asymmetric behavior

This table reports two-stage least squares (2SLS) coefficient estimates of model (1) augmented with two interaction variables to account for asymmetric responses to competitors' behavior: (i) peer banks' funding liquidity risk x a dummy variable equal to 1 if peer banks' funding liquidity risk decreased from the previous period, a 0 otherwise ("Decreased from *t-1*"); (ii) peer banks' funding liquidity risk x dummy variable equal to 1 if peer banks' funding liquidity risk increased from the previous period, and 0 otherwise ("Increased from *t-1*"). Funding liquidity risk is captured by either the Liquidity Creation measure (Berger and Bowman, 2009 "cat nonfat" measure i.e., on-balance-sheet liquidity creation when classifying activities by category) or the NSFR*i* (inverse of the Net Stable Funding Ratio, defined as the ratio of the required amount of stable funding to the available amount of stable funding). Table A.1 shows the weights given to the different balance-sheet items when computing both measures. Peer groups are defined as commercial banks operating in the same country in the same year grouped into a maximum of 10, 20 or 30 banks according to their size (total assets). All regressions include the same key ("Key") or full ("All") set of bank, peer and country-level (lagged) controls as in Tables 2 and 3. Robust standard errors clustered at the bank level are in parentheses. *, ** and *** designate that the test statistic is significant at the 10%, 5% and 1% levels.

	Liquidity Creation						NSFR*i*					
	Peer group size: 10 banks		Peer group size: 20 banks		Peer group size: 30 banks		Peer group size: 10 banks		Peer group size: 20 banks		Peer group size: 30 banks	
Peer Banks' Liquidity Creation x Decreased from *t-1*	0.009	0.007	0.003	-0.002	0.005	0.002						
	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)						
Peer Banks' Liquidity Creation x Increased from *t-1*	0.012**	0.015**	0.009	0.012**	0.010**	0.015***						
	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)						
Peer Banks' NSFR*i* x Decreased from *t-1*							-0.002	-0.005	-0.005	-0.008	0.005	0.000
							(0.009)	(0.009)	(0.007)	(0.007)	(0.007)	(0.007)
Peer Banks' NSFR*i* x Increased from *t-1*							0.012	0.013*	0.012*	0.014**	0.013**	0.012*
							(0.007)	(0.007)	(0.006)	(0.007)	(0.006)	(0.006)
No. observations	12,169	11,582	14,006	13,376	14,564	13,933	12,169	11,582	14,006	13,376	14,564	13,933
No. banks	1,489	1,438	1,573	1,522	1,619	1,568	1,489	1,438	1,573	1,522	1,619	1,568
R-squared	0.057	0.104	0.054	0.102	0.053	0.101	0.193	0.205	0.192	0.205	0.190	0.202
Bank Controls	Key	All	Key	All	Key	All	Key	All	Key	All	Key	All
Peers Controls	Key	All	Key	All	Key	All	Key	All	Key	All	Key	All
Country controls	Key	All	Key	All	Key	All	Key	All	Key	All	Key	All
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 10. Peer effects in banks' funding liquidity choices and default risk

This table reports coefficient estimates of model (3) when using ln(Z-Score) as dependent variable. Z-score is defined as the sum of equity capital over total assets (E/A) and return on assets (ROA), divided by the three-year rolling standard deviation of ROA. The peer effects in funding liquidity decisions are estimated with model (2) when using Liquidity Creation and NSFRi as dependent variables ($\widehat{\beta_{j,t}^{LC}}$ and $\widehat{\beta_{j,t}^{NSFRi}}$, respectively), where the relationship between the liquidity of bank i and the liquidity of its peers is now allowed to vary across countries and over time. Liquidity Creation is the Berger and Bowman (2009) "cat nonfat" measure i.e., on-balance-sheet liquidity creation when classifying activities by category. NSFRi (inverse of the Net Stable Funding Ratio) is defined as the ratio of the required amount of stable funding (RSF) to the available amount of stable funding (ASF). Table A.1 shows the weights given to the different balance-sheet items when computing both measures. Peer groups are defined as commercial banks operating in the same country in the same year grouped into a maximum of 10, 20 or 30 banks according to their size (total assets). The control variables (lagged) are all defined in Table 1. Robust standard errors clustered at the bank level are in parentheses. *, ** and *** designate that the test statistic is significant at the 10%, 5% and 1% levels.

Dep. Variable: ln(Z-Score) i.e., ln$[(E/A+ROA)/\sigma(ROA)_{3y}]$	Peer group size: 10 banks		Peer group size: 20 banks		Peer group size: 30 banks	
Peer Effect:	-1.160***		-0.948***		-1.333***	
Liq. Creation - $\widehat{\beta_{j,t}^{LC}}$	(0.194)		(0.213)		(0.273)	
Peer Effect:		-0.463**		-0.642**		-0.615**
NSFRi - $\widehat{\beta_{j,t}^{NSFRi}}$		(0.220)		(0.268)		(0.277)
ln(Total Assets)	-0.119***	-0.117***	-0.118***	-0.117***	-0.119***	-0.118***
	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)
Deposits-to-Assets	0.109	0.083	0.102	0.085	0.100	0.086
	(0.233)	(0.229)	(0.231)	(0.230)	(0.231)	(0.230)
Provisions	-35.098***	-34.710***	-34.878***	-34.618***	-34.839***	-34.588***
	(2.070)	(2.065)	(2.066)	(2.062)	(2.064)	(2.060)
Cost-to-Income	-0.953***	-0.945***	-0.950***	-0.946***	-0.949***	-0.945***
	(0.062)	(0.062)	(0.062)	(0.062)	(0.062)	(0.062)
Non-interest revenue share	-0.621***	-0.594***	-0.614***	-0.599***	-0.619***	-0.598***
	(0.126)	(0.126)	(0.126)	(0.126)	(0.126)	(0.126)
Share of wholesale funding	0.012	-0.019	0.004	-0.012	0.008	-0.007
	(0.195)	(0.193)	(0.194)	(0.193)	(0.193)	(0.193)
Foreign Owned	-0.022	-0.022	-0.021	-0.020	-0.025	-0.023
	(0.134)	(0.135)	(0.134)	(0.134)	(0.133)	(0.134)
ln(GDP per capita)	2.125***	2.447***	2.244***	2.442***	2.291***	2.452***
	(0.413)	(0.409)	(0.414)	(0.409)	(0.411)	(0.409)
GDP growth volatility	-4.500**	-2.891	-3.544*	-2.823	-3.536*	-2.822
	(2.106)	(2.126)	(2.108)	(2.123)	(2.101)	(2.123)
Liquidity Regulation	-0.152***	-0.168***	-0.155***	-0.165***	-0.157***	-0.166***
	(0.058)	(0.058)	(0.058)	(0.058)	(0.058)	(0.058)
Deposit Insurance	0.002	0.012	0.006	0.011	0.009	0.008
	(0.212)	(0.210)	(0.211)	(0.210)	(0.211)	(0.210)
Concentration	0.176	0.106	0.116	0.114	0.113	0.102
	(0.335)	(0.334)	(0.335)	(0.335)	(0.336)	(0.335)
Global Integration	-0.389**	-0.628***	-0.467**	-0.627***	-0.494***	-0.631***
	(0.189)	(0.187)	(0.189)	(0.187)	(0.186)	(0.187)
IFRS	-0.124**	-0.170***	-0.139**	-0.172***	-0.149***	-0.172***
	(0.057)	(0.057)	(0.057)	(0.057)	(0.057)	(0.057)
No. observations	13,738	13,738	13,738	13,738	13,738	13,738
No. banks	1,659	1,659	1,659	1,659	1,659	1,659
Adj. R-squared	0.134	0.130	0.132	0.130	0.132	0.130
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 11. Peer effects in banks' funding liquidity choices and systemic risk: MES

This table reports coefficient estimates of model (3) when using the MES - Marginal Expected Shortfall (Acharya et al., 2012) as dependent variable. MES is defined as the bank i's expected equity loss (in %) per dollar in year t conditional on the market experiencing one of its 5% lowest returns in that given year (the higher a bank's MES, the larger its systemic risk exposure). The peer effects in funding liquidity decisions are estimated with model (2) when using Liquidity Creation and NSFRi as dependent variables ($\widehat{\beta_{j,t}^{LC}}$ and $\widehat{\beta_{j,t}^{NSFRi}}$, respectively), where the relationship between the liquidity of bank i and the liquidity of its peers is now allowed to vary across countries and over time. Liquidity Creation is the Berger and Bowman (2009) "cat nonfat" measure i.e., on-balance-sheet liquidity creation when classifying activities by category. NSFRi (inverse of the Net Stable Funding Ratio) is defined as the ratio of the required amount of stable funding (RSF) to the available amount of stable funding (ASF). Table A.1 shows the weights given to the different balance-sheet items when computing both measures. Peer groups are defined as commercial banks operating in the same country in the same year grouped into a maximum of 10, 20 or 30 banks according to their size (total assets). The control variables (lagged) are all defined in Table 1. Robust standard errors clustered at the bank level are in parentheses. *, ** and *** designate that the test statistic is significant at the 10%, 5% and 1% levels.

Dep. Variable: Marginal Expected Shortfall (MES)	Peer group size: 10 banks		Peer group size: 20 banks		Peer group size: 30 banks	
Peer Effect:	2.328***		1.722***		1.094*	
Liq. Creation - $\widehat{\beta_{j,t}^{LC}}$	(0.709)		(0.621)		(0.588)	
Peer Effect:		3.710***		3.449***		3.286***
NSFRi - $\widehat{\beta_{j,t}^{NSFRi}}$		(0.930)		(0.843)		(0.817)
ln(Total Assets)	0.539***	0.622***	0.658***	0.690***	0.723***	0.747***
	(0.202)	(0.208)	(0.154)	(0.156)	(0.148)	(0.150)
Capital Ratio	2.547	2.359	3.552	3.452	3.229	3.107
	(2.532)	(2.521)	(2.298)	(2.310)	(2.251)	(2.249)
Return-on-Assets	-2.148	-2.598	1.114	1.584	2.985	4.237
	(10.602)	(10.663)	(10.803)	(11.000)	(10.331)	(10.365)
Deposits-to-Assets	-0.037	-0.404	-0.234	-0.485	-0.097	-0.422
	(0.823)	(0.772)	(0.759)	(0.736)	(0.741)	(0.713)
Provisions	6.910	4.363	9.359	8.730	11.738	11.474
	(9.414)	(9.774)	(9.113)	(9.338)	(8.824)	(9.012)
Cost-to-Income,	0.760**	0.785**	0.684*	0.722*	0.647*	0.696*
	(0.382)	(0.366)	(0.389)	(0.383)	(0.379)	(0.373)
Non-interest revenue share	0.327	0.239	0.132	0.143	0.149	0.171
	(0.438)	(0.433)	(0.404)	(0.405)	(0.403)	(0.398)
Share of wholesale funding	-0.559	-0.672	-0.563	-0.741	-0.560	-0.812
	(0.703)	(0.682)	(0.652)	(0.640)	(0.647)	(0.627)
Foreign Owned	-0.771**	-0.773*	-0.747*	-0.739*	-0.736*	-0.716*
	(0.388)	(0.405)	(0.398)	(0.411)	(0.401)	(0.414)
ln(GDP per capita)	-1.449	-1.597	-1.065	-1.248	-1.012	-1.219
	(1.085)	(1.042)	(0.893)	(0.876)	(0.866)	(0.856)
GDP growth volatility	18.701***	15.093**	23.951***	22.061***	24.428***	23.689***
	(6.435)	(6.009)	(5.739)	(5.547)	(5.753)	(5.526)
Liquidity Regulation	-0.234	-0.188	-0.291**	-0.273*	-0.301**	-0.288**
	(0.161)	(0.156)	(0.144)	(0.143)	(0.143)	(0.140)
Deposit Insurance	-0.175	-0.182	-0.155	-0.131	-0.175	-0.148
	(0.397)	(0.396)	(0.375)	(0.372)	(0.376)	(0.367)
Concentration	0.780	0.780	0.278	0.322	0.252	0.351
	(1.101)	(1.054)	(0.912)	(0.912)	(0.850)	(0.866)
Global Integration	-0.254	0.278	-0.494	-0.152	-0.685	-0.374
	(0.743)	(0.705)	(0.713)	(0.695)	(0.768)	(0.722)
IFRS	0.119	0.115	0.160	0.183	0.140	0.125
	(0.177)	(0.173)	(0.170)	(0.167)	(0.167)	(0.165)
No. observations	1,775	1,775	2,192	2,192	2,379	2,379
No. banks	276	276	303	303	330	330
Adj. R-squared	0.533	0.536	0.486	0.488	0.475	0.480
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 12. Peer effects in banks' funding liquidity choices and systemic risk: SRISK

This table reports coefficient estimates of model (3) when using the Systemic Capital Shortfall - SRISK (Acharya et al., 2012; Engle et al., 2015) as dependent variable which corresponds to the expected bank i's capital shortage (in US$ billion) during a period of system distress and severe market decline. Unlike MES, SRISK is also a function of the bank's book value of debt, its market value of equity and a minimum capital ratio that bank firm needs to hold. To ensure comparability across countries, I follow Engle et al. (2015) and set this prudential capital ratio to 4% for banks reporting under IFRS and to 8% for all other accounting standards, including US GAAP. The peer effects in funding liquidity decisions are estimated with model (2) when using Liquidity Creation and NSFRi as dependent variables ($\widehat{\beta_{j,t}^{LC}}$ and $\widehat{\beta_{j,t}^{NSFRi}}$, respectively), where the relationship between the liquidity of bank i and the liquidity of its peers is now allowed to vary across countries and over time. Liquidity Creation is the Berger and Bowman (2009) "cat nonfat" measure i.e., on-balance-sheet liquidity creation when classifying activities by category. NSFRi (inverse of the Net Stable Funding Ratio) is defined as the ratio of the required amount of stable funding (RSF) to the available amount of stable funding (ASF). Table A.1 shows the weights given to the different balance-sheet items when computing both measures. Peer groups are defined as commercial banks operating in the same country in the same year grouped into a maximum of 10, 20 or 30 banks according to their size (total assets). The control variables (lagged) are all defined in Table 1. Robust standard errors clustered at the bank level are in parentheses. *, ** and *** designate that the test statistic is significant at the 10%, 5% and 1% levels.

Dep. Variable: SRISK	Peer group size: 10 banks		Peer group size: 20 banks		Peer group size: 30 banks	
Peer Effect:	3.847*		3.738**		3.222*	
Liq. Creation - $\widehat{\beta_{j,t}^{LC}}$	(1.985)		(1.774)		(1.772)	
Peer Effect:		6.644***		8.677***		8.572***
NSFRi - $\widehat{\beta_{j,t}^{NSFRi}}$		(2.492)		(2.783)		(2.872)
ln(Total Assets)	0.131	0.270	0.333	0.404	0.380	0.448
	(0.917)	(0.915)	(0.635)	(0.635)	(0.636)	(0.632)
Capital Ratio	0.427	0.061	1.813	1.522	0.936	0.676
	(7.588)	(7.518)	(6.132)	(6.082)	(5.985)	(5.915)
Return-on-Assets	1.464	0.750	-5.845	-4.457	-2.040	1.060
	(19.555)	(19.780)	(16.978)	(17.128)	(15.877)	(16.326)
Deposits-to-Assets	-3.410	-4.082*	-3.565*	-4.248**	-3.423*	-4.208**
	(2.152)	(2.141)	(1.942)	(1.959)	(1.952)	(1.963)
Provisions	-13.280	-17.469	-12.927	-14.219	-8.764	-9.814
	(22.956)	(23.250)	(17.705)	(17.615)	(17.256)	(17.137)
Cost-to-Income,	1.509	1.558	1.150	1.264	1.133	1.258
	(1.176)	(1.196)	(1.031)	(1.049)	(1.030)	(1.046)
Non-interest revenue share	0.454	0.311	0.176	0.227	0.001	0.058
	(1.681)	(1.687)	(1.404)	(1.408)	(1.372)	(1.360)
Share of wholesale funding	-2.371	-2.598	-2.664	-3.164	-2.539	-3.170
	(3.046)	(3.063)	(2.573)	(2.582)	(2.470)	(2.493)
Foreign Owned	-1.653	-1.648	-1.364	-1.349	-1.345	-1.300
	(1.169)	(1.192)	(1.015)	(1.030)	(1.013)	(1.024)
ln(GDP per capita)	1.420	1.222	2.321	1.938	2.530	1.933
	(2.864)	(2.841)	(2.464)	(2.401)	(2.401)	(2.272)
GDP growth volatility	8.663	2.830	9.759	5.383	9.910	7.562
	(17.068)	(16.029)	(16.440)	(15.992)	(16.154)	(15.472)
Liquidity Regulation	-1.033*	-0.940	-1.225**	-1.172**	-1.224**	-1.198**
	(0.575)	(0.576)	(0.543)	(0.540)	(0.540)	(0.540)
Deposit Insurance	0.462	0.444	0.508	0.559	0.472	0.551
	(0.754)	(0.782)	(0.630)	(0.651)	(0.619)	(0.648)
Concentration	8.347*	8.424*	6.876*	7.096*	6.087	6.331
	(4.869)	(4.871)	(4.120)	(4.151)	(3.936)	(3.940)
Global Integration	-7.727**	-6.831**	-7.267**	-6.471**	-7.480**	-6.593**
	(3.458)	(3.255)	(3.303)	(3.167)	(3.379)	(3.201)
IFRS	-2.944***	-2.969***	-2.657***	-2.633***	-2.527***	-2.554***
	(0.867)	(0.868)	(0.763)	(0.751)	(0.717)	(0.717)
No. observations	1,775	1,775	2,184	2,184	2,371	2,371
No. banks	278	278	305	305	332	332
Adj. R-squared	0.105	0.108	0.093	0.099	0.090	0.098
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes

Table A.1. Liquidity Creation and NSFR weights

This table presents the weights assigned to each bank balance sheet item to construct the Liquidity Creation and NSFR*i* measures, as well as the respective Bankscope item codes. Liquidity Creation is the Berger and Bowman (2009) "cat nonfat" measure i.e., on-balance-sheet liquidity creation when classifying activities by category. NSFR*i* (inverse of the Net Stable Funding Ratio) is defined as the ratio of the required amount of stable funding (RSF) to the available amount of stable funding (ASF). "Other Non-earning Assets" includes Foreclosed Real Estate, Goodwill, Other Intangibles, Current Tax Assets, Deferred Tax Assets, Discontinued Operations and Other Assets. "Other liabilities (tax, pension, insurance)" comprises Credit Impairment Reserves, Reserves for Pensions and Other Reserves, Fair Value Portion of Debt, Deferred Tax Liabilities, Other Deferred Liabilities, Discontinued Operations, Insurance Liabilities, Other Liabilities and Current Tax Liabilities. "Deposits from Banks" contains Bank Deposits, and Repos and Cash Collateral. "Loans and Advances to Banks" comprises Bank Loans and Advances, and Reverse Repos and Cash Collateral. "Long-Term Funding" includes Senior Debt Maturing after 1 Year, Subordinated Borrowing, Other Funding and Pref. Shares and Hybrid Capital accounted for as Debt. "Other Equity" consists of Non-controlling Interest, Securities Revaluation Reserves, Foreign Exchange Revaluation Reserves, Fixed Asset Revaluations and Other Accumulated OCI and Pref. Shares and Hybrid Capital accounted for as Equity. "Other Securities" includes Trading Securities and at FV through Income, Available for Sale Securities and Other Securities. "Other Earning Assets" comprises Investments in Property, Insurance Assets and Other Earning Assets.

Assets	*NSFR (RSF)*	*Liquidity Creation*	
Loans			
Residential Mortgage Loans: data11040	85%	0.5	Illiquid
Other Mortgage Loans: data11045	85%	0.5	Illiquid
Other Consumer/Retail Loans: data11050	85%	0.5	Illiquid
Corporate & Commercial Loans: data11060	85%	0.5	Illiquid
Other Loans: data11070	85%	0.5	Illiquid
Gross Loans: data2001			
Less: Reserves for Impaired Loans/NPLs: data2002	100%	0.5	Illiquid
Net Loans: data2000			
Other Earning Assets			
Loans and Advances to Banks: data2180	15%	0	Semi-liquid
Government Securities: data11215	5%	-0.5	Liquid
Derivatives: data2007	50%	0	Semi-liquid
Held to Maturity Securities: data11180	100%	0.5	Liquid
At-equity Investments in Associates: data11190	100%	0.5	Liquid
Trading Securities and at FV through Income: data11150	50%	0	Semi-liquid
Other Securities: data2008-data11190-data11215- data11180-data11150	50%	0	Semi-liquid
Other Earning Assets: data2009	100%	0.5	Illiquid
Total Earning Assets: data2010			
Non-earning Assets			
Cash and Due From Banks: data11270	0%	-0.5	Liquid
Fixed Assets: data2015	100%	0.5	Illiquid
Other Non-earning Assets: data2020-data11270	100%	0.5	Illiquid
Total Assets: data2025			

Liabilities	*NSFR (ASF)*	*Liquidity Creation*	
Interest-bearing Liabilities			
Customer Deposits – Current: data11520	90%	0.5	Liquid
Customer Deposits – Savings: data11530	95%	0	Semi-Liquid
Customer Deposits – Term: data11540	95%	0	Semi-Liquid
Total Customer Deposits: data2031			
Deposits from Banks: data2185	0%	0	Semi-Liquid
Other Deposits and Short-Term Borrowings: data2033	0%	0.5	Liquid
Long Term Funding*: data2038	100%	-0.5	Illiquid
Derivatives: data2036	0%	0	Semi-Liquid
Trading Liabilities: data2037	0%	0	Semi-Liquid
Total Funding: data11650			
Non-interest Bearing Liabilities			
Other liabilities (tax, pension, insurance): data11750-data11650	0%	-0.5	Illiquid
Total Liabilities: data11750			

Equity			
Common Equity: data11800	100%	-0.5	Illiquid
Other Equity: data2055-data11800	100%	-0.5	Illiquid
Total Equity: data2055			

Appendix. Computation of the return shock

To extract the idiosyncratic component of stock returns, I follow Leary and Roberts (2014) by using, in addition to the market factor traditional in asset pricing models, an industry factor to remove any common variation in returns across the same peer group. The model is specified as follows:

$$R_{i,j,t} = \alpha_{i,j,t} + \lambda_{i,j,t}\left(RM_{j,t} - Rf_{j,t}\right) + \phi_{i,j,t}\left(\bar{R}_{-i,j,t} - Rf_{j,t}\right) + \epsilon_{i,j,t} \quad (5)$$

where $R_{i,j,t}$ refers to the stock return for bank i in country j over month t, $\left(RM_{j,t} - Rf_{j,t}\right)$ is the excess market returns (i.e., market factor) and $\left(\bar{R}_{-i,j,t} - Rf_{j,t}\right)$ is the excess return on an equally-weighted portfolio excluding bank i's return (i.e., industry factor). The intercept $\alpha_{i,j,t}$ measures the mean monthly abnormal return. I use the one-month US T-Bill Rate to proxy for the risk-free rate and the Morgan Stanley Capital International (MSCI) Country equity market indices to proxy for the market factor for the individual countries considered. Equation (5) is estimated for each bank in a rolling regression using a minimum of 24 and a maximum of 60 past monthly returns. In detail, to compute expected and idiosyncratic returns of bank i in month m of year t, I first estimate equation (5) using monthly returns from month m of year $t-5$ to month $m+12$ of year $t-1$. Using the estimated coefficients and the factor returns from bank i in month m of year t, the idiosyncratic return component, $\hat{\eta}_{i,j,t}$, is computed as the difference between the actual return $R_{i,j,t}$ and the expected return $\hat{R}_{i,j,t}$:

$$\hat{R}_{i,j,t} = \hat{\alpha}_{i,j,t} + \hat{\lambda}_{i,j,t}\left(RM_{j,t} - Rf_{j,t}\right) + \hat{\phi}_{i,j,t}\left(\bar{R}_{-i,j,t} - Rf_{j,t}\right) \quad (6)$$

$$\hat{\eta}_{i,j,t} = R_{i,j,t} - \hat{R}_{i,j,t} \quad (7)$$

In order to ensure consistency with the frequency of accounting data, I compound the monthly idiosyncratic return component to have an annual measure. This quantity is then averaged over the peer banks for each country j in each year t. In short, the exogenous source of variation for peer banks' liquidity choices is the lagged average peer bank equity return shock. The idiosyncratic return obtained from the above model is then the return of the bank after removing all known sources of systematic variation (i.e., exposure to market and industry). Thus, the residuals obtained from (5) should be purely bank specific and hence, free from any commonalities across the bank.

INTERNET APPENDIX

Strategic complementarity in banks' funding liquidity choices and financial stability

by André Silva

May, 2016

Table IA.1. Sample distribution by country and percentage of foreign-owned banks by country and year

This table presents the sample distribution by country and the percentage of foreign-owned commercial banks (no. foreign-owned banks/total no. banks) for each country-year combination. N denotes the number of bank-year observations. To avoid double-counting within a single institution and have financial information at the most disaggregated level possible, I discard consolidated entries if banks report information at the unconsolidated level. I also restrict the coverage to the largest 100 commercial banks in each country i.e., a bank is excluded from the sample if and only if it is not in the Top 100 in terms of assets in the country it operates in all the years it is active. Branches of foreign banks are also not included since they generally do not report individual information. The full sample consists of 19,125 bank-year observations corresponding to 2,047 commercial banks operating in 32 OECD countries from 1999 to 2014.

% Foreign-Owned Banks	N	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Australia	295	20%	25%	33%	31%	20%	13%	38%	35%	36%	43%	30%	26%	28%	22%	20%	21%
Austria	536	17%	35%	29%	31%	26%	27%	30%	31%	26%	25%	32%	38%	34%	36%	45%	41%
Belgium	337	43%	48%	55%	63%	56%	60%	60%	61%	55%	56%	60%	58%	56%	47%	44%	54%
Canada	497	69%	73%	59%	55%	53%	53%	50%	50%	48%	46%	47%	60%	43%	45%	46%	46%
Chile	272	40%	37%	37%	33%	32%	28%	29%	29%	41%	57%	54%	41%	38%	38%	38%	38%
Czech Republic	251	64%	79%	69%	75%	75%	78%	76%	83%	83%	80%	76%	75%	79%	73%	79%	77%
Denmark	745	5%	4%	7%	8%	8%	10%	6%	8%	8%	8%	9%	10%	10%	9%	3%	4%
Estonia	74	50%	60%	60%	60%	60%	60%	80%	60%	67%	60%	50%	60%	67%	75%	75%	75%
Finland	152	0%	0%	20%	25%	20%	20%	20%	25%	25%	29%	22%	20%	14%	8%	8%	12%
France	1,493	26%	34%	31%	32%	31%	27%	30%	28%	26%	22%	25%	22%	23%	23%	21%	22%
Germany	1,440	28%	29%	27%	28%	29%	29%	33%	37%	35%	37%	32%	31%	32%	32%	28%	33%
Greece	200	8%	9%	8%	7%	13%	21%	24%	31%	33%	27%	27%	27%	25%	33%	0%	0%
Hungary	285	85%	85%	82%	78%	88%	84%	78%	82%	82%	78%	63%	56%	56%	58%	58%	56%
Ireland	147	57%	63%	63%	63%	57%	63%	70%	73%	60%	60%	67%	64%	73%	80%	75%	75%
Italy	1,483	4%	3%	4%	7%	6%	5%	6%	5%	7%	5%	7%	9%	8%	9%	10%	8%
Japan	1,706	0%	0%	0%	0%	0%	0%	0%	1%	1%	1%	1%	2%	2%	2%	2%	3%
Luxembourg	878	98%	96%	97%	97%	98%	98%	98%	98%	98%	98%	98%	98%	96%	95%	95%	94%
Mexico	429	56%	48%	46%	52%	50%	48%	38%	42%	33%	34%	32%	29%	28%	30%	27%	26%
Netherlands	382	46%	54%	56%	59%	59%	59%	41%	43%	41%	50%	50%	50%	46%	44%	52%	57%
New Zealand	104	50%	50%	60%	60%	50%	67%	60%	60%	60%	67%	67%	57%	63%	67%	67%	70%
Norway	178	20%	18%	18%	17%	27%	30%	33%	30%	20%	10%	8%	9%	8%	8%	8%	7%
Poland	442	55%	53%	63%	73%	69%	67%	67%	75%	68%	70%	64%	71%	61%	69%	66%	70%
Portugal	247	18%	24%	22%	31%	31%	29%	36%	29%	33%	44%	29%	29%	21%	38%	33%	33%
South Korea	227	0%	0%	7%	7%	13%	14%	14%	15%	15%	15%	17%	15%	14%	13%	13%	13%
Slovakia	108	43%	83%	83%	100%	100%	100%	89%	88%	78%	75%	86%	86%	83%	100%	100%	100%
Slovenia	177	18%	18%	25%	50%	50%	43%	45%	42%	45%	38%	38%	38%	38%	36%	33%	31%
Spain	568	21%	22%	22%	24%	26%	24%	28%	26%	22%	24%	27%	20%	26%	24%	28%	27%
Sweden	302	11%	11%	5%	5%	6%	6%	5%	6%	6%	5%	5%	5%	5%	4%	4%	4%
Switzerland	1,656	35%	36%	35%	34%	35%	35%	34%	34%	36%	36%	34%	33%	32%	30%	29%	29%
Turkey	239	14%	13%	14%	17%	20%	33%	25%	38%	50%	42%	40%	42%	39%	38%	46%	46%
United Kingdom	1,084	48%	47%	47%	53%	51%	54%	54%	52%	49%	52%	52%	58%	57%	58%	55%	54%
Unites States	2,191	6%	6%	8%	9%	10%	11%	12%	13%	13%	14%	17%	17%	18%	15%	17%	17%

Table IA.2. Peer effects in banks' funding liquidity choices: robustness test – OLS

This table reports Ordinary Least Squares (OLS) coefficient estimates of model (1) when using Liquidity Creation and NSFR*i* as dependent variables. Liquidity Creation is the Berger and Bowman (2009) "cat nonfat" measure i.e., on-balance-sheet liquidity creation when classifying activities by category. NSFR*i* (inverse of the Net Stable Funding Ratio) is defined as the ratio of the required amount of stable funding (RSF) to the available amount of stable funding (ASF). Table A.1 shows the weights given to the different balance-sheet items when computing both measures. Peer groups are defined as commercial banks operating in the same country in the same year grouped into a maximum of 10, 20 or 30 banks according to their size (total assets). The regressions correspond to and include the same key ("Key") or full ("All") set of bank, peer and country-level (lagged) controls as in Tables 2 and 3, as well as year and bank fixed-effects. Robust standard errors clustered at the bank level are in parentheses. *, ** and *** designate that the test statistic is significant at the 10%, 5% and 1% levels.

	Liquidity Creation						NSFR*i*					
	Peer group size: 10 banks		Peer group size: 20 banks		Peer group size: 30 banks		Peer group size: 10 banks		Peer group size: 20 banks		Peer group size: 30 banks	
Peer Banks' Liquidity Creation	0.354***	0.325***	0.516***	0.470***	0.590***	0.550***						
	(0.023)	(0.022)	(0.029)	(0.028)	(0.031)	(0.030)						
Peer Banks' NSFR*i*							0.074***	0.077***	0.138***	0.126***	0.158***	0.146***
							(0.022)	(0.021)	(0.030)	(0.030)	(0.036)	(0.037)
No. observations	16,726	16,080	16,727	16,083	16,727	16,083	16,726	16,080	16,727	16,083	16,727	16,083
No. banks	1,913	1,859	1,913	1,860	1,913	1,860	1,913	1,859	1,913	1,860	1,913	1,860
Adj. R-squared	0.100	0.147	0.122	0.164	0.131	0.172	0.185	0.198	0.186	0.198	0.186	0.198
Bank Controls	Key	All	Key	All	Key	All	Key	All	Key	All	Key	All
Peers Controls	Key	All	Key	All	Key	All	Key	All	Key	All	Key	All
Country controls	Key	All	Key	All	Key	All	Key	All	Key	All	Key	All
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table IA.3. Peer effects in banks' liquidity choices: robustness test – NSFD

This table reports two-stage least squares (2SLS) coefficient estimates of model (1) when using the Net Stable Funding Difference (NSFD) as the dependent variable i.e., (required amount of stable funding - available amount of stable funding)/total assets. Table A.1 presents the balance-sheet weights given when computing this measure. Peer groups are defined as commercial banks operating in the same country in the same year grouped into a maximum of 10, 20 or 30 banks according to their size (total assets). The control variables (lagged) are defined in Table 1. Robust standard errors clustered at the bank level are in parentheses. *, ** and *** designate that the test statistic is significant at the 10%, 5% and 1% levels.

Dep. Variable: NSFD	Peer group size: 10 banks		Peer group size: 20 banks		Peer group size: 30 banks	
Peer Banks' NSFD	0.314**	0.322**	0.392***	0.355***	0.379***	0.366**
	(0.138)	(0.141)	(0.114)	(0.118)	(0.134)	(0.142)
ln(Total Assets)	-0.011	-0.014**	-0.007	-0.011	-0.001	-0.006
	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)
Capital Ratio	-0.521***	-0.347***	-0.506***	-0.331***	-0.509***	-0.329***
	(0.065)	(0.073)	(0.061)	(0.069)	(0.059)	(0.068)
Return-on-Assets	0.335**	0.020	0.282*	0.024	0.316*	0.108
	(0.167)	(0.222)	(0.164)	(0.212)	(0.164)	(0.211)
Deposits-to-Assets	-0.556***	-0.328***	-0.537***	-0.312***	-0.542***	-0.313***
	(0.022)	(0.042)	(0.021)	(0.039)	(0.020)	(0.038)
Provisions	0.017	-0.140	0.007	-0.105	0.085	-0.006
	(0.303)	(0.329)	(0.285)	(0.304)	(0.279)	(0.300)
Cost-to-Income		-0.023**		-0.021**		-0.016*
		(0.010)		(0.010)		(0.010)
Non-interest revenue share		-0.014		-0.018		-0.017
		(0.016)		(0.016)		(0.016)
Share of wholesale funding		0.227***		0.230***		0.232***
		(0.035)		(0.032)		(0.031)
Foreign Owned		0.034**		0.030**		0.028**
		(0.016)		(0.014)		(0.013)
Peer Banks' ln(Total Assets)	0.002	0.001	0.006*	0.006*	-0.001	-0.000
	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)
Peer Banks' Capital Ratio	0.063	0.081	0.150	0.235**	0.178	0.209*
	(0.079)	(0.082)	(0.104)	(0.110)	(0.117)	(0.119)
Peer Banks' Return-on-Assets	0.286	0.392	0.130	-0.043	0.519	0.216
	(0.313)	(0.366)	(0.362)	(0.441)	(0.400)	(0.488)
Peer Banks' Deposits-to-Assets	0.069	0.113**	0.083	0.188***	0.088	0.152**
	(0.047)	(0.053)	(0.059)	(0.063)	(0.077)	(0.073)
Peer Banks' Provisions	-0.047	0.059	-0.191	-0.372	0.039	-0.213
	(0.435)	(0.456)	(0.545)	(0.566)	(0.583)	(0.609)
Peer Banks' Cost-to-Income		0.002		-0.013		-0.020
		(0.018)		(0.023)		(0.026)
Peer Banks' Non-interest revenue share		0.020		0.031		0.035
		(0.019)		(0.023)		(0.026)
Peer Banks' Share of wholesale funding		0.040		0.107*		0.062
		(0.046)		(0.064)		(0.077)
Peer Banks' Foreign Owned		0.001		-0.012		-0.008
		(0.011)		(0.016)		(0.021)
ln(GDP per capita)	0.089*	0.094*	0.066	0.086*	0.049	0.067
	(0.054)	(0.053)	(0.048)	(0.048)	(0.049)	(0.050)
GDP growth volatility	0.296	0.276	0.204	0.218	0.204	0.194
	(0.282)	(0.273)	(0.261)	(0.248)	(0.260)	(0.248)
Liquidity Regulation	0.002	0.009	0.003	0.010	0.004	0.010
	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)
Deposit Insurance	0.014	0.020	0.009	0.017	0.008	0.015
	(0.022)	(0.020)	(0.021)	(0.019)	(0.021)	(0.019)
Concentration	0.078	0.076	0.068	0.071*	0.060	0.062
	(0.047)	(0.047)	(0.041)	(0.041)	(0.039)	(0.039)
Global Integration		-0.003		-0.004		-0.004
		(0.026)		(0.025)		(0.025)
IFRS		0.010		0.012		0.011
		(0.009)		(0.008)		(0.008)
No. observations	12,169	11,582	14,006	13,376	14,564	13,933
No. banks	1,489	1,438	1,573	1,522	1,619	1,568
R-squared	0.244	0.261	0.255	0.276	0.254	0.274
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap F-stat	112.6	109.5	199.4	187.3	207.4	196.6
IV	0.085***	0.081***	0.127***	0.119***	0.136***	0.127***
(1st stage)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)

Table IA.4. Peer effects in banks' liquidity choices: robustness test – liquidity ratio

This table reports two-stage least squares (2SLS) coefficient estimates of model (1) when using the Liquidity Ratio as the dependent variable i.e., liquid assets/total assets. Peer groups are defined as commercial banks operating in the same country in the same year grouped into a maximum of 10, 20 or 30 banks according to their size (total assets). The control variables (lagged) are all defined in Table 1. Robust standard errors clustered at the bank level are in parentheses. *, ** and *** designate that the test statistic is significant at the 10%, 5% and 1% levels.

Dep. Variable: Liquidity Ratio	Peer group size: 10 banks		Peer group size: 20 banks		Peer group size: 30 banks	
Peer Banks' Liquidity Ratio	0.321***	0.316***	0.478***	0.452***	0.608***	0.540***
	(0.076)	(0.077)	(0.135)	(0.143)	(0.186)	(0.207)
ln(Total Assets)	0.012*	0.017**	0.001	0.008	-0.002	0.004
	(0.008)	(0.007)	(0.008)	(0.007)	(0.007)	(0.007)
Capital Ratio	0.018	0.006	0.000	0.009	0.000	0.016
	(0.067)	(0.067)	(0.063)	(0.063)	(0.062)	(0.062)
Return-on-Assets	-0.402**	-0.140	-0.393**	-0.236	-0.375*	-0.300
	(0.196)	(0.243)	(0.193)	(0.233)	(0.193)	(0.229)
Deposits-to-Assets	0.056**	0.043	0.047**	0.055	0.045**	0.057
	(0.025)	(0.044)	(0.023)	(0.040)	(0.022)	(0.040)
Provisions	-0.425	-0.173	-0.478*	-0.326	-0.567**	-0.452
	(0.299)	(0.313)	(0.288)	(0.296)	(0.278)	(0.289)
Cost-to-Income		0.031***		0.026**		0.020**
		(0.011)		(0.010)		(0.010)
Non-interest revenue share		0.057***		0.055***		0.060***
		(0.017)		(0.016)		(0.016)
Share of wholesale funding		-0.013		0.002		0.005
		(0.032)		(0.030)		(0.030)
Foreign Owned		-0.018		-0.018		-0.017
		(0.016)		(0.015)		(0.015)
Peer Banks' ln(Total Assets)	-0.002	-0.005	0.002	-0.003	0.004	0.001
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
Peer Banks' Capital Ratio	-0.022	-0.145*	-0.115	-0.309***	-0.170	-0.310**
	(0.079)	(0.086)	(0.109)	(0.119)	(0.116)	(0.132)
Peer Banks' Return-on-Assets	0.200	0.191	0.376	0.607	0.097	0.170
	(0.318)	(0.366)	(0.411)	(0.457)	(0.474)	(0.534)
Peer Banks' Deposits-to-Assets	0.017	-0.115**	0.037	-0.183***	0.016	-0.183**
	(0.022)	(0.051)	(0.029)	(0.069)	(0.036)	(0.092)
Peer Banks' Provisions	-0.354	-0.460	0.063	0.208	0.211	0.141
	(0.452)	(0.474)	(0.589)	(0.578)	(0.668)	(0.637)
Peer Banks' Cost-to-Income		-0.011		0.008		0.007
		(0.019)		(0.023)		(0.028)
Peer Banks' Non-interest revenue share		-0.051***		-0.060***		-0.088***
		(0.019)		(0.023)		(0.030)
Peer Banks' Share of wholesale funding		-0.135***		-0.202***		-0.183**
		(0.042)		(0.062)		(0.086)
Peer Banks' Foreign Owned		0.005		-0.003		-0.019
		(0.011)		(0.018)		(0.023)
ln(GDP per capita)	-0.189***	-0.228***	-0.096	-0.149**	-0.035	-0.105
	(0.058)	(0.061)	(0.064)	(0.066)	(0.072)	(0.073)
GDP growth volatility	-0.548**	-0.709***	-0.393	-0.509*	-0.237	-0.370
	(0.264)	(0.259)	(0.273)	(0.280)	(0.295)	(0.317)
Liquidity Regulation	-0.022**	-0.024***	-0.014*	-0.016**	-0.013*	-0.014*
	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)
Deposit Insurance	0.001	0.005	-0.017	-0.015	-0.017	-0.016
	(0.019)	(0.019)	(0.019)	(0.020)	(0.019)	(0.019)
Concentration	-0.083**	-0.050	-0.065	-0.038	-0.051	-0.021
	(0.042)	(0.042)	(0.040)	(0.040)	(0.039)	(0.039)
Global Integration		0.029		0.037		0.042
		(0.030)		(0.029)		(0.030)
IFRS		-0.017*		-0.016		-0.015
		(0.010)		(0.010)		(0.012)
No. observations	12,389	11,796	14,252	13,616	14,842	14,204
No. banks	1,508	1,457	1,603	1,552	1,648	1,597
R-squared	0.027	0.040	0.049	0.062	0.053	0.070
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap F-stat	318	312.8	138.2	123.1	122.6	120.3
IV	0.180***	0.176***	0.130***	0.124***	0.096***	0.087***
(1st stage)	(0.010)	(0.010)	(0.011)	(0.011)	(0.009)	(0.008)

Table IA.5. Peer effects in banks' capital choices: robustness test - common equity/assets

This table reports two-stage least squares (2SLS) coefficient estimates of model (1) when using the capital ratio defined as common equity to total assets as dependent variable. As in the benchmark case, peer groups are defined as commercial banks operating in the same country in the same year grouped into a maximum of 10, 20 or 30 banks according to their size (total assets). All regressions correspond to those in Table 6 which include the same key ("Key") or full ("All") set of bank, peer and country-level (lagged) controls as in Tables 2 and 3 except that the "Capital Ratio" and "Peer Banks' Capital Ratio" are now removed as control variables, and the "Liquidity Ratio" (liquid assets to total assets) and "Peer Banks' Liquidity Ratio" are added instead. Robust standard errors clustered at the bank level are in parentheses. *, ** and *** designate that the test statistic is significant at the 10%, 5% and 1% levels.

	Capital Ratio (Common Equity/Assets)					
	Peer group size: 10 banks		Peer group size: 20 banks		Peer group size: 30 banks	
Peer Banks' Capital Ratio (CE/A)	-0.199	-0.080	-0.145	-0.053	-0.083	-0.040
	(0.362)	(0.318)	(0.308)	(0.278)	(0.330)	(0.290)
No. observations	12,380	11,785	14,226	13,590	14,820	14,182
No. banks	1,512	1,461	1,603	1,552	1,647	1,596
R-squared	0.072	0.155	0.094	0.159	0.112	0.168
Bank Controls	Key	All	Key	All	Key	All
Peers Controls	Key	All	Key	All	Key	All
Country controls	Key	All	Key	All	Key	All
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap F-stat	14.70	17.44	27.65	33.66	27.87	37.58
IV - 1st stage	0.049***	0.052***	0.066***	0.069***	0.071***	0.078***
	(0.013)	(0.012)	(0.013)	(0.012)	(0.013)	(0.013)

Table IA.6. Asymmetric behavior: robustness test – sample splits

This table reports two-stage least squares (2SLS) coefficient estimates of model (1) when splitting the sample into two scenarios: (i) when peer banks' funding liquidity risk increased from the previous period (Panel A); (ii) when peer banks' funding liquidity risk decreased from the previous period (Panel B). Funding liquidity risk is captured by either the Liquidity Creation measure (Berger and Bowman, 2009 "cat nonfat" measure i.e., on-balance-sheet liquidity creation when classifying activities by category) or the NSFR*i* (inverse of the Net Stable Funding Ratio, defined as the ratio of the required amount of stable funding to the available amount of stable funding). Table A.1 shows the weights given to the different balance-sheet items when computing both measures. Peer groups are defined as commercial banks operating in the same country in the same year grouped into 10, 20 or 30 banks according to their size (total assets). All regressions include the same key ("Key") or full ("All") set of bank, peer and country-level (lagged) controls as Tables 2 and 3. Robust standard errors clustered at the bank level are in parentheses. *, ** and *** designate that the test statistic is significant at the 10%, 5% and 1% levels.

Panel A: Funding liquidity risk of competitors increased from previous period

	Liquidity Creation						NSFR*i*					
	Peer group size: 10 banks		Peer group size: 20 banks		Peer group size: 30 banks		Peer group size: 10 banks		Peer group size: 20 banks		Peer group size: 30 banks	
Peer Banks' Liquidity Creation	0.655*	0.746*	0.615***	0.576**	0.734***	0.660***						
	(0.337)	(0.414)	(0.228)	(0.259)	(0.196)	(0.231)						
Peer Banks' NSFR*i*							1.080**	1.180**	0.705**	0.730**	1.042***	0.992**
							(0.501)	(0.550)	(0.319)	(0.355)	(0.395)	(0.427)
No. observations	6,029	5,739	6,736	6,427	7,002	6,687	5,741	5,457	6,421	6,143	6,486	6,197
No. banks	1,257	1,203	1,339	1,282	1,333	1,280	1,262	1,206	1,323	1,269	1,329	1,274
R-squared	0.047	0.079	0.082	0.123	0.084	0.140	0.077	0.113	0.156	0.160	0.129	0.148
Bank Controls	Key	All	Key	All	Key	All	Key	All	Key	All	Key	All
Peers Controls	Key	All	Key	All	Key	All	Key	All	Key	All	Key	All
Country controls	Key	All	Key	All	Key	All	Key	All	Key	All	Key	All
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Funding liquidity risk of competitors decreased from previous period

	Liquidity Creation						NSFR*i*					
	Peer group size: 10 banks		Peer group size: 20 banks		Peer group size: 30 banks		Peer group size: 10 banks		Peer group size: 20 banks		Peer group size: 30 banks	
Peer Banks' Liquidity Creation	0.544	0.420	0.550***	0.456*	0.851***	0.861*						
	(0.340)	(0.330)	(0.211)	(0.254)	(0.314)	(0.455)						
Peer Banks' NSFR*i*							1.610	1.505	0.797	0.650	0.308	0.253
							(1.065)	(0.994)	(0.699)	(0.755)	(0.602)	(0.709)
No. observations	5,748	5,449	6,940	6,615	7,197	6,884	6,061	5,754	7,236	6,879	7,671	7,335
No. banks	1,237	1,186	1,372	1,321	1,423	1,374	1,244	1,190	1,387	1,330	1,419	1,372
R-squared	0.059	0.114	0.102	0.142	0.101	0.135	0.137	0.055	0.159	0.196	0.209	0.223
Bank Controls	Key	All	Key	All	Key	All	Key	All	Key	All	Key	All
Peers Controls	Key	All	Key	All	Key	All	Key	All	Key	All	Key	All
Country controls	Key	All	Key	All	Key	All	Key	All	Key	All	Key	All
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table IA.7. Peer effects in banks' funding liquidity choices and default risk: robustness test – Z-score with a 5-year window

This table reports coefficient estimates of model (3) when using ln(Z-Score) as dependent variable where the Z-score is now defined as the sum of equity capital over total assets (E/A) and return on assets (ROA), divided by the five-year rolling standard deviation of ROA. The peer effects in funding liquidity decisions are estimated with model (2) when using Liquidity Creation and NSFRi as dependent variables ($\widehat{\beta_{J,t}^{LC}}$ and $\widehat{\beta_{J,t}^{NSFRi}}$, respectively), where the relationship between the liquidity of bank i and the liquidity of its peers is now allowed to vary across countries and over time. Liquidity Creation is the Berger and Bowman (2009) "cat nonfat" measure i.e., on-balance-sheet liquidity creation when classifying activities by category. NSFRi (inverse of the Net Stable Funding Ratio) is defined as the ratio of the required amount of stable funding (RSF) to the available amount of stable funding (ASF). Table A.1 shows the weights given to the different balance-sheet items when computing both measures. Peer groups are defined as commercial banks operating in the same country in the same year grouped into a maximum of 10, 20 or 30 banks according to their size (total assets). The control variables (lagged) are all defined in Table 1. Robust standard errors clustered at the bank level are in parentheses. *, ** and *** designate that the test statistic is significant at the 10%, 5% and 1% levels.

Dep. Variable: ln(Z-Score) i.e., ln$[(E/A+ROA)/\sigma(ROA)_{5y}]$	Peer group size: 10 banks		Peer group size: 20 banks		Peer group size: 30 banks	
Peer Effect:	-0.525***		-0.600***		-1.110***	
Liq. Creation - $\widehat{\beta_{J,t}^{LC}}$	(0.169)		(0.194)		(0.237)	
Peer Effect:		-0.488**		-0.621***		-0.479**
NSFRi - $\widehat{\beta_{J,t}^{NSFRi}}$		(0.190)		(0.232)		(0.234)
ln(Total Assets)	-0.170***	-0.168***	-0.169***	-0.167***	-0.171***	-0.167***
	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)
Deposits-to-Assets	-0.341	-0.331	-0.339	-0.333	-0.328	-0.337
	(0.243)	(0.242)	(0.243)	(0.242)	(0.243)	(0.242)
Provisions	-26.908***	-26.685***	-26.851***	-26.587***	-26.864***	-26.548***
	(2.095)	(2.073)	(2.088)	(2.073)	(2.084)	(2.071)
Cost-to-Income	-0.904***	-0.898***	-0.904***	-0.899***	-0.904***	-0.897***
	(0.067)	(0.067)	(0.067)	(0.067)	(0.068)	(0.067)
Non-interest revenue share	-0.285**	-0.271**	-0.287**	-0.278**	-0.300**	-0.274**
	(0.116)	(0.116)	(0.116)	(0.116)	(0.117)	(0.116)
Share of wholesale funding	-0.036	-0.043	-0.037	-0.038	-0.024	-0.037
	(0.196)	(0.195)	(0.196)	(0.195)	(0.195)	(0.196)
Foreign Owned	-0.181	-0.185	-0.181	-0.184	-0.181	-0.187
	(0.148)	(0.149)	(0.148)	(0.148)	(0.147)	(0.148)
ln(GDP per capita)	3.229***	3.428***	3.244***	3.411***	3.238***	3.424***
	(0.427)	(0.424)	(0.429)	(0.424)	(0.422)	(0.424)
GDP growth volatility	-0.605	-0.017	-0.364	0.191	-0.592	0.214
	(2.480)	(2.484)	(2.468)	(2.471)	(2.444)	(2.473)
Liquidity Regulation	-0.104*	-0.110**	-0.104*	-0.108*	-0.098*	-0.108*
	(0.055)	(0.056)	(0.055)	(0.056)	(0.055)	(0.056)
Deposit Insurance	0.063	0.066	0.066	0.067	0.060	0.060
	(0.224)	(0.224)	(0.224)	(0.224)	(0.224)	(0.224)
Concentration	0.188	0.112	0.153	0.123	0.155	0.111
	(0.332)	(0.338)	(0.334)	(0.338)	(0.337)	(0.339)
Global Integration	-0.408*	-0.534**	-0.415*	-0.532**	-0.403*	-0.534**
	(0.213)	(0.210)	(0.212)	(0.210)	(0.208)	(0.210)
IFRS	-0.142***	-0.163***	-0.142***	-0.163***	-0.141***	-0.161***
	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)
No. observations	10,519	10,519	10,519	10,519	10,519	10,519
No. banks	1,394	1,394	1,394	1,394	1,394	1,394
Adj. R-squared	0.154	0.153	0.154	0.153	0.156	0.153
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes

Table IA.8. Peer effects in banks' funding liquidity choices and default risk: robustness test – Z-score with liquidity risk controls

This table reports coefficient estimates of model (3) when using ln(Z-Score) as dependent variable. Z-score is defined as the sum of equity capital over total assets (E/A) and return on assets (ROA), divided by the three-year rolling standard deviation of ROA. The peer effects in funding liquidity decisions are estimated with model (2) when using Liquidity Creation and NSFRi as dependent variables ($\widehat{\beta_{J,t}^{LC}}$ and $\widehat{\beta_{J,t}^{NSFRi}}$, respectively), where the relationship between the liquidity of bank i and the liquidity of its peers is now allowed to vary across countries and over time. Liquidity Creation is the Berger and Bowman (2009) "cat nonfat" measure i.e., on-balance-sheet liquidity creation when classifying activities by category. NSFRi (inverse of the Net Stable Funding Ratio) is defined as the ratio of the required amount of stable funding (RSF) to the available amount of stable funding (ASF). Table A.1 shows the weights given to the different balance-sheet items when computing both measures. Peer groups are defined as commercial banks operating in the same country in the same year grouped into a maximum of 10, 20 or 30 banks according to their size (total assets). The control variables (lagged) are all defined in Table 1. The Liquidity Ratio is defined as liquid assets to total assets. Robust standard errors clustered at the bank level are in parentheses. *, ** and *** designate that the test statistic is significant at the 10%, 5% and 1% levels.

Dep. Variable: ln(Z-Score) i.e., $\ln[(E/A+ROA)/\sigma(ROA)_{3y}]$	Peer group size: 10 banks		Peer group size: 20 banks		Peer group size: 30 banks	
Peer Effect:	-1.198***		-0.948***		-1.323***	
Liq. Creation - $\widehat{\beta_{J,t}^{LC}}$	(0.203)		(0.224)		(0.279)	
Peer Effect:		-0.484**		-0.645**		-0.616**
NSFRi - $\widehat{\beta_{J,t}^{NSFRi}}$		(0.221)		(0.272)		(0.279)
Liquidity Creation	-0.069	-0.285**	-0.141	-0.282**	-0.164	-0.284**
	(0.142)	(0.136)	(0.143)	(0.137)	(0.139)	(0.136)
NSFR	-0.068	-0.041	-0.061	-0.037	-0.060	-0.039
	(0.050)	(0.049)	(0.050)	(0.050)	(0.049)	(0.050)
Liquidity Ratio	-0.510***	-0.480***	-0.492***	-0.478***	-0.488***	-0.476***
	(0.143)	(0.143)	(0.143)	(0.143)	(0.143)	(0.142)
ln(Total Assets)	-0.116***	-0.116***	-0.116***	-0.116***	-0.116***	-0.117***
	(0.039)	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)
Deposits-to-Assets	0.110	0.157	0.124	0.159	0.130	0.160
	(0.227)	(0.225)	(0.226)	(0.225)	(0.225)	(0.225)
Provisions	-35.320***	-34.853***	-35.060***	-34.756***	-35.013***	-34.726***
	(2.076)	(2.066)	(2.070)	(2.065)	(2.067)	(2.063)
Cost-to-Income	-0.943***	-0.938***	-0.941***	-0.939***	-0.940***	-0.938***
	(0.062)	(0.062)	(0.062)	(0.062)	(0.062)	(0.062)
Non-interest revenue share	-0.598***	-0.580***	-0.593***	-0.585***	-0.599***	-0.584***
	(0.126)	(0.126)	(0.126)	(0.126)	(0.126)	(0.126)
Share of wholesale funding	0.053	0.080	0.065	0.082	0.076	0.089
	(0.191)	(0.190)	(0.191)	(0.190)	(0.190)	(0.190)
Foreign Owned	-0.022	-0.019	-0.020	-0.018	-0.023	-0.021
	(0.132)	(0.134)	(0.133)	(0.134)	(0.132)	(0.134)
ln(GDP per capita)	2.030***	2.343***	2.155***	2.339***	2.201***	2.349***
	(0.417)	(0.413)	(0.418)	(0.414)	(0.415)	(0.414)
GDP growth volatility	-4.999**	-3.477	-4.023*	-3.392	-4.023*	-3.392
	(2.114)	(2.133)	(2.116)	(2.130)	(2.110)	(2.130)
Liquidity Regulation	-0.152***	-0.161***	-0.154***	-0.158***	-0.154***	-0.158***
	(0.058)	(0.058)	(0.058)	(0.058)	(0.058)	(0.058)
Deposit Insurance	0.001	0.014	0.006	0.012	0.009	0.009
	(0.215)	(0.211)	(0.214)	(0.211)	(0.213)	(0.211)
Concentration	0.173	0.133	0.123	0.141	0.124	0.129
	(0.336)	(0.334)	(0.336)	(0.335)	(0.336)	(0.335)
Global Integration	-0.355*	-0.569***	-0.430**	-0.568***	-0.453**	-0.572***
	(0.189)	(0.187)	(0.189)	(0.187)	(0.186)	(0.188)
IFRS	-0.131**	-0.166***	-0.143**	-0.168***	-0.151***	-0.168***
	(0.057)	(0.058)	(0.057)	(0.058)	(0.057)	(0.058)
No. observations	13,733	13,733	13,733	13,733	13,733	13,733
No. banks	1,658	1,658	1,658	1,658	1,658	1,658
Adj. R-squared	0.136	0.132	0.134	0.132	0.134	0.132
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes

Table IA.9. Peer effects in banks' funding liquidity choices and systemic risk: robustness test – MES with liquidity risk controls

This table reports coefficient estimates of model (3) when using the MES - Marginal Expected Shortfall (Acharya et al., 2012) as dependent variable. MES is defined as the bank i's expected equity loss (in %) per dollar in year t conditional on the market experiencing one of its 5% lowest returns in that given year (the higher a bank's MES, the larger its systemic risk exposure). The peer effects in funding liquidity decisions are estimated with model (2) when using Liquidity Creation and NSFRi as dependent variables ($\widehat{\beta_{J,t}^{LC}}$ and $\widehat{\beta_{J,t}^{NSFRi}}$, respectively), where the relationship between the liquidity of bank i and the liquidity of its peers is now allowed to vary across countries and over time. Liquidity Creation is the Berger and Bowman (2009) "cat nonfat" measure i.e., on-balance-sheet liquidity creation when classifying activities by category. NSFRi (inverse of the Net Stable Funding Ratio) is defined as the ratio of the required amount of stable funding (RSF) to the available amount of stable funding (ASF). Table A.1 shows the weights given to the different balance-sheet items when computing both measures. Peer groups are defined as commercial banks operating in the same country in the same year grouped into a maximum of 10, 20 or 30 banks according to their size (total assets). The control variables (lagged) are all defined in Table 1. The Liquidity Ratio is defined as liquid assets to total assets. Robust standard errors clustered at the bank level are in parentheses. *, ** and *** designate that the test statistic is significant at the 10%, 5% and 1% levels.

Dep. Variable: Marginal Expected Shortfall (MES)	Peer group size: 10 banks		Peer group size: 20 banks		Peer group size: 30 banks	
Peer Effect:	2.374***		1.545**		0.880	
Liq. Creation - $\widehat{\beta_{J,t}^{LC}}$	(0.742)		(0.652)		(0.629)	
Peer Effect:		3.462***		3.027***		2.985***
NSFRi - $\widehat{\beta_{J,t}^{NSFRi}}$		(0.902)		(0.822)		(0.802)
Liquidity Creation	-0.578	0.050	-0.204	0.086	-0.094	-0.046
	(0.517)	(0.490)	(0.460)	(0.436)	(0.426)	(0.395)
NSFR	0.576**	0.432*	0.617**	0.510*	0.545*	0.463
	(0.249)	(0.248)	(0.299)	(0.300)	(0.289)	(0.285)
Liquidity Ratio	-0.123	-0.145	-0.316	-0.346	-0.275	-0.317
	(0.573)	(0.567)	(0.513)	(0.515)	(0.479)	(0.478)
ln(Total Assets)	0.547***	0.608***	0.662***	0.683***	0.714***	0.734***
	(0.203)	(0.209)	(0.151)	(0.154)	(0.149)	(0.150)
Capital Ratio	2.620	2.269	3.197	3.006	2.943	2.818
	(2.525)	(2.553)	(2.239)	(2.270)	(2.222)	(2.234)
Return-on-Assets	-1.835	-1.939	2.031	2.556	3.706	4.815
	(10.250)	(10.240)	(10.340)	(10.501)	(9.901)	(9.962)
Deposits-to-Assets	0.162	-0.393	-0.109	-0.441	-0.026	-0.360
	(0.823)	(0.779)	(0.746)	(0.730)	(0.740)	(0.720)
Provisions	7.714	5.145	9.541	8.884	12.146	11.896
	(9.467)	(9.696)	(9.026)	(9.210)	(8.700)	(8.860)
Cost-to-Income,	0.818**	0.848**	0.752*	0.782**	0.707*	0.746**
	(0.376)	(0.357)	(0.383)	(0.378)	(0.372)	(0.367)
Non-interest revenue share	0.316	0.219	0.108	0.110	0.120	0.142
	(0.437)	(0.433)	(0.403)	(0.403)	(0.402)	(0.399)
Share of wholesale funding	-0.767	-0.972	-0.921	-1.104*	-0.885	-1.087*
	(0.691)	(0.679)	(0.660)	(0.654)	(0.654)	(0.640)
Foreign Owned	-0.788**	-0.790*	-0.763*	-0.757*	-0.754*	-0.731*
	(0.392)	(0.408)	(0.402)	(0.413)	(0.403)	(0.416)
ln(GDP per capita)	-1.537	-1.710	-1.305	-1.472*	-1.215	-1.383
	(1.110)	(1.066)	(0.905)	(0.888)	(0.884)	(0.868)
GDP growth volatility	17.839***	14.501**	22.515***	20.959***	23.166***	22.715***
	(6.403)	(5.985)	(5.661)	(5.504)	(5.654)	(5.507)
Liquidity Regulation	-0.234	-0.194	-0.299**	-0.287**	-0.308**	-0.293**
	(0.161)	(0.157)	(0.145)	(0.144)	(0.145)	(0.141)
Deposit Insurance	-0.149	-0.172	-0.132	-0.115	-0.145	-0.126
	(0.409)	(0.407)	(0.384)	(0.381)	(0.385)	(0.376)
Concentration	0.671	0.704	0.231	0.290	0.216	0.337
	(1.127)	(1.098)	(0.946)	(0.952)	(0.879)	(0.895)
Global Integration	-0.182	0.234	-0.469	-0.210	-0.646	-0.396
	(0.742)	(0.710)	(0.716)	(0.700)	(0.754)	(0.718)
IFRS	0.140	0.130	0.183	0.193	0.151	0.131
	(0.176)	(0.174)	(0.170)	(0.169)	(0.169)	(0.168)
No. observations	1,775	1,775	2,192	2,192	2,379	2,379
No. banks	276	276	303	303	330	330
Adj. R-squared	0.535	0.537	0.489	0.491	0.478	0.482
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes

Table IA.10. Peer effects in banks' funding liquidity choices and systemic risk: robustness test – SRISK with liquidity risk controls

This table reports coefficient estimates of model (3) when using the Systemic Capital Shortfall - SRISK (Acharya et al., 2012; Engle et al., 2015) as dependent variable which corresponds to the expected bank i's capital shortage (in US$ billion) during a period of system distress and severe market decline. Unlike MES, SRISK is also a function of the bank's book value of debt, its market value of equity and a minimum capital ratio that bank firm needs to hold. To ensure comparability across countries, I follow Engle et al. (2015) and set this prudential capital ratio to 4% for banks reporting under IFRS and to 8% for all other accounting standards, including US GAAP. The peer effects in funding liquidity decisions are estimated with model (2) when using Liquidity Creation and NSFRi as dependent variables, where the relationship between the liquidity of bank i and the liquidity of its peers is now allowed to vary across countries and over time. Liquidity Creation is the Berger and Bowman (2009) "cat nonfat" measure i.e., on-balance-sheet liquidity creation when classifying activities by category. NSFRi (inverse of the Net Stable Funding Ratio) is defined as the ratio of the required amount of stable funding (RSF) to the available amount of stable funding (ASF). Table A.1 shows the weights given to the different balance-sheet items when computing both measures. Peer groups are defined as commercial banks operating in the same country in the same year grouped into a maximum of 10, 20 or 30 banks according to their size (total assets). The control variables (lagged) are all defined in Table 1. The Liquidity Ratio is defined as liquid assets to total assets. Robust standard errors clustered at the bank level are in parentheses. *, ** and *** designate that the test statistic is significant at the 10%, 5% and 1% levels.

Dep. Variable: SRISK	Peer group size: 10 banks		Peer group size: 20 banks		Peer group size: 30 banks	
Peer Effect:	6.165***		5.518***		4.466**	
Liq. Creation - $\widehat{\beta_{j,t}^{LC}}$	(2.204)		(1.918)		(1.851)	
Peer Effect:		5.648***		7.640***		7.348***
NSFRi - $\widehat{\beta_{j,t}^{NSFRi}}$		(2.171)		(2.412)		(2.426)
Liquidity Creation	-6.652***	-4.977***	-4.836***	-3.701**	-4.064***	-3.530**
	(1.923)	(1.716)	(1.624)	(1.510)	(1.497)	(1.409)
NSFR	5.242***	4.968***	3.967***	3.661***	3.868***	3.644***
	(1.735)	(1.722)	(1.425)	(1.388)	(1.428)	(1.386)
Liquidity Ratio	7.618**	7.473**	5.577**	5.442*	5.026*	4.874*
	(3.075)	(3.079)	(2.771)	(2.765)	(2.566)	(2.547)
ln(Total Assets)	0.177	0.336	0.480	0.559	0.444	0.511
	(0.764)	(0.774)	(0.583)	(0.590)	(0.581)	(0.580)
Capital Ratio	3.991	3.473	4.409	3.814	3.701	3.287
	(7.327)	(7.299)	(6.087)	(6.045)	(6.014)	(5.956)
Return-on-Assets	1.807	0.862	-4.854	-3.250	0.666	2.586
	(19.265)	(19.486)	(16.920)	(17.109)	(15.975)	(16.328)
Deposits-to-Assets	-0.232	-1.350	-0.879	-1.754	-1.134	-1.929
	(2.098)	(2.051)	(1.917)	(1.905)	(1.868)	(1.847)
Provisions	-4.419	-10.637	-8.933	-11.151	-4.851	-6.848
	(21.981)	(22.155)	(16.857)	(16.950)	(16.885)	(16.837)
Cost-to-Income,	1.678	1.707	1.352	1.440	1.329	1.411
	(1.108)	(1.116)	(0.990)	(1.004)	(0.983)	(0.997)
Non-interest revenue share	0.179	-0.006	0.236	0.238	-0.076	-0.009
	(1.636)	(1.651)	(1.393)	(1.394)	(1.355)	(1.344)
Share of wholesale funding	-3.214	-3.682	-3.425	-3.928	-3.402	-3.884
	(2.751)	(2.767)	(2.427)	(2.447)	(2.370)	(2.395)
Foreign Owned	-1.874	-1.919	-1.489	-1.482	-1.442	-1.426
	(1.153)	(1.193)	(1.007)	(1.035)	(1.010)	(1.027)
ln(GDP per capita)	3.329	2.977	2.922	2.467	3.116	2.415
	(3.181)	(3.130)	(2.833)	(2.745)	(2.794)	(2.677)
GDP growth volatility	9.589	0.685	7.998	3.269	7.990	4.671
	(17.939)	(16.999)	(16.962)	(16.565)	(16.914)	(16.526)
Liquidity Regulation	-1.080**	-1.036*	-1.338**	-1.320**	-1.347**	-1.348**
	(0.547)	(0.547)	(0.544)	(0.547)	(0.556)	(0.559)
Deposit Insurance	0.350	0.366	0.328	0.417	0.335	0.471
	(0.681)	(0.718)	(0.601)	(0.628)	(0.589)	(0.620)
Concentration	6.399	6.250	5.900*	5.830	5.088	5.101
	(4.080)	(4.152)	(3.532)	(3.587)	(3.357)	(3.377)
Global Integration	-5.962**	-5.142*	-6.149**	-5.425*	-6.726**	-5.725*
	(2.989)	(2.892)	(2.989)	(2.920)	(3.144)	(2.966)
IFRS	-2.647***	-2.642***	-2.370***	-2.313***	-2.184***	-2.213***
	(0.756)	(0.760)	(0.670)	(0.660)	(0.626)	(0.629)
No. observations	1,775	1,775	2,184	2,184	2,371	2,371
No. banks	278	278	305	305	332	332
Adj. R-squared	0.165	0.161	0.137	0.137	0.130	0.134
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes

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