Strategic complementarity in banks’ funding liquidity choices and financial stability

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Abstract

This paper examines whether, how, and why banks’ liquidity holding choices are affected by the decisions of its peers and the impact of these strategic funding liquidity policies on financial stability. Using a novel identification strategy where bank interactions are structured through a social network and a large sample of commercial banks from OECD countries, I find that financial institutions do take into consideration their competitors’ liquidity decisions when determining their own. Banks’ liquidity holdings are in large part direct responses to the liquidity choices of their respective peers and, to a lesser extent, their characteristics. Further, consistent with both learning and collective moral-hazard channels, while large banks’ liquidity decisions are only sensitive to their large counterparts, small banks’ liquidity choices are affected by both small and large banks. Finally, I show that strategic complementarity in funding liquidity risk management policies increase both individual banks’ default risk and overall systemic risk. From a macro-prudential regulatory perspective, these results highlight the importance of dealing with the systemic component of funding liquidity risk for financial stability.

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1. Introduction

Although until very recently banks' funding liquidity risk was not the main focus of regulators, the current consensus is that insufficient liquidity buffers were one of the main causes of the global financial crisis and the still ongoing disruptions in the economy, making liquidity supervision a key issue for the coming years (Brunnermeier, 2009). In fact, by funding their lending activities using a broader range of liabilities, banks became exposed 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). Due to this increased complexity of the banking system, funding liquidity risk is now inherently systemic as funding arrangements connect banks with other financial institutions and the non-financial sector i.e., one agent's liquid asset in another agent's liquid liability (Hardy and Hochreiter, 2014).

Against this framework, an adequate regulatory mechanism beyond the traditional reserve requirements should be in place to address and mitigate the systemic component of funding liquidity risk. Deposit-insurance schemes may also not be sufficient to prevent all liquidity-related risks and can instigate a freeze in interbank markets (Bruche and Suarez, 2010). But notwithstanding the impact of recent initiatives to establish or reform existing liquidity risk frameworks, the proposed binding requirements (e.g., Basel III Liquidity Coverage Ratio and Net Stable Funding Ratio) are idiosyncratic by design, depending on the characteristics of individual banks and abstracting from systemic-wide conditions and any interconnections between them. In addition, despite the prominent theoretical literature on the consequences that liquidity risk may have for the economy (e.g., Diamond and Rajan, 2001, 2005, 2011; Allen and Gale, 2004a, 2004b), as well as the adverse effects strategic risk-taking behaviour may entail for financial stability (e.g., Ratnovski, 2009; Allen et al., 2012; Farhi and Tirole, 2012), there is surprisingly scarce empirical evidence on this issue. This paper aims to fill this gap in the literature by analysing (i) whether, how and why funding liquidity risk management decisions of a specific bank are influenced by the choices of its competitors and (ii) the impact of strategic funding liquidity policies on the stability of the financial system.

Peer effects can arise and be rationalised from at least two different channels. First, the implicit or explicit commitment of the Lender of Last Resort (LOLR) may create incentives for banks to engage in collective risk-taking strategies when there is a strong belief that a collective bailout is possible (Ratnovski, 2009; Farhi and Tirole, 2012). Therefore, a given bank may be willing to take more risk and hold a sub-optimal level of liquidity when other banks competing in the same market are pursuing a similar policy. From the perspective of the individual banks, holding liquid assets is costly as they provide lower returns than their illiquid counterparts. Therefore, collective moral-hazard may be optimal as it allows them to increase profitability without affecting their likelihood of bankruptcy (Ratnovski, 2009). Mimicking behaviour in liquidity choices may also arise from learning motives i.e., free-riding in information acquisition. Because a certain bank may be unsure about its optimal funding liquidity risk management policy, it may consider the liquidity decisions of its peer banks as informative for its own. In other words, the actions of competitors explicitly enter in the bank's objective function. In fact, banks may rationally put more weight on the decisions of others than on their own information (Banerjee, 1992), particularly when other banks are perceived as having greater expertise (Bikhchandani et al., 1998).

While theoretically intuitive, identifying peer effects is empirically challenging because of the reflection problem (Manski, 1993). More specifically, if peers' liquidity choices affect the liquidity decisions of a particular bank, the decision of this bank may also in turn affect the choice made by the peers. To overcome reverse causality, I use a novel identification strategy based on Bramoullé et al. (2009) extended version of linear-in-means model where bank interactions are structured through a social network. In such network, an agent's friend's friend may not be a (direct) friend of 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 (i.e., different peer groups for the different banks in the sample) 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 attractive when studying funding liquidity risk since large cross-border banking groups tend to manage liquidity on a global scale (Cetorelli and Goldberg, 2012). As a result, 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.

I find that banks do follow their competitors when making funding liquidity risk management decisions. In fact, these peer effects are more important for funding liquidity determination than most bank and country-specific factors previously identified in the literature (e.g., Kashyap et al., 2002; Bonfim and Kim, 2014; Bonner et al., 2015).

Furthermore, banks' liquidity decisions are in large part direct responses to the liquidity choices of peer banks and, to a lesser extent, to changes in their characteristics. Estimates also indicate that the economic impact is large and consistent with coordinated behaviour where each bank constantly adjusts to each other's funding liquidity decisions e.g., a one standard deviation change in peers' liquidity creation (0.15) is associated with change in liquidity creation of bank *i* of 0.07 to 0.08. These results are robust to the use of numerous alternative liquidity risk measures, peer groups definitions, IVs and model specifications. I also find that peer effects in banks' funding liquidity policies are generally concentrated in banks with low capital ratios, profitability and non-interest revenue share, high share of wholesale funding and loans-to-assets, and non-foreign owned banks. This is consistent with strategic behaviour being driven by the incentive of improving profitability (Ratnovski, 2009, Farhi and Tirole, 2012) and suggests that higher levels of funding liquidity risk are not being compensated with higher capital ratios. Consistent with both learning and collective moral-hazard channels, I show that while large banks' liquidity decisions are only sensitive to their large counterparts, small banks' liquidity choices are affected by the decisions of both small and large banks.

Banks' collective risk-taking behaviour 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 (Acharya and Yorulmazer, 2008; Allen et al., 2012). Besides, insufficient cash holdings make banks and the banking system less resilient from a default risk perspective (Calomiris et al., 2015). Ultimately, excessive risk-taking and associated bank failures can generate costly crises that are in turn linked with sharp recessions, prolonged recoveries and large increases in government debt (Reinhart and Rogoff, 2009). In this respect, I find that strategic complementarity in funding liquidity risk management policies increase both individual banks' default risk and overall systemic risk. The results are robust across multiple model specifications, financial stability measures - Z-Score and Merton's Distance-to-Default to capture individual banks' financial stability; MES and SRISK (Acharya et al., 2012; Brownlees and Engle, 2015) to capture systemic risk - and when considering either liquidity creation or the liquidity ratio to capture funding liquidity risk. Furthermore, this effect is both statistically and economically significant e.g., a one standard deviation increase in the peer effect in liquidity choices (0.24 to 0.30) leads to a decrease in the Z-score of bank *i* of 0.08 to 0.14 - where the mean of Z-Score is 3.46.

The contribution of this paper is threefold. First, to the best of my knowledge, this is the first study to explicitly analyse 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 direction through which peer effects operate and, more importantly, the consequences they may have 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 initiatives to reform existing regulatory frameworks are sufficient to deter banks' excessive risk-taking behaviour. In this regard, this paper delivers a detailed analysis that is beneficial to regulators and supervisory agencies, particularly concerning the macro-prudential regulation of funding liquidity risk.

Second, I examine the channels through which these peer effects materialise i.e., learning vs. collective moral-hazard due to LOLR bailout commitment. While broadly consistent with the literature analysing the direct effects of implicit bailout guarantees on bank risk-taking (e.g., Nier and Baumann, 2006; Dam and Koetter, 2012; Brandao-Marques et al., 2013), the results in this paper show that moral-hazard is not confined to situations in which banks choose to bear excessive exogenous risk. Instead, as theoretically conjectured by Farhi and Tirole (2012), banks also create aggregate risk by mimicking each other's balance sheet structures strategically. Besides, the framework I use avoids relying on credit rating agencies expectations of external support to construct bank-specific bail-out probabilities, and does not restrict collective risk-taking behaviour to be only driven by government bailout incentives (e.g., Gropp et al., 2011; Mariathasan et al., 2014). In fact, I show that learning motives and free-riding in information acquisition also play an important role.

Finally, this paper also complements the recent and growing literature showing that competitors have a significant role on individual firm's decision-making. Empirical evidence on peer effects in corporate actions suggest that they affect capital structure choices (Leary and Roberts, 2014; Todorov, 2014), bank credit policies (Rajan, 1994; Jain and Gupta, 1987; Uchida and Nakagawa, 2007), stock splits (Kaustia and Rantala, 2015), investment decisions (Foucault and Fresard, 2014; Dougal et al., 2015), among other domains.[1] In a related study,

[1] 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

Bonfim and Kim (2014) find strong evidence of peers affecting banks' liquidity risk management policies. This paper however differs from theirs in several dimensions. First, I distinguish between the two channels through which peer effects operate and disentangle whether banks are reacting to peers' liquidity risk management policies per se or to chances in peers' other characteristics e.g., size, profitability, capitalisation. The latter issue is particularly important as one can observe common liquidity choices because banks share similar characteristics rather than by true strategic behaviour. Omitting other peer characteristics from the model can also confound the economic magnitudes of the peer effect coefficient of interest since it would be capturing both channels, which is particularly important for policy. In addition, I assemble a unique bank ownership database and use this distinctive source of information to provide a rigorous econometric treatment for the endogeneity of peer effects. More specifically, this study explores systematic variation in peer group composition to capture and identify the peer effect of interest, thus solving the reflection problem (Manski, 1993) and causing the potential bias from weak instruments to fall away (Angrist, 2014).

The remainder of the paper is organised as follows. Section 2 summarises the relevant literature. Section 3 describes the identification strategy to detect and quantify peer effects and to examine their impact on financial stability. The sample and descriptive statistics are presented in section 4. Section 5 discusses the empirical results and section 6 concludes.

2. Literature Review

2.1. Peer effects in banks' funding liquidity choices

To reduce the maturity gap between assets and liabilities and thus alleviate their exposure to funding liquidity risk, banks can hold a buffer of market-liquid assets (e.g., cash or government securities) that they can easily dispose in case of transitory cash-flow shortfalls due to market-wide or idiosyncratic funding disruptions (Rochet and Vives, 2004; Acharya et al, 2011; Tirole, 2011; Vives, 2014). Focusing on the substitutability of minimum regulatory capital and liquid asset requirements, Calomiris et al. (2015) suggest that liquid asset

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.

holdings may also reduce incentives for bank runs, increase inter-bank liquidity risk-sharing and mitigate managerial moral-hazard incentives. Carlson et al. (2015) argue that liquidity buffers further ensure that financial authorities have the necessary time to access banks' condition when a problem is detected and determine the extent to which solvency or market-wide concerns are driving the liquidity need. However, from the perspective of individual banks, holding liquid assets is costly since they provide lower returns than their illiquid, higher-yielding counterparts. The determination of banks' optimal liquid buffers therefore involves a trade-off between self-insurance against liquidity risk and profitability.

While regulators can set binding quantitative liquidity requirements to ensure that banks have an appropriate buffer of liquid assets, these may not be sufficient to provide full insurance against a sudden bank-run or dry-up in interbank markets. In such scenario, the LOLR intervention plays a crucial role in ensuring the stability of the financial system.[2] The consensus is that a mechanism should be in place to allow solvent banks to obtain liquidity if markets fail to function properly. However, liquidity shocks might be undistinguishable from solvency shocks and thus, by providing insolvent banks with liquidity, the LOLR may allow them to escape market discipline. The LOLR mechanism therefore has an inherent moral hazard problem: on the one hand, it has to be credible ex-ante to prevent a crisis; one the other hand, if it is indeed credible, banks will know that they will very likely be rescued in case of severe financial distress thus generating incentives to engage in excessive risk-taking behaviour (Freixas et al., 2004; Gorton and Huang, 2004; Rochet and Vives, 2004; Dam and Koetter, 2012). As a result, when deciding whether to provide liquidity, the LOLR has to weight the costs of bank failure and potential managerial moral hazard from bailout expectations (Myers and Rajan, 1998). However, if several banks are at risk, the LOLR has to take the necessary actions to prevent contagion. In such case, the likelihood of a bailout increases i.e., if one bank has problems, very likely other banks will have problems as well, thus becoming too-many-to-fail (Acharya and Yorulmazer, 2007).

Ratnovski (2009) provides a theoretical framework rationalising the existence of strategic funding liquidity choices among banks. The author shows that the presence of the LOLR introduces distortions in banks' incentives during a crisis since the central bank is forced to bailout at least one of them to ensure systemic stability. This results in strategic

[2] As an example, the freeze in interbank money markets in the recent global financial crisis of 2007-2009 made lending from central banks essential worldwide (Brunnermeier, 2009; Cornett et al., 2011).

complementarity in banks' liquidity choices that may lead to a self-fulfilling equilibrium where banks have incentives to choose sub-optimal liquidity as long as other banks are expected to do the same. As a consequence of the implicit or explicit bailout commitment of LOLR, these collective risk-taking policies may be optimal from the perspective of the individual banks, allowing them to increase profitability without affecting the likelihood of insolvency. Similarly, Farhi and Tirole (2012) show that time-inconsistent, imperfectly target support to distressed banks makes their balance sheet choices strategic complements. Although policy-makers will be reluctant to incur the fixed costs associated with an intervention (either a direct supply of liquidity, or an active interest-rate policy) if only a minority of banks is at risk, when every bank engages in excessive risk-taking the central bank has little choice but to intervene, hence creating severe current and deferred social costs.

Acharya et al., (2011) consider how liquidity holdings of banks are affected by financial crises and their resolution. The authors suggest that interventions aiming to resolve bank failures (e.g., government-assisted sales or bailouts) can have noticeable effects on bank's levels of liquidity since either unrestricted support to banks in a good financial situation or liquidity support for failed banks reduces their incentives to hold liquid assets. Morrison and White (2013) also suggest that interventions can lead to a loss of reputation and subsequent moral-hazard which in turn can make the next crisis even more costly and likely. Eisert and Eufinger (2014) show that even abstracting from the above moral-hazard channels, there is still an incentive for banks to mimic each other's balance sheet structures, be highly interconnected in the interbank market and invest in correlated portfolios.

Mimicking behaviour in liquidity choices can also arise because of learning motives i.e., free-riding in information acquisition. In such case, peer influence can be prevalent when the optimal course of action is uncertain (Banerjee, 1992). As a result, banks can rationally put more weight on the decisions of others than on their own information, especially when other banks are perceived as having greater expertise (Bikhchandani et al., 1998). This is true even in settings where traditional corporate finance theory is better able to characterise an optimum (e.g., capital structure) since model uncertainty and estimation errors could introduce substantial noise (Kaustia and Rantala, 2015). Ultimately, a certain bank, particularly if small, may consider the liquidity decisions and other characteristics of its competitors as informative for its own liquidity risk management policy.

Most of these conclusions are nevertheless based on theoretical results and thus lack empirical support. In fact, while there is considerable evidence of bank "herding" in banks' lending decisions (e.g., Jain and Gupta, 1987; Uchida and Nakagawa, 2007)[3], little empirical work has been done to investigate the presence of peer effects in banks' funding liquidity choices. 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.[4] Bonfim and Kim (2014) analyse the behaviour of European and North-American banks from 2002 to 2009 and find strong evidence of "herding" in liquidity risk-management decisions. In addition to the relatively limited period analysed, the authors are however silent in relation to what drives this result. Furthermore, they do not distinguish between the two channels through which peer effects operate and thus cannot disentangle whether banks are reacting to peers' liquidity risk-management policies per se or to other common peer characteristics that were omitted from their model.

2.2. Strategic behaviour and financial stability

Acharya and Yorulmazer (2008) highlight the importance of examining the ex-ante drivers of bank fragility and systemic risk, of which the extent of banks' mimicking behaviour (i.e., "herding") may play an important role since it affects the likelihood that all banks fail altogether. In fact, if several banks operating in the same market engage in similar risk-taking strategies at the same time, there is a likely increase in individual bank's financial fragility and systemic risk. Allen et al. (2012), for instance, show that systemic risk increases when banks make similar portfolio decisions due to a higher correlation of defaults. Similarly, Calomiris et al. (2015) find that insufficient liquidity holdings make both individual banks and the banking system less resilient from a default risk perspective.

[3] Using Granger-causality tests, Jain and Gupta (1987) find that small US banks mimicked the behaviour of large banks in lending decisions during the 1980s and 1990s. Uchida and Nakagawa (2007) adapt the stock market "herding" measure developed by Lakonishok et al. (1992) and show that Japanese banks followed "herding" behaviour in the domestic loan market from 1975 through 2000. In a different framework, Rajan (1994) finds evidence of "herding" in banks' decisions to write down assets and set aside loan loss reserves.

[4] Van den End and Tabbae (2012) apply the stock market "herding" measure developed by Lakonishok et al. (1992) first used by Uchida and Nakagawa (2007) to capture bank "herding". The main problem of this methodology is that while it allows to investigate whether banks' liquidity holdings jointly deviate from what it could be expected from overall macroeconomic conditions, it does not allow for a complete characterisation of collective risk-taking behaviour (Bonfim and Kim, 2014). In fact, it is a static measure that only considers if there was an increase in risk (without considering its magnitude) and, more importantly, common behaviours among banks can be observed because they have common characteristics or are affected by common shocks that are not controlled for, rather than by true "herding" behaviour.

To the best of my knowledge, no study explicitly examines the impact of banks' coordinated and strategic balance-sheet decisions on financial stability. In fact, the literature has been so far limited to the analysis of the direct effects of implicit bailout guarantees – as measured by Fitch or Moody's ratings. Nier and Baumann (2006), for instance, find a negative relationship between the probability of government support and the levels of bank capital when analysing a cross-country sample of banks prior to the global financial crisis. Dam and Koetter (2012) examine how German banks' investment decisions are affected by bailout expectations and find that government guarantees intensify moral-hazard in the banking industry through increased risk-taking. Brandao-Marques et al. (2013) show that higher likelihood of government support is associated with higher bank risk-taking, particularly during the crisis. Moral-hazard, however, is not necessarily confined exclusively to situations in which banks choose to bear excessive exogenous risk. Instead, this paper examines risk-taking driven by collective moral-hazard where banks create aggregate risk by positioning themselves strategically e.g., support expectations may trigger strategic behaviour in the form of banks mimicking each other's balance sheet structures (Ratnovski, 2009; Acharya et al., 2011; Farhi and Tirole, 2012).

In this respect, the presence of government guarantees may not only affect risk-taking of protected banks but also, through competition, that of their competitors. As theoretically conjectured by Hakenes and Schnabel (2010), public guarantees reduce competitor banks' charter values and margins due to increased competition from banks that are able to refinance at subsidised rates and thus behave more aggressively e.g., by lowering loan rates or raising deposit rates. This may ultimately push competitors toward higher risk-taking and undermine financial stability. Gropp et al. (2011) examine the effects of implicit and explicit bailout commitments on banks' risk-shifting behaviour 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), however, obtain considerably different results when analysing 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.

This paper differs from the latter strand of research in several key points. First, I measure these competitive distortions and their impact on risk-taking directly by considering how banks' liquidity holdings choices react to their competitors' decisions across countries and over time. This framework thus avoids relying on credit rating agencies (CRA) expectations of external support to construct bank-specific bail-out probabilities and related measures of the competitive effects due to government protection. This issue is particularly important given the conflicts of interest and related distortions in CRA industry that ultimately may have had a strong responsibility in the global financial crisis (e.g., Pagano and Volpin, 2010; Bolton et al., 2012). Second, all the above studies abstract from examining the effect on systemic risk and, from a regulatory perspective of ensuring stability of the financial system, the correlation in the risk-taking behaviour of banks is increasingly more relevant than the absolute level of risk-taking in any individual institution (Anginer et al., 2014). Finally, I do not restrict collective risk-taking behaviour to be only driven by government bail-out incentives. In fact, I show that learning motives (i.e., free-riding in information acquisition) also play an important role, particularly when considering small banks.

3. Identification strategy

I employ a two-step method in order to examine if and how financial stability is affected by strategic behaviour of financial institutions in their funding liquidity risk policies. First, I investigate and quantify the influence of peer 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.'s (2009) social network framework. I then analyse the impact of peer effects in liquidity choices on financial stability by making use of the panel structure of the data and allowing the relationship between the liquidity of a certain bank and that of its peers to vary across countries and time.

3.1. Methodology to capture and quantify peer effects

In order to empirically assess whether strategic interactions matter for individual banks' liquidity choices, I specify the following baseline model:

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

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 4.2). $\overline{LIQ}_{-i,j,t}$ 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 because (i) it limits the amount of time for banks to respond to one another, thus making more difficult to identify mimicking behaviour; (ii) it mitigates the scope for confounding effects by reducing the likelihood of other financial structure changes; (iii) banks can observe each other contemporaneously in the interbank market. $\bar{X}_{-i,j,t-1}$ 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. 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 (Gormley and Matsa, 2014). Finally, $\varepsilon_{i,j,t}$ is the residual term that is assumed to be heteroskedastic and correlated within banks. As a result, I use heteroskedasticity-consistent (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' actions on funding liquidity risk management decisions of bank *i*. I hypothesise that liquidity choices of a specific bank are positively related to the decisions of its competitor banks i.e., $\beta > 0$.

The above naïve empirical specification 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, $\overline{LIQ}_{-i,j,t}$, as an explanatory variable in the regression i.e., peer firm average liquidity is an endogenous explanatory variable in (1) since it is determined simultaneously with the outcome variable.

I use a novel identification strategy based on Bramoullé et al. (2009) extended and generalised version of the linear-in-means model where interactions between banks 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 large cross-border banking groups tend to manage liquidity on a global scale (Cetorelli and Goldberg, 2012). Consistent with this idea, De Haas and Van Lelyveld (2010) find that global banks actively support their foreign affiliates through cross-border internal capital markets. 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. While this exclusion condition cannot be formally tested, addressing this assumption guides much of the analysis.

[Figure 1 here]

As a robustness test, I instrument peer firms' liquidity choices with the lagged idiosyncratic component of peer firms' equity returns. Intuitively, based on the identification strategy in Leary and Roberts (2014), 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 firms' liquidity choices – see appendix B for a detailed description of the return shock construction. Due to the firm-specific nature of idiosyncratic stock returns and the vast asset pricing literature aimed at isolating this component, the instrument is unlikely to affect individual firm's liquidity decisions directly. Besides, stock returns are relatively free from manipulation and impound most, if not all, value-relevant events. 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, this instrument however requires the use of market data and thus only allows to identify a limited sub-set of publicly-listed banks in the sample.

3.2. 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, 2000). Following previous literature, information sources used by practitioners (e.g., Bankscope, SNL Financial) and supervisory and regulatory practice, I use three different criteria to form peer groups.

First, following the theoretical arguments in Ratnovski (2009), Acharya et al., (2011) and Farhi and Tirole (2012), within-country banks are expected to have higher incentives to mimic their peers since they share the same LOLR. Similarly, free-riding in information acquisition and peer influence for learning motives (Banerjee, 1992; and Bikhchandani et al., 1998) is more likely to occur within countries where information for bank managers is more accessible. As a result, peer groups are first defined as banks operating in the same country in the same year. Second, since only commercial banks are included in the sample, I also implicitly define peer groups based on their business model. Cooperative and saving banks are not considered since a vast proportion are domestically owned and consequently, this particular sub-set of banks would not be identified.

Finally, to further incorporate heterogeneity in peer group choice, peer groups are also defined 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 also 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. 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. In the benchmark case, each peer group in each country j in each year t has a maximum of 20 banks. A bank in the sample has on average 16 peers in any given year and the number of peers varies between 3 and 19. 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.[5]

A similar set of criteria to define peer groups is also used in Acharya et al. (2014) to study the relationship between incentives of non-executives and bank risk-taking. They specify peer groups according to headquarters' location and bank size such that each peer group has 5 other banks whose headquarters are located in either the same US state or in neighbouring states. I choose a larger peer group of 20 banks since in this case we need to have at least 1 foreign-owned subsidiary within the 20 banks to identify the remaining 19, and at least 2 foreign-owned subsidiaries so that all banks in the peer group are identified. This choice is also consistent with Bizjak et al. (2011) that find 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.

[5] Because peer group definition is crucial for identification, I run an exhaustive set of robustness tests with multiple alternative definitions of peer groups e.g., no bank size criteria; maximum of 25 banks in each peer group; peer groups only split by large and small banks in a certain country-year; using peer weighted-averages based on the size similarity (inverse of the Euclidean distance) between the banks in a certain country-year.

3.3. 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:

$$LIQ_{i,j,t} = \omega + \beta_{j,t}\overline{LIQ}_{-i,j,t} + \lambda'\bar{X}_{-i,j,t-1} + \gamma' X_{i,j,t-1} + \eta' Z_{j,t-1} + \mu_i + v_t + \varepsilon_{i,j,t} \tag{2}$$

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, $\overline{LIQ}_{-i,j,t}$ denotes the peer firms' average liquidity excluding firm *i* in year *t* within country *j*, $\bar{X}_{-i,j,t-1}$ and $X_{i,j,t-1}$ are average peer bank characteristics and bank-specific factors. 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:

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

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

$$STA_{i,j,t} = \kappa + \delta\hat{\beta}_{j,t} + \gamma' X_{i,j,t-1} + v_{j,t} + u_{i,j,t} \tag{3}$$

where the dependent variable $STA_{i,j,t}$ is a measure of financial stability of bank *i* in country *j* in year *t* (see Section 4.3), $\hat{\beta}_{j,t}$ is the country and time-varying peer effect estimated in (2) and $X_{i,j,t-1}$ contain bank-specific characteristics. I also include country-year fixed effects $\nu_{j,t}$ in the model. Beck et al. (2013), for instance, show that the relationship between competition and financial stability varies across different regulatory frameworks, market structures and levels of institutional development, thus highlighting the need to also control for all country-specific shocks that vary over time. As before, I use robust standard errors clustered at the bank level in all specifications.

I analyse the consequences of these peer effects on both individual banks' financial stability (the solvency risk of individual financial 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 hypothesised to decrease individual banks' financial stability and increase systemic risk. Thus, I expect $\delta < 0$ when considering the Merton distance-to-default and the Z-score as the dependent variables (i.e., peer effects decrease individual bank's financial stability) and, in contrast, $\delta > 0$ when analysing systemic risk (i.e., peer effects increase systemic risk).

4. Sample and Descriptive Statistics

4.1. Data

Given that the main objective of this study is to investigate the impact of strategic behaviour in banks' liquidity choices and that these peer effects are hypothesised to vary not only with time but also by country as LOLR support is generally done at a national level, I consider a heterogeneous sample of commercial banks across 32 OECD countries covering the period before, during and after the global financial crisis. Information on banks' balance sheets and income statements are obtained from Bankscope. This database compiled by Bureau Van Dijk/Fitch is adjusted to ease international comparison of banks' financial statements and retains financial data for a rolling period of 16 years i.e., if a new year of data is available for a given bank, the oldest is dropped. The sample thus covers the period 1999-2013 since information prior to 1999 would only include banks that did not survive over the following

16-year period, resulting in a selection bias. I restrict the coverage to the largest 100 commercial banks in each of the countries considered.[6] This excludes smaller (mostly regional) banks in the US and Japan and hence limits over-representation of these countries in the sample. While the analysis is restricted to commercial banks, I also consider bank holding companies (BHCs) since some commercial banks are incorrectly specified as BHC in Bankscope. Nevertheless, BHC represent a relatively small proportion of the sample (10.9%). I also exclude branches of foreign banks since they generally do not report individual information and are not covered by the national LOLR where they operate. Consistent with Gropp et al. (2011), to avoid double-counting within a single institution and have financial information at the most disaggregated level possible, I also discard consolidated entries if banks report information at the unconsolidated level.[7] While most bank-specific variables are expressed in ratios, all variables in levels (e.g., total assets) are adjusted for inflation and converted to US dollars to facilitate comparisons across countries.

Bank ownership data is manually collected using various sources including Bureau van Dijk ownership database, banks' annual reports, banks and national central banks' websites, and newspaper articles.[8] This data is further cross-checked with the Claessens and van Horen's (2014) 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's (2014) 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 these foreign-owned banks actually is and its respective Bankscope identifier.[9] Further, while Claessens and van Horen (2014) report the country of ownership based on direct ownership, I obtain information and consider throughout the paper the ultimate owner based on a 50%

[6] Out of the current 34 OECD member countries, Iceland and Israel are excluded because the very limited number of foreign-owned commercial banks would not allow for identification (see Section 3.1). I also drop all bank/year observations in Chile after 2007 since the vast majority of banks only have financial statement information on Bankscope up to that year.

[7] I go to great lengths to identify duplicate observations in a given country/year and thus avoid capturing spurious peer effects. In addition to discarding consolidated entries if banks report information at the unconsolidated level, I also look for banks having for instance the same address, website or phone number. If there is at least one duplicate and among those is a commercial bank, I drop those that are not commercial banks (i.e., the bank holding companies).

[8] Although Bureau van Dijk's ownership database (available through Bankscope's online version) has historical data on banks' ownership structures, this information (i) is only partially recorded for a considerable number of banks in some of the countries analysed and (ii) is only available from 2002.

[9] Consider the US banking system as a practical example. While the Claessens and van Horen's (2014) bank ownership database only indicates that the home-country of the majority shareholder of HSBC Bank USA is the UK, the database I construct specifies who it is ('HSBC Holdings Plc') and respective Bankscope identifier. With this information in hand, one can then compute the liquidity position of the parent bank in order to construct the instrumental variable (see Section 3.1).

ownership threshold. While more limited in coverage, the data collected is therefore considerably more detailed and provides a distinctive and novel source of information.

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) identifier for the listed banks. With respect to the country-level variables, I collect GDP per capita, GDP growth rate, and the Consumer Price Index (CPI) from the World Bank's World Development Indicators (WDI) Database and the IMF International Financial Statistics. Country and country/sector equity market indices are from Morgan Stanley Capital International (MSCI). Additional information is obtained from the World Bank's Doing Business Database and the four waves (2001, 2003, 2007 and 2012) of the Bank Regulation and Supervision Survey (Barth et al., 2008). The final sample yields a panel of 17,831 bank-year observations corresponding to 2,058 commercial banks in the 32 OECD countries from 1999 to 2013.

4.2. Liquidity indicators

The literature provides two distinct, though 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 (Brunnermeier, 2009; Brunnermeier and Pedersen, 2009). Unlike market liquidity, funding liquidity can be considered as a binary concept i.e., at any point in time, a financial institution is either funding liquid or not (Drehmann and Nikolau, 2013). For the purpose of this study, I restrict my attention to banks' holdings of liquid assets 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.

To reduce the maturity gap between assets and liabilities, banks can hold a buffer of liquid assets that can be used in case of transitory cash-flow shortfalls due to market-wide or idiosyncratic funding disruptions. As a result, I use the standard *Liquidity Ratio* to capture liquidity in the asset-side of banks' balance sheet. Following Acharya and Mora (2015) and many others, this ratio is defined as liquid to total assets. Liquid assets include cash, short-term claims on other banks, government bonds and the trading portfolio where appropriate.[10] Because the standard liquidity ratio is bounded within the intervals [0,1] and thus is unsuitable as a dependent variable (Karolyi et al., 2012; Anginer et al., 2014), I use its logistic transformation throughout the paper i.e., Liquidity Ratio=log[(liquid assets/total assets)/(1-liquid assets/total assets)].

A more comprehensive indicator of funding liquidity risk is given by Berger and Bowman (2009) that, by considering every item on both sides of banks' balance sheet, provides a broader picture of the overall liquidity mismatch between assets and liabilities. Berger and Bowman's (2009) *Liquidity Creation* measure is constructed as follows: first, all bank assets and liabilities are classified as liquid, semi-liquid, or illiquid (according to their category) and one assigns a liquidity score of -0.5, 0 or 0.5 to each of them based on their respective classification. Then, a weighted average of the liquidity scores across different assets classes is calculated for each bank (where all components are scaled by total assets).[11]

Since some accounting items are reported differently in Bankscope and in Call Reports (i.e., Report of Condition and Income for banks operating in the US) used in Berger and Bouwman (2009), I adapt the classification based on the authors' categories. The weights for each accounting item in Bankscope (universal format) are displayed in Table A1 in appendix. Ceteris paribus, a bank creates 1$ of liquidity by investing 1$ of liquid liabilities (e.g., deposits from banks) into 1$ of illiquid assets (e.g., corporate loans). Similarly, a bank destroys 1$ of liquidity by investing 1$ of illiquid liabilities (e.g., subordinated debt) or equity into 1$ of liquid assets (e.g., cash or treasury securities) i.e., the bank removes 1$ of liquidity from the non-banking sector by replacing liquid cash or treasury securities with illiquid liabilities or bank equity. In short, the higher the liquidity creation measure, the more liquidity bank is creating - the larger is its maturity transformation role. Liquidity creation is positively related to funding liquidity risk since banks creating more liquidity have less liquid assets to meet short-term funding pressures.[12]

[10] Bankscope harmonises the data from different countries to obtain a globally comparable indicator.

[11] Berger and Bowman (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.

[12] One could argue that the *Interbank Ratio* also captures an important dimension of liquidity risk: given that interbank markets are usually characterised by very short maturities, banks that structurally rely on this source

Figure 2 illustrates the evolution of banks' funding liquidity risk between 1999 and 2013 as measured by the liquidity ratio and the Berger and Bowman's (2009) liquidity creation measure. 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. Despite sporadic increases in banks' liquidity ratios (e.g., 2000-2002, 2004-2006, 2008-2009), this indicator shows a clear decreasing trend during the entire sample period. On the other hand, although following a stable decreasing trend from 1999 until 2004, liquidity creation had a steady increase between 2006 and 2008 and later stabilisation afterwards, suggesting that banks continued to create liquidity during the 2007-2009 financial crisis. In general, Figure 2 indicates that, particularly from 2006 to 2013, funding liquidity risk has been building up for the sample of commercial banks analysed.

[Figure 2 here]

4.3. Financial stability indicators

4.3.1. Individual bank's default risk

I use compute the Z-score as my main measure of individual bank's default risk as in Laeven and Levine (2009), Demirguc-Kunt and Huizinga (2010), Beltratti and Stulz (2012), Beck et al. (2013) and many others. The Z-score 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 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 (Beck et al., 2013). Furthermore, by not relying on the full sample period, the denominator is no longer computed over different window lengths for different banks. Given

of funding may have severe difficulties in rolling over their debt in distress periods (Brunnermeier, 2009). However, Bankscope only has information to compute this measure for a very limited portion of the sample (the necessary information is missing, for instance, for most US and Japanese banks before 2009) and therefore it is not included in the empirical analysis.

that the Z-score is highly skewed, I use its natural logarithm to allow for a more uniform distribution.

I also compute the marked-based Merton's distance-to-default (MDD). This measure has also been extensively applied in empirical research to model and estimate individual bank risk - see Anginer et al. (2014) for an overview.[13] The Merton's (1974) structural default model specifies that the equity value of a bank can be viewed as call option on the underlying value of bank's assets. When the latter falls below the face value of its liabilities (i.e., the strike price), the call option is not exercised and the bank is passed to its debtholders. At any given point in time, MDD is then defined as the difference between the bank's asset value and the face value of its debt, scaled by the standard deviation of its asset value. I follow Bharath and Shumway (2008) in implementing the structural approach and estimating the MDD measure. The procedure is described in detail in Appendix C. The market-based MDD can only be estimated for publicly-traded banks and, as a result, only covers about a third of the banks in the sample.

Figure 3 shows the evolution of financial stability of the banks in the sample between 1999 and 2013 measured by MDD and Z-score. To ensure each country receives equal weight, both measures are calculated for each bank in a given year and subsequently averaged by country on a yearly basis. MDD and Z-score follow a fairly similar trend, suggesting that the accounting-based Z-score has a relatively good performance in predicting defaults when compared to the market-based MDD. Both indicators show a stable increase in distance-to-defaults from 1999 to 2004 and later stabilisation up to 2007. Subsequently, distance-to-defaults declined sharply during the financial crisis of 2007-2009, reaching their lowest values in 2009 but recovering afterwards to approximately their 2002-2003 levels.

[Figure 3 here]

4.3.2. Systemic risk

I use two different measures of systemic risk. The first, Marginal Expected Shortfall (Acharya et al., 2012) is defined as the bank *i*'s expected equity loss (in %) per dollar in year

[13] In practice, this framework is widely used by practitioners for predicting non-financial corporate default in the proprietary implementation by Moody's KMV. Despite the Moody's KMV model differing from the one applied here in several aspects and being based on proprietary information, Bharath and Shumway (2008) find a correlation of 79% between the estimated probability of defaults using the methodology applied here and those reported by Moody's KMV.

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 second, SRISK (Acharya et al., 2012; Brownlees and Engle, 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-exp($-18 \times$ 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 4 depicts the evolution of systemic risk of the banks in the sample between 1999 and 2013. Both measures are first calculated for each bank *i* in each year *t* and subsequently averaged by country across years. The time-series pattern is very similar to that of previous research (e.g., Anginer et al., 2014). Systemic risk peaked in 2009 following the 2007-2009 global financial crisis, decreased afterwards and jumped again in 2011 following the European sovereign debt crisis.

[Figure 4 here]

4.4. Control variables

I consider a large set of bank-specific, macroeconomic and financial development indicators that previous literature consistently show to impact bank risk (e.g., Berger and Bowman, 2009; Laeven and Levine, 2009; Karolyi et al., 2012; Beltratti and Stulz, 2012; Beck et al., 2006, 2013; Anginer et al., 2014; Acharya and Mora, 2015).

Bank-level controls include the capital ratio (book capital to asset ratio), total assets (in billion US$), loans-to-total assets, return-on-assets (ROA), the cost-to-income ratio, provisions (loan loss provisions to total interest income), share of wholesale funding (the share of money market funding in money market funding and total deposits), non-interest revenue share (non-interest income in total income), annual growth in total assets, and foreign owned (a dummy variable that equals 1 if a bank is foreign-owned and 0 otherwise). I winsorise all financial variables at the 1st and 99th percentile levels to mitigate the influence of extreme observations and eliminate any data coding errors.

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 market concentration as measured by the market share of the three largest banks in a country. Finally, I also control for the existence of country-specific binding quantitative regulatory liquidity requirements. Based on Bonner et al. (2015), the four waves (2001, 2003, 2007 and 2012) of the World Bank's Bank Regulation and Supervision Survey (Barth et al., 2008) and information collected from national central banks' and the European Systemic Risk Board (ESRB) websites[14], I compute a dummy variable that equals 1 if a quantitative regulatory 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.

4.5. Descriptive Statistics

Table 1 reports descriptive statistics for the different variables used in this paper. All numbers are comparable to those in previous studies (e.g., Karolyi et al., 2012; Beck et al., 2013; Anginer et al., 2014). In the sample, an average bank has a distance-to-default of 3.12 to 3.46, a liquidity ratio of 26% and is creating liquidity (0.277). Furthermore, it has total assets of 41.62 billion US$, capital ratio of 13.9% and return-on-assets of 0.9%. The table also shows the distribution of the sample across years. The sample varies from 1,331 bank-year observations in 1999 to 922 in 2013 and it is also fairly well distributed across the 32 OECD countries considered. This is because the sample is restricted to the largest 100 commercial banks in each of the countries considered, thus avoiding over-representation of some of them (e.g., US, Japan). The full sample consists of 17,831 bank-year observations corresponding in 32 OECD countries from 1999 to 2013.

[Table 1 here]

[14] See here: https://www.esrb.europa.eu/mppa/html/index.en.html

5. Results

5.1. Peer effects in banks funding liquidity choices

In this section I examine whether funding liquidity decisions of a specific bank are positively associated with the choices of its competitors. From the perspective of individual banks, the determination of their optimal liquidity holdings involves a trade-off between self-insurance against liquidity risk and profitability i.e., the opportunity cost from holding liquid assets rather than loans or other higher-yielding assets. Nonetheless, it may be the case that liquidity holding determination is not made strictly at the individual level, but collectively either because these joint risk-taking strategies allow each bank to increase profitability without affecting the likelihood of bankruptcy due to the LOLR commitment, or because of learning motives due to the fact that the optimal risk management policy is uncertain.

Table 2 presents the coefficient estimates of model (1) when using Berger and Bowman's (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 peer banks' actions on the funding liquidity risk profile of bank *i*. The benchmark peer group is defined as commercial banks operating in the same country in the same year grouped in a maximum of 20 banks according to their size. Columns (3) and (4) show the 2SLS coefficient estimates when including key firm-specific, peer characteristics and country-level controls (all lagged) while columns (7) to (10) include additional lagged bank, peer and country-level controls in the regression. Columns (1), (2), (5) and (6) report the OLS estimates for comparison. All specifications include standard errors clustered at the bank-level.

[Table 2 here]

The table shows that the liquidity creation of bank *i* and that of its peers are indeed positively associated. The coefficients are highly statistically significant for all specifications and are robust to the use of alternative controls and fixed-effects combinations, thus suggesting that banks do follow their competitors when making funding liquidity decisions. The estimated 2SLS coefficients on the peer effect of interest range between 0.455 (when using the full set of controls, bank and year fixed-effects) and 0.597 (when using the key set of controls, year and country). This effect is still significant but considerably underestimated when using OLS. Moreover, the amount of liquidity created by each individual bank is in general negatively associated with bank size, capital ratios and liquidity regulation, but positively related to cost-to-income, share of wholesale funding, loan-to-assets ratio and concentration. The direction of the different coefficients is broadly consistent with previous studies on the determinants of banks' liquidity buffers. Kashyap et al. (2002) show a strong effect of bank size on liquidity holdings for a large panel of US banks, 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 (e.g., Berger and Bouwman, 2009). Bonner et al. (2015) highlight the role of liquidity regulation. Besides, consistent with the evidence 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.

While liquidity creation of each bank is, on average, mostly driven by direct responses to actions of peer banks (i.e., peer banks' liquidity creation), some peer average characteristics such as peer banks' size and peer banks' capital ratios 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. Further, when standardising the coefficient estimates (untabulated), the results show that these peer effects are one of the most important determinants for liquidity holding determination i.e., together with the bank-specific capital and loans as a percentage of total assets. To test the robustness of the results, columns (9) and (10) add country-year fixed effects to the regressions to make sure that the results are not being driven by unobserved time-varying and country-specific effects that are correlated with the peer banks' average liquidity creation variable. The peer effect of interest remains positive and statistically significant and all other controls retain their expected sign.

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 this is indeed the case i.e., the instrument is always significant at 1% level in the 1st stage of the 2SLS estimation for all specifications. F-statistics for under and weak identification also reject these hypotheses. Identification threats thus come from a correlation between the instrument used and omitted or mismeasured bank *i* 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 emphasise 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, country, year or country-year fixed-effects used to control for differences not captured by the other exogenous variables and 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 peer bank characteristic that is relevant for bank *i*'s liquidity choices. However, the results suggest a limited role for peer bank characteristics in funding liquidity decisions, implying that any remaining bias is likely to be very small.

Table 3 reports the results when using the liquidity ratio to analyse the relationship between funding liquidity choices of a specific bank and the decisions of its peer banks. I use the logistic transformation of the liquidity ratio throughout since the standard liquidity ratio is bounded within the intervals [0,1] and thus is unsuitable as a dependent variable (Karolyi et al., 2012; Anginer et al., 2014). The table follows the same structure as Table 2 (see above). The 2SLS estimated coefficients of model (1) corroborate the previous findings: (i) the first-stage regression coefficient estimates show that the instrument is indeed relevant; (ii) the relationship between asset liquidity of bank *i* and the asset liquidity 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 liquidity choices of their respective competitors when determining their own. These peer effects are more important for funding liquidity determination than most firm and country-specific factors previously identified in the literature and included in the regressions (e.g., Kashyap et al., 2002; Bonfim and Kim, 2014; Bonner et al., 2015). Furthermore, banks' liquidity holdings are in large part direct responses to the liquidity choices of their respective peers and, to a lesser extent, their characteristics. Estimates also suggest that the economic impact is large and consistent with coordinated behaviour where each bank constantly adjusts to each other's funding liquidity decisions e.g., a one standard deviation change in peers' liquidity creation (0.15) is associated with change in liquidity creation of bank *i* of 0.07 to 0.08 (where the mean of liquidity creation is 0.28).

I conduct a battery of tests to ensure that previous results are robust. In particular, Table 4 reiterates the previous analysis when using alternative peer group definitions, different econometric specifications and when using other IVs. The reported coefficients (i.e., the peer effect) correspond to specification (4) and (8) of both Table 2 and 3 that include the key and full set of bank, peer and country-level controls in the regression (all lagged), respectively. As before, I also account for two sources of unobserved heterogeneity: bank fixed effects (which subsume country fixed effects) and year fixed effects. All specifications include standard errors clustered at the bank-level.

[Table 4 here]

Panel A of Table 4 presents the 2SLS estimated coefficients when using alternative peer groups definitions. First, I remove a bank size requirement in forming peer groups i.e., peer groups are simply defined as commercial banks operating in the same country in the same year. I then introduce different bank size requirements by (i) splitting within-country-year banks into small and large banks; (ii) splitting within-country-year banks into small, medium and large banks; (iii) grouping them into a maximum of 25 banks (instead of 20) by size. In general, the results show consistent evidence of strategic complementarity in funding liquidity choices, with the peer effect of interest being highly statistically significant for all specifications and peer group definitions used. It is important to note, however, that the economic magnitude of this effect does change as I adjust the peer group definition. This confirms that the peer group characterisation is a crucial issue in the analysis of peer effects since firms do not interact equally and directly with everyone (Manski, 2000; Bramoullé et al., 2014). Given the implausible coefficient estimates close to unity if one does not include a bank size requirement when forming peer groups (i.e., one of the "perils of peer effects" described in Angrist, 2014), the results also highlight the importance of considering bank size when defining how banks interact with each other, a fact that was ignored in previous research analysing this issue e.g., Van den End and Tabbae (2012), Bonfim and Kim (2014).

Panel B of Table 4 confirms the robustness of the results when considering alternative econometric specifications i.e., without controls, with contemporaneous controls, excluding countries with less than 20 commercial banks in a given year, removing from the sample banks with asset growth above 40% in a certain year since these banks may have been involved in mergers and acquisitions. The conclusions remain unchanged.

Panel C of Table 4 re-runs the analysis when using alternative IVs. Together with the relevance condition, the exclusion restriction implies that the only role that the instrument plays in influencing the outcome variable is through its effect on the endogenous variable. In practical terms, and using Figure 1 as an example, the liquidity holdings of the foreign bank-holding company (Bank X) should not be directly associated with the liquidity decisions of bank *i* (e.g., bank C1), but instead influence them indirectly through its effect on peer banks' average liquidity holdings (the endogenous variable) due to the presence of Bank X's subsidiary (Bank A) in the peer group. This identifying assumption may not be satisfied if the country where the foreign bank-holding company is based and the country where the domestic banks operate were subject to similar shocks that may influence banks' liquidity holdings e.g., macro-economic conditions in euro-zone countries during the sovereign debt crisis. To address this concern, instead of using the raw liquidity holdings of the parent bank-holding group to instrument the liquidity holdings of the domestic banks where its foreign subsidiary operates, I now regress the liquidity holdings of the parent bank-holding group with observed country-level characteristics (e.g., GDP per capita, GDP growth volatility, market concentration) and country and time fixed-effects (first row of Panel C), or country-time fixed effects (second row of Panel C). The residual from this model is then used to instrument peer firms' liquidity choices. As before, the results show that financial institutions do take into consideration their competitors' liquidity decisions when determining their own.

Following the identification strategy in Leary and Roberts (2014), in the last row of Panel C I instrument peer firms' liquidity choices with the lagged idiosyncratic component of peer firms' equity returns. Briefly, one extracts the idiosyncratic variation in stock returns using a traditional asset pricing model augmented by a factor to purge common variation among peers and the residual from this model is then lagged by one year and used to extract the exogenous variation in peer firms' liquidity choices (see appendix B). This instrument requires the use of market data and thus only allows identifying a limited sub-set of publicly-listed banks in the sample. Nevertheless, the conclusions do not change and the coefficients are of similar magnitude when compared to those of Tables 2 and 3.

As an additional robustness test, specifications (1) to (4) of Table 5 report coefficient estimates of model (1) extended to include lagged liquidity ratio or liquidity creation as an explanatory variable. Because OLS or standard fixed effects models would yield biased estimates in the presence of a lagged dependent variable and a short panel (Flannery and Hankins, 2013; De Jonghe and Oztekin, 2015), I estimate the regressions using the system

GMM estimator. The GMM standard errors in parentheses are Windmeiijer robust standard errors. As in Table 4, the main conclusions do not change.

Finally, in specifications (5) to (12) of Table 5 the liquidity holdings of the peers are constructed based on size-similarity weights between bank *i* and each peer bank. In fact, given that in the benchmark case each bank *i* in country *j* in year *t* belongs to a certain peer group of a maximum of 20 banks based on their size, bank 20 and 21 in a size rank, for instance, never interact with each other as they belong to different size groups. Besides, bank 20 gives equal weight to the liquidity holdings of banks 1, 2, …, 19, even if there is a substantial difference between the size of bank 1 and bank 19. To address this issue, I construct peer weighted-averages based on the size similarity (inverse of the Euclidean distance) between all banks 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

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

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. Similarly, the liquidity holdings of the foreign peer's parent bank (i.e., the IV) is also weighted to account for the disproportional influence a foreign-owned bank may have on bank *i*. No matter what variable is used to account for funding liquidity risk, the results show that banks do follow their competitors when making funding liquidity risk management decisions.

[Table 5 here]

5.2. Peer effects in banks funding liquidity choices: heterogeneity and channels

What type of banks behave strategically? To examine whether a particular sub-set of banks within a country is more sensitive to their peers' liquidity policies, I explore the heterogeneity in the coefficient β from equation (1) using both liquidity creation and liquidity ratio as the outcome variable of interest. In detail, to ensure proper identification and allow for a more accurate comparison across groups, for each country-year combination I split the sample by the lower and upper third of the within country-year distribution of lagged values for bank-specific measures of solvency, profitability, revenue mix, funding structure and asset mix i.e., capital ratio (book capital to asset ratio), return on assets, non-interest revenue share (non-interest income in total income), share of wholesale funding (the share of money market funding in money market funding and total deposits) and loans-to-total assets, respectively. The middle third of the distribution is excluded for each of these variables to allow for a more accurate comparison between groups. Foreign owned is a dummy variable that equals 1 if a bank is foreign-owned and 0 otherwise.

[Table 6 here]

Table 6 shows that peer effects in banks' funding liquidity policies are generally concentrated in banks with low capital ratios, profitability and non-interest revenue share, high share of wholesale funding and loans-to-assets, and non-foreign owned banks. This is consistent with strategic behaviour 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. The effect is also concentrated in non-foreign owned banks, thus suggesting that collective moral-hazard driven by the LOLR implicit or explicit commitment to bailout distressed banks may be driving the results.

Table 7 examine more directly why are liquidity holding choices of a bank influenced by the behaviour of its peers. Banks are classified as "Small" or "Large" by splitting the sample by the lower and upper third of the within country-year distribution of bank size i.e., total assets. As before, the middle third of the distribution is excluded for each of the regressions to allow for a more accurate comparison between the two groups. For the same reason, I also exclude countries with less than 20 commercial banks in a given year. 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. First, the results suggest that learning (i.e., free-riding in information acquisition) does play a role since small banks' liquidity choices are affected by the decisions of large banks, but not the opposite. This is consistent with Leary and Roberts (2014) that consider a sample of US firms (excluding financial corporations) and find that peer firm relevance is driven by a leader–follower model in which small firms are sensitive to large firms but not vice-versa. Nevertheless, as Ratnovski (2009) and Farhi and Tirole (2012) theoretically show, collective moral-hazard due to the LOLR bailout commitment may in fact be the main driver of peer effects in banks' balance-sheet choices: large banks' liquidity decisions are highly sensitive to their large counterparts, and small banks' liquidity choices are also strongly affected by small banks.

[Table 7 here]

5.3. Strategic behaviour and financial stability

As shown in the previous section, banks do take into consideration their peer banks' liquidity decisions when determining their own. While the theoretical literature suggests this may have an adverse effect on both individual banks' financial stability and overall systemic risk (e.g., Acharya and Yorulmazer, 2008; Allen et al., 2012), to the best of my knowledge this is the first study to empirically examine this issue explicitly.

Table 8 presents the baseline results on the impact of peer effects in liquidity holding decisions on individual banks' financial stability. The dependent variable is the Z-score when using a 3-year window to compute the standard deviation of ROA. I use a set of firm- specific and country-level controls to key variables that previous literature consistently show to impact bank risk (e.g., Laeven and Levine, 2009; Karolyi et al., 2012; Beck et al., 2006, 2013; Anginer et al., 2014).

[Table 8 here]

As initially hypothesised, peer effects in liquidity choices are negatively associated with Z-scores, suggesting a decrease in individual banks' distance-to-default and hence an increase in their fragility. The results are robust across multiple model specifications and when considering either liquidity creation or the liquidity ratio to capture funding liquidity risk. Furthermore, this effect is both statistically and economically significant e.g., a one standard deviation increase in the peer effect in liquidity choices (0.24 to 0.30) leads to a decrease in the Z-score of bank *i* of 0.08 to 0.14 (where the mean of Z-Score is 3.46). Table 9 shows that the conclusions do not change when using a 5-year window to compute Z-Scores, or when applying the market-based Merton Distance-to-Default.

[Table 9 here]

Table 10 reports the results when using systemic risk measures to analyse the consequences of peer effects in funding liquidity choices. Specifications (1) to (4) consider the Marginal Expected Shortfall (Acharya et al., 2012) 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. Specifications (5) to (8) use SRISK (Acharya et al., 2012; Brownlees and Engle, 2015) as the dependent variable that 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 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.

[Table 10 here]

The estimated coefficients from model (3) indicate that peer effects in 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 behaviour 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. As before, the results are robust across multiple model specifications, systemic risk proxies and when considering either liquidity creation or the liquidity ratio to capture funding liquidity risk. It is important to note, however, that both MES and SRISK are based on market data and therefore the sample size is significantly reduced. But notwithstanding the potential power issues in the regressions, the estimated coefficients are still significant at conventional levels in all specifications. Overall, Tables 8, 9 and 10 provide evidence that strategic complementarity in funding liquidity risk management policies decrease the stability of the financial system.

6. Conclusion

I empirically examine whether liquidity holdings of a bank are influenced by the choices of its peers and the impact of potential strategic funding liquidity policies on financial stability. Analysing commercial banks in 32 OECD countries from 1999 to 2013, I find that banks do take into consideration their competitor banks' liquidity decisions when determining their own. Banks' liquidity decisions are in large part direct responses to the liquidity choices of peer banks and, to a lesser extent, to changes in their characteristics. Estimates also indicate that the economic impact is large and consistent with coordinated behaviour where each bank constantly adjusts to each other's funding liquidity decisions. Consistent with both learning and collective moral-hazard channels, I show that while large banks' liquidity decisions are only sensitive to their large counterparts, small banks' liquidity choices are affected by the decisions of both small and large banks.

With respect to the consequences of strategic behaviour for the financial system, I find 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. From a macro-prudential perspective, these results highlight the importance of dealing with the systemic component of funding liquidity risk for financial stability. Since information spillovers are a defining characteristic of panics due to financial agents' imperfect knowledge regarding cross-exposures (Brunnermeier et al., 2014), and given that, as shown in this paper, these information spillovers between banks do occur, a static and time-invariant prudential liquidity requirement whose liquid assets mainly depend on individual banks' idiosyncratic risk - rather than system-wide conditions - may in fact not be suited to prevent a systemic liquidity crisis.[15]

[15] Recent proposals for macro-prudential liquidity regulation include liquidity risk charges where a unit of short-term funding would be taxed in proportion to its marginal contribution to a bank's contribution to systemic vulnerability (Perotti and Suarez, 2009), establishment of a central register that would enable macro-prudential authorities to monitor the extent of the aggregate maturity mismatch and its contribution to systemic liquidity risk (Milne, 2013), time-varying LCR and NSFR ratios (ESRB, 2014), and a macro-prudential liquidity buffer in which each bank would be required to hold systemically-liquid assets (Hardy and Hochreiter, 2014).

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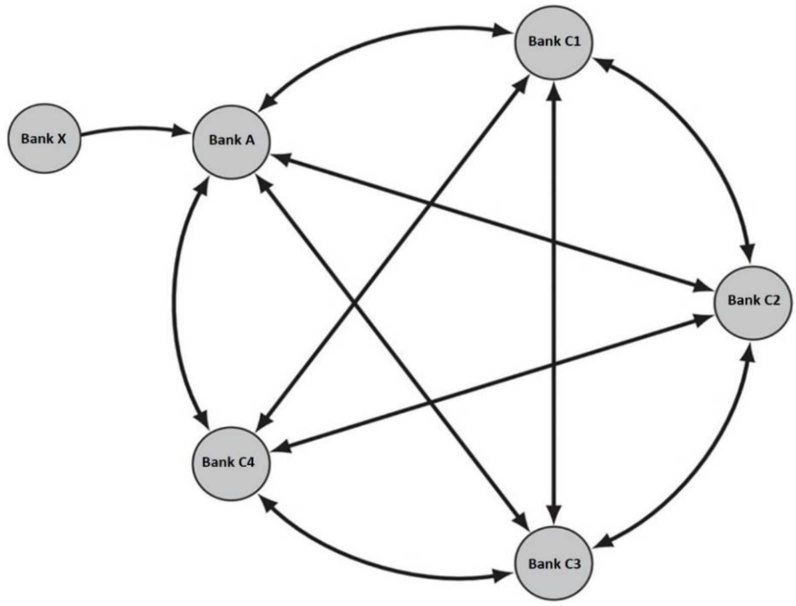

Figure 1: Example of simple network of banks. This figure shows a "complete financial network" (Acemoglu et al., 2015) of banks operating in country *j* in year *t* but with the presence of a cross-border banking-holding company based in country *p*, Bank X, that affects the decisions of Bank A - its foreign-owned subsidiary operating in country *p*. The 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 - 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 liquidity risk indicators over time (1999-2013). This figure shows the time-series pattern of the liquidity ratio and liquidity creation measure. Liquidity ratio is defined as liquid to total assets and captures the liquidity in the asset-side of banks' balance sheet. Liquid assets include cash, short-term claims on other banks, government bonds and the trading portfolio where appropriate. Liquidity Creation is the Berger and Bowman (2009) "cat nonfat" measure i.e., liquidity creation without considering off-balance positions and by combining activities other than loans by category. In contrast with the liquidity ratio, liquidity creation is positively associated with funding liquidity risk since banks creating more liquidity have less liquid assets to meet short-term funding pressures. 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.

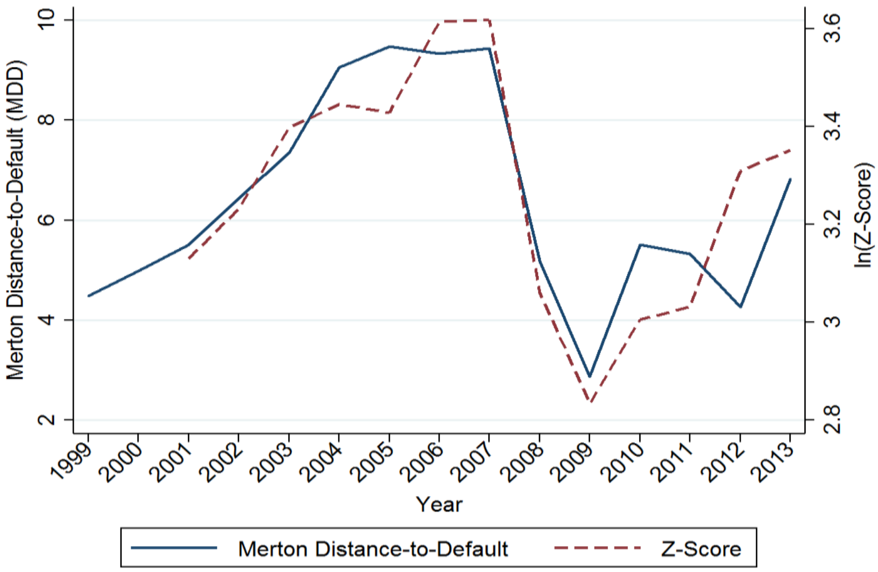

Figure 3: Evolution of individual banks' financial stability over time (1999-2013). This figure shows the time-series pattern of the Merton Distance-to-Default (MDD) and the natural logarithm of the Z-score, ln(Z-score). MDD for each bank at any given point in time equals the difference between its asset value and the face value of its debt, scaled by the standard deviation of its asset value. This variable is estimated using the Merton (1974) model following the implementation in Bharath and Shumway (2008). The Z-score is defined as the sum of equity capital over total assets and return-on-assets (ROA), divided by the three-year rolling standard deviation of ROA. 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.

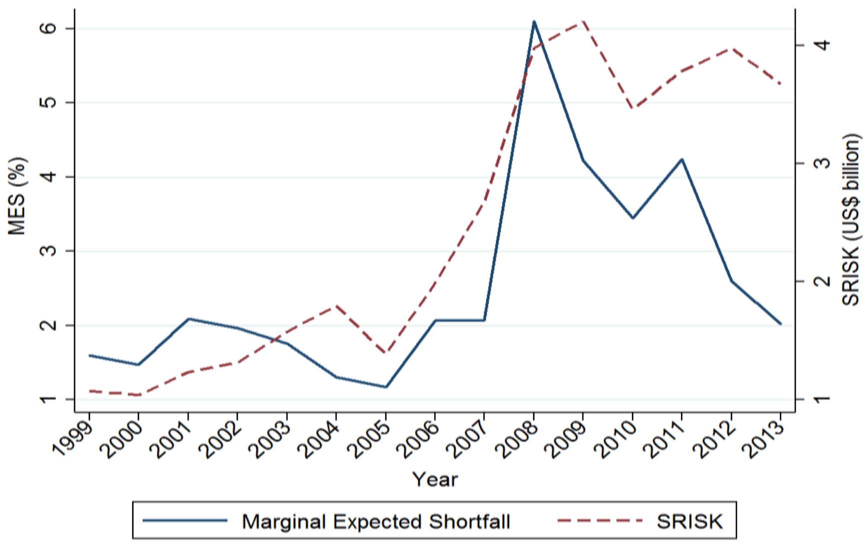

Figure 4: Evolution of systemic risk over time (1999-2013). This figure shows the time-series pattern of (i) the Marginal Expected Shortfall (Acharya et al., 2012) that is defined as the bank *i*'s expected equity loss (in %) per dollar in year *t* conditional on the market experiencing one of its 5% lowest returns in that given year (the higher a bank's MES, the larger its systemic risk exposure) and (ii) SRISK (Acharya et al., 2012; Brownlees and Engle, 2015) that 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 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. Both 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.

Table 1: Summary Statistics

Variables	N	Mean	SD	P25	P50	P75
Bank-level characteristics						
Liquidity Ratio	17,624	0.260	0.246	0.071	0.172	0.381
Liquidity Creation	16,754	0.277	0.290	0.102	0.303	0.482
Capital Ratio	17,811	0.139	0.193	0.049	0.076	0.125
Total Assets (bil US$)	17,831	41.62	122.0	0.833	3.175	22.17
Loans-to-Assets	17,083	0.519	0.267	0.311	0.577	0.727
Return-on-Assets	17,698	0.009	0.026	0.002	0.006	0.012
Cost-to-Income	16,416	0.649	0.303	0.500	0.627	0.748
Provisions	16,951	0.114	0.214	0.000	0.053	0.146
Share of wholesale funding	16,332	0.297	0.296	0.055	0.194	0.457
Non-interest revenue share	16,623	0.378	0.247	0.196	0.337	0.506
Growth in total assets	15,581	0.114	0.329	-0.049	0.061	0.194
Foreign Owned	17,373	0.359	0.480	0.000	0.000	1.000
Financial stability indicators						
Ln(Z-score) – 3-year window	13,130	3.464	1.565	2.706	3.545	4.360
Ln(Z-score) – 5-year window	9,843	3.121	1.434	2.485	3.235	3.909
Merton Distance-to-Default	4,151	5.773	4.733	2.895	4.766	7.501
Marginal Expected Shortfall (%)	4,135	2.193	2.197	0.596	1.756	3.107
S-RISK (bil US$)	3,965	2.157	6.430	0.000	0.060	1.384
Country-specific characteristics						
Ln(GDP per capita)	17,831	10.37	0.570	10.33	10.49	10.65
GDP growth volatility	17,831	0.019	0.012	0.010	0.015	0.026
Concentration	17,831	0.580	0.198	0.431	0.598	0.719
Liquidity Regulation	17,831	0.360	0.480	0.000	0.000	1.000
Global Integration	17,831	0.835	0.637	0.501	0.619	0.960

Year	N	Percent
1999	1,331	7.46
2000	1,306	7.32
2001	1,264	7.09
2002	1,251	7.02
2003	1,235	6.93
2004	1,230	6.90
2005	1,218	6.83
2006	1,201	6.74
2007	1,174	6.58
2008	1,136	6.37
2009	1,150	6.45
2010	1,153	6.47
2011	1,155	6.48
2012	1,105	6.20
2013	922	5.17
Total	17,831	100

This table shows summary statistics for all variables used in this study. Liquidity Ratio is defined as liquid to total assets. Liquidity Creation is the Berger and Bowman's (2009) "cat nonfat" measure i.e., liquidity creation without considering off-balance positions and by combining activities by category. Bank-level characteristics include the capital ratio (book capital to asset ratio), total assets (in billion US$), loans-to-total assets, return-on-assets (ROA), the cost-to-income ratio, provisions (loan loss provisions to total interest income), share of wholesale funding (the share of money market funding in money market funding and total deposits), non-interest revenue share (non-interest income in total income), annual growth in total assets, and Foreign Owned (a dummy variable that equals 1 if a bank is foreign-owned and 0 otherwise). The Z-score is defined as the sum of equity capital over total assets and ROA, divided by either the three or five-year rolling standard deviation of ROA. Merton Distance-to-Default (MDD) equals the difference between the asset value of a bank and the face value of its debt, scaled by the standard deviation of its asset value. Marginal Expected Shortfall (in %) corresponds to bank i's expected equity loss per dollar in a certain year conditional on the market experiencing one of its 5% lowest returns in that given year. Similarly, SRISK measures the expected capital shortage (in billion US$) during a period of system distress when the market declines substantially. Country-level characteristics include the natural logarithm of GDP per capita, the standard deviation of the GDP growth rate over the past 5 years (GDP growth volatility), imports plus exports of goods and service divided GDP (Global Integration), Concentration as measured by the market share of the three largest banks in a country and Liquidity Regulation, a dummy variable that equals 1 if a country has specific binding quantitative regulatory liquidity requirements in a certain year, and 0 otherwise. The full sample consists of 17,831 bank-year observations corresponding to 2,058 commercial banks in 32 OECD countries from 1999 to 2013.

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

Panel A: key set of bank-specific, peer-average and country controls

Dep. Variable: Liquidity Creation	(1) OLS	(2) OLS	(3) 2SLS	(4) 2SLS
Peer Banks' Liquidity Creation	0.364***	0.349***	0.597**	0.513***
	(0.043)	(0.031)	(0.246)	(0.133)
ln(Total Assets)	-0.017***	-0.002	-0.017***	-0.004
	(0.004)	(0.009)	(0.004)	(0.009)
Capital Ratio	-0.877***	-0.429***	-0.853***	-0.422***
	(0.044)	(0.057)	(0.045)	(0.058)
Return-on-Assets	0.214	0.067	0.191	0.030
	(0.253)	(0.146)	(0.261)	(0.155)
Provisions	0.152***	0.012	0.163***	0.014
	(0.025)	(0.012)	(0.024)	(0.012)
Peer Banks' ln(Total Assets)	0.002	0.007**	0.003	0.009**
	(0.006)	(0.003)	(0.006)	(0.004)
Peer Banks' Capital Ratio	0.023	0.108**	0.140	0.157***
	(0.090)	(0.050)	(0.145)	(0.059)
Peer Banks' Return-on-Assets	0.179	0.138	-0.076	0.074
	(0.419)	(0.269)	(0.443)	(0.274)
Peer Banks' Provisions	-0.065*	0.069**	-0.102**	0.043
	(0.037)	(0.027)	(0.045)	(0.028)
ln(GDP per capita)	-0.068	-0.075	-0.034	-0.022
	(0.067)	(0.072)	(0.069)	(0.072)
GDP growth volatility	-0.103	-0.283	-0.081	-0.022
	(0.433)	(0.358)	(0.488)	(0.373)
Liquidity Regulation	-0.029**	-0.018*	-0.015	-0.007
	(0.012)	(0.010)	(0.018)	(0.013)
No. Observations	13,370	13,370	12,243	12,243
No. Banks	1,756	1,756	1,503	1,503
Adj. R^2	0.319	0.091	0.304	0.069
Year FE	Y	Y	Y	Y
Country FE	Y	-	Y	-
Bank FE	N	Y	N	Y
IV (1st stage)	-	-	0.162***	0.177***
	-	-	(0.014)	(0.015)

Panel B: full set of bank-specific, peer-average and country controls

Dep. Variable: Liquidity Creation	(5) OLS	(6) OLS	(7) 2SLS	(8) 2SLS	(9) 2SLS	(10) 2SLS
Peer Banks' Liquidity Creation	0.278***	0.296***	0.455**	0.522***	0.532***	0.462***
	(0.030)	(0.028)	(0.222)	(0.134)	(0.194)	(0.157)
ln(Total Assets)	-0.007**	-0.010	-0.007**	-0.013*	-0.007**	-0.013*
	(0.003)	(0.007)	(0.003)	(0.007)	(0.003)	(0.007)
Capital Ratio	-0.645***	-0.351***	-0.644***	-0.354***	-0.640***	-0.369***
	(0.040)	(0.056)	(0.041)	(0.058)	(0.041)	(0.059)
Return-on-Assets	0.332	0.081	0.368	0.098	0.378	0.047
	(0.234)	(0.170)	(0.237)	(0.179)	(0.237)	(0.174)
Provisions	0.001	-0.002	0.002	-0.001	0.004	-0.002
	(0.015)	(0.012)	(0.016)	(0.012)	(0.016)	(0.012)
Cost-to-Income	0.044***	0.008	0.045***	0.011	0.046***	0.011
	(0.014)	(0.011)	(0.015)	(0.011)	(0.015)	(0.011)
Non-interest revenue share	-0.007	-0.005	-0.003	-0.009	-0.003	-0.004
	(0.020)	(0.016)	(0.021)	(0.017)	(0.020)	(0.017)
Share of wholesale funding	0.096***	0.083***	0.097***	0.083***	0.095***	0.085***
	(0.016)	(0.018)	(0.017)	(0.018)	(0.016)	(0.018)
Loans-to-Assets	0.660***	0.450***	0.657***	0.432***	0.654***	0.433***
	(0.022)	(0.025)	(0.023)	(0.027)	(0.023)	(0.026)
Peer Banks' ln(Total Assets)	0.005	0.009**	0.004	0.009**	0.004	0.007**
	(0.004)	(0.003)	(0.005)	(0.003)	(0.004)	(0.003)
Peer Banks' Capital Ratio	0.096	0.115**	0.110	0.123**	0.121**	0.084
	(0.061)	(0.049)	(0.068)	(0.051)	(0.062)	(0.053)
Peer Banks' Return-on-Assets	0.105	0.173	0.093	0.195	0.053	-0.035
	(0.362)	(0.279)	(0.374)	(0.291)	(0.373)	(0.278)
Peer Banks' Provisions	0.008	0.050**	-0.009	0.030	0.004	0.043*
	(0.028)	(0.025)	(0.030)	(0.026)	(0.027)	(0.026)
Peer Banks' Cost-to-Income	0.032	0.034	0.038	0.033	0.051*	0.035
	(0.026)	(0.021)	(0.029)	(0.023)	(0.030)	(0.022)
Peer Banks' Non-interest revenue share	0.001	0.022	-0.021	0.012	-0.015	0.035
	(0.038)	(0.029)	(0.042)	(0.031)	(0.039)	(0.031)
Peer Banks' Share of wholesale funding	0.009	0.001	0.007	0.007	-0.014	-0.006
	(0.034)	(0.025)	(0.034)	(0.026)	(0.031)	(0.027)
Peer Banks' Loans-to-Assets	-0.053	-0.014	-0.170	-0.114*	-0.237*	-0.079
	(0.043)	(0.033)	(0.146)	(0.064)	(0.123)	(0.053)
ln(GDP per capita)	-0.260***	-0.145**	-0.202**	-0.065		
	(0.066)	(0.068)	(0.079)	(0.072)		
GDP growth volatility	-0.884**	-0.742**	-0.608	-0.348		
	(0.384)	(0.356)	(0.399)	(0.366)		
Liquidity Regulation	-0.049***	-0.027***	-0.035*	-0.010		
	(0.010)	(0.009)	(0.020)	(0.013)		
Concentration	0.072**	0.074**	0.059	0.059*		
	(0.036)	(0.036)	(0.037)	(0.036)		
Global Integration	0.045	0.033	0.038	0.020		
	(0.029)	(0.029)	(0.030)	(0.031)		
No. Observations	12,653	12,653	11,574	11,574	11,749	11,574
No. Banks	1,649	1,649	1,416	1,416	1,416	1,416
Adj. R^2	0.593	0.193	0.583	0.162	0.579	0.185
Year FE	Y	Y	Y	Y	N	N
Country FE	Y	-	Y	-	N	-
Bank FE	N	Y	N	Y	N	Y
Country-Year FE	N	N	N	N	Y	Y
IV (1st stage)	-	-	0.129***	0.160***	0.141***	0.125***
	-	-	(0.013)	(0.014)	(0.013)	(0.011)

The table reports ordinary least squares (OLS) and two-stage least squares (2SLS) coefficient estimates of model (1) when using Berger and Bowman's (2009) liquidity creation measure as the dependent variable. Peer averages are constructed based on the benchmark peer group definition: commercial banks operating in the same country in the same year grouped in a maximum of 20 banks according to their size. 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.

Table 3: Peer effects in banks' funding liquidity choices – liquidity ratio

Panel A: key set of bank-specific, peer-average and country controls

Dep. Variable: Liquidity Ratio	(1) OLS	(2) OLS	(3) 2SLS	(4) 2SLS
Peer Banks' Liquidity Ratio	0.322***	0.308***	0.407**	0.400***
	(0.048)	(0.030)	(0.177)	(0.118)
ln(Total Assets)	-0.021	-0.104*	-0.022	-0.091
	(0.024)	(0.055)	(0.024)	(0.056)
Capital Ratio	-1.125***	-0.173	-1.146***	-0.177
	(0.279)	(0.342)	(0.289)	(0.358)
Return-on-Assets	-4.999***	-1.262	-5.078***	-1.223
	(1.319)	(0.821)	(1.367)	(0.849)
Provisions	-1.083***	-0.116*	-1.132***	-0.136**
	(0.130)	(0.064)	(0.135)	(0.066)
Peer Banks' ln(Total Assets)	0.018	0.013	0.018	0.012
	(0.034)	(0.021)	(0.035)	(0.021)
Peer Banks' Capital Ratio	1.224**	-0.251	1.103**	-0.309
	(0.525)	(0.275)	(0.561)	(0.282)
Peer Banks' Return-on-Assets	-1.689	-0.586	-0.264	0.156
	(2.383)	(1.580)	(2.574)	(1.629)
Peer Banks' Provisions	0.235	-0.370**	0.327	-0.342**
	(0.219)	(0.145)	(0.260)	(0.155)
ln(GDP per capita)	-1.313***	-0.966**	-1.313**	-1.069**
	(0.414)	(0.435)	(0.576)	(0.496)
GDP growth volatility	-4.496*	-3.266*	-4.882*	-3.581*
	(2.383)	(1.896)	(2.774)	(2.105)
Liquidity Regulation	0.074	0.001	0.048	-0.032
	(0.067)	(0.052)	(0.071)	(0.055)
No. Observations	13,850	13,850	12,688	12,688
No. Banks	1,826	1,826	1,561	1,561
Adj. R^2	0.236	0.042	0.225	0.039
Year FE	Y	Y	Y	Y
Country FE	Y	-	Y	-
Bank FE	N	Y	N	Y
IV (1st stage)	-	-	0.251***	0.205***
	-	-	(0.013)	(0.013)

Panel B: full set of bank-specific, peer-average and country controls

Dep. Variable: Liquidity Ratio	(5) OLS	(6) OLS	(7) 2SLS	(8) 2SLS	(9) 2SLS	(10) 2SLS
Peer Banks' Liquidity Ratio	0.241***	0.269***	0.574***	0.474***	0.596***	0.250**
	(0.034)	(0.025)	(0.152)	(0.102)	(0.159)	(0.110)
ln(Total Assets)	-0.020	-0.030	-0.015	-0.014	-0.013	-0.046
	(0.016)	(0.048)	(0.016)	(0.049)	(0.016)	(0.047)
Capital Ratio	-0.948***	-0.339	-0.927***	-0.374	-0.910***	-0.402
	(0.317)	(0.331)	(0.327)	(0.346)	(0.325)	(0.322)
Return-on-Assets	-4.207***	-1.607*	-4.276***	-1.544	-4.325***	-1.358
	(1.583)	(0.933)	(1.626)	(0.967)	(1.626)	(0.962)
Provisions	-0.119	-0.042	-0.131	-0.059	-0.138	-0.055
	(0.081)	(0.058)	(0.085)	(0.060)	(0.086)	(0.060)
Cost-to-Income	0.013	0.026	0.012	0.032	0.008	0.027
	(0.089)	(0.054)	(0.090)	(0.056)	(0.090)	(0.055)
Non-interest revenue share	0.400***	0.033	0.394***	0.041	0.401***	0.015
	(0.121)	(0.098)	(0.123)	(0.099)	(0.123)	(0.097)
Share of wholesale funding	-0.109	-0.189*	-0.086	-0.160	-0.087	-0.167*
	(0.090)	(0.097)	(0.092)	(0.099)	(0.091)	(0.100)
Loans-to-Assets	-3.864***	-2.458***	-3.850***	-2.398***	-3.836***	-2.325***
	(0.123)	(0.140)	(0.126)	(0.137)	(0.126)	(0.142)
Peer Banks' ln(Total Assets)	-0.025	0.007	-0.018	0.011	-0.010	0.018
	(0.025)	(0.019)	(0.027)	(0.019)	(0.025)	(0.019)
Peer Banks' Capital Ratio	0.242	-0.338	0.456	-0.181	0.639*	-0.233
	(0.339)	(0.244)	(0.358)	(0.249)	(0.357)	(0.251)
Peer Banks' Return-on-Assets	2.962	0.354	3.841*	0.581	3.722*	1.837
	(1.935)	(1.452)	(1.982)	(1.486)	(2.005)	(1.418)
Peer Banks' Provisions	-0.174	-0.326**	-0.046	-0.283**	-0.069	-0.264**
	(0.166)	(0.134)	(0.176)	(0.140)	(0.163)	(0.132)
Peer Banks' Cost-to-Income	0.234	-0.031	0.160	-0.042	0.111	-0.080
	(0.156)	(0.093)	(0.162)	(0.098)	(0.161)	(0.095)
Peer Banks' Non-interest revenue share	-0.224	-0.299*	-0.322	-0.325**	-0.254	-0.292*
	(0.240)	(0.159)	(0.248)	(0.161)	(0.233)	(0.156)
Peer Banks' Share of wholesale funding	-0.311	-0.321**	-0.159	-0.267*	-0.167	-0.312**
	(0.192)	(0.140)	(0.209)	(0.147)	(0.184)	(0.143)
Peer Banks' Loans-to-Assets	0.235	-0.286*	1.180***	0.134	1.409***	0.060
	(0.230)	(0.172)	(0.437)	(0.240)	(0.466)	(0.204)
ln(GDP per capita)	-0.536	-0.923**	-0.141	-0.745*		
	(0.387)	(0.366)	(0.435)	(0.396)		
GDP growth volatility	1.430	0.431	0.987	-0.172		
	(1.830)	(1.625)	(1.918)	(1.732)		
Liquidity Regulation	0.210***	0.085*	0.117*	0.025		
	(0.054)	(0.047)	(0.063)	(0.051)		
Concentration	-0.228	-0.460**	-0.060	-0.309		
	(0.210)	(0.204)	(0.215)	(0.200)		
Global Integration	0.110	0.235	0.122	0.232		
	(0.162)	(0.165)	(0.166)	(0.169)		
No. Observations	12,642	12,642	11,567	11,567	11,567	11,567
No. Banks	1,647	1,647	1,418	1,418	1,418	1,418
Adj. R^2	0.596	0.174	0.582	0.158	0.580	0.185
Year FE	Y	Y	Y	Y	N	N
Country FE	Y	-	Y	-	N	-
Bank FE	N	Y	N	Y	N	Y
Country-Year FE	N	N	N	N	Y	Y
IV (1st stage)	-	-	0.216***	0.202***	0.203***	0.178***
	-	-	(0.010)	(0.012)	(0.010)	(0.012)

The table reports ordinary least squares (OLS) and two-stage least squares (2SLS) coefficient estimates of model (1) when using the logistic transformation of the standard liquidity ratio as dependent variable i.e., Liquidity Ratio=log[(liquid assets/total assets)/(1- liquid assets/total assets)]. This is because the standard liquidity ratio is unsuitable as a dependent variable as it is bounded within the intervals [0,1] (Morck et al., 2000; Karolyi et al., 2012; Anginer et al., 2014). 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. 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.

Table 4: Peer effects in banks' funding liquidity choices – robustness tests

	(1)	(2)	(3)	(4)
	Peer Effect: Liquidity Creation		Peer Effect: Liquidity Ratio	
Baseline specification	0.513***	0.522***	0.400***	0.474***
	(0.133)	(0.134)	(0.118)	(0.102)
	[12,243]	[11,574]	[12,688]	[11,567]
Panel A: Alternative peer groups				
Commercial banks operating in the same country/year (i.e., no bank size requirement)	0.846***	0.815***	0.909***	0.954***
	(0.177)	(0.181)	(0.207)	(0.173)
	[13,286]	[12,583]	[13,758]	[12,577]
Commercial banks operating in the same country/year & split into 2 size groups (i.e., small and large)	0.646***	0.608***	0.464***	0.502***
	(0.171)	(0.164)	(0.150)	(0.120)
	[12,428]	[11,757]	[12,858]	[11,748]
Commercial banks operating in the same country/year & split into 3 size groups (i.e., S, M and L)	0.327**	0.319*	0.253**	0.277***
	(0.152)	(0.166)	(0.105)	(0.082)
	[11,673]	[11,030]	[12,079]	[11,025]
Commercial banks operating in the same country/year & size grouped into a maximum of 25 banks	0.572***	0.479**	0.410***	0.443***
	(0.188)	(0.200)	(0.120)	(0.105)
	[12,451]	[11,775]	[12,911]	[11,767]
Panel B: Alternative specifications				
Without controls	0.516***	0.516***	0.307**	0.307**
	(0.119)	(0.119)	(0.120)	(0.120)
	[14,794]	[14,794]	[15,431]	[15,431]
With contemporaneous controls	0.424***	0.604***	0.364***	0.540***
	(0.136)	(0.191)	(0.134)	(0.196)
	[14,115]	[13,305]	[14,658]	[13,260]
Excluding countries with less than 20 commercial banks in a given year	0.470***	0.526***	0.322***	0.418***
	(0.138)	(0.142)	(0.121)	(0.101)
	[10,244]	[9,677]	[10,692]	[9,670]
Excluding commercial banks with asset growth above 40%	0.541***	0.542***	0.404***	0.436***
	(0.135)	(0.137)	(0.121)	(0.104)
	[10,998]	[10,421]	[11,393]	[10,417]
Panel C: Alternative IVs				
Idiosyncratic liquidity creation/ratio of the foreign-owned peers' parents:	0.704***	0.660***	0.756***	0.828***
	(0.161)	(0.168)	(0.216)	(0.190)
$\hat{\varepsilon}_{p,j,t} = \widehat{Liq}_{p,j,t} - \hat{\tau}' Z_{j,t-1} - \widehat{\omega_p} - \widehat{v_t}$	[11,843]	[11,189]	[12,279]	[11,183]
Idiosyncratic liquidity creation/ratio of the foreign-owned peers' parents:	0.671***	0.708***	0.582***	0.640***
	(0.212)	(0.208)	(0.132)	(0.113)
$\hat{\varepsilon}_{p,j,t} = \widehat{Liq}_{p,j,t} - \hat{\tau}' Z_{j,t-1} - \widehat{m}_{tj}$	[11,878]	[11,224]	[12,314]	[11,218]
Idiosyncratic component of stock returns (i.e., as in Leary and Roberts, 2014)	0.769***	0.714***	0.733***	0.739***
	(0.146)	(0.150)	(0.219)	(0.190)
	[3,878]	[3,224]	[3,314]	[3,218]

The table reports the two-stage least square (2SLS) coefficient estimates of model (1) when using the liquidity creation measure and the logistic transformation of the standard liquidity ratio as dependent variables. Liquidity ratio is defined as liquid to total assets. Liquidity creation is the Berger and Bowman's (2009) "cat nonfat" measure. 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 specification (4) and (8) of Tables 2 and 3 where the key and full set of bank, peer and country-level controls (lagged) 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.

Table 5: Peer effects in banks’ funding liquidity choices – additional robustness tests

	(1) S-GMM: L. Creation	(2) S-GMM: L. Creation	(3) S-GMM: L. Ratio	(4) S-GMM: L. Ratio	(5) 2SLS: L. Creation	(6) 2SLS: L. Creation	(7) 2SLS: L. Creation	(8) 2SLS: L. Creation	(9) 2SLS: L. Ratio	(10) 2SLS: L. Ratio	(11) 2SLS: L. Ratio	(12) 2SLS: L. Ratio
Peer Banks’ Liquidity Creation	0.207*	0.388***			0.687**	0.890***	0.883***	1.068***				
	(0.105)	(0.127)			(0.303)	(0.274)	(0.290)	(0.258)				
Liquidity Creation (lagged)	0.771***	0.897***										
	(0.036)	(0.055)										
Peer Banks’ Liquidity Ratio			0.396***	0.665***					0.615**	0.858***	0.742**	0.922***
			(0.115)	(0.162)					(0.288)	(0.291)	(0.315)	(0.322)
Liquidity Ratio (lagged)			0.616***	0.740***								
			(0.034)	(0.068)								
No. Observations	12,376	11,742	12,825	11,714	12,382	12,191	11,596	11,421	12,043	11,859	11,583	11,406
No. Banks	1,689	1,587	1,756	1,585	1,462	1,462	1,362	1,362	1,415	1,415	1,358	1,358
Controls	Key	Full	Key	Full	Key	Key	Full	Full	Key	Key	Full	Full
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country FE	-	-	-	-	Y	-	Y	-	N	Y	N	Y
Bank FE	Y	Y	Y	Y	N	Y	N	Y	Y	Y	Y	Y

The table reports the system GMM (S-GMM) and 2SLS coefficient estimates of model (1) when using the liquidity creation measure and the logistic transformation of the standard liquidity ratio as dependent variables. Specifications (1) to (4) refer to model (1) extended to include a lagged dependent variable as an explanatory variable. Because OLS or a standard fixed effects model would yield biased estimates in the presence of a lagged dependent variable and a short panel (Flannery and Hankins, 2013), I estimate the extended model (1) using Blundell and Bond’s (1998) generalized GMM estimator. The GMM standard errors in parentheses are Windmeijer robust standard errors. Specifications (5) to (12) refer to model (1) when using peer weighted-averages based on the size similarity (inverse of the Euclidean distance) between the banks in country *j* in year *t*. The smaller the distance between two banks, the more weight it has. 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.

Table 6: Which banks strategically mimic their peers?

	Peer Effect: Liquidity Creation		Peer Effect: Liquidity Ratio	
	(1)	(2)	(3)	(4)
Low Capital Ratio	0.898***	1.114***	0.383**	0.444**
	(0.337)	(0.400)	(0.195)	(0.177)
	[4,258]	[4,068]	[4,320]	[4,077]
High Capital Ratio	0.354*	0.194	0.203	0.154
	(0.207)	(0.203)	(0.199)	(0.185)
	[3,294]	[2,990]	[3,668]	[2,987]
Low Profitability	0.476**	0.497**	0.426**	0.503***
	(0.217)	(0.217)	(0.204)	(0.166)
	[3,968]	[3,683]	[4,079]	[3,685]
High Profitability	0.342	0.447**	0.073	0.188
	(0.214)	(0.213)	(0.201)	(0.189)
	[3,500]	[3,271]	[3,779]	[3,263]
Low non-interest revenue share	0.638***	0.662***	0.522***	0.760***
	(0.196)	(0.216)	(0.179)	(0.171)
	[3,907]	[3,688]	[4,015]	[3,679]
High non-interest revenue share	0.420	0.498**	-0.024	0.101
	(0.255)	(0.238)	(0.238)	(0.202)
	[3,591]	[3,426]	[3,771]	[3,432]
Low share of wholesale funding	0.374**	0.292	0.191	0.241
	(0.188)	(0.179)	(0.217)	(0.194)
	[3,839]	[3,763]	[3,886]	[3,770]
High share of wholesale funding	0.942***	1.085***	0.544***	0.521***
	(0.302)	(0.313)	(0.196)	(0.185)
	[3,715]	[3,625]	[3,717]	[3,604]
Low loan-to-assets ratio	0.374**	0.354**	0.212	0.201
	(0.175)	(0.175)	(0.190)	(0.189)
	[3,916]	[3,669]	[3,978]	[3,679]
High loan-to-assets ratio	0.675***	0.743***	0.801***	0.928***
	(0.200)	(0.224)	(0.250)	(0.226)
	[3,849]	[3,599]	[3,838]	[3,578]
Foreign-owned banks	0.182	0.410	0.174	0.310*
	(0.313)	(0.288)	(0.195)	(0.159)
	[4,662]	[4,408]	[4,806]	[4,414]
Non-foreign-owned banks	0.739***	0.663***	0.485***	0.565***
	(0.169)	(0.178)	(0.153)	(0.138)
	[7,407]	[7,001]	[7,704]	[6,991]

The table reports the two-stage least square (2SLS) coefficient estimates of model (1) when using the liquidity creation measure and the logistic transformation of the liquidity ratio as dependent variables and splitting the sample by the lower and upper third of the within country-year distribution of lagged values for bank-specific measures of solvency, profitability, revenue mix, funding structure and asset mix i.e., capital ratio (book capital to asset ratio), return on assets, non-interest revenue share (non-interest income in total income), share of wholesale funding (the share of money market funding in money market funding and total deposits) and loans-to-total assets, respectively. The middle third of the distribution is excluded for each of these variables to allow for a more accurate comparison between groups. Foreign owned is a dummy variable that equals 1 if a bank is foreign-owned and 0 otherwise. Liquidity ratio is defined as liquid to total assets. Liquidity creation is the Berger and Bowman's (2009) "cat nonfat" measure. 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 specification (4) and (8) of Tables 2 and 3 where the key and full set of bank, peer and country-level controls (lagged) 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.

Table 7: Who mimics who?

	Peer Effect: Liquidity Creation				Peer Effect: Liquidity Ratio			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Large banks mimicking Large banks	0.981***	0.773***	0.732***	0.995***	0.909**	1.185***	1.211**	1.421***
	(0.164)	(0.179)	(0.273)	(0.262)	(0.396)	(0.327)	(0.558)	(0.397)
	[3,413]	[3,334]	[3,240]	[3,169]	[3,521]	[3,439]	[3,246]	[3,175]
Large banks mimicking Small banks	0.227	0.045	0.195	0.001	-0.059	0.218	0.079	0.195
	(0.300)	(0.293)	(0.220)	(0.215)	(0.212)	(0.173)	(0.172)	(0.142)
	[3,184]	[3,108]	[3,016]	[2,950]	[3,281]	[3,204]	[3,022]	[2,956]
Small banks mimicking Small banks	1.332***	0.803**	0.681***	0.479*	0.943***	0.428**	0.564***	0.399**
	(0.379)	(0.373)	(0.257)	(0.251)	(0.285)	(0.209)	(0.197)	(0.161)
	[3,073]	[2,946]	[2,860]	[2,737]	[3,237]	[3,103]	[2,849]	[2,729]
Small banks mimicking Large banks	0.765***	0.886***	0.645**	0.922***	1.155**	1.178***	1.285**	1.092**
	(0.211)	(0.192)	(0.278)	(0.264)	(0.530)	(0.453)	(0.614)	(0.487)
	[3,312]	[3,184]	[3,096]	[2,972]	[3,495]	[3,358]	[3,085]	[2,964]
Controls	Key	Key	Full	Full	Key	Key	Full	Full
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Bank FE	N	Y	N	Y	N	Y	N	Y
Country FE	Y	-	Y	-	Y	-	Y	-

The table reports the two-stage least square (2SLS) coefficient estimates of model (1) when using the liquidity creation measure and the logistic transformation of the liquidity ratio as dependent variables. Liquidity creation is the Berger and Bowman's (2009) "cat nonfat" measure. Liquidity ratio is defined as liquid to total assets. Banks are classified as "Small" or "Large" by splitting the sample by the lower and upper third of the within country-year distribution of bank size i.e., log of total assets. The middle third of the distribution is excluded for each of the regressions to allow for a more accurate comparison between the two groups. For the same reason, I also exclude countries with less than 20 commercial banks in a given year. 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), (4), (7) and (8) of Tables 2 and 3 where either the key or full set of bank, peer and country-level controls (lagged) are included in the regression. Robust standard errors clustered at the bank level are in parentheses and the number of bank-year observations in square brackets. *, ** and *** designate that the test statistic is significant at the 10%, 5% and 1% levels.

Table 8: Peer effects in banks' funding liquidity choices and financial stability

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ln(Z-Score) – 3-year window: $\ln[(E/A + ROA)/\sigma(ROA)_{3y}]$							
Peer Effect:	-0.335**	-0.319**	-0.374***	-0.360**				
Liq. Creation - $\widehat{\beta_{j,t}^{LC}}$	(0.143)	(0.142)	(0.144)	(0.144)				
Peer Effect:					-0.458***	-0.442***	-0.383***	-0.366***
Liq. Ratio - $\widehat{\beta_{j,t}^{LR}}$					(0.128)	(0.132)	(0.119)	(0.118)
ln(Total Assets)	-0.046***	-0.076***	-0.085	-0.079	-0.044***	-0.075***	-0.079	-0.077
	(0.015)	(0.014)	(0.054)	(0.054)	(0.015)	(0.014)	(0.053)	(0.054)
Provisions	-1.958***	-1.914***	-1.386***	-1.432***	-1.932***	-1.911***	-1.368***	-1.428***
	(0.136)	(0.134)	(0.127)	(0.124)	(0.135)	(0.133)	(0.126)	(0.124)
Non-interest Revenue Sh.	-1.386***	-1.227***	-0.505***	-0.342**	-1.377***	-1.228***	-0.443**	-0.327**
	(0.125)	(0.110)	(0.168)	(0.155)	(0.125)	(0.111)	(0.178)	(0.154)
Loans-to-Assets	0.516***	0.328***	-0.033	-0.129	0.544***	0.324***	-0.035	-0.142
	(0.106)	(0.105)	(0.200)	(0.194)	(0.107)	(0.106)	(0.197)	(0.193)
Cost-to-Income		-1.102***		-0.859***		-1.095***		-0.862***
		(0.097)		(0.103)		(0.097)		(0.102)
Sh. Wholesale Funding		-0.220***		-0.082		-0.223***		-0.098
		(0.081)		(0.133)		(0.082)		(0.133)
Growth in Total Assets		-0.358***		-0.208***		-0.364***		-0.208***
		(0.052)		(0.050)		(0.052)		(0.050)
Foreign-Owned		-0.128**		0.068		-0.127**		0.064
		(0.057)		(0.175)		(0.057)		(0.176)
ln(GDP per capita)	2.366***	2.566***			2.515***	2.764***		
	(0.498)	(0.523)			(0.504)	(0.536)		
GDP growth Volatility	-5.891*	-6.122**			-5.146*	-5.717*		
	(3.111)	(3.064)			(3.087)	(3.029)		
Liquidity Regulation	-0.010	-0.071			0.012	-0.058		
	(0.071)	(0.070)			(0.070)	(0.070)		
Concentration		0.291				0.327		
		(0.382)				(0.389)		
Global Integration		-0.293				-0.290		
		(0.220)				(0.218)		
No. observations	10,535	10,051	10,535	10,051	10,594	10,049	10,594	10,049
No. banks	1,490	1,406	1,490	1,406	1,499	1,407	1,499	1,407
Adj. R^2	0.214	0.269	0.098	0.126	0.213	0.269	0.097	0.127
Year FE	Y	Y	N	N	Y	Y	N	N
Bank FE	N	N	Y	Y	N	N	Y	Y
Country FE	Y	Y	-	-	Y	Y	-	-
Country-Year FE	N	N	Y	Y	N	N	Y	Y

The table reports coefficient estimates of model (3). 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. Peer effects in liquidity decisions are estimated with model (2) when using the liquidity creation measure and the logistic transformation of the standard liquidity ratio as dependent variables, and where the relationship between the liquidity of bank i and the liquidity of its peers, $\beta_{j,t}$, is now allowed to vary across countries and over time. The key set of bank, peer and country-level controls (lagged), as well as year and bank fixed-effects, are included in the regressions when estimating $\beta_{j,t}$, and 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. Liquidity ratio is defined as liquid to total assets. Liquidity creation is the Berger and Bowman's (2009) "cat nonfat" measure. 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.

Table 9: Peer effects in banks' funding liquidity choices and financial stability – robustness tests

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ln(Z-Score) -5-year window: $\ln[(E/A+ROA)/\sigma(ROA)_{5y}]$				Merton Distance-to-Default (MDD)			
Peer Effect:	-0.235**	-0.246**			-1.390**	-1.212**		
Liq. Creation - $\widehat{\beta_{j,t}^{LC}}$	(0.104)	(0.101)			(0.563)	(0.590)		
Peer Effect:			-0.113**	-0.131**			-1.522***	-1.593***
Liq. Ratio - $\widehat{\beta_{j,t}^{LR}}$			(0.054)	(0.056)			(0.270)	(0.264)
ln(Total Assets)	-0.147**	-0.168***	-0.153***	-0.168***	-0.632**	-1.321***	-0.475*	-1.192***
	(0.059)	(0.060)	(0.059)	(0.059)	(0.277)	(0.273)	(0.264)	(0.253)
Capital Ratio					0.720	-1.817	3.104	-3.176
					(2.621)	(2.725)	(3.978)	(3.210)
Return-on-Assets					14.327**	4.781	7.242	4.973
					(6.815)	(8.142)	(8.933)	(8.214)
Provisions	-1.143***	-1.113***	-1.119***	-1.103***	-2.818***	-2.374***	-2.949***	-2.417***
	(0.140)	(0.134)	(0.138)	(0.133)	(0.548)	(0.570)	(0.573)	(0.566)
Non-interest Revenue Sh.	-0.315*	-0.094	-0.264	-0.064	2.122***	2.047**	2.283***	2.182***
	(0.179)	(0.155)	(0.188)	(0.154)	(0.718)	(0.822)	(0.761)	(0.806)
Loans-to-Assets	0.078	0.008	0.056	-0.000	-0.837	-1.298	-0.611	-1.020
	(0.246)	(0.234)	(0.243)	(0.232)	(1.358)	(1.400)	(1.352)	(1.383)
Cost-to-Income		-0.860***		-0.866***		-2.297***		-2.380***
		(0.127)		(0.127)		(0.563)		(0.566)
Sh. Wholesale Funding		-0.054		-0.075		-1.180		-0.982
		(0.149)		(0.150)		(0.812)		(0.799)
Growth in Total Assets		-0.119**		-0.123**		2.017***		1.857***
		(0.057)		(0.056)		(0.333)		(0.318)
Foreign-Owned		0.092		0.089		-0.870		-0.924
		(0.207)		(0.207)		(1.636)		(1.656)
No. observations	7,962	7,650	8,011	7,646	2,354	2,179	2,387	2,185
No. banks	1,252	1,199	1,260	1,197	339	314	343	315
Adj. R^2	0.132	0.165	0.131	0.165	0.215	0.256	0.210	0.259
Bank FE	Y	Y	Y	Y	Y	Y	Y	Y
Country-Year FE	Y	Y	Y	Y	Y	Y	Y	Y

The table reports coefficient estimates of model (3). Z-score is 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. Merton Distance-to-Default (MDD) for each bank at any given point in time equals the difference between its asset value and the face value of its debt, scaled by the standard deviation of its asset value. This variable is estimated using the Merton (1974) model following the implementation in Bharath and Shumway (2008). Peer effects in liquidity decisions are estimated with model (2) when using the liquidity creation measure and the logistic transformation of the standard liquidity ratio as dependent variables, and where the relationship between the liquidity of bank i and the liquidity of its peers, $\beta_{j,t}$, is now allowed to vary across countries and over time. The key set of bank, peer and country-level controls (lagged), as well as year and bank fixed-effects, are included in the regressions when estimating $\beta_{j,t}$, and 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. Liquidity ratio is defined as liquid to total assets. Liquidity creation is the Berger and Bowman's (2009) "cat nonfat" measure. 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.

Table 10: Peer effects in banks' funding liquidity choices and systemic risk

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Marginal Expected Shortfall (MES)				SRISK			
Peer Effect:	1.793***	1.761***			1.892*	1.945*		
Liq. Creation - $\widehat{\beta_{j,t}^{LC}}$	(0.444)	(0.492)			(1.004)	(1.005)		
Peer Effect:			0.581***	0.598***			0.679***	0.698**
Liq. Ratio - $\widehat{\beta_{j,t}^{LR}}$			(0.157)	(0.175)			(0.257)	(0.283)
ln(Total Assets)	1.104***	1.145***	1.039***	1.063***	-0.014	-0.219	-0.086	-0.282
	(0.163)	(0.169)	(0.157)	(0.165)	(0.473)	(0.641)	(0.483)	(0.645)
Capital Ratio	3.944***	4.389**	2.629**	2.423	2.920	-2.555	4.845	-1.651
	(1.454)	(2.030)	(1.218)	(1.925)	(5.260)	(4.808)	(5.622)	(4.877)
Return-on-Assets	-3.285	0.653	-0.947	2.684	0.951	20.736	-0.080	22.622*
	(3.504)	(4.817)	(3.138)	(4.989)	(8.207)	(13.207)	(7.040)	(13.286)
Provisions	-0.181	-0.315	-0.235	-0.381	0.632	0.902	0.567	0.864
	(0.382)	(0.389)	(0.367)	(0.382)	(1.013)	(1.105)	(0.965)	(1.087)
Non-interest Revenue Sh.	0.468	0.452	0.633	0.754	-4.382**	-6.008**	-4.373**	-6.038**
	(0.439)	(0.507)	(0.416)	(0.493)	(2.209)	(2.798)	(2.146)	(2.775)
Loans-to-Assets	0.844	0.849	1.184*	1.157*	-3.282	-3.392	-3.125	-3.197
	(0.665)	(0.692)	(0.641)	(0.673)	(2.467)	(2.639)	(2.388)	(2.590)
Cost-to-Income		0.912**		1.035**		3.500*		3.785**
		(0.437)		(0.427)		(1.859)		(1.797)
Sh. Wholesale Funding		0.096		0.029		0.152		0.129
		(0.514)		(0.496)		(1.655)		(1.700)
Growth in Total Assets		-0.105		-0.099		1.336*		1.333*
		(0.197)		(0.192)		(0.776)		(0.765)
Foreign-Owned		-0.650		-0.613		-4.303		-4.211
		(0.728)		(0.751)		(3.904)		(3.878)
No. observations	2,377	2,201	2,410	2,207	2,262	2,092	2,290	2,098
No. banks	340	316	344	317	337	313	341	314
Adj. R^2	0.161	0.161	0.158	0.157	0.229	0.245	0.227	0.243
Bank FE	Y	Y	Y	Y	Y	Y	Y	Y
Country-Year FE	Y	Y	Y	Y	Y	Y	Y	Y

The table reports coefficient estimates of model (3). 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 (the higher a bank's MES, the larger its systemic risk exposure). SRISK (Acharya et al., 2012; Brownlees and Engle, 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 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. Peer effects in liquidity decisions are estimated with model (2) when using the liquidity creation measure and the logistic transformation of the standard liquidity ratio as dependent variables, and where the relationship between the liquidity of bank i and the liquidity of its peers, $\beta_{j,t}$, is now allowed to vary across countries and over time. The key set of bank, peer and country-level controls (lagged), as well as year and bank fixed-effects, are included in the regressions when estimating $\beta_{j,t}$, and 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. Liquidity ratio is defined as liquid to total assets. Liquidity creation is the Berger and Bowman's (2009) "cat nonfat" measure. 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.

Table A1: Berger and Bowman (2009) liquidity measure creation

Assets		
Loans		
Residential Mortgage Loans	0	Semi-liquid
Other Mortgage Loans	0	Semi-liquid
Other Consumer/Retail Loans	0	Semi-liquid
Corporate & Commercial Loans	0.5	Iliquid
Other Loans	0.5	Iliquid
Less: Reserves for Impaired Loans/NPLs		
Net Loans		
Gross Loans		
Other Earning Assets		
Loans and Advances to Banks	0	Semi-liquid
Reverse Repos and Cash Collateral	-0.5	Liquid
Trading Securities and at FV through Income	-0.5	Liquid
Derivatives	-0.5	Liquid
Available for Sale Securities	-0.5	Liquid
Held to Maturity Securities	-0.5	Liquid
At-equity Investments in Associates	-0.5	Liquid
Other Securities	-0.5	Liquid
Total Securities		
Investments in Property	0.5	Iliquid
Insurance Assets	0.5	Iliquid
Other Earning Assets	0.5	Iliquid
Total Earning Assets		
Non-earning Assets		
Cash and Due From Banks	-0.5	Liquid
Foreclosed Real Estate	0.5	Iliquid
Fixed Assets	0.5	Iliquid
Goodwill	0.5	Iliquid
Other Intangibles	0.5	Iliquid
Current Tax Assets	0.5	Iliquid
Deferred Tax Assets	0.5	Iliquid
Discontinued Operations	0.5	Iliquid
Other Assets	0.5	Iliquid
Total Assets		

Liabilities		
Interest-bearing Liabilities		
Customer Deposits - Current	0.5	Liquid
Customer Deposits - Savings	0.5	Liquid
Customer Deposits - Term	0	Semi-Liquid
Total Customer Deposits		
Deposits from Banks	0.5	Liquid
Repos and Cash Collateral	0.5	Liquid
Other Deposits and Short-Term Borrowings	0.5	Liquid
Total Deposits, Money Market and Short-Term Funding		
Senior Debt Maturing after 1 Year	-0.5	Iliquid
Subordinated Borrowing	-0.5	Iliquid
Other Funding	0	Semi-Liquid
Total Long Term Funding		
Derivatives	0.5	Liquid
Trading Liabilities	0.5	Liquid
Total Funding		
Non-interest Bearing Liabilities		
Fair Value Portion of Debt	-0.5	Iliquid
Credit Impairment Reserves	-0.5	Iliquid
Reserves for Pensions and Other	-0.5	Iliquid
Current and Deferred Tax Liabilities	-0.5	Iliquid
Other Deferred Liabilities	-0.5	Iliquid
Discontinued Operations	-0.5	Iliquid
Insurance Liabilities	-0.5	Iliquid
Other Liabilities	-0.5	Iliquid
Total Liabilities		
Equity		
Common Equity	-0.5	Iliquid
Non-controlling Interest	-0.5	Iliquid
Securities Revaluation Reserves	-0.5	Iliquid
Foreign Exchange Revaluation Reserves	-0.5	Iliquid
Fixed Asset Revaluations and Other Accumulated OCI	-0.5	Iliquid
Total Equity		

This table presents the weights assigned to each accounting item in Bankscope (universal format) to construct the Berger and Bowman's (2009) liquidity creation measure (some accounting items are reported differently in Bankscope and in Call Reports). Liquidity Creation is the Berger and Bowman's (2009) "cat nonfat" measure (i.e., liquidity creation without considering off-balance positions and by combining activities other than loans by category).

Table A2: Sample distribution by country and percentage of foreign-owned banks by country-year

% Foreign-Owned Banks	N	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
Australia	326	38%	42%	42%	43%	37%	37%	41%	39%	42%	40%	32%	27%	30%	28%	24%
Austria	872	32%	31%	33%	33%	31%	24%	25%	26%	27%	32%	33%	38%	33%	36%	35%
Belgium	488	43%	43%	49%	59%	52%	53%	53%	52%	45%	46%	48%	47%	52%	48%	43%
Canada	623	63%	67%	60%	53%	45%	44%	40%	40%	40%	39%	38%	39%	39%	40%	38%
Chile	181	38%	43%	43%	40%	38%	35%	37%	37%	47%	-	-	-	-	-	-
Czech Republic	247	71%	72%	81%	81%	81%	83%	83%	88%	94%	94%	88%	88%	94%	94%	92%
Denmark	763	7%	7%	9%	11%	11%	11%	9%	10%	9%	9%	10%	11%	10%	8%	3%
Estonia	73	50%	60%	60%	60%	60%	60%	80%	60%	67%	60%	50%	60%	80%	80%	75%
Finland	137	0%	13%	25%	25%	25%	25%	13%	13%	13%	20%	18%	20%	15%	14%	25%
France	1,220	22%	30%	28%	30%	30%	28%	28%	26%	24%	21%	19%	19%	18%	18%	19%
Germany	1,160	33%	35%	32%	30%	34%	32%	36%	37%	35%	35%	34%	34%	34%	34%	37%
Greece	215	7%	9%	8%	7%	13%	19%	24%	31%	33%	25%	25%	24%	15%	17%	0%
Hungary	273	79%	79%	76%	79%	89%	90%	86%	90%	85%	79%	72%	56%	56%	59%	58%
Ireland	170	69%	79%	79%	79%	75%	80%	77%	79%	75%	70%	70%	73%	82%	86%	80%
Italy	1,235	4%	1%	4%	4%	6%	4%	5%	4%	7%	5%	7%	10%	10%	8%	5%
Japan	1,355	0%	0%	1%	1%	1%	1%	1%	2%	2%	1%	1%	1%	1%	1%	1%
Luxembourg	1,031	95%	97%	98%	99%	99%	100%	100%	100%	100%	100%	100%	98%	95%	94%	89%
Mexico	503	49%	49%	47%	59%	52%	50%	46%	48%	45%	45%	49%	47%	45%	43%	37%
Netherlands	503	49%	53%	58%	58%	54%	54%	44%	47%	50%	45%	44%	44%	45%	44%	42%
New Zealand	94	57%	50%	60%	60%	50%	67%	60%	60%	60%	80%	83%	75%	75%	67%	63%
Norway	224	23%	20%	20%	13%	21%	23%	33%	29%	21%	14%	6%	6%	6%	6%	6%
Poland	541	49%	56%	74%	81%	76%	73%	72%	75%	74%	73%	73%	76%	69%	72%	82%
Portugal	346	27%	26%	25%	30%	30%	33%	29%	29%	28%	40%	32%	33%	32%	47%	40%
South Korea	276	0%	0%	0%	0%	6%	11%	15%	16%	17%	17%	16%	16%	16%	11%	11%
Slovakia	122	43%	67%	57%	86%	83%	83%	80%	78%	78%	75%	75%	78%	89%	80%	100%
Slovenia	169	18%	18%	25%	50%	50%	43%	50%	46%	50%	43%	43%	43%	43%	36%	31%
Spain	735	19%	18%	19%	20%	23%	26%	27%	25%	21%	27%	26%	25%	26%	24%	26%
Sweden	333	15%	14%	9%	9%	9%	9%	5%	5%	5%	4%	4%	4%	4%	4%	4%
Switzerland	1,126	33%	36%	36%	36%	36%	37%	38%	36%	37%	37%	34%	37%	32%	29%	25%
Turkey	289	11%	18%	10%	18%	33%	30%	18%	43%	44%	47%	46%	46%	46%	41%	44%
United Kingdom	1,226	44%	44%	44%	45%	45%	45%	46%	49%	49%	49%	51%	54%	53%	54%	54%
Unites States	942	11%	13%	13%	16%	16%	19%	22%	22%	23%	27%	28%	27%	26%	24%	23%

This table presents distribution of the sample per country and the percentage of foreign-owned commercial banks (i.e., no. foreign-owned banks/total no. banks) for each country-year combination. N denotes the number of bank-year observations. I restrict the coverage to the largest 100 commercial banks in each of the countries considered. To avoid double-counting within a single institution and have financial information at the most disaggregated level possible, I also discard consolidated entries if banks report information at the unconsolidated level. The full sample consists of 17,831 bank-year observations corresponding to 2,058 banks in 32 OECD countries from 1999 to 2013

Appendix B: 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:

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

where $R_{i,j,t}$ refers to the stock return for firm *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 firm *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. When the index is not available for a specific country, I use the MSCI index of the region that specific country belongs to.

Equation (5) is estimated for each firm 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 $\hat{R}_{i,j,t}$:

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

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

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 firms for each country *j* in each year *t*. In short, the exogenous source of variation for peer firms' liquidity choices is the lagged average peer firm equity return shock. The idiosyncratic return obtained from the above model is then the return of the firm after removing all known sources of systematic variation (i.e., exposure to market and industry). Thus, the residuals obtained from (5) should be purely firm specific and hence, free from any commonalities across the firms.

Appendix C: Merton's (1974) distance-to-default

Under the assumption of normal distributed log asset returns implicit in the Merton's (1974) contingent claim framework, the equity value is defined as a function of the firm's asset value such that

$$V_E = V_A N(d) - Fe^{-r_f T} N(d - \sigma_A \sqrt{T}) \tag{8}$$

with,

$$d = \frac{\log\left(\frac{V_A}{F}\right) + \left(r_f + \frac{\sigma_A^2}{2}\right)T}{\sigma_A \sqrt{T}} \tag{9}$$

where V_E is the market value of the firm's equity, F is the face value of debt maturing at time *T*, V_A is the value of the firm's assets, σ_A is the volatility of the firm's value of assets, r_f is the continuously compounded risk-free interest rate and *N(.)* is the cumulative normal distribution function. Equity volatility σ_E and asset volatility σ_A are associated by

$$\sigma_E = \frac{V_A N(d) \sigma_A}{V_E} \tag{10}$$

In order to calculate the distance-to-default, one needs to estimate the market value of assets V_A and asset volatility σ_A, neither of which directly observable. To achieve this, equations (1) and (3) are solved simultaneously based on an iterative process that uses the Newton search algorithm that ends when the pair of values solves both equations.[16] In detail, the starting value $\sigma_A = \sigma_E [V_E / (V_E + F)]$ and equation (1) are used to infer the market value of

[16] I specify a maximum of 50 iterations. Nonetheless, 90% of the firm-time observations required 5 or less iterations. As in Bharath and Shumway (2008), non-converging observations are dropped.

each bank's assets every day for the previous year. The implied log returns on assets on each day then generates new estimates of σ_A and μ, the mean return of the firm's total assets. Finally, σ_A is iterated until it converges so that the absolute difference in adjacent σ_A's is less than 10^{-3}. I use daily observations of no. shares outstanding and stock prices from Datastream to compute the market value of equity (mil US$) to proxy for V_E. Historical daily returns data over a rolling window of 1 year are used to estimate σ_E. As in Anginer et al. (2014), I use the 1-year US Treasury Constant Maturity Rate obtained from the Board of Governors of the Federal Reserve System and total liabilities (million US$) obtained from Bankscope to proxy for the risk-free rate r_f and the face value of debt *F*, respectively. I nonetheless obtain similar results when using short-term plus one half long-term liabilities to proxy for the face value of the debt *F*. Since accounting information (e.g., total liabilities) is reported on an annual basis, I follow Anginer et al. (2014) and linearly interpolate the values for all dates over the period using the beginning and end of year values. The interpolation of accounting variables reported on an annual basis has the advantage of producing a smooth implied asset value process, thus avoiding jumps in the implied default probabilities. T equals 1 year. σ_E is the standard deviation of daily equity returns over the previous 12 months. In calculating standard deviation, I require each bank to have at least 50 non-missing daily returns over the previous year. The Merton (1974) distance to default measure (MDD) for each bank at any given year is then computed as:

$$MDD = \frac{\ln\left(\frac{V_A}{F}\right) + \left(\mu - \frac{\sigma^2{}_A}{2}\right)T}{\sigma_A\sqrt{T}} \qquad (11)$$

where μ is the mean return of the firm's total assets.