Liquidity risk and collective moral hazard *

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February 2017

Abstract

Banks individually optimize their liquidity risk management, often neglecting the externalities generated by their choices on the overall risk of the financial system. This is the main argument to support the regulation of liquidity risk. However, banks may have incentives to optimize their choices not strictly at the individual level, but engaging instead in collective risk-taking strategies, which may intensify systemic risk. In this paper we look for evidence of such collective behaviors, with an emphasis on the period preceding the global financial crisis. We find strong and robust evidence of peer effects in banks' liquidity risk management. This result suggests that incentives for collective risk taking behaviors may play a role in banks' choices, thus calling for a macroprudential approach to liquidity risk regulation.

JEL Codes: G21, G28.

Keywords: banks, liquidity risk, regulation, herding, peer effects, Basel III, macroprudential policy, systemic risk.

*We thank Rui Albuquerque, Paolo Angelini, António Antunes, Jan Marc Berk, Sigbjorn Berg, Arnoud Boot, Rosa Borges, Christa Bouwman, Martin Brown, Max Bruche, Jin Cao, Geraldo Cerqueiro, Ilan Cooper, Lammertjan Dam, Eduardo Dávila, Hans Degryse, John Driscoll, Jan Willem Van Den End, Falko Fecht, José Fique, Ralph de Haas, Florian Heider, Michael Koetter, Thea Kloster, Jan Pieter Krahnen, Ana Cristina Leal, Iman van Lelyveld, Antoine Martin, Jean-Stéphane Mésonnier, Steven Ongena, Ettore Panetti, Wayne Passmore, Alberto Pozzolo, Isabel Proença, Lev Ratnovski, Francisca Rebelo, Hugo Reis, Nuno Ribeiro, Kasper Roszbach, Abdelaziz Rouabah, Martín Saldías, Javier Suarez, Razvan Vlahu, Wolf Wagner, and participants in seminars in the Deutsche Bundesbank and in the University of Groningen, in the EEA 2014, IBEFA 2014 Summer Meeting, Day Ahead Conference 2013 at the Bank of England, PET 2013 Conference, 5th Banco de Portugal Conference on Financial Intermediation, 2nd MoFiR Workshop on Banking, 6th CEPR Winter Conference on Financial Intermediation, 4th Financial Stability Conference in Tilburg, EBA Research Workshop on Banks' business models after the crisis: incentives, strategies, de-risking, PFN2012, and CREDIT 2011 for insightful comments and suggestions. This paper was previously circulated with the title "Liquidity risk in banking: is there herding?". The analyses, opinions and findings of this paper represent the views of the authors, which are not necessarily those of Banco de Portugal or the Eurosystem.

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1 Introduction

Banks create liquidity in an economy, funding illiquid assets (such as loans) with liquid liabilities (such as deposits), as discussed by Berger and Bouwman (2009) and Bouwman (2014). This basic intermediation role of banks relies on a maturity mismatch between assets and liabilities, making them exposed to bank runs or, more generally, to funding liquidity risk. There is a vast and prominent theoretical literature on this problem. Diamond and Dybvig (1983) and Bryant (1980) provide the pillars for the analysis of banks' liquidity risk and bank runs, while other very relevant contributions include Klein (1971), Calomiris and Kahn (1991), Diamond and Rajan (2000, 2001a and 2001b), Allen and Gale (2004a, 2004b), Wagner (2007a), and Ratnovski (2009). However, there is surprisingly scarce empirical evidence on banks' maturity mismatches and funding liquidity risk.

In this paper, we contribute to fill in this gap by empirically analyzing the way banks manage their liquidity risk. More specifically, we analyze the determinants of banks' liquidity risk management choices, explicitly considering potential strategic interactions among banks. This issue has relevant policy implications, as banks may have incentives to engage in collective risk-taking strategies when there is a strong belief that a (collective) bailout is possible (Farhi and Tirole, 2012, Acharya and Yorulmazer, 2007, Acharya et al, 2015). When other banks are taking more risk, a given bank may be encouraged to pursue similar strategies if its managers believe they will likely be rescued in case of distress. These collective risk-taking strategies may be optimal from an individual perspective, as they should allow banks to increase profitability without increasing the likelihood of bankruptcy, due to the explicit or implicit commitment of the lender of last resort. Hence, these risk-taking strategies may be mutually reinforcing in some circumstances. This collective behavior transforms a traditionally microprudential dimension of banking risk into a macroprudential risk, which may ultimately generate much larger costs to the economy.

However, it is important to note that the empirical estimation of these peer effects amongst banks raises some econometric challenges. As discussed by Manski (1993), the identification of endogenous and exogenous effects is undermined by the reflection problem associated with the reverse causality of peer effects. In other words, if we argue that peers' choices may affect the decisions of a specific bank, we cannot rule out that the decisions of that bank will not, in turn, affect the choices made by peers.

In our setting, the best solution available to this critical identification problem relies on the use of instrument variables, which have to be orthogonal to systematic or herding effects. Given the identification challenges associated with peer effects estimation (Angrist, 2014), we rely on two main approaches. First, we use as an instrument for the peer effects the predicted values of liquidity indicators of peer banks based on regressions analyzing the determinants of liquidity indicators. In this setting, the predicted values depend on observable characteristics of the banks in the peer group. In other words, the predicted value of the liquidity indicators of peer banks should not directly affect the liquidity indicators of bank i at time t, as these predicted values are based solely on observable bank characteristics. By controlling also for country-year fixed effects, we are able to orthogonalize all country-specific time-varying shocks, such as changes in macroeconomic and financial conditions, as well as changes in the regulatory environment. Second, we consider the approach suggested by Leary and Roberts (2014). These authors identify the role of peer effects in corporate finance decisions using the idiosyncratic component of peer firms' equity returns. Given that this idiosyncratic component is entirely firm-specific, it affects only the decisions of each firm individually, thereby satisfying the necessary exclusion restrictions for identification. However, this identification scheme only allows to consider publicly listed banks, which account for less than 30% of the sample, being mostly US banks (92%). In both approaches, the benchmark peer group is the banks operating in the same country in each year, as these are the banks that are more likely to share common beliefs about the likelihood of being bailed out by their common lender of last resort.

We obtain strong and consistent evidence of collective risk-taking behaviors in liquidity risk management. We are aware that to perfectly estimate the magnitude of peer effects we would need a fully experimental setting, which is not available when studying banks' behavior. Thus, to further minimize the perils of peer effects estimation (Angrist, 2013), we run exhaustive robustness tests, including the use of alternative identification strategies and other peer group definitions. Our main results remain valid, supporting the existence of significant peer effects between banks in their liquidity risk management strategies.

Having established the existence of peer effects, it is important to dig dipper and understand where are these strategic interactions coming from. Are peer effects stronger for some groups of banks? Are there leaders and followers in this strategic game? We find that collective risk-taking strategies are much weaker for small banks, as well as for the very large banks. The core of strategic interactions in liquidity risk management is concentrated in large banks which are just below the threshold of being too-big-to-fail. These results are entirely consistent with the theoretical predictions of Farhi and Tirole (2012) and Ratnovski (2009). Smaller banks will hardly ever be bailed out. In contrast, the largest banks expect to be bailed out in almost any circumstance. However, large banks just below this threshold might expect to be bailed out if the stability of the whole financial system or the economy is at stake. This would be the case if systemic risk and contagion fears are heightened. By correlating their decisions and adopting collective risk-taking strategies, these banks thus increase the likelihood of being bailed out.

Our results have relevant policy implications: liquidity risk is usually regulated from a microprudential perspective, but our results show that a macroprudential approach to the regulation of systemic liquidity risk should not be disregarded. Given this, even though the new Basel III package on liquidity risk is a huge step forward in the regulation of liquidity risk, additional macroprudential policy tools may need to be considered, as the new regulation is still dominantly microprudential. For instance, macroprudential authorities may consider imposing tighter liquidity regulation or limits to certain types of exposures, in order to mitigate contagion and systemic risks, thereby providing the correct incentives to minimize negative externalities.

The contribution of our paper is manyfold. Even though the theoretical literature provides many relevant insights and testable hypotheses regarding banks' liquidity risk, there is scarce empirical evidence on banks' liquidity risk management. Furthermore, we focus on a period of particular relevance, as there is an extensive discussion regarding excessive risk-taking in the years preceding the global financial crisis. We provide detailed empirical evidence on the determinants of liquidity risk, and, more importantly, we extend the analysis by focusing on strategic interactions. Further, we make an effort to provide a correct and rigorous econometric treatment for the endogeneity of peer effects in a multivariate setting. Finally, our results provide important insights for policy makers, most notably in what concerns the macroprudential regulation of systemic liquidity risk.

This paper is organized as follows. We begin by reviewing the expanding literature on bank's funding liquidity risk and its regulation, in Section 2. In Section 3 we discuss several indicators of banks' liquidity risk and characterize the dataset used for the empirical analysis, including an overview of banks' liquidity and funding choices in the run up to the recent global financial crisis. In Section 4 we analyze how banks manage their liquidity risk and in Section 5 we address the most relevant question in our paper: do banks take into account peers' liquidity strategies when making their own choices on liquidity risk management? In Section 6 we summarize our main findings and discuss their policy implications.

2 Related literature

Over recent years, banks became increasingly complex institutions, being exposed to an intertwined set of risks. Traditionally, most bank loans would be funded with customer deposits. These liquid claims allow consumers to intertemporally optimize their consumption preferences, but leave banks exposed to the risk of bank runs, as shown by Diamond and Dybvig (1983). Over time, banks gained access to a more diversified set of liabilities to fund their lending activities (Strahan, 2008), thus being exposed not only to traditional runs from depositors, but also to the drying up of funds in wholesale markets, as discussed by Huang and Ratnovski (2011) or Borio (2010).

The 2008 global financial crisis placed liquidity risk in the spotlight and made clear that something was missing in the international regulatory consensus (Bouwman, 2014, Vives, 2014). While banks voluntarily hold buffers of liquid assets to manage the risks associated with the maturity gap between assets and liabilities (Acharya et al, 2011, Acharya et al, 2015, Allen and Gale, 2004a and 2004b, Bouwman, 2014, Calomiris et al, 2013, Farhi et al, 2009, Feinman, 1993, Gale and Yorulmazer, 2013, Rochet and Vives, 2004, Tirole, 2011, and Vives, 2014), these buffers will hardly ever be sufficient to fully insure against a bank run or a sudden dry up in wholesale markets.

Allen and Gale (2004a, 2004b) show that liquidity risk regulation is necessary when financial markets are incomplete, though emphasizing that all interventions inevitably create distortions. Furthermore, Rochet (2004) argues that banks take excessive risk if they anticipate that there is a high likelihood of being bailed-out in case of distress. Regulation may mitigate this behavior (Acharya et al, 2011, Brunnermeier et al, 2009, Cao and Illing, 2010, Gale and Yorulmazer, 2013, Holmstrom and Tirole, 1998, and Tirole, 2011).[1]

When regulation fails to preemptively address risks, the intervention of the lender of last resort might be necessary. However, the lender of last resort has an intrinsic moral hazard problem (see, for example, Freixas et al, 2004, Gorton and Huang, 2004, Ratnovski, 2009, Rochet and Tirole, 1996, Rochet and Vives, 2004, Wagner, 2007a). This mechanism has to be credible ex-ante to prevent crises. But if the mechanism is in fact credible, banks will know they will be helped out if they face severe difficulties, thus having perverse incentives to engage in excessive risk-taking behaviors (Ratnovski, 2009). Repullo (2005) shows that the existence of a lender of last resort does not lead to risk-taking in banks' illiquid portfolios (i.e., their lending activities), but it reduces banks' incentives to hold liquid assets, thereby aggravating liquidity risk.

[1]Many authors discuss the importance of imposing minimum holdings of liquid assets (Acharya et al, 2011, Allen and Gale, 2004a and 2004b, Farhi et al, 2009, Gale and Yorulmazer, 2013, Ratnovski, 2009, 2013, Rochet and Vives, 2004, Tirole, 2011, and Vives, 2014). However, Wagner (2007b) shows that, paradoxically, holding more liquid assets may induce more risk-taking by banks. Freixas et al (2011) show that central banks can manage interest rates to induce banks to hold liquid assets, i.e., monetary policy can help to promote financial stability. In turn, Bengui (2010) finds arguments to support a tax on short-term debt, whereas Cao and Illing (2011) show that imposing minimum liquidity standards for banks ex-ante is a crucial requirement for sensible lender of last resort policies. Finally, Diamond and Rajan (2005) and Wagner (2007a) focus on ex-post interventions.

The moral hazard problem associated with the existence of a safety net provided by a lender of last resort is further aggravated by systemic behavior[2]. Indeed, when most banks are taking excessive risks, each bank manager has clear incentives to herd, instead of leaning against the wind. Ratnovski (2009) argues that, in equilibrium, banks have incentives to herd in risk management, choosing suboptimal liquidity as long as other banks are expected to do the same. These collective risk-taking strategies may be optimal from an individual perspective, as they should allow banks to increase profitability without increasing the likelihood of bankruptcy, due to the explicit or implicit bail out commitment of the lender of last resort. Ratnovski (2009) thus identifies strategic complementarities between banks in their liquidity risk decisions. Banks will choose be more exposed to liquidity risk when other banks do so, as this increases the likelihood of a systemic liquidity crisis and an ensuing bailout. Comparative statistics derived from the model show that this is more likely to happen when banks have lower charter values or expect shocks that may decrease that value, such as in the run up to a crisis.

Some of these arguments are discussed in detail by Farhi and Tirole (2012), who argue that when banks simultaneously increase their liquidity risk, through larger maturity mismatches, current and future social costs are being created. In the presence of strategic complementarities between banks' maturity transformation decisions, central banks are forced to intervene as lenders of last resort. This creates not only social costs in the moment of intervention, but also helps to change beliefs and sows the seeds for the next crisis. Given all these market failures, regulation is needed to ensure that these externalities are considered by banks in their liquidity risk management. In their model, optimal regulation is associated with the imposition of a liquidity requirement or an equivalent limit on short term debt. Nevertheless, the costs and distortions generated by such regulation also need to be taken into account. The model suggests that regulation should be applied only to a subset of key institutions, which would be more likely to be bailed out. However, the market failure behind regulation is not linked to a too-big-to-fail problem, but rather to a too-correlated-to fail, as banks adopt excessive maturity mismatches together with correlated risks.

Acharya and Yorulmazer (2007) and Acharya et al (2015) also discuss bailouts when there are many potentially correlated failures. Acharya et al (2011) consider the effect of the business cycle on banks' optimal liquidity choices and prove that during upturns banks' choice of liquid assets jointly decreases. In turn, Allen et al (2012) show that when banks make similar portfolio decisions systemic risk increases, as defaults become more correlated. Jain and Gupta (1987) find (weak) evidence on bank herding during a crisis period. Brown

[2]Citigroup's former CEO, Charles Prince, has been repeatedly quoted by saying before August 2007 that "When the music stops, in terms of liquidity, things will be complicated. But as long as the music is playing, you've got to get up and dance. We're still dancing".

and Dinç (2011) provide evidence that governments are more likely to bail out a bank when the whole banking system is in distress, using a sample of banks from 21 emerging markets in the 1990s. Perotti and Suarez (2002) prove the existence of strategic interactions between banks, though their results support the existence of strategic substitutions rather than strategic complementarities. They show that if banks expect to obtain larger rents if their competitors fail, their speculative lending decisions are strategic substitutes. Collective risk-taking incentives and strategic complementarities are also discussed by Acharya (2009), Acharya and Yorulmazer (2008), Barron and Valev (2000), Boot (2011), Malherbe (2014), Rajan (2006), Tirole (2011), Van den End and Tabbae (2012), and Vives (2014).

This emerging evidence on systemic liquidity risk calls for adequate macroprudential instruments that address the sources of such risks, as discussed by Farhi and Tirole (2012), Boot (2011), and Cao and Illing (2010). Nevertheless, most of these conclusions are supported by theoretical results, lacking empirical support. Our paper intends to help fill this gap in the literature, by providing empirical evidence of collective risk-taking in liquidity risk management, anchored essentially on the theoretical findings of Farhi and Tirole (2012) and Ratnovski (2009) on strategic complementarities.[3]

3 How to measure liquidity risk?

The maturity transformation role of banks generates funding liquidity risk (Diamond and Dybvig, 1983). As banks' liabilities usually have shorter maturities than those of banks' assets, banks have to repeatedly refinance their assets. In the run up to the global financial crisis, many banks were engaging in funding strategies that heavily relied on short-term funding (Brunnermeier, 2009 and CGFS, 2010), thus significantly increasing their exposure to funding liquidity risk.

In this section, we describe the data used and briefly review several ways to measure funding liquidity risk, which will later be used in our empirical analysis.

[3] Silva (2016) also documents peer effects in liquidity risk, being closely related to our paper. However, our papers differ in several dimensions. First, we consider that peer effects are mainly driven by common beliefs about the possible intervention of a lender of last resort (Ratnovski, 2009). As such, we consider that our empirical strategy to deal with the estimation of peer effects is more adequate for the purpose of our study than that used in Silva (2016), where parent banks of domestic subsidiaries may also belong to peer groups. Second, Silva (2016) uses data up to 2014, while our analysis is based on data only up to 2009. We believe that extending the sample for the 2010-2014 period might bias the estimation of peer effects, as the Basel Committee issued its first guidelines on the new liquidity regulation that would be part of Basel III in 2010 (Basel Committee, 2010). We should thus expect that banks began to change their liquidity ratios in the same direction simultaneously in reaction to the new Basel rules, what can lead to an overestimation of peer effects. Finally, while Silva (2016) makes an effort to understand if the estimated peer effects have effects on overall financial stability, we try to understand where do these peer effects come from, by exploring interactions between different groups of banks.

3.1 Data

Given that one of our objectives is to assess the extent to which banks take each others' choices into account when managing liquidity risk, it is relevant to consider a sufficiently heterogeneous group of banks. With that in mind, we collect data from Bankscope for the period between 2002 and 2009, thus covering both crisis and pre-crisis years. We collect data on European and North-American banks, selecting only commercial banks and bank holding companies for which consolidated statements are available in universal format, so as to ensure the comparability of variables across countries. Savings and investment banks are not included in the dataset, as they usually have different liquidity risk profiles and funding strategies. Using these filters, we obtain data for almost 3,500 banks during 8 years, for 45 countries[4]. Excluding banks without information on total assets, we obtain 17,643 bank-year observations.

In Table 1 we summarize the major characteristics of the banks included in the sample.

Insert Table 1 about here

3.2 Liquidity indicators

In Table 2 we present summary statistics on liquidity risk for the banks included in the sample. As discussed by Tirole (2011), liquidity cannot be measured by relying on a single variable or ratio, given its complexity and the multitude of potential risk sources. Ideally, a complete liquidity indicator would rely on the overall liquidity mismatch between assets and liabilities. However, the data necessary for such an indicator is usually not publicly available. Nevertheless, some approximation is feasible. Taking that into account, we focus our analysis on two indicators which offer an encompassing view of banks' liquidity risk: i) *Liquidity Creation* and ii) *Net Stable Funding Ratio.*

Insert Table 2 about here

Liquidity creation as a percentage of total assets is a proxy of the liquidity indicator proposed by Berger and Bouwman (2009). These authors define liquidity creation as:

[4]These countries are Albania, Andorra, Austria, Belarus, Belgium, Bosnia-Herzegovina, Bulgaria, Canada, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Liechtenstein, Lithuania, Luxembourg, Malta, Moldova Republic, Montenegro, Netherlands, Norway, Poland, Portugal, Romania, Russian Federation, San Marino, Serbia, Slovakia, Slovenia, Spain, Sweden, Switzerland, Turkey, Ukraine, United Kingdom, and United States. In Albania, Bosnia-Herzegovina, Liechtenstein, Moldova Republic, Montenegro and San Marino there are less than 10 observations for the entire sample period. Given this, we exclude these six countries from all cross-country analysis.

$$\begin{aligned} liquidity\_creation = & \{1/2 * illiq\_assets + 0 * semi\_liq\_assets - 1/2 * liq\_assets\} \\ & + \{1/2 * liq\_liabilities + 0 * semi\_liq\_liab. - 1/2 * illiq\_liab.\} \\ & - 1/2 * capital \end{aligned}$$

The higher this variable is, the more liquidity a bank is creating, i.e., the larger is its maturity transformation role. More liquidity is created when illiquid assets are transformed into liquid liabilities. Of course, liquidity creation is positively related with funding liquidity risk, given that banks that create more liquidity have less liquid assets to meet short-term funding pressures[5].

Liquidity creation increased steadily during the sample period, including during the crisis years. Actually, its highest value was recorded in 2009, thus showing that banks continued to create liquidity even during the global financial crisis. However, this also implies that liquidity risk increased during this period, according to this indicator. However, it is important to note that this indicator continued to increase during the crisis because banks' total assets contracted more than liquidity creation itself.

Figure 1 shows that this variable exhibits some dispersion during our sample period.

Insert Figure 1 about here

In turn, the Net Stable Funding Ratio (NSFR) included in the Basel III package is a structural ratio designed to address liquidity mismatches and to encourage an increased reliance on medium and long-term funding, thus increasing the average maturity of banks' liabilities. The NSFR is the ratio between the available and the required amount of stable funding, which should be at least 100%. The higher this ratio is, the more comfortable is the institution's liquidity position. Though the available data does not allow for the accurate computation of this indicator, a gross approximation is possible[6].

The NSFR showed some deterioration in the run up to the crisis. Figure 2 shows that most banks record high values in this ratio. It is important to stress that this indicator is a rough approximation of the indicator proposed by the Basel Committee. As such, the 100 per cent minimum threshold defined for this ratio for prudential purposes cannot be considered for our indicator.

[5] Berger and Bouwman (2009) consider two different measures of liquidity creation. Besides the one presented above, there is another definition that considers off-balance sheet data. Tough the latter definition is more encompassing, capturing better the liquidity created by a bank, the data available in Bankscope does not allow us to compute it for our sample. Please see the Data Appendix for further details.

[6] Please see the Data Appendix for further details.

Insert Figure 2 about here

The two liquidity indicators used in our analysis offer an encompassing view of banks' liquidity risk because they contain information from all assets and liabilities. However, other liquidity indicators are often used in the literature. For the sake of completeness, we report in the Appendix all the tables of the paper including the results on three other commonly used liquidity indicators: i) *loans to customer deposits*; ii) *interbank ratio,* defined as the ratio between interbank assets (loans to other banks) and interbank liabilities (loans from other banks, including central bank funding); and iii) *liquidity ratio*, defined as liquid assets (deposits and loans to banks with less than 3 months residual maturity, quoted/listed government bonds realizable within 3 months, cash and equivalents) as a percentage of customer deposits and short-term funding.

These three additional indicators are not analyzed in detail because they face several shortcomings. First, the loan to deposit ratio is insufficient to globally assess the liquidity position of credit institutions. The increased use of securitization operations by banks during the last decade undermines to some extent the analysis of this indicator (when banks securitize loans, these are usually removed from their loan books, thus generating a somewhat misleading decrease in the credit to deposit ratio). More importantly, this indicator does not take into account the maturity mismatch between assets and liabilities, which is a key element of liquidity risk analysis, and focuses only on one item on banks' assets and one item on banks' liabilities.

Second, the interbank ratio, which captures whether banks are net borrowers or net lenders in interbank markets, offers a very partial view of liquidity risk. Furthermore, this indicator is highly volatile, as banks daily change their positions in interbank markets. End-of-year data for this ratio may sometimes be subject to some window-dressing, thus not fully reflecting the average values shown throughout the year. In addition, the freeze in interbank markets observed since the financial market turmoil started in August 2007 makes the intertemporal analysis of this ratio more challenging (see for instance Cornett et al, 2011).

Finally, the liquidity ratio captures an important dimension of liquidity risk. Refinancing risk may be mitigated if banks hold a comfortable buffer of high quality very liquid assets that they can easily dispose of in case of unexpected funding constraints. This ratio may be regarded as a rough proxy of Basel III's Liquidity Coverage Ratio (LCR). The LCR requires banks to hold sufficient high-quality liquid assets to withstand a 30-day stressed funding scenario, being a ratio between the value of the stock of high quality liquid assets in stressed conditions and total net cash outflows, calculated according to scenario parameters defined in the regulation. However, the information publicly available is clearly insufficient to compute a liquidity indicator that truly captures the 30-day stress scenario foreseen in Basel III. As such, this indicator, which also covers only a limited part of banks' balance sheets, will also be reported only in the Appendix.

Our main research question is to understand if collective strategies played a role in these developments. But before we address this question, in the next section we will provide some insight on which factors are relevant to explain the heterogeneity in liquidity indicators. This analysis is relevant given the lack of empirical evidence on the determinants of liquidity risk. Only after having clarified that we will be able to understand how peer effects work over and above the individual determinants of liquidity indicators.

4 How do banks manage liquidity risk?

Even though liquidity risk management is one of the most important decisions in the prudent management of financial institutions, there is scarce empirical evidence on the determinants of liquidity indicators. Using our dataset, we are able to explore which bank characteristics may be relevant in explaining liquidity indicators. In Table 3 we present some results on the two main liquidity indicators described in the previous section: i) liquidity creation (column 1); and ii) net stable funding ratio (column 2). Results for the other three liquidity indicators (loan to deposits, interbank ratio and liquidity ratio) are reported in the appendix. All specifications use robust standard errors, bank fixed-effects and country-year fixed effects, such that:

$$Liqx_{it} = \alpha_0 + \alpha_i + \alpha_{nt} + \beta_1 Capital_{it-1} + \beta_2 Banksize_{it} + \beta_3 Profitability_{it-1} +$$

$$+\beta_4 Cost\_inc_{it-1} + \beta_5 Lend\_spec_{it-1} + \beta_6 (Liq - x_{it-1}) + i_t + \varepsilon_{it} \quad (1)$$

where $Liqx_{it}$ is the liquidity indicator analyzed, α_0 is a constant, α_i is the bank fixed effect, α_{nt} is the country-year fixed effect, i_t is the year fixed effect and ε_{it} is the estimation residual. Bank fixed effects allow to control for all time-invariant bank characteristics, while country-year fixed effects control for all country-specific time-varying shocks, such as changes in macroeconomic and financial conditions, or changes in the regulatory environment. By controlling also for time fixed-effects, we are able to orthogonalize all systematic and common shocks to banks.

As explanatory variables, we use a set of core bank indicators on solvency, size, profitability, efficiency and specialization. $Capital_{it}$ is the total capital ratio calculated according to the rules defined by the Basel Committee. Pierret (2015) shows that there are important interactions between liquidity risk and banks' solvency. Banks face higher refinancing risk if markets question their solvency in a crisis. Based on this, we could expect that banks with lower capital ratios have more prudent liquidity risk management policies. Indeed, de Haan and van den End (2013) find that there is a negative relationship between capital ratios and liquidity buffers of Dutch banks. However, Bonner et al (2015) and Dinger (2009) obtain the opposite result using data from banks in multiple countries. This might reflect the fact that some banks engage in globally more prudent risk management strategies, holding larger capital and liquidity buffers, while others do the opposite.

$Banksize_{it}$ is measured by the log of Assets. Larger banks might show worse liquidity indicators for two reasons. First, larger banks can more easily have access to markets and might thus afford to hold less liquid assets. Second, larger banks are often perceived as too-big-to-fail, thus having fewer incentives to have very prudent (and costlier) liquidity risk management strategies. Indeed, Kashyap et al (2002) and Dinger (2009) find that larger banks hold less liquid assets, though Aspachs et al (2005) do not find significant effects for UK banks.

$Profitability_{it}$ is proxied by the return on assets and the net interest margin. On the one hand, more profitable banks may allocate part of their cash-flows to holdings of liquid assets. On the other hand, these banks may be confident on their ability to continue to generate cash-flows, thus holding less liquidity buffers. Indeed, the results on the literature are mixed. Bonner et al (2015) find that there is a positive relationship between profitability and liquidity holdings, while Deléchat et al (2012) find a negative effect, and Aspachs et al (2005) do not find any significant effect.

$Cost\_inc_{it}$ refers to the cost-to-income ratio, which is a proxy for cost-efficiency. Banks' liquidity risk management policies might also be related with their operational efficiency. However, as for profitability, the sign of this relationship is uncertain.

Finally, $lend\_spec_{it}$ measures to what extent a bank is specialized in lending, by considering net loans as a percentage of total assets. We include this variable to control for banks' business models. Banks that are specialized in lending have a more traditional intermediation profile. On the one hand, this may mean that they also have more conservative risk management practices. On the other hand, given that loans are an illiquid asset, they may hold proportionally less liquid assets than a more diversified bank.

$(Liq - x_{it})$ refers to the other liquidity indicators, i.e., $x_{it} \neq -x_{it}$ (the only exception is the interbank ratio, which is never included as an explanatory variable, given that it would imply a considerable reduction in the sample size). All variables are lagged by one period to mitigate concerns of simultaneity and reverse causality.

Insert Table 3 about here

Even though some relationship between capital and liquidity could be expected (Berger and Bouwman, 2009, Diamond and Rajan, 2000, 2001a), the total capital ratio is not statistically significant in any of the specifications tested.

The results on bank size are mixed. While larger banks create less liquidity (column 1), thereby showing less liquidity risk, they have lower NSFRs (column 2), thus being riskier in this dimension.

The relationship between profitability and liquidity risk is rather mixed. On the one hand, when banks obtain larger net interest margins, they seem to display lower liquidity risk, both when measured by liquidity creation and by NSFR. On the other hand, when banks record higher overall profitability, as measured by return on assets, they show more liquidity risk (more liquidity creation and less stable funding structures). Banks that are more profitable in their basic intermediation function seem to have less risky funding structures, while banks that are broadly more profitable (possibly obtaining larger gains from other income sources) tend to be riskier in their liquidity risk management. These are possibly banks that adopt riskier strategies in order to boost profitability, thus being more vulnerable to funding liquidity risk. This result is in line with Demirgüç-Kunt and Huizinga (2010), who show that banks that rely on strategies based on non-interest income and on short-term funding are significantly riskier.

In turn, when banks become more efficient, with lower cost-to-income ratios, they create, on average, less liquidity and have larger net stable funding ratios.

Finally, the relationship between liquidity risk and bank specialization is different depending on the liquidity indicator used. On the one hand, banks that become more specialized in lending to customers tend to create more liquidity. On the other hand, these banks show more stable funding structures.

Finally, it is relevant to note that a large part of the variation in liquidity ratios cannot be attributable to the observed financial ratios. Indeed, as shown in the table, bank fixed effects account for a very large fraction of the variance. This result is entirely consistent with evidence obtained by Gropp and Heider (2010) regarding the determinants of banks' capital ratios. These authors find that unobserved time invariant bank fixed effects are ultimately the most important determinant of banks' capital ratios.

5 Are other banks' decisions relevant?

In the previous section we shed some light on the role of different bank characteristics on their observed liquidity strategies. However, it is possible to argue that banks do not optimize their liquidity choices strictly individually and may take into account other banks' choices. In fact, when banks believe that they may be bailed out in case of severe financial distress (for being too-big, too-systemic or too-interconnected to fail), they may actually have incentives to herd, engaging in similar risk-taking and management strategies.

In this section, we try to find evidence of possible herding behavior of banks in liquidity risk management, especially in the years before the global financial crisis. The identification and measurement of peer effects on individual choices is a challenging econometric problem, as discussed by Manski (1993). In section 5.1 we briefly discuss these identification problems and in section 5.2 we propose an empirical strategy to address these concerns and in section 5.3 we present our main results. To mitigate the perils of peer effect estimation (Angrist, 2014), we perform an extensive robustness analysis including, for instance, using alternative identification strategies and running estimations for subsets of countries, banks and time periods. We also consider other peer group definitions, as this issue is critical for identification. For instance, we consider the role of strategic interactions between large and small banks, and test also whether small banks follow the strategies of large banks.

5.1 The reflection problem and identification strategies

In a multivariate setting, the impact of peers' liquidity indicators on a bank's liquidity decisions could be estimated through the following adapted version of equation 1:

$$Liqx_{it} = \alpha_0 + \alpha_i + \alpha_{nt} + \beta_0 \sum_{j \neq i} \frac{Liqx_{jt}}{N_{it} - 1} + \beta_1 capital_{it-1} + \beta_2 banksize_{it} +$$

$$+\beta_3 profitability_{it-1} + \beta_4 Cost\_inc_{it-1} + \beta_5 lend\_spec_{it-1} + \beta_6 (Liq - x_{it-1}) + i_t + \varepsilon_{it} \quad (2)$$

where $\sum_{j \neq i} \frac{Liqx_{jt}}{N_{it}-1}$ represents the average liquidity indicators of peers and all the other variables and parameters are defined as in equation 1. In the baseline specification, the peer banks are all the other banks operating in the same country, which share common beliefs about the lender of last resort. The coefficient β_0 captures the extent to which banks' liquidity choices reflect those of the relevant peer group. We recall that we are controlling for bank, time and country-year fixed effects.

However, this estimation entails some econometric problems: as we argue that peer choices may affect the decisions of a specific bank, we cannot rule out that the decisions of that bank will not, in turn, affect the choices made by peers. This reverse causality problem in peer effects is usually referred to as the reflection problem. This problem was initially described by Manski (1993), who distinguishes three different dimensions of peer effects: i) endogenous effects; ii) exogenous or contextual effects; and iii) correlated effects. Endogenous effects arise from the influence of peer outcomes and are what we usually think of as "pure" peer effects. In our case, this is directly related to observed liquidity decisions. Banks chose their liquidity risk management strategies taking into account the choices made by other banks. Exogenous or contextual effects are related with the influence of exogenous peer characteristics. For instance, if other banks are making higher profits, bank i may engage in risk-taking strategies to increase its profitability. This may be achieved by assuming less prudent liquidity risk management strategies. In this case, the peer effect is not so directly linked to the outcome variable. When we control for banks' time varying characteristics we try to mitigate this concern. Finally, there are correlated effects, which affect simultaneously all elements of a peer group. For instance, changes in monetary policy, macroeconomic conditions or bailout expectations may lead to simultaneous changes in banks' liquidity strategies. We are able to control these using time fixed effects and country-year fixed effects.

Empirically, it is very challenging to disentangle these three effects. More specifically, Manski (1993) discusses the difficulties arising from the distinction between effective peer effects (either endogenous or exogenous) from other correlated effects. Furthermore, the identification of endogenous and exogenous effects is undermined by this reflection problem, as the simultaneity in peers' decisions should result in a perfect collinearity between the expected mean outcome of the group and its mean characteristics, as discussed also by Bramoullé et al (2009) and Carrell et al (2009).

This discussion makes clear that the estimation of equation 2 may not allow for the accurate estimation of peer effects. Our solution to this important identification problem relies on the use of instrumental variables to address this endogeneity problem. Manski (2000) argues that the reflection problem can be solved if there is an instrumental variable that directly affects the outcomes of some, but not all, members of the peer group[7]. As discussed in Leary and Roberts (2014) and Brown et al (2008), such an instrument must be orthogonal to systematic or herding effects. We considered two different approaches.

First, we use the predicted values of liquidity indicators of peer banks based on the regressions of the determinants of liquidity indicators presented in Table 3. The predicted values depend on the characteristics of the banks in the peer group, excluding bank i. These predicted values depend only on observable bank characteristics and should thus be

[7] Other solutions to the reflection problem found in the literature are, for example, having randomly assigned peer groups (Sacerdote, 2001), variations in group sizes (Lee, 2007) or identifying social networks using spatial econometrics techniques (Bramoullé et al, 2009). Given the characteristics of peer groups in our sample, none of these solutions can be applied in our setting.

orthogonal to systematic or herding effects. In other words, the predicted value of the liquidity indicators of peer banks should not directly affect $Liqx_{it}$, the liquidity indicator of bank i at time t, as these predicted values are based solely on observable bank characteristics. Furthermore, the predicted values of peer banks should be highly correlated with the average of the observed liquidity indicators, our potentially endogenous variable.

Importantly, as we control also for time effects, we are able to orthogonalize all systematic shocks to banks. In addition, we also control for country-year fixed effects, in order to consider the effect of time-varying country characteristics that may simultaneously affect all banks in a given country. As such, the estimated peer effects are orthogonal to time-varying common factors that affect all banks.

Formally, our instrumental variables approach is equivalent to the estimation of

$$Liqx_{it} = \alpha_0 + \alpha_i + \alpha_{nt} + \beta_0 \sum_{j \neq i} \frac{\widehat{Liqx_{jt}}}{N_{it}-1} + \beta_1 capital_{it-1} + \beta_2 banksize_{it} + \beta_3 profitability_{it-1} +$$

$$+\beta_4 Cost\_inc_{it-1} + \beta_5 lend\_spec_{it-1} + \beta_6 (Liq - x_{it-1}) + i_t + \varepsilon_{it} \tag{3}$$

where the first step equation is

$$\sum_{j \neq i} \frac{\widehat{Liqx_{jt}}}{N_{it}-1} = \alpha_0 + \alpha_j + \alpha_{nt} + \gamma_1 \sum_{j \neq i} \frac{Liq\_predx_{jt}}{N_{it}-1} + \beta_1 capital_{jt-1} + \beta_2 banksize_{jt} +$$

$$+\beta_3 profitability_{jt-1} + \beta_4 Cost\_inc_{jt-1} + \beta_5 lend\_spec_{jt-1} + \beta_6 (Liq - x_{jt-1}) + i_t + \varepsilon_{it}$$

with $\sum_{j \neq i} \frac{Liq\_predx_{jt}}{N_{it}-1}$ representing the average predicted values for $Liqx_{it}$ for the peer group in the equation:

$$Liq\_predx_{it} = \alpha_0 + \alpha_i + \alpha_{nt} + \beta_1 Capital_{it-1} + \beta_2 Banksize_{it} + \beta_3 Profitability_{it-1} +$$

$$+\beta_4 Cost\_inc_{it-1} + \beta_5 Lend\_spec_{it-1} + \beta_6 (Liq - x_{it-1}) + i_t$$

Second, we consider an entirely different instrument, based on the empirical strategy followed by Leary and Roberts (2014). To identify peer effects in corporate financial policy, these authors looked for an instrument that would not affect directly the financing decisions of a given firm, but that would influence those of the peer group of firms. An instrument that fulfills these exclusion and relevance conditions is the idiosyncratic component of peer firms' equity returns. We follow a similar approach, by computing bank-specific equity returns as the difference between the bank's returns and those of the S&P banks index in a given year[8].

As before, we define the benchmark peer group as the banks operating in the same country and in the same year. These are the banks that are more likely to engage in collective risk-taking behaviors due to implicit or explicit bailout expectations. Let us suppose that in a given country several banks engage in funding liquidity strategies that are deemed as globally risky (e.g., excessive reliance in short term debt to finance long-term assets, large funding gaps or persistent tapping of interbank markets). If several banks engage in these strategies simultaneously, there is naturally an increase in systemic risk. As discussed by Rochet and Tirole (1996) and Ratnovski (2009), a lender of last resort is not necessarily going to bailout one bank that gets into trouble because of its own idiosyncratic wrong choices (unless this bank is clearly too big or too systemic to fail). However, if several banks are at risk, the lender of last resort needs to take the necessary actions to contain systemic risk. In this case, the likelihood of a bailout should increase, as if one of these banks gets into trouble, very likely other banks will follow very soon, thus becoming too-many-to-fail (Acharya and Yorulmazer, 2007). Given this incentive structure, a given bank in that country has clearly high incentives to engage in similar risky but profitable strategies. However, the same cannot be said for a bank operating in another country, where there is a different lender of last resort. This reasoning justifies our choice for the reference peer group. Nevertheless, we will later relax this hypothesis and test other possible peer groups.

Using the two approaches, we are able to identify peer effects, after having dealt with the reflection problem through the use of instrumental variables. However, given that iden-

[8]This approach is simpler than that used by Leary and Roberts (2014), who estimate idiosyncratic returns using an augmented factor model such that:

$$R_{ijt} = \alpha_{ijt} + \beta_{ijt}^{M}(RM_t - RF_t) + \beta_{ijt}^{SMB}(SMB_t) + \beta_{ijt}^{HML}(HML_t) + \beta_{ijt}^{MOM}(MOM_t) + \beta_{ijt}^{IND}(R_{jt} - RF_t) + \eta_{ijt}$$

where R_{ijt} refers to the total return for firm i in industry j over month t. The first four factors are those commonly used in empirical asset pricing studies (Fama and French, 1993).The fifth factor is the excess return on an equally weighted industry portfolio. This augmented model is justified by the fact that in this paper peer effects are being estimated at the industry level, while our paper focuses only in the banking sector. We simplified our approach even further for two main reasons. First, in these regressions we are dealing with a relatively small number of banks (around 400), thus raising issues about the definitions of the small minus big portfolio return (SMB), of the high minus low portfolio return (HML) and of the momentum portfolio return (MOM). Furthermore, adapting these definitions for a sample of international banks is not trivial and would require significant assumptions. The alternative of using the regular factors calibrated for US non-financial firms does not seem entirely reasonable and it might bias the results in uncertain directions. Finally, Schuermann and Stiroh (2006) show that the market factor plays a central role in explaining bank returns, when compared to the Fama-French factors. Taking all these factors into account, we considered that it would be more prudent to use a one-factor model in the estimation of idiosyncratic returns, while still respecting the intuition behind the instrumental variables approach used by Leary and Roberts (2014).

tification hinges on the quality of the instrument, we considered alternative approaches, discussed in detail in Section 5.3.1. These include using another instrument inspired in the social multiplier approach proposed by Sacerdote (2011) and Glaeser et al (2003). We remain aware that perfectly estimating the magnitude of peer effects would only be possible in a natural experimental setting, with random assignment of peers, which is not feasible in our setting. Nevertheless, we implement a wide array of robustness tests, that at least allows us to be confident that there are statistically significant peer effects between banks in their liquidity risk management strategies.

5.2 Empirical results

In Table 4 we present the results of the first instrumental variable approach in the estimation of peer effects in liquidity risk management.

In the first two columns we present the results of the estimation of equation 2. Hence, in these columns the peer effects are included in the regressions without properly addressing the reflection problem discussed before. When running this simple, yet possibly biased, estimation, we find strong evidence of positive peer or herding effects in individual banks' choices for the two liquidity indicators. The riskier are the funding and liquidity strategies of other banks in a given country, the riskier will tend to be the choices of each bank individually. However, as discussed above, these preliminary estimates may not be dealing adequately with the endogeneity problem underlying the estimation of peer effects.

Insert Table 4 about here

The second group of columns (3-4) displays our main empirical results, when explicitly dealing with the endogeneity problem created by considering peer effects. When we use the predicted values of peer's liquidity indicators as instruments, we conclude that the results presented in the first columns are no longer significant for the NSFR. For liquidity creation, peer effects continue to be strongly statistically significant (with a coefficient of 0.56). The different results obtained when the endogeneity problem is addressed are an indication that neglecting endogeneity in peer effects may originate biased and incorrect results.

As discussed before, a good instrument should have an important contribution in explaining the potentially endogenous variable, i.e. the average peers' liquidity choices, but it should not directly affect the dependent variable. In the previous sub-section we discussed why the latter condition holds in our setting, whereas in the last group of columns of Table 4 we show that the chosen instrument is strongly statistically significant in both regressions.

In Table 5 we present our results using our second identification strategy, based on Leary and Roberts (2014). Even though the sub-sample of listed banks used to compute this alternative estimation of peer effects is much smaller than the original (roughly one quarter), we are still able to obtain statistically significant peer effects. In this case, the results are significant not only for liquidity creation, but also for the NSFR. However, the statistically significance of the results is weaker.[9]

Insert Table 5 about here

5.2.1 Who follows whom: alternative peer group definitions

One key issue in the analysis of peer effects is the definition of the relevant peer group (Manski, 2000). So far we have assumed that the relevant peer group for collective risk-taking behaviors are the other banks in the same country. This hypothesis is anchored in the theoretical framework of Ratnovski (2009) and Farhi and Tirole (2012) that guides our analysis. Given that banks operating in the same country share the same lender of last resort, we argue that they likely share common beliefs about the likelihood of being bailed out in case of heightened systemic risk. However, it is possible that bailout probabilities are not the same for all banks in the same country. Actually, Farhi and Tirole (2012) show that this is true and argue that regulation should be applied only to a subset of key institutions that benefit from these implicit support guarantees, thus having incentives to take excessive risk.

To address these concerns, in Table 6 we test alternative peer group definitions, in order to gain more insights about where are collective risk-taking behaviors coming from.

Insert Table 6 about here

The first very simple exercise is to explore time dynamics within our baseline peer group definition. Until now we assumed that banks take their decisions contemporaneously. However, it is possible that there are dynamic and lagged effects that are not being captured when using this definition. To check that, we run our estimations using lagged peer effects. The results obtained are very similar, suggesting that there is some persistency in banks' strategic interactions.

An additional possibility is to consider that banks focus on peer groups outside borders, implying that the lender of last resort may not be the only motive for excessive risk-taking in

[9] The sample used in Table 5 is much smaller than that used in Table 4. The difference in the significance and magnitude of peer effects between these two tables could thus be due to the difference in the way peer effects are measured or to the different sample used. To clarify this issue, we estimated our baseline peer effect estimation (Table 4) using the sample of listed firms used for the estimation of the results reported in Table 5. The results using this smaller sample are broadly consistent with those of Table 4, thus suggesting that the differences in the results come mainly from identification strategy used than from the decrease in sample size.

liquidity management. For example, large international players may follow similar strategies because they are competing to achieve higher returns on equity, possibly through riskier funding and liquidity strategies. To test this additional hypothesis, we consider as peers all the other banks of the same size quartile, regardless of their country of origin. This hypothesis seems to be implausible, as peer effects are not statistically significant in any of the indicators analyzed. Collective risk-taking strategies seem to play a role mainly at the national level, possibly reflecting common lender of last resort beliefs previously discussed.

Another possibility is that the lender of last resort may only be willing to support banks that are too big or too systemic to fail, even if several banks are taking risks at the same time. Hence, it is possible that herding incentives are stronger for larger banks. To test this hypothesis, we run our regressions only for the largest banks in the sample, defined as those in the fourth quartile of the total assets distribution in each country. When we use instrumental variables for the identification of peer effects, we continue to obtain evidence supporting the existence of collective risk-taking strategies. However, the results are now significant only for the NSFR.

A bank that is very large within borders may be a small bank in international terms. This should be especially relevant in smaller countries, with smaller banking systems. We might argue that large internationally active banks could also act as a peer group. To take that into account, we estimate the same regressions for the largest banks, but now defined as those in the fourth quartile of the worldwide total assets distribution. We still find evidence of peer effects, but remarkably weaker, thus providing further evidence that collective risk-taking is important mainly within borders.

To further examine the role of peer effects amongst larger banks, we compare peer effects estimates for banks above the median to those below. The statistical significance of peer effects is more robust for the largest banks, though there is also significant evidence of herding among the smaller banks. However, when only the five largest banks in each country are considered, the results on peer effects entirely vanish. Taking all this together, peer effects seem to be more prevalent among large banks, though not the largest ones.

Estimating peer effects only for the smallest banks also allows to exclude large internationally active banks from the sample. These banks may have complex liquidity risk management strategies, with cross-border implications. As we still obtain statistically significant peer effects for these smaller banks, we can be confident that our results are not being influenced by these large international players, with sophisticated risk management and hedging tools.

Even though the pre-crisis debate on systemic risk focused essentially on bank size, the global financial crisis made clear that a small or medium-sized institution can also be systemic if, for instance, it is too-interconnected-to-fail. Given this, size may be an imperfect measure of systemic risk. Indeed, the Basel Committee considers that systemically important banks should be identified using five different sets of indicators, taking into account i) cross-jurisdictional activity, ii) size, iii) interconnectedness, iv) substitutability, and v) complexity[10]. Each set of indicators has an equal weight of 20%. That said, size is only one of the dimensions that allows identifying a systemically important institution. However, the other four dimensions rely on a set of indicators that are generally not publicly available. Against this background, we also considered the list of systemically important financial institutions (SIFIs) recently disclosed by the Financial Stability Board, in order to test whether there are significant peer effects within this group of banks. The results for these very large institutions are also weaker than for the initial large banks definition. In addition, we also considered the set of banks that belong to the Euribor panel, which may be seen as an alternative list of systemic financial institutions. In this case, the results are marginally significant only for the NSFR.

In sum, when we consider stricter definitions of large banks, such as banks that are classified among the top 5 in each country, banks belonging to the systemically important financial institutions (SIFIs) list disclosed by the Financial Stability Board or banks in the Euribor panel, the results are relatively weaker. This is not surprising, as these are the banks that have fewer incentives to engage in collective risk-taking strategies. Indeed, these very large banks are generally too-big-to-fail, benefiting permanently from implicit bailout guarantees. As such, these banks are the ones who face lower incentives to engage in riskier strategies when other banks are doing so, given that their probability of being bailed out hardly changes. Indeed, when we exclude the top five banks from the estimation, the results remain virtually unchanged, thus showing that herd behavior is not dominated by the largest banks.

Given these results, another important dimension to test is whether small banks tend to replicate the behavior of the larger banks. These smaller banks are those that could benefit more from engaging in collective risk-taking strategies, as argued above, most notably when larger banks are already taking more risk, thereby increasing the likelihood of systemic distress (Dávila, 2012). Using different definitions of small and large banks, we obtain evidence of significant peer effects. However, in contrast to what we could expect initially, we obtain negative peer effects in some specifications for liquidity creation and for the NSFR in most specifications. This means that, in these cases, small banks actually decrease liquidity risk when the largest banks are increasing it. Collective risk-taking strategies are

[10] http://www.bis.org/publ/bcbs255.pdf.

not prevalent among the smaller banks. These banks do not seem to replicate liquidity risk management strategies between themselves, nor replicate those of the largest banks.

Summing up what we learned so far from considering different definitions of peer groups and peer interactions based on bank size and systemic importance, we can claim that peer effects are stronger for larger banks, though not for the largest of them all. This is consistent with the view that the largest banks are too-big-to-fail and expect to be bailed out in any circumstance. In turn, smaller banks will hardly ever be bailed out. However, relatively large banks, just below the top ones, might expect to be bailed out in exceptional circumstances. This would be the case if systemic risk and contagion fears are heightened. In such a scenario, the likelihood of a bail out in case of distress might increase, as the responsible authorities will be worried about mitigating contagion. This creates incentives for banks to engage in collective risk-taking strategies. If every player adopts similar strategies, it will be hard to single out one institution for excessive risk-taking, thus making a bail out more justifiable (Farhi and Tirole, 2012, Ratnovski, 2009).

5.2.2 Robustness analysis

To better understand how these peer effects work and to ensure that the results are consistent under a wide set of specifications, we run a large battery of robustness tests.

In Table 7 we present some of the most relevant tests conducted. All the estimations were performed without and with instrumental variables, in columns (1)-(2) and (3)-(4), respectively.

Insert Table 7 about here

Given the challenges of peer effects estimation (Angrist, 2014, Manski, 1993, 2000), we begin by testing alternative identification strategies.

First, we consider an adapted version of our identification strategy, based on the social multiplier proposed by Sacerdote (2011) and Glaeser et al (2003). The basic idea is to use the peer group average of the predicted values arising from the regressions on liquidity determinants directly in the peer effects regressions (equation 1), instead of using them as instruments for the peer effects[11]. The results of this alternative estimation approach confirm the existence of peer effects, though only for liquidity creation.

[11] Our estimates of the social multiplier are an adaption because of the level of aggregation considered. As discussed by Glaeser et al (2003), several levels of aggregation may be considered in the estimations of the social multiplier. In our case, we use the coefficients from an individual level regression to predict aggregate level outcomes for the peer group of each bank. We then regress observed individual outcomes on these aggregate predicted values to obtain the social multiplier.

A potentially relevant econometric issue is related with the use of predicted regressors in the estimations. To be sure that this is not affecting the results, we present the results using bootstrapped standard errors[12]. The results are generally consistent.

For robustness, we exclude the crisis period, so as to focus the analysis on possible peer effects in the years before the global financial crisis. The peer effect coefficient for liquidity creation remains significant, while for the NSFR we now have marginally significant results, when using instrumental variables. This shows that collective risk-taking behaviors were more prevalent before the crisis.

In addition, we remove from the sample banks with year-on-year asset growth above 50%, as these banks may have been involved in mergers and acquisitions. Our results become significantly stronger in this case, most notably for the NSFR.

US banks represent slightly more than three quarters of the sample. In order to ensure that the results are not influenced by this, we exclude all US banks from the estimation. In this case, we obtain statistically significant effects only for the NSFR. In addition, we also estimate the regressions separately for Western and Eastern European banks, and for US, Canada and Western Europe banks together. The results are not statistically significant when only Western Europe banks are considered and are marginally significant for Eastern European banks. All this suggests that collective risk-taking strategies in the run up to the crisis were more prevalent among US banks.

Furthermore, we exclude the countries more directly affected by the global financial crisis from the regressions (US, Iceland, Greece, Ireland, Portugal, Spain and Italy). When banks from these countries are excluded, we do not obtain evidence on collective risk-taking strategies, suggesting that the countries more hardly hit by the crisis were indeed those where these behaviors were more prevalent.

Given the strong financial integration in the euro area, we also tested whether banks operating in euro area countries behave as a peer group. The results are consistent with the baseline specification, showing that it is indifferent to consider euro area members individually or as a unique group. When all banks in our sample are considered, we obtain statistically significant peer effects on liquidity creation regardless of whether we consider euro area banks as one single peer group or as separate country-level peer groups.

For robustness purposes, we also run our estimates without using country-year fixed effects, with separate country and year fixed effects (using random-effects estimation) and without controlling for liquidity indicators. In all cases, the results are robust.

[12] The estimated coefficients display minor differences because it was necessary to exclude two year dummies from the estimations, in order to obtain the degrees of freedom necessary for the bootstrapping.

In our baseline specification, we used the total capital ratio as an explanatory variable. However, the global financial crisis showed that, in many cases, the leverage ratio was better able to capture the financial situation of banks. To address this issue, we estimated the peer effect regressions using the leverage ratio (measured as equity over total assets) instead of the total capital ratio. The results are stronger, as the peer effects on the NSFR become statistically significant and increase for liquidity creation.

We also consider data only from 2004 onwards, in order to avoid using accounting information that is time inconsistent, given that in many countries common accounting reporting standards (IFRS) were introduced around this time. The results become generally stronger.

Finally, we estimated the models including a lagged dependent variable and weighing peers by their size. The results are qualitatively and quantitatively consistent in both cases.

All in all, the robustness analysis points to consistent evidence of significant peer effects in liquidity risk decisions.

5.2.3 Peer effects by year

In Section 3.2, we looked into the evolution and dispersion of liquidity indicators in the run up to the global financial crisis, observing that there was a general deterioration in liquidity indicators during this period. In this subsection, we estimate peer effects for each year. The results are presented in Table 8.

Insert Table 8 about here

In terms of statistical significance, when we consider as instruments the predicted values of liquidity indicators (columns 1 and 2), there were peer effects in almost all years in liquidity creation, with the exception of 2009. The results are somewhat weaker for the NSFR. When we use the idiosyncratic component of equity returns as an instrument as in Leary and Roberts (2014), thereby focusing on a smaller subsample of publicly listed banks, the results are slightly weaker, though there is still statistically significant evidence of peer effects in the NSFR (columns 3 and 4).

Looking at the economic significance of the estimated peer effects, some interesting conclusions may be drawn. Peer effects were larger in the years immediately before the global financial crisis. This suggests that there were indeed observable collective risk-taking behaviors right before the global financial crisis, which possibly made banks more vulnerable to the shocks they were later faced with. It is also interesting to note that there were significant peer effects during the crisis years, when banks were simultaneously reshaping their balance sheets to manage risks in the new environment in which they were operating, marked by heightened funding pressures and deleveraging incentives.

6 Concluding remarks and policy implications

Banks' liquidity risk was at the core of the global financial crisis in its early days. By transforming liquid liabilities (deposits) into illiquid claims (loans), banks are intrinsically exposed to funding liquidity risk, though this risk materializes only occasionally. In this paper we provide empirical insight into how banks manage their liquidity risk and consider explicitly the role of collective risk-taking strategies on herding behavior. Indeed, when other banks are taking more risk, any given bank may have incentives to engage in similar strategies.

The empirical estimation of these peer effects amongst banks in such a framework raises some econometric challenges. Based on the arguments put forth by Manski (1993), if we consider that peer choices may affect the decisions of a specific bank, we cannot rule out that the decisions of that bank will not, in turn, affect the choices made by peers (reflection problem). To overcome this critical identification problem we use two strategies based on instrumental variables. First, we consider as an instrument for peer effects the predicted values of liquidity indicators of peer banks based on the regressions of the determinants of liquidity indicators. These predicted values depend only on observable bank characteristics and should thus be orthogonal to systematic or herding effects. Second, we follow an empirical strategy based on Leary and Roberts (2014), using the idiosyncratic component of equity returns as an instrument for peer effects.

Using these two methodologies, we can find evidence of significant peer effects, which is strengthened by extensive robustness tests. Peer effects are stronger for larger banks, though not for the largest ones. The latter are typically perceived as being too-big-to-fail and probably do not need to change their behavior when other banks are taking more risk. The smallest banks will hardly ever be bailed out. So, strategic interactions are stronger for large banks below the top tier, which do not expect to be bailed out under normal circumstances, but that may be so in a situation of heightened systemic risk, when a large bank failure could lead to a collapse in the financial system. These results lend empirical support to the theoretical findings of Farhi and Tirole (2012) and Ratnovski (2009).

Our results provide an important contribution to the ongoing policy debate. These collective risk-taking behaviors call for regulation to adequately align the incentives and minimize negative externalities. The collective behavior of banks transforms a traditionally microprudential dimension of banking risk into a macroprudential risk, which may ultimately generate much larger costs to the economy.

The new Basel III regulatory framework represents a huge step forward in the international regulation of banks. At the microprudential level, new liquidity requirements are going to be gradually imposed, reducing excessive maturity mismatches and ensuring that banks hold enough liquid assets to survive during a short stress period. However, our results suggest that there may be a missing element in the new regulatory framework: the systemic component of liquidity risk. The new liquidity risk regulation will ensure that, at the microprudential level, institutions are less exposed to liquidity risk. Nevertheless, additional macroprudential policy tools may eventually be considered to mitigate the incentives for collective risk-taking strategies. These may include tighter (cyclical or sectoral) liquidity regulation or limits to certain types of exposures or funding sources. Moreover, a well functioning resolution and bail-in framework is critical to mitigate bail-out expectations.

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Data appendix

	Liquidity creation		NSFR
	Classification	Weights	Weights
Residential Mortgage Loans	SL	0	0.65
Other Mortgage Loans	SL	0	0.65
Other Consumer/ Retail Loans	SL	0	0.85
Corporate & Commercial Loans	I	0.5	0.85
Other Loans	I	0.5	0.85
Less: Reserves for Impaired Loans/ NPLs			-1.00
Net Loans			
Loans and Advances to Banks	SL	0	0.50
Reverse Repos and Cash Collateral			0.00
Trading Securities and at FV through Income			0.50
Derivatives			0.50
Available for Sale Securities			0.50
Held to Maturity Securities			1.00
At-equity Investments in Associates			1.00
Other Securities			1.00
Total Securities	L	-0.5	
Investments in Property	I	0.5	1.00
Insurance Assets	I	0.5	1.00
Other Earning Assets	I	0.5	1.00
Total Earning Assets			
Cash and Due From Banks	L	-0.5	0.00
Foreclosed Real Estate	I	0.5	1.00
Fixed Assets	I	0.5	1.00
Goodwill	I	0.5	1.00
Other Intangibles	I	0.5	1.00
Current Tax Assets	I	0.5	1.00
Deferred Tax Assets	I	0.5	1.00
Discontinued Operations	I	0.5	1.00
Other Assets	I	0.5	1.00
Total Assets			

	Liquidity creation		NSFR
	Classification	Weights	Weights
Customer Deposits - Current	L	0.5	
Customer Deposits - Savings	L	0.5	
Customer Deposits - Term	SL	0	
Total Customer Deposits			0.85
Deposits from Banks	L	0.5	0.00
Repos and Cash Collateral	L	0.5	0.00
Other Deposits and Short-term Borrowings	L	0.5	0.00
Total Deposits, Money Market and Short-term Funding			
Total Long Term Funding	I	-0.5	1.00
Derivatives	L	0.5	0.00
Trading Liabilities	L	0.5	0.00
Total Funding			
Fair Value Portion of Debt	SL	0.0	0.00
Credit impairment reserves	SL	0.0	0.00
Reserves for Pensions and Other	SL	0.0	0.00
Current Tax Liabilities	SL	0.0	0.00
Deferred Tax Liabilities	SL	0.0	0.00
Other Deferred Liabilities	SL	0.0	0.00
Discontinued Operations	SL	0.0	0.00
Insurance Liabilities	SL	0.0	0.00
Other Liabilities	SL	0.0	0.00
Total Liabilities			
Pref. Shares and Hybrid Capital accounted for as Debt	I	-0.5	1.00
Pref. Shares and Hybrid Capital accounted for as Equit	I	-0.5	1.00
Total Equity	I	-0.5	1.00
Total Liabilities and Equity			

Notes: Liquidity creation is a proxy of the liquidity indicator proposed by Berger and Bouwman (2009). The higher this variable is, the more liquidity a bank is creating, i.e., the larger is its maturity transformation role. The variable is defined as:

$$\begin{aligned} liquidity\_creation = &\{1/2 * illiq\_assets + 0 * semi\_liq\_assets - 1/2 * liq\_assets\} \\ &+ \{1/2 * liq\_liab. + 0 * semi\_liq\_liab. - 1/2 * illiq\_liab.\} - 1/2 * capital \end{aligned}$$

Assets and liabilities are classified as liquid, semi-liquid or illiquid based on the criteria used by Berger and Bouwman (2009). The classification for each accounting item is displayed in the table above. Some assumptions were made, as the accounting classification is not identical to the one used in Berger and Bouwman (2009). We consider liquidity creation as a percentage of total assets.

NSFR is an approximation of the Net Stable Funding Ratio defined in Basel III, which considers the available stable funding relative to the required stable funding (i.e., assets that need to be funded). The higher this ratio is, the more comfortable is the institution's liquidity position. It is defined as:

$$NSFR = \frac{available\_stable\_funding}{required\_stable\_funding} * 100$$

Each accounting item was given a weight based on the Basel Committee's guidelines. However, it is important to note that this is a rough approximation, as the accounting data available on Bankscope does not allow to accurately classify all the items. The weights chosen are presented in the table above.

Tables and figures

Table 1 - Banks' characteristics

	N	mean	min	p25	p50	p75	max
Total assets	17,620	21,200	92	295	659	2,183	772,000
Total capital ratio	10,211	14.5	7.3	11.3	12.9	15.6	44.5
Tier 1 ratio	9,851	12.6	4.7	9.5	11.2	13.9	41.6
Net interest margin	17,561	3.7	0.3	3.0	3.8	4.4	10.4
Return on assets	17,596	0.9	-4.9	0.5	1.0	1.3	5.1
Cost to income	17,510	67.1	27.4	56.7	65.0	74.2	165.1
Net loans to total assets	17,509	63.0	5.1	55.1	66.4	75.2	90.6

Notes: Total assets in millions of USD. The total capital and Tier 1 ratios are calculated according to the regulatory rules defined by the Basel Committee. Net interest margin is defined as net interest income as a percentage of earning assets. Return on assets computed as net income as a percentage of average assets. The cost-to-income ratio is computed as banks' operational costs (overheads) as a percentage of income generated before provisions. These variables are included in the Bankscope database. The statistics presented refer to data after outliers were winsorized.

Table 2 - Liquidity indicators - summary statistics

Panel A - Global summary statistics

	N	mean	min	p25	p50	p75	max
Liquidity creation	17,620	9.1	-35.7	-4.8	4.8	22.1	69.2
NSFR	17,618	115.1	27.8	106.7	121.2	129.9	155.1

Panel B - Liquidity indicators over time (mean)

	2002	2003	2004	2005	2006	2007	2008	2009	Total
Liquidity creation	2.7	2.5	3.8	6.9	13.0	13.7	13.9	24.9	9.1
NSFR	122.2	122.6	119.9	116.9	109.4	108.5	108.2	104.5	115.1

Notes: Liquidity creation is a proxy of the liquidity indicator proposed by Berger and Bouwman (2009). The higher this variable is, the more liquidity a bank is creating, i.e., the larger is its maturity transformation role. NSFR is an approximation of the Net Stable Funding Ratio defined in Basel III, which considers the available stable funding as a percentage of the required stable funding (i.e., assests that need to be funded). These two variables are negatively correlated (i.e., more liquidity risk is associated with higher liquidity creation and lower NSFR) and are defined in detail in the Data Appendix. The statistics presented refer to data after outliers were winsorized.

Table 3 - Determinants of liquidity indicators

Dependent variable:	Liquidity creation		NSFR	
	(1)		(2)	
Total capital ratio $_{t-1}$	-0.14		0.07	
	-1.56		*0.85*	
Log Assets $_{t}$	-5.87	***	-2.69	**
	-4.96		*-2.46*	
Net interest margin $_{t-1}$	-1.37	***	2.11	***
	-3.96		*5.95*	
Return on assets $_{t-1}$	0.68	*	-1.43	***
	1.81		*-3.66*	
Cost-to-income $_{t-1}$	0.08	***	-0.04	**
	3.72		*-2.10*	
Net loans to total assets $_{t-1}$	0.29	***	0.11	**
	6.72		*2.03*	
Loans to customer deposits $_{t-1}$	-0.02	**	-0.08	***
	-2.01		*-5.77*	
Liquidity ratio $_{t-1}$	0.23	***	0.04	
	7.90		*1.36*	
Liquidity creation $_{t-1}$	-		-0.14	***
	-		*-4.22*	
NSFR $_{t-1}$	-0.15	***	-	
	-5.31		-	
D2004	-3.74	***	2.10	***
	-10.36		*5.36*	
D2005	-3.66	***	1.13	**
	-8.58		*2.55*	
D2006	-7.35	***	4.49	***
	-21.51		*11.57*	
D2007	-9.08	***	4.79	***
	-23.22		*12.18*	
D2008	-11.59	***	5.08	***
	-27.44		*13.43*	
Constant	-593.2	***	355.24	***
	-15.33		*9.92*	
Number of observations	7,020		7,020	
Number of banks	1,738		1,738	
R2 within	0.366		0.160	
R2 between	0.139		0.165	
R2 overall	0.103		0.138	
Frac. of variance due to bank FE	0.998		0.984	

Notes: All regressions include country-year fixed-effects, bank fixed-effects and robust standard errors. t-statistics in italics. The total capital ratio is calculated according to the regulatory rules defined by the Basel Committee. Net interest margin is defined as net interest income as a percentage of earning assets. Return on assets computed as net income as a percentage of average assets. The cost-to-income ratio is computed as banks operational costs (overheads) as a percentage of income generated before provisions. Liquidity creation is a proxy of the liquidity indicator proposed by Berger and Bouwman (2009). The higher this variable is, the more liquidity a bank is creating, i.e., the larger is its maturity transformation role. NSFR is an approximation of the Net Stable Funding Ratio defined in Basel III, which considers the available stable funding as a percentage of the required stable funding (i.e., assests that need to be funded). These two variables are negatively correlated (i.e., more liquidity risk is associated with higher liquidity creation and lower NSFR) and are defined in detail in the Data Appendix. *** significant at 1%; ** significant at 5%; * significant at 10%.

Table 4 - Regressions on peer effects in liquidity strategies

	Bank peer effects - country year peer group (without IV)		Bank peer effects - country year peer group - (IV = predicted values of rivals' liquidity ratios)			
			Second-step		First-step	
	Liquidity creation	NSFR	Liquidity creation	NSFR	Liquidity creation	NSFR
	(1)	(2)	(3)	(4)	(5)	(6)
Peer effects	0.81 ***	0.43 ***	0.56 ***	0.36	0.92 ***	0.24 ***
	18.62	*7.54*	*9.02*	*1.08*	*31.28*	*7.21*
Total capital ratio $_{t-1}$	-0.19 **	0.08	-0.18 ***	0.08	0.03	-0.02
	-2.29	*0.91*	*-3.63*	*1.51*	*1.15*	*-0.83*
Log Assets $_{t}$	-1.73	-2.86 **	-3.02 ***	-2.80 ***	-2.86 ***	0.87 ***
	-1.61	*-2.56*	*-4.95*	*-4.77*	*-10.22*	*3.47*
Net interest margin $_{t-1}$	-1.08 ***	1.90 ***	-1.17 ***	1.94 ***	-0.29 ***	0.41 ***
	-3.26	*5.28*	*-5.71*	*7.18*	*-2.76*	*4.39*
Return on assets $_{t-1}$	0.56	-1.34 ***	0.60 ***	-1.36 ***	-0.05	-0.19 *
	1.59	*-3.46*	*2.60*	*-5.25*	*-0.39*	*-1.85*
Cost-to-income $_{t-1}$	0.05 ***	-0.04 *	0.06 ***	-0.04 ***	0.02 ***	-0.02 ***
	2.64	*-1.81*	*4.43*	*-2.80*	*2.79*	*-2.93*
Net loans to tot assets $_{t-1}$	0.26 ***	0.12 **	0.26 ***	0.12 ***	0.04 **	-0.01
	6.34	*2.18*	*9.17*	*3.72*	*2.54*	*-0.99*
Loans to cust deposits $_{t-1}$	0.00	-0.08 ***	0.00	-0.08 ***	-0.02 ***	0.00
	0.43	*-6.02*	*-0.51*	*-10.95*	*-6.33*	*0.63*
Liquidity ratio $_{t-1}$	0.12 ***	0.05 *	0.15 ***	0.05 **	0.12 ***	-0.04 ***
	4.34	*1.90*	*6.72*	*2.22*	*11.05*	*-4.50*
Liquidity creation $_{t-1}$	-	-0.13 ***	-	-0.13 ***	-	-0.04 ***
	-	*-3.79*	-	*-5.92*	-	*-4.65*
NSFR $_{t-1}$	-0.12 ***	-	-0.13 ***	-	-0.03 ***	-
	-4.53	-	*-7.58*	-	*-3.84*	-
Constant	69.7	72.8	-137.2 **	119.3	-100.9 ***	587.8 ***
	1.27	*1.31*	*-2.44*	*0.54*	*-3.84*	*39.78*
Number of observations	7,019	7,019	7,012	7,012	7,012	7,012
Number of banks	1,737	1,737	1,736	1,736	1,736	1,736
F-test	127.9	37.7			785.0	308.7
R2 within	0.477	0.186	0.467	0.186	0.705	0.484
R2 between	0.329	0.501	0.095	0.524	0.399	0.555
R2 overall	0.331	0.455	0.055	0.471	0.313	0.494

Notes: All regressions include year, country-year and bank fixed-effects. t-statistics in italics. Peers are defined as the j≠i banks operating in the same country and in the same year as bank i. Columns 1-2 show the results obtained when peer liquidity choices are considered directly in the regressions, i.e., not addressing the reflection problem. Columns 3-4 show the results of the instrumental variables regressions (one for each liquidity indicator), where the instruments are the predicted values of peers' liquidity ratios. These predicted values result from the estimation of the regressions in Table 3. Columns 5-6 show the first stage estimation results for these three instrumental variables regressions. The total capital ratio is calculated according to the regulatory rules defined by the Basel Committee. Net interest margin is defined as net interest income as a percentage of earning assets. Return on assets computed as net income as a percentage of average assets. The cost-to-income ratio is computed as banks operational costs (overheads) as a percentage of income generated before provisions.

Liquidity creation is a proxy of the liquidity indicator proposed by Berger and Bouwman (2009). The higher this variable is, the more liquidity a bank is creating, i.e., the larger is its maturity transformation role. NSFR is an approximation of the Net Stable Funding Ratio defined in Basel III, which considers the available stable funding as a percentage of the required stable funding (i.e., assests that need to be funded). These two variables are negatively correlated (i.e., more liquidity risk is associated with higher liquidity creation and lower NSFR) and are defined in detail in the Data Appendix. *** significant at 1%; ** significant at 5%; * significant at 10%.

Table 5 - Regressions on peer effects in liquidity strategies using an alternative identification strategy (Leary and Roberts, 2014)

	Bank peer effects - country year peer group (without IV)		Bank peer effects - country year peer group			
			Second-step regressions		First-step regressions	
	Liquidity creation	NSFR	Liquidity creation	NSFR	Liquidity creation	NSFR
	(1)	(2)	(3)	(4)	(5)	(6)
Peer effects	0.53 ***	0.48 ***	1.28 *	0.59 **	0.00 ***	0.01 ***
	4.31	*5.31*	*1.70*	*2.00*	*-3.71*	*9.52*
Total capital ratio $_{t-1}$	-0.69 ***	0.43 ***	-0.66 ***	0.44 ***	-0.06	-0.06
	-4.23	*3.50*	*-5.21*	*4.21*	*-1.35*	*-1.61*
Log Assets $_{t}$	-2.57	-2.32	-1.85	-2.20 **	-0.96 **	-1.16 ***
	-0.76	*-1.61*	*-1.26*	*-2.00*	*-2.09*	*-3.13*
Net interest margin $_{t-1}$	-0.31	2.55 ***	-0.11	2.59 ***	-0.25	-0.46 ***
	-0.32	*4.72*	*-0.19*	*5.88*	*-1.34*	*-3.07*
Return on assets $_{t-1}$	1.11	-1.98 ***	1.73 **	-2.04 ***	-0.82 ***	0.58 ***
	1.41	*-3.46*	*2.15*	*-4.57*	*-4.51*	*4.01*
Cost-to-income $_{t-1}$	0.11 ***	-0.06 *	0.13 ***	-0.06 ***	-0.03 ***	0.01 *
	2.66	*-1.82*	*3.86*	*-3.05*	*-3.52*	*1.75*
Net loans to tot assets $_{t-1}$	0.28 ***	0.28 ***	0.26 ***	0.29 ***	0.02	-0.05 **
	3.02	*3.21*	*3.70*	*4.75*	*0.87*	*-2.39*
Loans to cust deposits $_{t-1}$	-0.02	-0.16 ***	0.03	-0.16 ***	-0.07 ***	0.02 **
	-0.56	*-5.18*	*0.56*	*-7.75*	*-7.06*	*2.51*
Liquidity ratio $_{t-1}$	0.31 ***	0.01	0.22 **	0.01	0.13 ***	0.02
	3.69	*0.21*	*1.97*	*0.26*	*6.51*	*1.01*
Liquidity creation $_{t-1}$	-	-0.28 ***	-	-0.28 ***	-	0.03 **
	-	*-5.07*	-	*-7.37*	-	*1.99*
NSFR $_{t-1}$	-0.17 ***	-	-0.14 ***	-	-0.03 **	-
	-2.75	-	*-2.93*	-	*-2.18*	-
Constant	-300.2 *	185.4 **	437.8	115.1	-987.7 ***	652.3 ***
	-1.80	*2.30*	*0.59*	*0.58*	*-56.12*	*46.40*
Number of observations	1,986	1,986	1,986	1,986	1,986	1,986
Number of banks	428	428	428	428	428	428
R2 within	0.492	0.319	0.453	0.318	0.000	0.000
R2 between	0.010	0.073	0.056	0.441	0.131	0.610
R2 overall	0.001	0.063	0.050	0.407	0.053	0.494

Notes: All regressions include year, country-year and bank fixed-effects. t-statistics in italics. Peers are defined as the j≠i banks operating in the same country and in the same year as bank i. Columns 1-2 show the results obtained when peer liquidity choices are considered directly in the regressions, i.e., not addressing the reflection problem. Columns 3-4 show the results of the instrumental variables regressions (one for each liquidity indicator), where the instruments are the idiosyncratic component of peer banks' equity returns (computed as the difference between the bank's returns and those of the S&P banks index in a given year). Columns 5-6 show the first stage estimation results for these three instrumental variables regressions. The total capital ratio is calculated according to the regulatory rules defined by the Basel Committee. Net interest margin is defined as net interest income as a percentage of earning assets. Return on assets computed as net income as a percentage of average assets. The cost-to-income ratio is computed as banks operational costs (overheads) as a percentage of income generated before provisions.

Liquidity creation is a proxy of the liquidity indicator proposed by Berger and Bouwman (2009). The higher this variable is, the more liquidity a bank is creating, i.e., the larger is its maturity transformation role. NSFR is an approximation of the Net Stable Funding Ratio defined in Basel III, which considers the available stable funding as a percentage of the required stable funding (i.e., assests that need to be funded). These two variables are negatively correlated (i.e., more liquidity risk is associated with higher liquidity creation and lower NSFR) and are defined in detail in the Data Appendix. *** significant at 1%; ** significant at 5%; * significant at 10%.

Table 6 - Regressions on peer effects in liquidity strategies - robustness on peer group definition

	Bank peer effects - country year peer group (without IV)				Bank peer effects (with IV) - Second-step regressions			
	Liquidity creation		NSFR		Liquidity creation		NSFR	
	(1)		(2)		(3)		(4)	
Baseline								
Peer effects	0.81	***	0.43	***	0.56	***	0.36	
	18.62		*7.54*		*9.02*		*1.08*	
Lagged peers								
Peer effects	0.38	***	0.03		0.74	***	0.79	
	5.83		*0.65*		*6.00*		*0.67*	
Peers as other banks (in other countries) in the same quartile								
Peer effects	0.82	***	0.21	***	0.30		-0.11	
	9.50		*3.59*		*1.22*		*-0.39*	
Large banks (4th quartile in each country)								
Peer effects	0.40	***	0.27	***	0.10		0.35	***
	5.97		*4.40*		*0.33*		*5.05*	
Large banks (4th quartile in the sample)								
Peer effects	0.30	***	0.23	***	1.60	*	0.21	*
	4.83		*4.12*		*1.67*		*1.69*	
Only larger banks (3rd and 4th quartiles)								
Peer effects	0.63	***	0.39	***	0.59	***	0.33	**
	10.45		*7.38*		*6.64*		*2.46*	
Only smaller banks (1st and 2nd quartiles)								
Peer effects	0.75	***	0.34	***	0.98	**	0.16	
	12.19		*4.14*		*1.98*		*1.50*	
Only larger banks (top 5 in each country)								
Peer effects	0.15	*	0.17	**	-0.04		0.26	
	1.78		*2.27*		*-0.12*		*1.27*	
Only larger banks (banks classified as SIFIs)								
Peer effects	-0.03		0.21		-0.27		0.48	
	-0.14		*1.11*		*-0.52*		*1.27*	
Only larger banks (banks that belong to the Euribor panel)								
Peer effects	0.46	**	0.17	*	-0.37		0.38	*
	2.55		*1.70*		*-0.38*		*1.87*	
Excluding larger banks (top 5 in each country)								
Peer effects	0.76	***	0.40	***	0.58	***	-0.55	
	14.15		*6.40*		*9.01*		*-0.81*	
Small banks following large banks (4th quartile)								
Peer effects	0.59	***	-0.01		-0.41	**	-0.15	**
	7.41		*-0.24*		*-2.35*		*-2.15*	
Small banks following large banks (top 5)								
Peer effects	-0.84	***	-0.30	***	-1.38	***	-0.27	***
	-9.66		*-7.13*		*-4.33*		*-5.71*	
Small banks following large banks (SIFI list)								
Peer effects	-0.47	***	0.00		-1.84	***	0.33	***
	-5.82		*-0.01*		*-14.06*		*3.42*	
Small banks following large banks (Euribor panel)								
Peer effects	-0.21	***	-0.03		-0.86	***	-0.30	***
	-3.41		*-0.51*		*-9.77*		*-4.92*	

Notes: t-statistics in italics. Each line shows the coefficients for peer effects for different robustness tests. Bank quartiles were defined based on banks' total assets. Top 5 referes to the banks classified as being in the top 5 by assets in each country in Bankscope. The list of SIFIs (systemically important financial institutions) is the one disclosed by the Financial Stability Board in 2011. Columns 1-2 show the results obtained when peer liquidity choices are considered directly in the regressions, i.e., not addressing the reflection problem. Columns 3-4 show the results of the instrumental variables regressions, where the instruments are the predicted values of peers' liquidity ratios. These predicted values result from the estimation of the regressions in Table 3. All the regressions use the same control variables as those reported in Table 5. All regressions include year, country-year and bank fixed-effects. *** significant at 1%; ** significant at 5%; * significant at 10%.

Table 7 - Regressions on peer effects in liquidity strategies - robustness

	Bank peer effects - country year peer group (without IV)				Bank peer effects (with IV) - Second-step regressions			
	Liquidity creation		NSFR		Liquidity creation		NSFR	
	(1)		(2)		(3)		(4)	
Baseline								
Peer effects	0.81	***	0.43	***	0.56	***	0.36	
	18.62		*7.54*		*9.02*		*1.08*	
Peer effects using predicted values (without IV)								
Peer effects	0.51	***	0.09		-		-	
	8.32		*1.06*					
Accounting for predicted regressors with bootstrapped standard errors								
Peer effects	0.81	***	0.43	***	0.56	***	0.34	
	17.13		*7.62*		*4.74*		*0.81*	
Before the crisis								
Peer effects	0.46	***	0.12		0.35	***	0.33	*
	5.24		*1.54*		*2.74*		*1.94*	
Removing banks with asset growth above 50%								
Peer effects	0.79	***	0.39	***	0.53	***	0.42	***
	17.94		*7.00*		*7.97*		*2.60*	
Excluding US banks								
Peer effects	0.24	***	0.19	***	-1.87		0.28	*
	2.92		*2.94*		*-1.47*		*1.95*	
Excluding smaller countries (less than 50 observations)								
Peer effects	0.84	***	0.46	***	0.56	***	0.25	
	18.78		*7.06*		*10.60*		*1.06*	
Western Europe banks								
Peer effects	0.24	**	0.19	***	-10.43		0.24	
	2.45		*2.79*		*-0.42*		*0.43*	
Eastern Europe banks								
Peer effects	0.20		0.13		0.28		0.25	*
	1.59		*1.22*		*0.26*		*1.73*	
US, Canada and Western Europe banks								
Peer effects	0.79	***	0.43	***	0.63	***	0.23	
	13.12		*6.60*		*8.78*		*1.47*	
Excluding countries more directly affected during the global crisis								
Peer effects	0.21	**	0.15	**	-1.35		0.18	
	2.41		*2.06*		*-1.48*		*1.18*	
Euro area as one peer group								
Peer effects	0.85	***	0.47	***	1.29	***	4.00	
	18.87		*7.49*		*10.47*		*0.68*	
Without country-year fixed effects								
Peer effects	0.81	***	0.43	***	0.43	***	0.36	
	18.62		*7.54*		*3.46*		*1.08*	
With country and year fixed effects (random-effects estimation)								
Peer effects	0.78	***	0.37	***	0.46	***	0.02	
	19.34		*6.95*		*5.21*		*0.11*	
Without liquidity controls								
Peer effects	0.81	***	0.41	***	0.54	***	0.25	
	19.91		*6.90*		*8.58*		*0.44*	
Controlling for leverage (instead of capital ratio)								
Peer effects	0.76	***	0.46	***	0.66	***	0.23	***
	21.44		*9.97*		*16.09*		*3.50*	
Only after 2004								
Peer effects	0.89	***	0.53	***	0.58	***	0.45	**
	20.90		*9.01*		*6.41*		*2.31*	
Lagged dependent variables								
Peer effects	0.76	***	0.42	***	0.55	***	0.00	
	18.14		*7.90*		*8.87*		*0.00*	
Peers weighted by size								
Peer effects	0.82	***	0.44	***	0.51	***	0.27	
	18.04		*7.41*		*4.33*		*0.81*	

Notes: Peers are defined as the $j \neq i$ banks operating in the same country and in the same year as bank i. t-statistics in italics. Each line shows the coefficients for peer effects for different robustness tests. In the regressions with bootstrapped standard errors two year dummies had to be excluded. The pre-crisis period refers to the years 2002-2006. Countries considered as most directly affected by the global financial crisis include US, Iceland, Greece, Ireland, Portugal, Spain and Italy. Columns 1-2 show the results obtained when peer liquidity choices are considered directly in the regressions, i.e., not addressing the reflection problem. Columns 3-4 show the results of the instrumental variables regressions, where the instruments are the predicted values of peers' liquidity ratios. These predicted values result from the estimation of the regressions in Table 3.

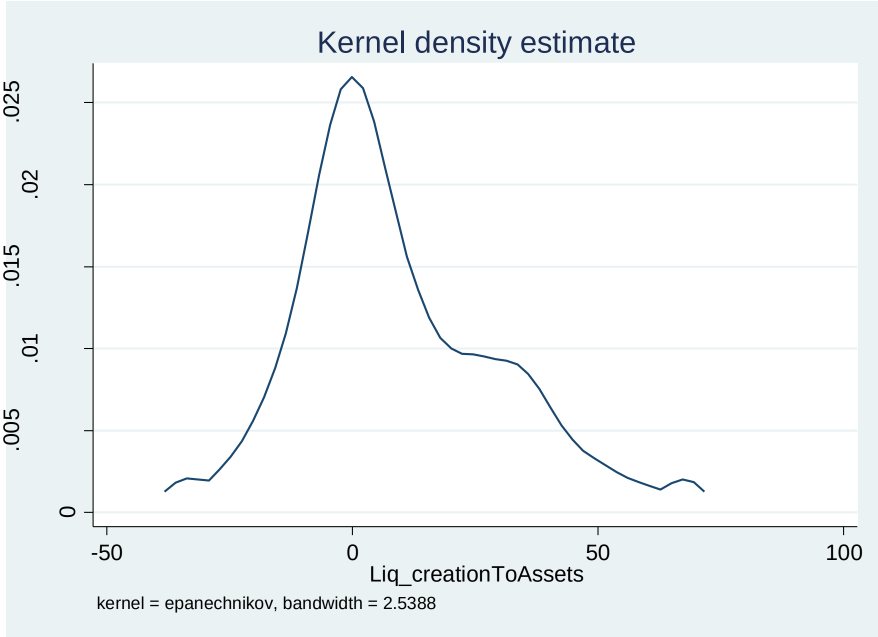
All the regressions use the same control variables as those reported in Table 5. All regressions include year, country-year and bank fixed-effects, unless otherwise stated. *** significant at 1%; ** significant at 5%; * significant at 10%.

Table 8 - Peer effects by year

	Bank peer effects - country year peer group - (IV = predicted values of rivals' liquidity ratios) Second-step regressions		Bank peer effects - country year peer group - (IV = idiosyncratic equity returns) Second-step regressions	
	Liquidity creation	NSFR	Liquidity creation	NSFR
	(1)	(2)	(3)	(4)
Full sample	0.56 ***	0.36	1.28 *	0.59 **
	9.02	*1.08*	*1.70*	*2.00*
2003	0.52 ***	0.14 *	0.61	-5.54
	8.44	*1.92*	*1.60*	*-0.35*
2004	0.38 ***	0.18 **	-3.75	-2.36 *
	4.89	*2.04*	*-0.59*	*-1.77*
2005	0.51 ***	0.03	1.51	0.34
	6.49	*0.44*	*0.74*	*0.37*
2006	0.68 ***	-0.04	0.80	3.08
	12.93	*-0.94*	*1.01*	*0.30*
2007	0.74 ***	-0.08 *	0.28	0.43 **
	14.01	*-1.66*	*0.85*	*2.51*
2008	0.76 ***	0.09 **	-0.10	0.38
	14.18	*2.02*	*-0.29*	*1.28*
2009	0.13	0.21 ***	-3.49	0.73 ***
	1.25	*3.69*	*-0.87*	*3.42*

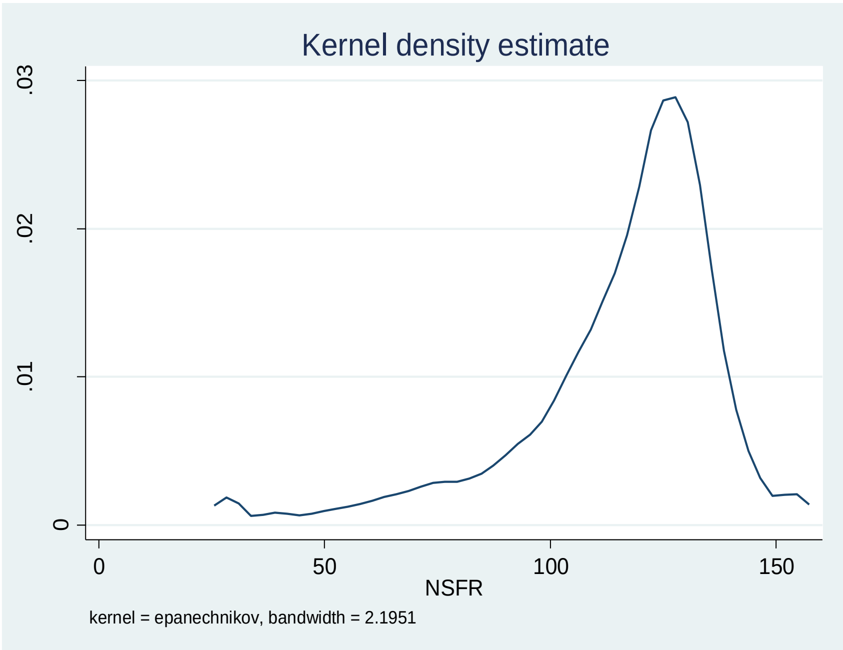
Notes: t-statistics in italics. Each line shows the coefficients for peer effects for different years. All the regressions use the same control variables as those reported in Table 4. All regressions include year, country-year and bank fixed-effects. *** significant at 1%; ** significant at 5%; * significant at 10%.

Figure 1
Empirical distribution of the liquidity creation ratio



Note: Liquidity creation is a proxy of the liquidity indicator proposed by Berger and Bouwman (2009). The higher this variable is, the more liquidity a bank is creating, i.e., the larger is its maturity transformation role. Please see Data Appendix for further details.

Figure 2
Empirical distribution of the NSFR



Note: NSFR is an approximation of the Net Stable Funding Ratio defined in Basel III, which considers the available stable funding as a percentage of the required stable funding (i.e., assests that need to be funded). Please see Data Appendix for further details.

Appendix - Tables and figures

Table A2 - Liquidity indicators - summary statistics

Panel A - Global summary statistics

	N	mean	min	p25	p50	p75	max
Loans to customer deposits	17175	94.5	0.0	73.9	88.1	102.7	365.6
Interbank ratio	3599	143.0	0.0	31.8	71.7	168.1	895.2
Liquidity ratio	17494	16.3	1.2	4.2	7.5	16.7	125.6
Liquidity creation	17620	9.1	-35.7	-4.8	4.8	22.1	69.2
NSFR	17618	115.1	27.8	106.7	121.2	129.9	155.1

Panel B - Liquidity indicators over time (mean)

	2002	2003	2004	2005	2006	2007	2008	2009	Total
Loans to customer deposits	84.1	84.9	89.6	93.0	103.1	106.0	107.9	98.7	94.5
Interbank ratio	195.7	172.2	163.2	152.2	143.8	132.2	122.8	122.1	143.0
Liquidity ratio	14.7	13.4	13.7	15.0	20.6	19.7	18.1	19.1	16.3
Liquidity creation	2.7	2.5	3.8	6.9	13.0	13.7	13.9	24.9	9.1
NSFR	122.2	122.6	119.9	116.9	109.4	108.5	108.2	104.5	115.1

Notes: The interbank ratio is defined as interbank assets as a percentage of interbank liabilities (loans to other banks as a percentage of loans from other banks). The liquidity ratio is defined as liquid assets (deposits and loans to banks with less than 3 months residual maturity, quoted/listed government bonds realizable within 3 months, cash and equivalent), as a percentage of customer deposits and short term funding. The first three variables in this table are included in the Bankscope database. Liquidity creation is a proxy of the liquidity indicator proposed by Berger and Bouwman (2009). The higher this variable is, the more liquidity a bank is creating, i.e., the larger is its maturity transformation role. NSFR is an approximation of the Net Stable Funding Ratio defined in Basel III, which considers the available stable funding as a percentage of the required stable funding (i.e., assests that need to be funded). These last two variables are defined in detail in the Data Appendix. The statistics presented refer to data after outliers were winsorized.

Table A3 - Determinants of liquidity indicators

Dependent variable:	Loan to deposits		Interbank ratio		Liquidity ratio		Liquidity creation		NSFR	
	(1)		(2)		(3)		(4)		(5)	
Total capital ratio $_{t-1}$	0.19		-0.46		0.08		-0.14		0.07	
	1.01		*-0.46*		*1.15*		*-1.56*		*0.85*	
Log Assets $_t$	5.09	**	-8.05		-2.50	**	-5.87	***	-2.69	**
	2.09		*-0.46*		*-2.23*		*-4.96*		*-2.46*	
Net interest margin $_{t-1}$	-1.82	**	3.35		-0.05		-1.37	***	2.11	***
	-2.29		*0.78*		*-0.17*		*-3.96*		*5.95*	
Return on assets $_{t-1}$	1.42	*	-1.51		-0.63	**	0.68	*	-1.43	***
	1.73		*-0.25*		*-2.11*		*1.81*		*-3.66*	
Cost-to-income $_{t-1}$	0.02		-0.13		0.00		0.08	***	-0.04	**
	0.43		*-0.54*		*-0.04*		*3.72*		*-2.10*	
Net loans to total assets $_{t-1}$	1.04	***	-2.24	**	-0.20	***	0.29	***	0.11	**
	8.79		*-2.24*		*-5.51*		*6.72*		*2.03*	
Loans to customer deposits $_{t-1}$	-		0.16		0.00		-0.02	**	-0.08	***
	-		*1.31*		*-0.39*		*-2.01*		*-5.77*	
Interbank ratio $_{t-1}$	-		-		-		-		-	
	-		-		-		-		-	
Liquidity ratio $_{t-1}$	0.30	***	0.02		-		0.23	***	0.04	
	3.54		*0.05*		-		*7.90*		*1.36*	
Liquidity creation $_{t-1}$	-0.49	***	1.59	***	0.11	***	-		-0.14	***
	-5.13		*3.21*		*3.63*		-		*-4.22*	
NSFR $_{t-1}$	-0.61	***	1.30	***	0.17	***	-0.15	***	-	
	-7.38		*2.73*		*6.16*		*-5.31*		-	
D2004	1.67	**	0.48		-0.34		-3.74	***	2.10	***
	2.18		*0.03*		*-0.93*		*-10.36*		*5.36*	
D2005	2.27	**	6.28		-0.53		-3.66	***	1.13	**
	2.26		*0.43*		*-1.49*		*-8.58*		*2.55*	
D2006	3.64	***	9.37		0.36		-7.35	***	4.49	***
	4.44		*0.72*		*1.15*		*-21.51*		*11.57*	
D2007	5.56	***	-0.93		-0.02		-9.08	***	4.79	***
	6.58		*-0.08*		*-0.07*		*-23.22*		*12.18*	
D2008	7.50	***	-6.93		-1.38	***	-11.59	***	5.08	***
	10.76		*-0.80*		*-5.37*		*-27.44*		*13.43*	
Constant	348.9	***	445.2		-19.8		-593.2	***	355.24	***
	4.82		*0.66*		*-0.63*		*-15.33*		*9.92*	
Number of observations	7,018		1,885		7,018		7,020		7,020	
Number of banks	1,735		529		1,736		1,738		1,738	
R2 within	0.160		0.059		0.102		0.366		0.160	
R2 between	0.151		0.038		0.303		0.139		0.165	
R2 overall	0.129		0.017		0.276		0.103		0.138	
Frac. of variance due to bank FE	0.965		0.729		0.966		0.998		0.984	

Notes: All regressions include country-year fixed-effects, bank fixed-effects and robust standard errors. t-statistics in italics. The total capital ratio is calculated according to the regulatory rules defined by the Basel Committee. Net interest margin is defined as net interest income as a percentage of earning assets. Return on assets computed as net income as a percentage of average assets. The cost-to-income ratio is computed as banks operational costs (overheads) as a percentage of income generated before provisions. The interbank ratio is defined as interbank assets as a percentage of interbank liabilities (loans to other banks as a percentage of loans from other banks). The liquidity ratio is defined as liquid assets (deposits and loans to banks with less than 3 months residual maturity, quoted/listed government bonds realizable within 3 months, cash and equivalent), as a percentage of customer deposits and short term funding. All these variables are included in the Bankscope database. Liquidity creation is a proxy of the liquidity indicator proposed by Berger and Bouwman (2009). The higher this variable is, the more liquidity a bank is creating, i.e., the larger is its maturity transformation role. NSFR is an approximation of the Net Stable Funding Ratio defined in Basel III, which considers the available stable funding as a percentage of the required stable funding (i.e., assests that need to be funded). These last two variables are defined in detail in the Data Appendix. *** significant at 1%; ** significant at 5%; * significant at 10%.

Table A4 - Regressions on peer effects in liquidity strategies

	Bank peer effects - country year peer group (without IV)					Bank peer effects - country year peer group - (IV = predicted values of rivals' liquidity ratios) Second-step regressions					First-step regressions				
	Loan to deposits	Interbank ratio	Liquidity ratio	Liquidity creation	NSFR	Loan to deposits	Interbank ratio	Liquidity ratio	Liquidity creation	NSFR	Loan to deposits	Interbank ratio	Liquidity ratio	Liquidity creation	NSFR
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Peer effects	0.32 ***	0.19 **	0.46 ***	0.81 ***	0.43 ***	0.39 ***	0.81	0.72 ***	0.56 ***	0.36	1.13 ***	0.35 ***	0.86 ***	0.92 ***	0.24 ***
	4.87	*2.33*	*7.96*	*18.62*	*7.54*	*6.64*	*1.09*	*8.88*	*9.02*	*1.08*	*32.47*	*3.24*	*29.16*	*31.28*	*7.21*
Total capital ratio $_{t-1}$	0.19	-0.60	0.03	-0.19 **	0.08	0.18 *	-0.87	0.01	-0.18 ***	0.08	0.12 **	0.57	0.05 ***	0.03	-0.02
	1.01	*-0.61*	*0.46*	*-2.29*	*0.91*	*1.75*	*-0.78*	*0.15*	*-3.63*	*1.51*	*2.20*	*1.36*	*3.07*	*1.15*	*-0.83*
Log Assets $_{t}$	2.76	-6.20	-1.46	-1.73	-2.86 **	2.19 *	-3.24	-0.88 *	-3.02 ***	-2.80 ***	0.51	-4.98	-0.41 **	-2.86 ***	0.87 ***
	1.12	*-0.35*	*-1.23*	*-1.61*	*-2.56*	*1.77*	*-0.23*	*-1.82*	*-4.95*	*-4.77*	*0.79*	*-0.91*	*-2.05*	*-10.22*	*3.47*
Net interest margin $_{t-1}$	-1.42 *	3.17	-0.03	-1.08 ***	1.90 ***	-1.32 ***	2.72	-0.02	-1.17 ***	1.94 ***	-0.53 **	0.60	-0.15 **	-0.29 ***	0.41 ***
	-1.88	*0.74*	*-0.10*	*-3.26*	*5.28*	*-2.92*	*0.71*	*-0.10*	*-5.71*	*7.18*	*-2.26*	*0.38*	*-2.05*	*-2.76*	*4.39*
Return on assets $_{t-1}$	1.39 *	-0.70	-0.62 **	0.56	-1.34 ***	1.36 ***	0.99	-0.62 ***	0.60 ***	-1.36 ***	0.60 **	-4.16 **	-0.16 *	-0.05	-0.19 *
	1.78	*-0.12*	*-2.25*	*1.59*	*-3.46*	*2.69*	*0.18*	*-3.18*	*2.60*	*-5.25*	*2.25*	*-2.07*	*-1.88*	*-0.39*	*-1.85*
Cost-to-income $_{t-1}$	0.02	-0.11	0.00	0.05 ***	-0.04 *	0.02	-0.11	-0.01	0.06 ***	-0.04 ***	0.03 **	-0.12	-0.01	0.02 ***	-0.02 ***
	0.56	*-0.45*	*-0.22*	*2.64*	*-1.81*	*0.90*	*-0.36*	*-0.55*	*4.43*	*-2.80*	*2.28*	*-0.97*	*-1.31*	*2.79*	*-2.93*
Net loans to tot assets $_{t-1}$	0.95 ***	-2.15 **	-0.16 ***	0.26 ***	0.12 **	0.93 ***	-1.67 *	-0.13 ***	0.26 ***	0.12 ***	0.11 ***	-0.49	-0.05 ***	0.04 **	-0.01
	8.45	*-2.15*	*-4.46*	*6.34*	*2.18*	*15.20*	*-1.88*	*-5.39*	*9.17*	*3.72*	*3.37*	*-1.62*	*-5.37*	*2.54*	*-0.99*
Loans to cust deposits $_{t-1}$	-	0.15	0.00	0.00	-0.08 ***	-	0.10	0.00	0.00	-0.08 ***	-	0.05	0.00	-0.02 ***	0.00
	-	*1.24*	*-0.30*	*0.43*	*-6.02*	-	*0.74*	*-0.49*	*-0.51*	*-10.95*	-	*1.01*	*1.03*	*-6.33*	*0.63*
Interbank ratio $_{t-1}$	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Liquidity ratio $_{t-1}$	0.31 ***	-0.05	-	0.12 ***	0.05 *	0.32 ***	-0.20	-	0.15 ***	0.05 **	-0.02	0.23	-	0.12 ***	-0.04 ***
	3.81	*-0.15*	-	*4.34*	*1.90*	*7.47*	*-0.46*	-	*6.72*	*2.22*	*-1.07*	*1.36*	-	*11.05*	*-4.50*
Liquidity creation $_{t-1}$	-0.40 ***	1.54 ***	0.06 **	-	-0.13 ***	-0.38 ***	1.41 ***	0.03	-	-0.13 ***	-0.09 ***	0.11	0.06 ***	-	-0.04 ***
	-4.31	*3.17*	*1.98*	-	*-3.79*	*-7.78*	*3.29*	*1.49*	-	*-5.92*	*-3.68*	*0.65*	*7.54*	-	*-4.65*
NSFR $_{t-1}$	-0.55 ***	1.26 ***	0.13 ***	-0.12 ***	-	-0.54 ***	1.12 ***	0.11 ***	-0.13 ***	-	-0.11 ***	0.14	0.05 ***	-0.03 ***	-
	-7.11	*2.70*	*5.11*	*-4.53*	-	*-13.66*	*2.68*	*7.05*	*-7.58*	-	*-5.42*	*0.87*	*7.21*	*-3.84*	-
Constant	357.8 ***	288.2	-26.7	69.7	72.8	361.5 ***	-473.7	-30.1	-137.2 **	119.3	-303.9 ***	382.2	39.7 ***	-100.9 ***	587.8 ***
	4.95	*0.41*	*-0.86*	*1.27*	*1.31*	*6.83*	*-0.56*	*-1.48*	*-2.44*	*0.54*	*-10.48*	*1.40*	*4.59*	*-3.84*	*39.78*
Number of observations	7,016	1,882	7,016	7,019	7,019	7,010	1,877	7,010	7,012	7,012	7,010	1,877	7,010	7,012	7,012
Number of banks	1,734	528	1,735	1,737	1,737	1,733	527	1,734	1,736	1,736	1,733	527	1,734	1,736	1,736
F-test	29.8	3.1	22.1	127.9	37.7						244.9	12.3	12.3	785.0	308.7
R2 within	0.187	0.066	0.141	0.477	0.186	0.186	0.009	0.127	0.467	0.186	0.427	0.135	0.324	0.705	0.484
R2 between	0.155	0.079	0.135	0.329	0.501	0.158	0.003	0.000	0.095	0.524	0.330	0.041	0.573	0.399	0.555
R2 overall	0.132	0.051	0.105	0.331	0.455	0.134	0.013	0.001	0.055	0.471	0.316	0.036	0.466	0.313	0.494

Notes: All regressions include year, country-year and bank fixed-effects. t-statistics in italics. Peers are defined as the j≠i banks operating in the same country and in the same year as bank i. Columns 1-5 show the results obtained when peer liquidity choices are considered directly in the regressions, i.e., not addressing the reflection problem. Columns 6-10 show the results of the instrumental variables regressions (one for each liquidity indicator), where the instruments are the predicted values of peers' liquidity ratios. These predicted values result from the estimation of the regressions in Table 3. Columns 11-15 show the first stage estimation results for these three instrumental variables regressions. The total capital ratio is calculated according to the regulatory rules defined by the Basel Committee. Net interest margin is defined as net interest income as a percentage of earning assets. Return on assets computed as net income as a percentage of average assets. The cost-to-income ratio is computed as banks operational costs (overheads) as a percentage of income generated before provisions.

The interbank ratio is defined as interbank assets as a percentage of interbank liabilities (loans to other banks as a percentage of loans from other banks). The liquidity ratio is defined as liquid assets (deposits and loans to banks with less than 3 months residual maturity, quoted/listed government bonds realizable within 3 months, cash and equivalent), as a percentage of customer deposits and short term funding. All these variables are included in the Bankscope database. Liquidity creation is a proxy of the liquidity indicator proposed by Berger and Bouwman (2009). The higher this variable is, the more liquidity a bank is creating, i.e., the larger is its maturity transformation role. NSFR is an approximation of the Net Stable Funding Ratio defined in Basel III, which considers the available stable funding as a percentage of the required stable funding (i.e., assests that need to be funded). These last two variables are defined in detail in the Data Appendix. *** significant at 1%; ** significant at 5%; * significant at 10%.

Table A5 - Regressions on peer effects in liquidity strategies using an alternative identification strategy (Leary and Roberts, 2014)

	Bank peer effects - country year peer group (without IV)					Bank peer effects - country year peer group - (IV = predicted values of rivals' liquidity ratios) Second-step regressions					First-step regressions				
	Loan to deposits	Interbank ratio	Liquidity ratio	Liquidity creation	NSFR	Loan to deposits	Interbank ratio	Liquidity ratio	Liquidity creation	NSFR	Loan to deposits	Interbank ratio	Liquidity ratio	Liquidity creation	NSFR
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Peer effects	0.34 **	0.59 ***	0.23 **	0.53 ***	0.48 ***	0.06	-0.92	2.04 **	1.28 *	0.59 **	-0.01 ***	0.00	0.00 **	0.00 ***	0.01 ***
	2.29	*4.94*	*2.32*	*4.31*	*5.31*	*0.40*	*-0.01*	*2.11*	*1.70*	*2.00*	*-7.78*	*-0.01*	*2.34*	*-3.71*	*9.52*
Total capital ratio $_{t-1}$	0.10	-2.69	-0.19 *	-0.69 ***	0.43 ***	0.18	-11.47	-0.20 *	-0.66 ***	0.44 ***	0.18	-5.81 *	0.02	-0.06	-0.06
	0.42	*-1.08*	*-1.85*	*-4.23*	*3.50*	*1.16*	*-0.02*	*-1.82*	*-5.21*	*4.21*	*1.52*	*-1.93*	*0.31*	*-1.35*	*-1.61*
Log Assets $_{t}$	-0.18	65.24	-4.81	-2.57	-2.32	1.65	21.75	-0.89	-1.85	-2.20 **	6.77 ***	-28.66	-2.17 ***	-0.96 **	-1.16 ***
	-0.04	*1.64*	*-1.42*	*-0.76*	*-1.61*	*0.89*	*0.01*	*-0.37*	*-1.26*	*-2.00*	*5.45*	*-0.72*	*-4.35*	*-2.09*	*-3.13*
Net interest margin $_{t-1}$	-1.88	5.13	-0.68 **	-0.31	2.55 ***	-1.38 **	25.65	0.17	-0.11	2.59 ***	1.89 ***	13.56	-0.47 **	-0.25	-0.46 ***
	-1.13	*0.66*	*-2.29*	*-0.32*	*4.72*	*-2.01*	*0.01*	*0.26*	*-0.19*	*5.88*	*3.74*	*1.52*	*-2.36*	*-1.34*	*-3.07*
Return on assets $_{t-1}$	3.04 ***	-4.50	-0.71 *	1.11	-1.98 ***	2.67 ***	16.65	-2.20 **	1.73 **	-2.04 ***	-1.28 ***	13.98	0.81 ***	-0.82 ***	0.58 ***
	4.78	*-0.31*	*-1.80*	*1.41*	*-3.46*	*4.21*	*0.01*	*-2.42*	*2.15*	*-4.57*	*-2.65*	*1.34*	*4.19*	*-4.51*	*4.01*
Cost-to-income $_{t-1}$	0.02	0.74	-0.02	0.11 ***	-0.06 *	0.02	0.17	-0.10 **	0.13 ***	-0.06 ***	0.01	-0.38	0.05 ***	-0.03 ***	0.01 *
	0.52	*1.62*	*-0.73*	*2.66*	*-1.82*	*0.80*	*0.00*	*-2.02*	*3.86*	*-3.05*	*0.40*	*-0.61*	*4.78*	*-3.52*	*1.75*
Net loans to tot assets $_{t-1}$	1.07 ***	-6.16 ***	-0.10 *	0.28 ***	0.28 ***	1.17 ***	-8.21	0.15	0.26 ***	0.29 ***	0.33 ***	-1.36	-0.13 ***	0.02	-0.05 **
	5.09	*-3.29*	*-1.85*	*3.02*	*3.21*	*12.47*	*-0.05*	*1.00*	*3.70*	*4.75*	*5.64*	*-0.71*	*-4.76*	*0.87*	*-2.39*
Loans to cust deposits $_{t-1}$	-	0.90 **	-0.02	-0.02	-0.16 ***	-	1.39	-0.02	0.03	-0.16 ***	-	0.32	0.00	-0.07 ***	0.02 **
	-	*2.09*	*-0.99*	*-0.56*	*-5.18*	-	*0.03*	*-0.80*	*0.56*	*-7.75*	-	*0.82*	*-0.07*	*-7.06*	*2.51*
Interbank ratio $_{t-1}$	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Liquidity ratio $_{t-1}$	0.38 **	-1.57	-	0.31 ***	0.01	0.36 ***	2.77	-	0.22 **	0.01	-0.06	2.86 **	-	0.13 ***	0.02
	2.48	*-1.11*	-	*3.69*	*0.21*	*4.93*	*0.01*	-	*1.97*	*0.26*	*-1.01*	*2.16*	-	*6.51*	*1.01*
Liquidity creation $_{t-1}$	-0.68 ***	0.55	0.11 *	-	-0.28 ***	-0.76 ***	-1.17	-0.11	-	-0.28 ***	-0.30 ***	-1.14	0.12 ***	-	0.03 **
	-4.19	*0.40*	*1.66*	-	*-5.07*	*-9.28*	*-0.01*	*-0.89*	-	*-7.37*	*-5.50*	*-0.94*	*5.67*	-	*1.99*
NSFR $_{t-1}$	-0.59 ***	1.93	0.11 *	-0.17 ***	-	-0.64 ***	3.87	-0.10	-0.14 ***	-	-0.17 ***	1.28	0.11 ***	-0.03 **	-
	-3.77	*1.45*	*1.89*	*-2.75*	-	*-10.06*	*0.02*	*-0.86*	*-2.93*	-	*-3.71*	*1.21*	*6.01*	*-2.18*	-
Constant	160.8	2,179.5	-7.7	-300.2 *	185.4 **	198.9 ***	8,515.6	53.4	437.8	115.1	141.1 ***	4,183.5 ***	-34.0 *	-987.7 ***	652.3 ***
	1.47	*1.50*	*-0.15*	*-1.80*	*2.30*	*3.20*	*0.02*	*1.00*	*0.59*	*0.58*	*2.99*	*2.60*	*-1.81*	*-56.12*	*46.40*
Number of observations	1,983	190	1,986	1,986	1,986	1,983	190	1,986	1,986	1,986	1,983	190	1,986	1,986	1,986
Number of banks	427	50	428	428	428	427	50	428	428	428	427	50	428	428	428
R2 within	0.398	0.464	0.197	0.492	0.319	0.365	.	.	0.453	0.318	0.000	0.000	0.000	0.000	0.000
R2 between	0.339	0.030	0.304	0.010	0.073	0.305	0.027	0.312	0.056	0.441	0.362	0.109	0.506	0.131	0.610
R2 overall	0.383	0.017	0.272	0.001	0.063	0.331	0.020	0.331	0.050	0.407	0.293	0.058	0.418	0.053	0.494

Notes: All regressions include year, country-year and bank fixed-effects. t-statistics in italics. Peers are defined as the j≠i banks operating in the same country and in the same year as bank i. Columns 1-5 show the results obtained when peer liquidity choices are considered directly in the regressions, i.e., not addressing the reflection problem. Columns 6-10 show the results of the instrumental variables regressions (one for each liquidity indicator), where the instruments are the idiosyncratic of peer banks' equity returns (computed as the difference between the bank's returns and those of the S&P banks index in a given year). Columns 11-15 show the first stage estimation results for these three instrumental variables regressions. The total capital ratio is calculated according to the regulatory rules defined by the Basel Committee. Net interest margin is defined as net interest income as a percentage of earning assets. Return on assets computed as net income as a percentage of average assets. The cost-to-income ratio is computed as banks operational costs (overheads) as a percentage of income generated before provisions.

The interbank ratio is defined as interbank assets as a percentage of interbank liabilities (loans to other banks as a percentage of loans from other banks). The liquidity ratio is defined as liquid assets (deposits and loans to banks with less than 3 months residual maturity, quoted/listed government bonds realizable within 3 months, cash and equivalent), as a percentage of customer deposits and short term funding. All these variables are included in the Bankscope database. Liquidity creation is a proxy of the liquidity indicator proposed by Berger and Bouwman (2009). The higher this variable is, the more liquidity a bank is creating, i.e., the larger is its maturity transformation role. NSFR is an approximation of the Net Stable Funding Ratio defined in Basel III, which considers the available stable funding as a percentage of the required stable funding (i.e., assests that need to be funded). These last two variables are defined in detail in the Data Appendix. *** significant at 1%; ** significant at 5%; * significant at 10%.

Table A6 - Regressions on peer effects in liquidity strategies - robustness on peer group definition

	Bank peer effects - country year peer group (without IV)					Bank peer effects - country year peer group - Second-step regressions				
	Loan to deposits	Interbank ratio	Liquidity ratio	Liquidity creation	NSFR	Loan to deposits	Interbank ratio	Liquidity ratio	Liquidity creation	NSFR
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Baseline										
Peer effects	0.32 ***	0.19 **	0.46 ***	0.81 ***	0.43 ***	0.39 ***	0.81	0.72 ***	0.56 ***	0.36
	4.87	*2.33*	*7.96*	*18.62*	*7.54*	*6.64*	*1.09*	*8.88*	*9.02*	*1.08*
Lagged peers										
Peer effects	0.13 **	-0.09	0.32 ***	0.38 ***	0.03	0.38 ***	0.19	0.75 ***	0.74 ***	0.79
	2.47	*-1.20*	*5.18*	*5.83*	*0.65*	*5.78*	*0.23*	*5.76*	*6.00*	*0.67*
Peers as other banks (in other countries) in the same quartile										
Peer effects	0.11	-0.09	-0.04	0.82 ***	0.21 ***	0.08	2.01	0.22	0.30	-0.11
	1.04	*-0.36*	*-0.45*	*9.50*	*3.59*	*0.43*	*1.56*	*1.02*	*1.22*	*-0.39*
Large banks (4th quartile in each country)										
Peer effects	0.22 ***	0.07	0.30 ***	0.40 ***	0.27 ***	0.36 ***	-0.05	0.39 ***	0.10	0.35 ***
	3.37	*1.16*	*3.82*	*5.97*	*4.40*	*7.15*	*-0.27*	*5.05*	*0.33*	*5.05*
Large banks (4th quartile in the sample)										
Peer effects	0.19 ***	0.23 **	0.40 ***	0.30 ***	0.23 ***	0.30 ***	-0.04	0.34 ***	1.60 *	0.21 *
	3.22	*2.29*	*6.24*	*4.83*	*4.12*	*4.16*	*-0.07*	*3.21*	*1.67*	*1.69*
Only larger banks (3rd and 4th quartiles)										
Peer effects	0.26 ***	0.11	0.42 ***	0.63 ***	0.39 ***	0.34 ***	0.63 **	0.59 ***	0.59 ***	0.33 **
	3.39	*1.24*	*7.46*	*10.45*	*7.38*	*6.49*	*2.26*	*8.46*	*6.64*	*2.46*
Only smaller banks (1st and 2nd quartiles)										
Peer effects	0.21 ***	0.10	0.21 ***	0.75 ***	0.34 ***	0.24 ***	1.50 *	0.51 ***	0.98 **	0.16
	3.89	*1.07*	*3.71*	*12.19*	*4.14*	*3.71*	*1.69*	*3.74*	*1.98*	*1.50*
Only larger banks (top 5 in each country)										
Peer effects	0.04	0.07	0.21 **	0.15 *	0.17 **	0.31 **	-0.27	-0.09	-0.04	0.26
	0.75	*0.94*	*2.39*	*1.78*	*2.27*	*2.57*	*-0.40*	*-0.45*	*-0.12*	*1.27*
Only larger banks (banks classified as SIFIs)										
Peer effects	-0.69 ***	-0.20	0.70 ***	-0.03	0.21	-0.70 ***	0.16	0.71 **	-0.27	0.48
	-2.98	*-1.35*	*3.38*	*-0.14*	*1.11*	*-2.61*	*0.63*	*2.21*	*-0.52*	*1.27*
Only larger banks (banks that belong to the Euribor panel)										
Peer effects	0.10	-0.16	-0.02	0.46 **	0.17 *	0.05	-0.19	0.13	-0.37	0.38 *
	0.68	*-1.31*	*-0.08*	*2.55*	*1.70*	*0.26*	*-0.52*	*0.19*	*-0.38*	*1.87*
Excluding larger banks (top 5 in each country)										
Peer effects	0.30 ***	0.15	0.41 ***	0.76 ***	0.40 ***	0.33 ***	1.74	0.91 ***	0.58 ***	-0.55
	4.57	*1.25*	*5.98*	*14.15*	*6.40*	*4.14*	*1.01*	*8.13*	*9.01*	*-0.81*
Small banks following large banks (4th quartile)										
Peer effects	0.26 ***	0.21 **	0.26 ***	0.59 ***	-0.01	0.27 ***	0.11	0.60 ***	-0.41 **	-0.15 **
	5.01	*2.10*	*4.44*	*7.41*	*-0.24*	*6.07*	*0.48*	*11.18*	*-2.35*	*-2.15*
Small banks following large banks (top 5)										
Peer effects	0.22 ***	0.09	0.17 ***	-0.84 ***	-0.30 ***	0.16 ***	0.00	0.67 ***	-1.38 ***	-0.27 ***
	3.86	*1.28*	*4.47*	*-9.66*	*-7.13*	*3.59*	*0.00*	*10.40*	*-4.33*	*-5.71*
Small banks following large banks (SIFI list)										
Peer effects	0.10 *	0.16	0.32 ***	-0.47 ***	0.00	0.25 ***	0.71 **	1.02 ***	-1.84 ***	0.33 ***
	1.95	*1.17*	*3.29*	*-5.82*	*-0.01*	*4.57*	*2.46*	*12.33*	*-14.06*	*3.42*
Small banks following large banks (Euribor panel)										
Peer effects	0.17 **	0.91 ***	0.31 ***	-0.21 ***	-0.03	0.26 ***	2.12 ***	1.03 ***	-0.86 ***	-0.30 ***
	2.04	*2.89*	*3.36*	*-3.41*	*-0.51*	*4.37*	*3.58*	*14.41*	*-9.77*	*-4.92*

Notes: *t*-statistics in italics. Each line shows the coefficients for peer effects for different robustness tests. Bank quartiles were defined based on banks' total assets. Top 5 referes to the banks classified as being in the top 5 by assets in each country in Bankscope. The list of SIFIs (systemically important financial institutions) is the one disclosed by the Financial Stability Board in 2011. Columns 1-5 show the results obtained when peer liquidity choices are considered directly in the regressions, i.e., not addressing the reflection problem. Columns 6-10 show the results of the instrumental variables regressions, where the instruments are the predicted values of peers' liquidity ratios. These predicted values result from the estimation of the regressions in Table 3. All the regressions use the same control variables as those reported in Table 5. All regressions include year, country-year and bank fixed-effects. *** significant at 1%; ** significant at 5%; * significant at 10%.

Table A7- Regressions on peer effects in liquidity strategies - robustness

	Bank peer effects - country year peer group (without IV)					Bank peer effects - country year peer group - (IV = pred. values of rivals' liquidity ratios) Second-step regressions				
	Loan to deposits	Interbank ratio	Liquidity ratio	Liquidity creation	NSFR	Loan to deposits	Interbank ratio	Liquidity ratio	Liquidity creation	NSFR
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Baseline										
Peer effects	0.32 ***	0.19 **	0.46 ***	0.81 ***	0.43 ***	0.39 ***	0.81	0.72 ***	0.56 ***	0.36
	4.87	*2.33*	*7.96*	*18.62*	*7.54*	*6.64*	*1.09*	*8.88*	*9.02*	*1.08*
Peer effects using predicted values (without IV)										
Peer effects	0.44 ***	0.28	0.62 ***	0.51 ***	0.09	-	-	-	-	-
	6.57	*1.12*	*8.82*	*8.32*	*1.06*					
Accounting for predicted regressors with bootstrapped standard errors										
Peer effects	0.32 ***	0.19 **	0.46 ***	0.81 ***	0.43 ***	0.39 ***	0.83	0.73 ***	0.56 ***	0.34
	4.48	*2.19*	*7.57*	*17.13*	*7.62*	*3.45*	*0.96*	*4.74*	*4.74*	*0.81*
Before the crisis										
Peer effects	0.04	0.06	0.31 ***	0.46 ***	0.12	0.33	1.36	0.76 **	0.35 ***	0.33 *
	0.50	*0.51*	*2.86*	*5.24*	*1.54*	*1.44*	*0.37*	*2.32*	*2.74*	*1.94*
Removing banks with asset growth above 50%										
Peer effects	0.32 ***	0.16 *	0.42 ***	0.79 ***	0.39 ***	0.42 ***	0.21	0.64 ***	0.53 ***	0.42 ***
	4.50	*1.83*	*6.99*	*17.94*	*7.00*	*6.06*	*0.13*	*7.98*	*7.97*	*2.60*
Excluding US banks										
Peer effects	0.26 ***	0.18 **	0.25 ***	0.24 ***	0.19 ***	0.22 **	0.80	0.42 **	-1.87	0.28 *
	4.16	*2.15*	*4.24*	*2.92*	*2.94*	*2.22*	*0.92*	*2.43*	*-1.47*	*1.95*
Excluding smaller countries (less than 50 observations)										
Peer effects	0.37 ***	0.18	0.52 ***	0.84 ***	0.46 ***	0.48 ***	0.12	0.69 ***	0.56 ***	0.25
	5.33	*1.64*	*7.62*	*18.78*	*7.06*	*8.37*	*0.24*	*8.66*	*10.60*	*1.06*
Western Europe banks										
Peer effects	-0.01	0.15	0.00	0.24 **	0.19 ***	0.24	-0.71	-1.95	-10.43	0.24
	-0.12	*1.61*	*0.00*	*2.45*	*2.79*	*1.03*	*-0.77*	*-1.20*	*-0.42*	*0.43*
Eastern Europe banks										
Peer effects	0.42 ***	0.14	0.40 ***	0.20	0.13	0.35 ***	1.05	1.09 **	0.28	0.25 *
	5.24	*1.17*	*4.26*	*1.59*	*1.22*	*2.98*	*0.26*	*2.22*	*0.26*	*1.73*
US, Canada and Western Europe banks										
Peer effects	0.02	0.22 **	0.38 ***	0.79 ***	0.43 ***	0.05	-0.47	10.01	0.63 ***	0.23
	0.30	*2.47*	*4.41*	*13.12*	*6.60*	*0.57*	*-0.48*	*0.89*	*8.78*	*1.47*
Excluding countries more directly affected during the global crisis										
Peer effects	0.27 ***	0.19 **	0.28 ***	0.21 **	0.15 **	0.18 *	0.15	0.49 ***	-1.35	0.18
	4.09	*2.09*	*4.36*	*2.41*	*2.06*	*1.80*	*0.21*	*2.86*	*-1.48*	*1.18*
Euro area as one peer group										
Peer effects	0.37 ***	0.22 **	0.57 ***	0.85 ***	0.47 ***	0.30 ***	0.23	0.68 ***	1.29 ***	4.00
	5.22	*2.25*	*8.77*	*18.87*	*7.49*	*4.61*	*0.22*	*9.96*	*10.47*	*0.68*
Without country-year fixed effects										
Peer effects	0.32 ***	0.19 **	0.46 ***	0.81 ***	0.43 ***	0.33 **	0.81	0.72 ***	0.43 ***	0.36
	4.87	*2.33*	*7.96*	*18.62*	*7.54*	*2.57*	*1.09*	*8.88*	*3.46*	*1.08*
With country and year fixed effects (random-effects estimation)										
Peer effects	0.24 ***	0.03	0.37 ***	0.78 ***	0.37 ***	0.23 ***	-0.29	0.33 ***	0.46 ***	0.02
	4.13	*0.41*	*6.82*	*19.34*	*6.95*	*4.72*	*-0.71*	*5.02*	*5.21*	*0.11*
Without liquidity controls										
Peer effects	0.36 ***	0.21 **	0.53 ***	0.81 ***	0.41 ***	0.54 ***	1.33 **	0.83 ***	0.54 ***	0.25
	5.33	*2.47*	*8.51*	*19.91*	*6.90*	*6.37*	*1.97*	*7.17*	*8.58*	*0.44*
Controlling for leverage (instead of capital ratio)										
Peer effects	0.28 ***	0.16 ***	0.45 ***	0.76 ***	0.46 ***	0.36 ***	-0.11	0.59 ***	0.66 ***	0.23 ***
	4.05	*2.73*	*8.95*	*21.44*	*9.97*	*8.46*	*-0.38*	*10.69*	*16.09*	*3.50*
Only after 2004										
Peer effects	0.41 ***	0.24 ***	0.49 ***	0.89 ***	0.53 ***	0.47 ***	1.04 *	0.77 ***	0.58 ***	0.45 **
	6.18	*3.85*	*8.04*	*20.90*	*9.01*	*6.51*	*1.80*	*7.11*	*6.41*	*2.31*
Lagged dependent variables										
Peer effects	0.29 ***	0.13 *	0.41 ***	0.76 ***	0.42 ***	0.31 ***	0.02	0.66 ***	0.55 ***	0.00
	5.21	*1.70*	*8.13*	*18.14*	*7.90*	*6.34*	*0.03*	*9.84*	*8.87*	*0.00*
Peers weighted by size										
Peer effects	0.32 ***	0.20 **	0.47 ***	0.82 ***	0.44 ***	0.56 ***	-2.01	0.72 ***	0.51 ***	0.27
	4.79	*2.32*	*8.06*	*18.04*	*7.41*	*4.53*	*-0.79*	*7.26*	*4.33*	*0.81*

Notes: Peers are defined as the $j \neq i$ banks operating in the same country and in the same year as bank i. t-statistics in italics. Each line shows the coefficients for peer effects for different robustness tests. In the regressions with bootstrapped standard errors two year dummies had to be excluded. The pre-crisis period refers to the years 2002-2006. Countries considered as most directly affected by the global financial crisis include US, Iceland, Greece, Ireland, Portugal, Spain and Italy. Columns 1-5 show the results obtained when peer liquidity choices are considered directly in the regressions, i.e., not addressing the reflection problem. Columns 6-10 show the results of the instrumental variables regressions, where the instruments are the predicted values of peers' liquidity ratios. These predicted values result from the estimation of the regressions in Table 3. All the regressions use the same control variables as those reported in Table 5. All regressions include year, country-year and bank fixed-effects, unless otherwise stated. *** significant at 1%; ** significant at 5%; * significant at 10%.

Table A8 - Peer effects by year

	Bank peer effects - country year peer group - (IV = predicted values of rivals' liquidity ratios) Second-step regressions					Bank peer effects - country year peer group - (IV = idiosyncratic equity returns) Second-step regressions				
	Loan to deposits	Interbank ratio	Liquidity ratio	Liquidity creation	NSFR	Loan to deposits	Interbank ratio	Liquidity ratio	Liquidity creation	NSFR
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Full sample	0.39 ***	0.81	0.72 ***	0.56 ***	0.36	0.06	-0.92	2.04 **	1.28 *	0.59 **
	6.64	*1.09*	*8.88*	*9.02*	*1.08*	*0.40*	*-0.01*	*2.11*	*1.70*	*2.00*
2003	0.28 **	0.08	0.46 ***	0.52 ***	0.14 *	-1.60	-	0.99 ***	0.61	-5.54
	2.06	*0.15*	*9.75*	*8.44*	*1.92*	*-1.53*		*4.29*	*1.60*	*-0.35*
2004	0.27 **	-0.89	0.48 ***	0.38 ***	0.18 **	2.87	-	0.20	-3.75	-2.36 *
	2.06	*-0.97*	*8.48*	*4.89*	*2.04*	*0.59*		*0.64*	*-0.59*	*-1.77*
2005	0.38 ***	0.18	0.63 ***	0.51 ***	0.03	-3.21	5.76	1.92 *	1.51	0.34
	2.62	*0.65*	*12.01*	*6.49*	*0.44*	*-0.38*	*0.32*	*1.93*	*0.74*	*0.37*
2006	0.66 ***	0.21	0.63 ***	0.68 ***	-0.04	0.85 **	0.56	-0.09	0.80	3.08
	8.26	*0.83*	*18.63*	*12.93*	*-0.94*	*2.21*	*0.77*	*-0.07*	*1.01*	*0.30*
2007	0.52 ***	0.33	0.54 ***	0.74 ***	-0.08 *	0.38 **	0.36	0.37 **	0.28	0.43 **
	6.68	*1.46*	*14.90*	*14.01*	*-1.66*	*2.15*	*0.24*	*2.50*	*0.85*	*2.51*
2008	0.62 ***	0.39 *	0.51 ***	0.76 ***	0.09 **	-0.05	-1.09	-4.06	-0.10	0.38
	10.12	*1.75*	*13.27*	*14.18*	*2.02*	*-0.13*	*-0.35*	*-0.56*	*-0.29*	*1.28*
2009	0.41 ***	0.51 **	0.64 ***	0.13	0.21 ***	-0.30	-2.72	0.67 ***	-3.49	0.73 ***
	7.40	*2.50*	*14.37*	*1.25*	*3.69*	*-0.76*	*-0.36*	*2.75*	*-0.87*	*3.42*

Notes: t-statistics in italics. Each line shows the coefficients for peer effects for different years. All the regressions use the same control variables as those reported in Table 4. All regressions include year, country-year and bank fixed-effects. *** significant at 1%; ** significant at 5%; * significant at 10%.