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The analyses, opinions and findings of these papers represent the views of the authors, they are not necessarily those of the Banco de Portugal or the Eurosystem

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Liquidity risk in banking: is there herding? *

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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, there may be incentives, related for instance to the role of the lender of last resort, for banks 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 herding behaviors, with an emphasis on the period preceding the global financial crisis. Herding is significant only among the largest banks, after adequately controlling for relevant endogeneity problems associated with the estimation of peer effects. This result suggests that the regulation of systemically important financial institutions may play an important role in mitigating this specific component of liquidity risk.

JEL Codes: G21, G28.

Keywords: banks, liquidity risk, regulation, herding, peer effects, Basel III, macro-prudential policy, systemic risk.

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1 Introduction

Banks transform liquid liabilities (deposits) into illiquid claims (loans). 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 (Diamond and Dybvig, 1983). There is a vast and prominent theoretical literature on this problem, but there is surprisingly scarce empirical evidence on banks' maturity mismatches and funding liquidity risk. Diamond and Dybvig (1983) provided the pillars for the analysis of banks' liquidity risk and bank runs. Other very relevant contributions include Klein (1971), Calomiris and Kahn (1991), Diamond and Rajan (2000, 2001a and 2001b), Allen and Gale (2004a, 2004b), and, more recently, Wagner (2007a) or Ratnovski (2009).

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 may have 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). When other banks are taking more risk, a given bank may be encouraged to pursue similar strategies if its managers believe they are likely to be rescued in case of distress. 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. As liquidity risk is usually regulated from a microprudential perspective, a better knowledge of these interactions among banks may have very important consequences on the design of macroprudential policy.

In this paper, we shed light on this issue by providing detailed empirical evidence on banks' liquidity risk management. We begin by discussing how to measure banks' liquidity risk, as several indicators may be relevant to quantify how exposed to this risk is an institution (Tirole, 2011). Subsequently, using a panel dataset of European and North-American banks for the period 2002-2009, we analyze which factors may be relevant in explaining why some banks adopt a globally prudent behavior in managing the liquidity risk underlying their financial intermediation functions, whereas others engage in more aggressive risk-taking strategies. Even though banks that concentrate most of their assets in lending are usually perceived as having a more traditional and perhaps more stable intermediation profile, we find that these are the banks that tend to show worse liquidity ratios.

It is possible to argue that banks do not optimize their liquidity choices strictly at the individual level. When other banks are taking more risk, any given bank may have the

incentives to engage in similar strategies. 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. Using data for European and North-American banks in the run up to the global financial crisis of the last few years, we empirically assess whether there is evidence of collective herding behavior of these banks in their liquidity risk management choices. This analysis is very relevant from a policy perspective, as it may contribute to the discussion on how regulation can provide the correct incentives to minimize negative externalities. In case of evidence of herding on risk-taking strategies in the run up to the financial crisis, future regulation should include harsher penalties for banks with riskier liquidity positions. The new Basel III package on liquidity risk already includes some features that constitute a positive step in this direction. Nevertheless, this regulation is still dominantly microprudential. Hence, when there is evidence of collective risk-taking behaviors on liquidity risk, additional macroprudential policy tools may need to be considered, such as additional liquidity buffers on the entire banking system or limits to certain types of exposures, in order to mitigate contagion and systemic risks.

We begin by analyzing the statistical dispersion of several liquidity indicators, as well as of the residuals of the equations used to study the determinants of banks' liquidity choices. Furthermore, we compute a measure of herd behavior, based on Lakonishok et al (1992). Our results suggest that there was some herding in the pre-crisis period, reflected in a global deterioration of liquidity indicators.

Nevertheless, these measures are clearly insufficient to fully identify herding behavior, as many factors may be driving the results. A multivariate setting allows to consider this issue in a more integrated way, through the estimation of the impact of peer effects (other banks' liquidity choices) on the liquidity indicators of each bank, while controlling for other potentially relevant explanatory variables. However, it is important to notice 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. Our solution to this critical identification problem relies on the use of an instrument, which has to be orthogonal to systematic or herding effects. Specifically, the instrument used for the peer effects is the predicted values of liquidity indicators of peer banks used in the regressions of the determinants of liquidity indicators. Thus, the predicted values depend on the characteristics of the banks in the peer group. These predicted values depend only

on observable bank characteristics and should therefore be orthogonal to herding effects. 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. Furthermore, by controlling also for time fixed-effects, we are able to orthogonalize all systematic and common shocks to banks. The benchmark peer group is the banks operating in the same country in each year.

After adequately dealing with the peer effect estimation, the results are not generally supportive of herding. However, we do find consistent and significant peer effects for the largest banks¹. These banks have similarities that may help to explain these results, as they have access to more diversified funding sources, they use more sophisticated risk management tools and, more importantly, they are more likely to be bailed out in case of distress. Hence, our results provide a strong argument for the regulation of systemically important financial institutions (SIFIs). So far, the Basel Committee regulatory proposals for SIFIs have focused on imposing additional capital requirements on these institutions. Even though these proposals, together with the new regulatory framework for liquidity risk, constitute a major step forward in reducing risk in banks and mitigating externalities, our results allow us to argue that there may be a missing element in the new regulatory setting: the systemic component of liquidity risk. More demanding capital requirements are certainly going to reduce risk-taking incentives for SIFIs in general, but there is some consensus that this is not the most adequate regulatory tool to deal with liquidity risk. Against this background, it may be desirable to impose also tighter liquidity requirements on these large systemic institutions, not only at the global level, but also at the domestic level.

The contribution of our paper is manifold. Even though the theoretical literature provides many relevant insights 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 and herding behavior. In this respect, we consider not only traditional herding measures, but we also 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 regulators, most notably in what concerns the regulation of the liquidity risk of SIFIs.

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

¹These results hold for several definitions of large banks.

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? More importantly, was this relevant to the build-up of global risks in the financial system that eventually led to the Great Recession? In Section 6 we summarize our main findings and discuss their policy implications.

2 Related literature and regulation

Over recent years, banks became increasingly complex institutions, being exposed to an intertwined set of risks. The 2008 financial crisis provided a painful illustration of how severe these risks can be and how they can seriously affect the real economy. However, regardless of how complex banks have become, there is an intrinsic risk that lies deep in their core function: banks are special due to their unique intermediation role. They grant loans to entrepreneurs and consumers, providing them with the necessary liquidity to finance their investment and consumption needs. However, banks use only a limited amount of their own resources to obtain this funding. Capital requirements on risky assets constitute a binding constraint for the minimum amount of own funds needed. Most of the funds used by banks are associated with liabilities to third parties. Traditionally, these liabilities would take the form of 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). However, the risk of runs acts as a disciplining device on banks (Diamond and Rajan, 2001b), given that depositors (Calomiris and Kahn, 1991), as well as borrowers (Kim et al, 2005), have incentives to monitor the risks taken by banks.

Through time, banks gained access to a more diversified set of liabilities to fund their lending activities, 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), amongst many others. The events that took place in 2007-2008 included at least one traditional bank run from depositors (on Northern Rock, in the UK), but also many other "runs" in markets that were important for banks' funding². For a long period,

²In fact, Northern Rock was more affected by the "run" on wholesale funding than by the traditional depositor run.

interbank markets froze and most banks were not able to issue debt, even if guaranteed by high quality assets (as in the case of covered bonds)³.

The increased reliance on wholesale funding makes the relationship between funding and market liquidity risk much stronger, as discussed by Brunnermeier and Pedersen (2009), Cai and Thakor (2009), Drehmann and Nikolau (2009), Freixas et al (2011), Krishnamurthy (2010), Milne (2008), Strahan (2008), and Tirole (2011). Funding and market liquidity risk are two distinct concepts: whereas the former can be broadly defined as the risk of losing access to funding (through the form of runs or refinancing risk), the latter can be defined as the ability to sell assets without disrupting their markets prices (see, for instance, Cai and Thakor, 2009, Milne, 2008, or Tirole, 2011). Brunnermeier and Pedersen (2009) and Brunnermeier (2009) show that under certain conditions market and funding liquidity risk may be mutually reinforcing, leading to liquidity spirals, most notably when there are systemic risk concerns. For example, if a bank is not able to rollover some of its debt, it may be forced to sell some of its assets to obtain liquidity. However, the fire sale of assets will depress asset prices and shrink banks' assets, given that they are marked-to-market, thus making access to funding even more constrained (Nikolau, 2009).

Given this, even though banks are the main providers of liquidity to the economy (Berger and Bowman, 2009; Diamond and Dybvig, 1983), they have to adequately manage the liquidity risk underlying their balance sheet structure, as their maturity transformation function makes them inherently illiquid. To alleviate the maturity gap between assets and liabilities, banks can hold a buffer of liquid assets (Acharya et al, 2011, Allen and Gale, 2004a and 2004b, Farhi et al, 2009, Gale and Yorulmazer, 2011, Rochet and Vives, 2004, Tirole, 2011, and Vives, 2011). However, holding liquid assets is costly, given that they provide lower returns than illiquid assets. Moreover, holding a liquidity buffer may also be inefficient, as it limits banks' ability to provide liquidity to entrepreneurs and consumers. Hence, even though banks have some incentives to hold a fraction of liquid assets (in the form of cash, short term assets or government bonds, for instance), these buffers will hardly ever be sufficient to fully insure against a bank run or a sudden dry up in wholesale markets.

Against this setting, regulation becomes necessary to mitigate some of these risks. One justification for the need to regulate liquidity risk is related to the fact that banks do not take into account the social optimum when they optimize the relationship between risk and return. However, a bank failure may constitute a huge externality on other banks and, ultimately, on the whole economy. This risk is exacerbated by the fact that liquidity shocks are events with very low probability (though with potentially very high impact), thus

³For further details and analysis of the freeze in interbank markets and constraints in debt issuance during the global financial crisis see Acharya and Merrouche (2012), Afonso et al (2011), Allen and Carletti (2008), Angelini et al (2011), Brunnermeier (2009), or Cornett et al (2011).

making it easy to overlook them during good periods. 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. Ex-ante regulation of banks' liquidity may mitigate this behavior. Many other authors share the view that liquidity risk regulation is necessary (Acharya et al, 2011, Brunnermeier et al, 2009, Cao and Illing, 2010, Gale and Yourlmazer, 2011, Holmstrom and Tirole, 1998, and Tirole, 2011, for example).

However, a consensus is far from being reached on the optimal regulatory framework to mitigate liquidity risk, both academically and politically, though a remarkable progress has been achieved during the last few years. Traditionally, reserve requirements on bank deposits were the main tool for liquidity risk management, though they also play an important role in the implementation of monetary policy (Robitaille, 2011). More importantly, deposit insurance is by now broadly recognized as an important tool in preventing depositors' bank runs⁴. Explicit deposit insurance can sustain runs on bank deposits, as shown by Diamond and Dybvig (1983)⁵. However, deposit insurance can only be efficient in minimizing the likelihood of bank runs by depositors. For instance, Bruche and Suarez (2010) show that deposit insurance can cause a freeze in interbank markets, when there are differences in counterparty risk. Indeed, deposit insurance is not sufficient to forestall all liquidity-related risks and may generate moral hazard (Ioannidou and Penas, 2010, Martin, 2006). Given the increased diversification of banks' funding sources (Strahan, 2008), other regulatory mechanisms must be envisaged to ensure the correct alignment of incentives. The dispersion of creditors and the diversification of risks and activities undertaken by banks make this issue even more complex.

Recent and ongoing discussions have suggested the possibility of further increasing capital requirements to also include liquidity risks⁶ (Brunnermeier et al, 2009⁷). However, there are several opponents to this view. As argued by Ratnovski (2007), funding liquidity risk is in part related to asymmetric information on banks' solvency. Increasing solvency without reducing the asymmetric information problem would not reduce refinancing risk. Perotti

⁴During the recent crisis, many governments in advanced economies decided to increase the coverage of their national deposit insurance schemes to avoid panic runs.

⁵However, Demirgüç-Kunt and Detragiache (2002) find that explicit deposit insurance increases the likelihood of banking crises, using data for 61 countries. This empirical result is stronger when bank interest rates are deregulated, the institutional environment is weak and the scheme is run or funded by the government.

⁶In Basel II, capital requirements were set to explicitly cover credit, market and operational risks, but not liquidity risk.

⁷The model in Diamond and Rajan (2001b) implicitly considers this possibility.

and Suarez (2009) have also put forth a proposal regarding a liquidity insurance mechanism to avoid systemic crises.

Many authors discuss the importance of holding a liquidity buffer. In a recent paper, Ratnovski (2009) discusses the trade-offs between imposing quantitative requirements on banks' liquidity holdings and improving the incentive scheme in lender of last resort policies. This author argues that quantitative requirements can achieve the optimal liquidity level, but not without imposing costs, whereas a lender of last resort policy that takes into account bank capital information may reduce distortionary rents, thus allowing for a more efficient solution. Nevertheless, transparency seems to be a critical issue in the latter case, as also discussed in Ratnovski (2007). There are many other contributions in the academic literature pointing to the possibility of imposing minimum holdings of liquid assets (Acharya et al, 2011, Allen and Gale, 2004a and 2004b, Farhi et al, 2009, Gale and Yorulmazer, 2011, Rochet and Vives, 2004, Tirole, 2011, and Vives, 2011). 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.

Against this background, the new international regulatory framework will be based on imposing minimum holdings of liquid assets. Globally, liquidity risk regulation was perhaps somewhat overlooked before the global financial crisis, with almost non-existent internationally harmonized rules (Rochet, 2008). However, the role played by funding liquidity during the global financial crisis made clear that a new international regulatory framework was necessary. In December 2010, the Basel Committee disclosed the final version of the international framework for liquidity risk regulation (Basel Committee, 2010), which is an important part of the new Basel III regulatory package. This new regulation provides the necessary incentives for banks to hold adequate liquidity buffers and to avoid over relying on short-term funding. Liquidity risk regulation will be based upon two key indicators: the Liquidity Coverage Ratio (LCR) and the Net Stable Funding Ratio (NSFR). The LCR will require 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. In turn, the NSFR is a longer-term 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 two indicators are complementary and ensure that banks hold an adequate pool of liquid assets, while simultaneously adopting a reasonable and prudent maturity mismatch.

Still, when regulation fails to preemptively address risks, there is always the lender of last resort. Bagehot (1837) was amongst the first to acknowledge that such mechanism was a central piece in crisis management⁸. Since then, the consensus has been to lend freely, usually at penalty rates, to all solvent but illiquid banks (though it is in practice very hard to draw the line between solvency and liquidity problems). The recent financial crisis demonstrated the importance of the lender of last resort. From August 2007 onwards, the freeze in interbank money markets made lending from central banks worldwide crucial⁹. The failure of Lehman Brothers in September 2008 vividly demonstrated the dramatic consequences of a failure of a systemic financial institution¹⁰. 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. For instance, Gonzales-Eiras (2004) finds that banks' holding of liquid assets decrease when there is a lender of last resort, using a natural experiment in Argentina. This moral hazard problem is further aggravated by systemic behavior¹¹.

Indeed, when most banks are overtaking 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 prof-

⁸"Theory suggests, and experience proves, that in a panic the holders of the ultimate bank reserve (whether one bank or many) should lend to all that bring good securities quickly, freely, and readily. By that policy they allay a panic; by every other policy they intensify it.", Bagehot (1837).

⁹Lending from central banks during the initial stages of the crisis occurred mainly through monetary policy operations and not through emergency liquid assistance (which corresponds to the function of lender of last resort). Again, for further details and analysis of the freeze in interbank markets in 2007 we refer to Afonso et al (2011), Allen and Carletti (2008), Angelini et al (2011), Brunnermeier (2009), and Cornett et al (2011).

¹⁰Two excellent analyzes of the crisis are Acharya and Richardson (2009) and Brunnermeier et al (2009). Both present a set of proposals to rethink the regulation of the financial system globally.

¹¹Citigroup'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".

itability without increasing the likelihood of bankruptcy, due to the explicit or implicit bail out commitment of the lender of last resort. 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. Given all these market failures, regulation is needed to ensure that these externalities are considered by banks in their liquidity risk management. Nevertheless, the costs and distortions generated by such regulation also need to be taken into account. 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. Collective risk taking incentives and behaviors are also discussed by Acharya (2009), Acharya and Yorulmazer (2008), Boot (2011), Rajan (2006), and Tirole (2011). 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).

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 usually have to repeatedly refinance their assets. This refinancing risk is larger the wider is the mismatch between assets' and liabilities' average maturities. 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. Nevertheless, this risk can be mitigated if banks hold a sufficiently large buffer of highly liquid and good quality assets, which they can easily use when hit by unforeseen funding shocks.

In this section, we briefly review several ways to measure funding liquidity risk, which will later be used in our empirical analysis. 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. This section also includes a brief description of the data used in this paper and an overview of banks' liquidity and funding choices in the years preceding the global financial crisis.

3.1 Liquidity indicators

An analysis of balance sheet structure can provide an important insight on banks' liquidity risk. More specifically, the ratio between credit granted and deposits taken from customers provides a broad structural characterization of banks' main funding risks. Given that customers deposits are a broadly stable funding source (in the absence of bank runs), those banks that finance most or all of their credit with deposits should, *ceteris paribus*, be less exposed to liquidity risk. In contrast, banks that show a large funding gap, i.e., a very high loan-to-deposit ratio, will be more exposed to this risk, as they will need to rely on wholesale funding markets¹². Against this background, banks in which wholesale market funding as a percentage of assets is higher will be more sensitive to refinancing risk. This latter risk will be higher the shorter is the maturity of market funding. Hence, the analysis of the balance sheet structure based on the above mentioned liquidity indicators (loan-to-deposit ratio, funding gap or market funding as a percentage of assets) does not allow for a complete assessment of liquidity risk, as these indicators are unable to take into account the maturity mismatch between assets and liabilities.

Another important dimension of funding liquidity risk that became a key issue since the summer of 2007 is the reliance on interbank funding. Interbank markets allow markets to close, by allowing banks with short-term liquidity needs to obtain funds from other banks with temporary excess liquidity. However, after August 2007, unsecured money markets became severely impaired for a long period (Afonso et al, 2011, Cornett et al, 2011, Brunnermeier, 2009, Allen and Carletti, 2008, and Angelini et al, 2011). Wagner (2007a) shows that the interbank markets may be inefficient in providing liquidity when banks are hit by aggregate liquidity shocks. Against this background, the interbank ratio, measured, for instance, as the ratio between interbank assets and interbank liabilities, may also be an important input to the assessment of liquidity risk. In fact, if banks structurally rely on funding from interbank markets, which is usually characterized by very short maturities, they may have severe difficulties in rolling over their debt in periods of distress.

Finally, another important dimension of liquidity risk is related to the buffer of liquid assets held by banks. 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

¹²It is also possible that the mismatch between loans and deposits is financed with more equity, rather than with wholesale funding. If a bank has strong equity ratios and does not rely on wholesale funding, a high loan-to-deposit ratio does not imply strictly higher risk. However, very few banks rely entirely on deposit funding, as most banks approach the interbank market to match short-term mismatches between assets and liabilities and many banks obtain regular funding from debt markets. To control for this interaction between equity and the loan-to-deposit ratio, we control for capital ratios in the multivariate analysis conducted in this paper (see sections 3 and 4).

constraints. In this respect, the ratio of liquid assets to short-term funding also provides important insights into banks' liquidity risk.¹³

Given the challenges in measuring funding liquidity risk, our empirical analysis will be based on the analysis of three complementary indicators: the credit to deposit ratio, an interbank ratio and a liquidity ratio, defined in detail in Section 3.3. These indicators allow us to capture different dimensions of liquidity risk, including structural balance sheet risks, exposures to short-term funding in interbank markets and the availability of a pool of highly liquid assets to face unexpected shocks.

3.2 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 banks were not included in the dataset, as they usually have different liquidity risk profiles and funding strategies. Using these filters, we collect data for the 500 largest banks (according to Bankscope's universal ranking) during 8 years, for 43 countries¹⁴. Excluding banks without information on total assets, we obtain 2968 bank-year observations. Almost half of the observations refer to banks in Canada, France, Germany, Italy, Netherlands, Russian Federation, UK and US.

In Table 1 we summarize major characteristics of the banks included in the sample. To avoid having results affected by outliers, all variables were winsorised in their 1st and 99th percentiles. We observe that there is a substantial dispersion in bank size, measured by total assets. The average Tier 1 capital ratio is 12% (10.2% for the median bank). There is also substantial dispersion in banks' profitability, measured both by return on assets and by the net interest margin, and in banks' efficiency, measured by the cost-to-income ratio. Loans represent more than half of the assets of the banks included in the sample, even though

¹³A more complete liquidity indicator would rely on the overall maturity mismatch between assets and liabilities. However, the data necessary for such an indicator is not usually available.

¹⁴These countries are 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, Monaco, Netherlands, Norway, Poland, Portugal, Romania, Russian Federation, San Marino, Serbia, Slovakia, Slovenia, Spain, Sweden, Switzerland, Turkey, Ukraine, United Kingdom, and United States. In Bosnia-Herzegovina, Iceland, Liechtenstein, Monaco and San Marino there are less than 10 observations for the entire sample period. Given this, we exclude these five countries from all cross-country analysis.

the table shows that there are banks with very different specializations, as loans range from 2.6% to 92.8% of banks' assets.

Insert Table 1 about here

3.3 An overview of banks' liquidity and funding choices in the run up to the global financial crisis

In Table 2 we summarize the information on liquidity risk for the banks included in the sample. Taking into account our discussion of liquidity indicators in Section 3.1, we focus our analysis of liquidity risk on three different indicators: i) *loans to customer deposits*; ii) the *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) the *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. All these variables are computed in a standardized way in the Bankscope database. In Panel A of Table 2 we present summary statistics for these three indicators and in Panel B we depict their evolution during the sample period. In Figures 1 to 6 we present the empirical distributions of these indicators.

Insert Table 2 about here

As mentioned above, the ratio between loans and customer deposits is a structural indicator of funding liquidity risk. A ratio above 100% means that the bank has to finance part of its loans with wholesale market funding, which may be more expensive and less stable than customer deposits. The difference between loans and customer deposits is usually referred to as the funding gap. During the last decades, banks have moved from a traditional intermediation paradigm in which most loans were funded through deposits (thus implying loan to deposits ratios below 100%) to a new framework of bank funding. As access to wholesale markets became more generalized, banks were able to diversify their funding sources. This had implications on the maturity transformation role of banks. Looking at our sample period, we observe a consistent increase in this ratio, from 116.7 per cent in 2002 to 148.8 per cent in 2008. There is a significant dispersion in the ratios recorded by banks in different countries.

Insert Figures 1-2 about here

However, this indicator, in and by itself, is insufficient to globally assess the liquidity position of credit institutions. Several limitations of this indicator can be mentioned. First, it is essentially a structural indicator and thus strategic and cyclical changes may take some time to be reflected in the data. Second, the increased use of securitization operations by European 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). Finally, this indicator does not take into account the maturity mismatch between assets and liabilities, which is a key element of liquidity risk analysis.

The interbank ratio allows to assess another dimension of bank's funding liquidity risk, evaluating whether banks are net borrowers or net lenders in interbank markets. As we define this indicator as the ratio between loans to other banks and loans from other banks, a ratio above 100% means that a bank is a net lender in interbank markets, thus signaling a more comfortable liquidity position than otherwise.

During our sample period, this ratio decreased gradually, thus implying a deterioration on the average position of banks in these markets. Comparing the interbank positions at the beginning and end of the sample period, some countries recorded a significant decline, whereas others recorded the opposite evolution. All in all, Figure 4 clearly illustrates that the dispersion in this ratio decreased markedly during the sample period.

The freeze in interbank markets observed since the financial market turmoil started in August 2007 makes the intertemporal analysis of this ratio more challenging. During most of the global financial crisis, the lack of confidence led to severe disruptions in the functioning of interbank markets. Uncollateralized operations almost ceased to exist during significant periods and high haircuts were imposed on collateralized operations. Thus, there is a clear series break in this indicator from August 2007 onwards, which will be analyzed further ahead.

Insert Figures 3-4 about here

Again, the interbank ratio allows for the evaluation of only one dimension of liquidity risk. A perhaps more encompassing indicator is the ratio of liquid assets to customer and short-term funding. The lower the ratio, the more challenging it may be for banks to honor their short-term financial commitments. This ratio increased up until the financial turmoil in the summer of 2007. Hence, there does not seem to exist evidence of any dilapidation of the buffer of liquid assets or of a relative increase in short-term funding of European and North-American banks in the run up to the crisis. However, in 2008 there was a marked deterioration in this liquidity ratio, mainly due to the strong growth in customer and short-

term funding. As shown in Figure 6, there was a decrease in dispersion after the global financial crisis, with fewer banks showing good ratios.

Again, the cross-country dispersion is considerable. For most countries, this ratio shows a remarkable volatility during the sample period, as it easily reflects changes in banks' strategic behavior in terms of liquidity risk management.

Insert Figures 5-6 about here

All in all, the analysis of these complementary liquidity indicators shows that there is a considerable heterogeneity in liquidity indicators both across countries and over time. Before the crisis, the loan-to-deposit ratio and the interbank ratio showed some deterioration. In turn, the liquidity ratio decreased after the crisis started, with a marked growth of customer deposits and short-term funding (while liquid assets recorded only a mild increase). Hence, even though most banks did not have to sell liquid assets to face short term funding needs, their maturity profile took a pronounced turn for the worse. During this period, many banks were not able to issue medium and long-term debt securities, thus shortening the average maturity of their liabilities.

In the next section we will provide some insight on which factors are relevant to explain the heterogeneity in 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 three liquidity indicators described in the previous section: i) loans to customer deposits (column 1); ii) the interbank ratio (column 2); and iii) the liquidity ratio (column 3). All specifications use robust standard errors and bank fixed-effects, such that:

$$\begin{aligned}
 Liq_{it} = & \alpha_0 + \alpha_i + \beta_1 Capital_{it-1} + \beta_2 Banksize_{it} + \beta_3 Profitability_{it-1} + \beta_4 Cost_inc_{it-1} + \\
 & + \beta_5 Lend_spec_{it-1} + \beta_6 (Liq - x_{it-1}) + i_t + \varepsilon_{it}
 \end{aligned} \tag{1}$$

where Liq_{it} is one of the three liquidity indicators analyzed (loan-to-deposit ratio, interbank ratio and liquidity ratio, respectively), α_0 is a constant, α_i is the bank fixed effect,

i_t is the year fixed effect and ε_{it} is the estimation residual. As explanatory variables, we use a set of core bank indicators on solvency, size, profitability, efficiency and specialization. $Capital_{it}$ is the Tier 1 capital ratio calculated according to the rules defined by the Basel Committee. $Banksize_{it}$ is measured by the log of Assets and $profitability_{it}$ includes the return on assets and the net interest margin. $Cost_inc_{it}$ refers to the cost-to-income ratio, which is a proxy for cost-efficiency, and $lend_spec_{it}$ measures to what extent a bank is specialized in lending, by considering net loans as a percentage of total assets. Finally, $(Liq - x_{it})$ refers to the other liquidity indicators, i.e., $x_{it} \neq -x_{it}$. All variables are lagged by one period to mitigate concerns of simultaneity and reverse causality.

Insert Table 3 about here

Across the board, the most relevant variable in explaining liquidity indicators is bank specialization, measured as net loans as a percentage of total assets: banks that are more specialized in lending to customers have, as would be expected, higher loan to deposit ratios, but also lower interbank ratios (i.e., they are more likely net borrowers) and lower liquidity ratios. Globally, these are banks with more vulnerable funding structures. Bank size is an important determinant of interbank ratios, as larger banks seem more likely to be net borrowers than net lenders in the interbank market. This result is consistent with evidence for the US interbank market presented by King (2008). We also find that more profitable banks tend to show lower liquidity buffers. 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 sum, banks that concentrate most of their assets in lending are usually perceived as having a more traditional, and perhaps more stable, intermediation profile. Nevertheless, these are the banks that tend to show worse liquidity ratios. Hence, even though these banks are usually deemed as globally less prone to risk-taking, they tend to show larger funding gaps and maturity mismatches.

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. For instance, Goodhart and Schoenmaker (1995) show that banks are more often rescued than liquidated in case of distress. Against this background, when other banks are taking more risk, a specific bank may have the incentives to engage in similar strategies. 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, as theoretically conjectured by Ratnovski (2009).

In this section, we try to find evidence of possible herding behavior of banks in liquidity risk management, specially in the years before the global financial crisis. We begin by analyzing different statistics that may provide some insight on this issue. However, the identification and measurement of peer effects on individual choices is a challenging econometric problem, as discussed by Manski (1993). In section 5.2 we briefly discuss these identification problems and in section 5.3 we propose an empirical strategy to address these concerns and present our results.

5.1 Some statistics

Figures 1 to 6 show that there is considerable dispersion in liquidity indicators and, in some cases, the distribution of liquidity indicators changed significantly over time. Hence, a further analysis of the concentration of these liquidity indicators over time may provide some insight about possible trends in banks' collective or systematic behavior. Furthermore, this assessment may be complemented with an analysis of the distribution of the residuals from equation (1). Indeed, the explanatory variables considered are not able to fully capture the heterogeneity in liquidity indicators across banks (as exemplified by the low R^2). Thus, the analysis of what is left unexplained by the available observables may also provide some intuition on herding or collective behavior. The results of this analysis are presented in Table 4.

Insert Table 4 about here

In columns (1), (6) and (11) we compute the Gini coefficient over time for the three liquidity indicators. This coefficient is a measure of statistical dispersion and evaluates the inequality in a given distribution, ranging between 0 and 1. A higher Gini coefficient implies more dispersion. Moreover, the standard deviation and the coefficient of variation (which is the standard deviation normalized by the mean of the distribution) of the indicators

also allow to analyze how the distribution of liquidity indicators has evolved over time. These dispersion measures may also be used to characterize the residuals, assessing the dispersion in the component of liquidity indicators that is not explained by observable bank characteristics and how it changed during the sample period¹⁵.

The dispersion of the loan-to-deposit ratio increased slightly during the sample period according to all the dispersion measures considered, except in two years: 2003 and 2009. Indeed, after the crisis emerged, loan to deposit ratios became much more concentrated, as illustrated also in Figure 2. The coefficient of variation was relatively stable over the years. In turn, the dispersion in the residuals was higher from 2006 to 2008. The coefficient of variation of the residuals was specially large in 2006, immediately before the crisis. All in all, the choices of banks regarding the loan-to-deposit ratio became broadly less concentrated during the sample period.

In what concerns the interbank ratio, the overall concentration is less marked than in the loan-to-deposit ratio and it is harder to identify a clear pattern over time. The Gini coefficient and the coefficient of variation show that dispersion increased in 2007, 2008 and 2009. This observation may reflect the marked discrimination in interbank markets since mid-2007. The coefficient of variation for the residuals recorded its maximum in 2007. Hence, this was the year in which the regression model failed more acutely in predicting the interbank ratio based on bank characteristics. Taking all these results into account, it is not possible to find evidence suggesting possible strategic interactions between banks before the crisis, though it seems to be clear that the strong tensions in interbank markets in 2007 led to changes in these indicators.

Finally, the concentration in the liquidity ratio decreased considerably until 2005, but remained relatively stable after that. However, the maximum dispersion of the residuals was achieved between 2004 and 2006, showing that the unexplained part of the liquidity ratio became more dispersed during this period. All in all, this (partial) evidence may suggest some herding behavior immediately before the global financial crisis, though the evidence is not clear cut.

5.1.1 A traditional measure of bank herd behavior

A natural extension to the analysis conducted thus far is to estimate measures of herding frequently used in financial markets (see, for example, Graham, 1999, Grinblatt et al, 1995, Scharfstein and Stein, 1990, or Wermers, 1999). To do that, we adapt the often used herding measure proposed by Lakonishok et al (1992) and applied to bank herding by Uchida and Nakagawa (2007) and, more recently, by Van den End and Tabbae (2012). This methodology

¹⁵The Gini coefficient cannot be computed for the residuals, as these take negative values.

allows testing the extent to which the liquidity choices of banks collectively deviate from what could be suggested by overall macroeconomic conditions. Implicitly, we are considering a concept of "rational herding", as defined by Devenow and Welch (1996). In other words, we do not consider that banks simply mimic each other's behaviors, but rather that they do so because there are important externalities that affect the optimal decision making process.

We compute:

$$H_i = |P_i - P_t| - E|P_i - P_t|$$

where P_i is the proportion of banks that show an increase in risk for a given liquidity indicator in each country and in each year, computed as $\frac{X_i}{N_i}$. X_i is the number of banks that recorded a deterioration of a liquidity indicator in a country in a given year, and N_i is the total number of banks operating in each country and in each year. For the loan-to-deposit ratio, X_i refers to the number of banks that showed an increase in this ratio, while for the other two liquidity indicators X_i refers to the number of banks that recorded a decrease in these indicators, i.e., an increase in risk. P_t is the mean of P_i in each year. P_t can be interpreted as an indicator of banks' liquidity choices that reflect overall macroeconomic and financial conditions. The difference between P_i and P_t measures to what extent liquidity indicators in one country and in one year deviate from the overall liquidity indicators in that year, i.e. from common factors. According to the methodology proposed by Lakonishok et al (1992), when banks independently increase or decrease liquidity indicators, P_i and P_t become closer and $|P_i - P_t| \rightarrow 0$. However, when several banks collectively deviate and increase or decrease their liquidity indicators, P_i departs from P_t . The second term in the equation is used to normalize the herding measure.

Computing this at the country level is crucial if we consider that the incentives for herding are much stronger amongst national peers. The common belief of bail out is more likely to be shared by banks in the same country. Indeed, the arguments to support that banks take riskier strategies because banks operating in other countries do so are much weaker than when considered at the national level. This will be particularly true if competition between banks exists within markets segmented by national borders.

Table 5 shows our estimates for this herding measure for the three liquidity indicators. In some years we find significant evidence of herding behavior, most notably in the years preceding the global financial crisis. For the loan-to-deposit ratio, there was statistically significant herding behavior in 2003 and 2005. Collective risk-taking behavior also seems to have been present in interbank markets between 2004 and 2006. The results are even stronger for the liquidity ratio, with significant results for the entire pre-crisis period (2003 to 2007). Finally, we also observe some herding during the crisis in the loan-to-deposit ratio.

This may reflect a general decrease in this ratio due to a collective deleveraging process in some countries during this period.

Insert Table 5 about here

All in all, these results, taken together with previous evidence, support the hypothesis of collective risk taking before the crisis. Nevertheless, this traditional herding measure has several limitations and cannot be regarded as a full characterization of collective risk taking. This is essentially a static measure and, more importantly, it only considers whether or not there was an increase in risk, without considering its magnitude. Furthermore, this measure does not take into account all other possible determinants of liquidity choices. It is possible that common behaviors are observed because banks are affected by common shocks or because they share common characteristics, rather than by true herding behavior. Hence, only in a multivariate setting, where bank specific characteristics and time effects are explicitly controlled for, it becomes possible to isolate the impact of other banks' choices on each individual bank. In the next subsection we deal with the identification challenges raised by this multivariate analysis.

5.2 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:

$$\begin{aligned}
 Liqx_{it} = & \alpha_0 + \alpha_i + \beta_0 \sum_{j \neq i} \frac{Liqx_{jt}}{N_{it} - 1} + \beta_1 capital_{it-1} + \beta_2 banksize_{it} + \beta_3 profitability_{it-1} + \\
 & + \beta_4 Cost_inc_{it-1} + \beta_5 lend_spec_{it-1} + \beta_6 (Liq - x_{it-1}) + i_t + \varepsilon_{it}
 \end{aligned} \tag{2}$$

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 this setting, the coefficient β_0 captures the extent to which banks' liquidity choices reflect those of the relevant peer group.

However, this estimation entails serious 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) exogenous or contextual effects, related to the influence of exogenous peer characteristics; ii)

endogenous effects, arising from the influence of peer outcomes (in our case, peers’ liquidity choices); and iii) correlated effects, which affect simultaneously all elements of a peer group. Empirically, it is very challenging to disentangle these 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 would not allow for the accurate estimation of peer effects. Our solution to this important identification problem relies on the use of an instrument 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 group¹⁶. As discussed in Brown et al (2008) and Leary and Roberts (2010), such an instrument must be orthogonal to systematic or herding effects. Given this, 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 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. As we control also for time effects, we are able to orthogonalize all systematic shocks to banks. Furthermore, the predicted values of peer banks should be highly correlated with the average of the observed liquidity indicators, our potentially endogenous variable¹⁷.

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

$$\begin{aligned}
 Liqx_{it} = & \alpha_0 + \alpha_i + \beta_0 \sum_{j \neq i} \frac{Liqx_{jt}}{N_{it} - 1} + \beta_1 capital_{it-1} + \beta_2 banksize_{it} + \beta_3 profitability_{it-1} + \\
 & + \beta_4 Cost_inc_{it-1} + \beta_5 lend_spec_{it-1} + \beta_6 (Liq - x_{it-1}) + i_t + \varepsilon_{it}
 \end{aligned} \tag{3}$$

¹⁶Other 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.

¹⁷For a similar solution to the identification of peer effects using instrumental variables, see Leary and Roberts (2010).

where the first step equation is

$$\sum_{j \neq i} \frac{Liqx_{jt}}{N_{it} - 1} = \alpha_0 + \alpha_j + \gamma_1 \sum_{j \neq i} \frac{Liq_predx_{jt}}{N_{it} - 1} + \beta_1 capital_{jt-1} + \beta_2 banksize_{jt} + \beta_3 profitability_{jt-1} + \beta_4 Cost_inc_{jt-1} + \beta_5 lend_spec_{jt-1} + \beta_6 (Liq - x_{jt-1}) + i_t + \varepsilon_{it}$$

where $\sum_{j \neq i} \frac{Liq_predx_{jt}}{N_{it} - 1}$ represents the average predicted values for $Liqx_{it}$ for the peer group in the equation:

$$Liq_predx_{it} = \alpha_0 + \alpha_i + \beta_1 Capital_{it-1} + \beta_2 Banksize_{it} + \beta_3 Profitability_{it-1} + \beta_4 Cost_inc_{it-1} + \beta_5 Lend_spec_{it-1} + \beta_6 (Liq - x_{it-1}) + i_t$$

Using this specification, we are able to identify peer effects, after adequately having dealt with the reflection problem. If neglected, this problem could lead to severely biased results.

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 bail out 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. 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.

5.3 Empirical results

In Table 6 we present the results of the instrumental variable approach in the estimation of peer effects in liquidity risk management.

In the first three columns we present, for illustrative purposes, 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 biased, estimation, we find strong evidence of positive peer or herding effects in individual banks' choices of loan to deposit ratios (column (1)) and of the liquidity ratio (column (3)). The higher the funding gap of other banks in a given country, the higher should be the loan to deposit ratio of a given bank in that country. At the same time, the lower the average liquidity ratio of peers is (either because they hold few liquid assets or because they rely excessively on short-term funding) the more vulnerable is a bank's liquidity position. In what concerns the interbank ratio, this specification does not yield any significant results regarding peer effects.

Insert Table 6 about here

The second group of columns displays our main empirical results, when adequately dealing with the serious 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 three columns do not hold: peer effects are not statistically significant in any of the three regressions, even though for the liquidity ratio the associated coefficient remains positive and large. Thus, there seems to be a strong indication that neglecting endogeneity in peer effects may originate biased and incorrect results.

This lack of significance cannot be attributed to the weakness of the instrument used. 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 that 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 6 we show that the chosen instrument is strongly statistically significant in the two regressions most affected by the endogeneity problem: the one on loan-to-deposit ratios and the other on the liquidity ratio.

However, given that our previous measures of herding behavior suggested the existence of peer effects, we consider that it is important to run several robustness tests before rejecting the hypothesis of collective behavior in a multivariate setting.

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) to (3), and (4) to (6), respectively. First step regressions are reported in columns (7) to (9).

Insert Table 7 about here

First, we exclude the crisis period, so as to focus the analysis on possible peer effects in the years before the global financial crisis. By doing this, we obtain strong and significant peer effects for the liquidity ratio when we neglect the endogeneity problem, but when this issue is taken care of with the instrument, the results become statistically insignificant.¹⁸

Second, we include a set of country-specific macroeconomic variables, to better control for differences across countries¹⁹. Again, we obtain significant peer results when instruments are not considered, but they disappear as soon as endogeneity is addressed.

Third and fourth, we made some adaptations in the definition of variables: first we consider as the dependent variable the change in liquidity indicators (instead of the level), and then we consider all variables in first differences. In both cases, peer effects continue to lack statistical significance after the endogeneity problem is dealt with.

Fifth, we restrict our sample to banks that are using IFRS, so as to ensure that the results are not affected by changes in accounting standards during the sample period. Again, peer effects fail to be significant when the instrument is used.

Finally, 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. Still, the results remain consistent.

5.3.1 Alternative peer group definitions

In Table 8 we explore a different type of robustness analysis, by testing alternative definitions of peer groups. Indeed, the definition of the peer group is a critical issue in the analysis of peer effects (Manski, 2000) and deserves further analysis. Even though we believe that defining peers as other banks in the same country is the most reasonable assumption, due to the common lender of last resort, this definition may be challenged.

¹⁸We also interacted the peer effects with the year dummies, so as to identify possible peer effects in specific years. Still, the results are not statistically significant. In addition, we ran the regressions only with data from 2004 onwards, as there are slightly less observations for some countries in the first two years of the sample. Again, the peer effects continue to lack statistical significance. These results are available upon request.

¹⁹Macroeconomic and financial data were collected from the International Financial Statistics of the International Monetary Fund. The variables included are short-term interest rates, change in the consumer price index, real GDP growth and credit growth.

Insert Table 8 about here

First, we consider that it is possible to argue that peer choices should not necessarily affect the decisions of a given bank contemporaneously. To take that into account, we use lagged peer effects instead. Still, when we consider last year's liquidity indicators, we continue to be unable to obtain statistically significant and valid peer effects.

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 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 might not be implausible, as again we obtain some significant and valid peer effects, now for the liquidity ratio.

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. Quite interestingly, this peer group definition is able to deliver statistically significant peer effects in interbank ratios, after controlling for the endogeneity problem: when many other large banks are net borrowers (or lenders) in interbank markets, a given bank has a higher likelihood to follow the same trend.

We obtain further confirmation that peer effects seem indeed to be more relevant amongst larger banks when we run separate regressions for the larger banks (in the 3rd and 4th quartiles) and for the smaller banks (1st and 2nd quartiles), as we obtain significant results only in the former group.

When we consider other groups of large banks, such as banks that are classified among the top 5 in each country or banks belonging to the systemically important financial institutions (SIFIs) list recently disclosed by the Financial Stability Board, we obtain again significant results for the loan-to-deposit and the interbank ratios, respectively. Nevertheless, we do not obtain significant results for another group of large banks, namely those belonging to the Euribor panel.

Given the strong financial integration in the euro area, we also test whether banks operating in euro area countries behave as a peer group, but the results are not statistically significant.

Furthermore, we test whether banks with similar characteristics tend to herd. We obtain very significant results both for banks with similar liquidity indicators and for banks with similar characteristics. However, these results may be affected by some endogeneity problems.

Finally, we test if some banks are following other banks' choices, even if not belonging to the same peer group. More precisely, we test whether small banks follow large banks, using different size definitions. The only significant results are obtained for smaller banks following banks that belong to the Euribor panel.

5.3.2 Summary

In sum, when all banks are considered, evidence on peer effects is statistically weak, after dealing with the endogeneity problem. These results are consistent with the evidence obtained by Jain and Gupta (1987), who analyze herding effects between US commercial banks, finding only weak evidence of herd behavior.

However, we are able to find consistent and significant evidence that peer effects are important determinants in the liquidity choices of the largest banks. There are several possible related reasons behind this result. First, larger banks are likely to compete mainly among themselves, replicating risk-taking strategies that allow for profit maximization. Second, larger banks have access to more diversified funding sources, usually with lower funding costs, thus allowing them to collectively engage in similar funding and liquidity strategies. Third, larger banks may have better liquidity risk management tools, reflected in similar liquidity choices. Finally, and perhaps more importantly, larger banks are more likely to be bailed out in case of systemic distress than smaller banks, thus facing more similar incentives.

Given that peer effects in liquidity risk management are significant only for the largest banks, it is possible to argue that the regulation on systemically important financial institutions may play an important role in reducing incentives for collective risk-taking (Acharya, 2009, Acharya and Yorulmazer, 2008, Boot, 2011, Rajan, 2006, and Tirole, 2011). Hence, even though the Basel III regulatory package does not explicitly deal with the systemic component of liquidity risk, it is possible that the more demanding regulatory requirements for systemically important financial institutions help to better align risk-taking incentives.

6 Concluding remarks and policy implications

Banks' liquidity risk was at the core of the global financial crisis since 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 on 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.

By adapting the herding measure proposed by Lakonishok et al (1992) to our setting we find that there was some herding behavior in the pre-crisis period, reflected in a broad deterioration of liquidity indicators. Given the limitations of this measure, we extend our analysis to a multivariate setting. However, 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 as an instrumental variable 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. Using this methodology we can find evidence of robust and significant peer effects only for the largest banks. These banks are more likely to compete (internationally) among themselves, engaging in similar profit maximizing and risk taking strategies. Furthermore, these larger banks use more sophisticated risk management tools and have access to more diversified funding sources. However, more important than all this is to consider that these banks are usually perceived as being more likely to be bailed out in case of distress, as they are usually too-big or too-interconnected-to-fail. This serious moral hazard problem in banking encourages excessive risk-taking, and has fuelled an encompassing debate on the need to regulate systemically important financial institutions (SIFIs).

Our results provide an important contribution to this policy debate. As collective risk-taking incentives are concentrated mainly among the largest banks worldwide, regulation is warranted 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. At a different level,

the Basel Committee has also issued proposals for the regulation of SIFIs, focusing on the imposition of additional capital requirements on these institutions. 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. In addition, more demanding capital requirements are certainly going to reduce risk-taking incentives for SIFIs in general. However, there is some consensus that capital requirements are not the most adequate regulatory tool to deal with liquidity risk. Against this background, our results suggest that it may be desirable to impose also tighter liquidity requirements on these large systemic institutions, not only at the global level, but also at the domestic level.

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Tables and figures

Table 1 - Banks' characteristics

	N	mean	min	p1	p25	p50	p75	p99	max
Total assets	2944	490,722	495	495	3,200	12,557	60,015	26,700,000	26,700,000
Total capital ratio	2177	14.6	8.1	8.1	11.1	12.9	15.6	49.1	49.1
Tier 1 ratio	1958	12.0	4.9	4.9	8.3	10.2	13.1	49.1	49.1
Net interest margin	2931	3.0	0.0	0.0	1.4	2.4	3.9	11.8	11.8
Return on assets	2936	0.9	-4.2	-4.2	0.4	0.8	1.4	4.5	4.5
Cost to income	2915	61.6	16.1	16.1	49.8	59.5	70.8	150.5	150.5
Net loans to total assets	2932	55.6	2.6	2.6	42.0	59.7	72.1	92.8	92.8

Notes: 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.

Table 2 - Liquidity indicators - summary statistics

Panel A - Global summary statistics									
	N	mean	min	p1	p25	p50	p75	p99	max
Loans to customer deposits	2744	133.9	0.3	5.3	76.5	106.1	151.2	738.1	961.3
Interbank ratio	2403	139.5	0.0	0.5	29.5	70.6	160.9	892.1	998.6
Liquidity ratio	2926	37.8	-6.6	1.1	15.5	28.8	46.6	172.8	842.3

Panel B - Liquidity indicators over time (mean)									
	2002	2003	2004	2005	2006	2007	2008	2009	Total
Loans to customer deposits	116.7	105.2	116.4	131.0	134.9	137.5	148.8	139.7	133.9
Interbank ratio	212.3	182.3	156.4	148.0	147.1	136.6	106.8	116.2	139.5
Liquidity ratio	39.6	37.4	35.9	38.5	38.8	36.5	32.1	32.2	37.8

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 variables in this table are included in the Bankscope database.

Table 3 - Determinants of liquidity indicators

Dependent variable:	Loan to deposit ratio	Interbank ratio	Liquidity ratio
	(1)	(2)	(3)
Tier 1 ratio t_{-1}	-0,48 <i>-0,67</i>	0,90 <i>0,70</i>	0,27 <i>1,18</i>
Log Assets t	7,30 <i>0,78</i>	-29,31 * <i>-1,84</i>	-0,65 <i>-0,25</i>
Net interest margin t_{-1}	-2,36 <i>-1,22</i>	-3,98 <i>-0,76</i>	0,03 <i>0,05</i>
Return on assets t_{-1}	3,26 <i>0,80</i>	-2,54 <i>-0,47</i>	-1,29 * <i>-1,87</i>
Cost-to-income t_{-1}	0,09 <i>0,39</i>	0,17 <i>0,65</i>	-0,06 <i>-1,06</i>
Net loans to total assets t_{-1}	1,75 *** <i>4,19</i>	-2,25 *** <i>-2,64</i>	-0,43 *** <i>-5,13</i>
Loans to customer deposits t	- -	0,01 <i>0,19</i>	0,00 <i>0,12</i>
Interbank ratio t_{-1}	0,00 <i>-0,37</i>	- -	0,00 <i>0,17</i>
Liquidity ratio t_{-1}	0,34 * <i>1,84</i>	-0,31 <i>-0,79</i>	- -
D2004	-6,07 <i>-0,85</i>	-23,45 <i>-0,77</i>	-3,25 <i>-1,05</i>
D2005	-5,43 <i>-0,47</i>	-19,70 <i>-0,65</i>	-4,99 <i>-1,48</i>
D2006	-0,42 <i>-0,03</i>	-10,66 <i>-0,34</i>	-3,88 <i>-1,04</i>
D2007	-2,05 <i>-0,15</i>	-18,42 <i>-0,56</i>	-4,79 <i>-1,15</i>
D2008	8,66 <i>0,60</i>	-38,14 <i>-1,19</i>	-9,48 ** <i>-2,17</i>
D2009	-5,49 <i>-0,35</i>	-30,74 <i>-1,00</i>	-8,89 * <i>-1,94</i>
Constant	-40,0 <i>-0,43</i>	585,9 *** <i>3,16</i>	73,77 *** <i>2,58</i>
<hr/>			
Number of observations	1.217	1.253	1.216
Number of banks	323	342	322
R2 within	0,108	0,074	0,221
R2 between	0,125	0,007	0,440
R2 overall	0,140	0,007	0,411

Notes: All regressions include bank fixed-effects and robust standard errors. The Tier 1 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. The variables in this table are included in the Bankscope database.

Table 4 - Dispersion in liquidity indicators and residuals

	Loans to customer deposits			Residuals		Interbank ratio			Residuals		Liquidity ratio			Residuals	
	Gini coef.	Std. Dev	Coef. of variation	Std. Dev	Coef. of variation	Gini coeffic	Std. Dev	Coef. of variation	Std. Dev	Coef. of variation	Gini coeffic	Std. Dev	Coef. of variation	Std. Dev	Coef. of variation
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
2002	0,42	121,3	1,0			0,54	221,5	1,0			0,39	29,7	0,8		
2003	0,34	84,5	0,8	92,7	-25,5	0,56	209,8	1,2	219,5	-17,3	0,39	28,2	0,8	16,8	-3,3
2004	0,34	90,6	0,8	73,2	-6,4	0,55	181,4	1,2	187,0	8,9	0,41	29,3	0,8	19,7	-28,4
2005	0,36	111,1	0,8	70,5	-10,8	0,59	195,2	1,3	189,9	70,9	0,43	32,6	0,8	22,2	47,4
2006	0,37	114,7	0,9	99,8	-672,1	0,57	182,4	1,2	172,3	37,2	0,42	32,3	0,8	22,3	38,8
2007	0,37	111,5	0,8	91,1	72,1	0,58	181,2	1,3	160,8	-98,2	0,42	30,3	0,8	21,5	37,9
2008	0,38	124,8	0,8	117,5	17,8	0,59	142,7	1,3	134,1	-38,0	0,43	27,8	0,9	19,3	47,4
2009	0,37	117,7	0,8	83,0	-95,6	0,61	166,0	1,4	163,7	-45,9	0,44	28,7	0,9	19,9	-25,7
Total	0,37	112,5	0,8	94,4	-	0,59	164,6	1,2	220,4	-	0,42	30,1	0,8	20,7	-

Notes: The table displays the Gini coefficients of the three liquidity indicators (columns 1, 6 and 11), the standard deviations of these indicators (columns 2, 7 and 12) and of the residuals of the regressions on the determinants of these liquidity indicators (columns 4, 9 and 14), as well as the coefficient of variation for the indicators and the residuals (columns 3, 5, 8, 10, 13 and 15). The residuals refer to the results of the estimations shown in Table 3. The coefficient of variation for the total residuals is impossible to compute as the average of the residuals is zero. 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 ratio of liquid assets to customer and short term funding 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 variables in this table are included in the Bankscope database.

Table 5 - Measurement of herd behavior (mean)

	Loans to customer deposits			Interbank ratio	Liquidity ratio
2003	0.063	***		-0.004	-0.019 **
2004	0.011			0.024 ***	0.039 ***
2005	0.028	***		-0.014 **	-0.017 ***
2006	-0.008			-0.017 ***	0.022 ***
2007	-0.005			0.003	-0.032 ***
2008	-0.011	*		0.001	0.004
2009	-0.028	***		0.010	0.005

Notes: Herd behavior measure based on Uchida and Nakagawa (2007) and Lakonishok et al (1992). The herding measure is computed as $H_i = |P_i - P_t| - E|P_i - P_t|$, where P_i is the proportion of banks that show an increase in risk for a given liquidity indicator in each country and in each year (i.e., increases in loan to deposit ratios or decreases in the interbank or liquidity ratio) and P_t is the mean of P_i in each year. Liquidity indicators as defined in previous tables. *** significant at 1%; ** significant at 5%; * significant at 10%.

Table 6 - Regressions on peer effects in liquidity strategies

	Interaction with other banks - country year rivals (without IV)			Interaction with other banks (country year rivals) - IV = predicted values of rivals' liquidity ratios			First-step regressions		
	Loans to customer deposits	Interbank ratio	Liquidity ratio	Loans to customer deposits	Interbank ratio	Liquidity ratio	Loans to customer deposits	Interbank ratio	Liquidity ratio
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Peers' loans to customer deposits	0,223 *** <i>3,04</i>	-	-	-0,118 <i>-0,26</i>	-	-	0,453 *** <i>3,58</i>	-	-
Peers' interbank ratio	-	0,158 <i>1,31</i>	-	-	-0,785 <i>-0,20</i>	-	-	-0,062 <i>-0,60</i>	-
Peers' liquidity ratio	-	-	0,248 *** <i>2,82</i>	-	-	0,224 <i>0,38</i>	-	-	0,250 *** <i>3,65</i>
Tier 1 ratio $t-1$	-0,673 <i>-0,94</i>	0,767 <i>0,58</i>	0,259 <i>1,10</i>	-0,494 <i>-0,88</i>	0,481 <i>0,33</i>	0,272 ** <i>2,48</i>	0,688 ** <i>2,37</i>	-0,197 <i>-0,38</i>	0,023 <i>0,45</i>
Loans to customer deposits $t-1$	-	-0,013 <i>-0,20</i>	0,000 <i>0,03</i>	-	0,015 <i>0,07</i>	0,000 <i>-0,04</i>	-	0,047 <i>1,06</i>	0,000 <i>0,08</i>
Interbank ratio $t-1$	-0,004 <i>-0,42</i>	-	0,000 <i>0,10</i>	-0,003 <i>-0,19</i>	-	-0,001 <i>-0,34</i>	0,012 <i>1,43</i>	-	0,000 <i>0,02</i>
Liquidity ratio $t-1$	0,341 * <i>1,91</i>	-0,380 <i>-0,98</i>	-	0,345 ** <i>2,04</i>	-0,176 <i>-0,19</i>	-	0,021 <i>0,20</i>	0,209 <i>1,15</i>	-
Log Assets t	4,527 <i>0,50</i>	-25,788 <i>-1,48</i>	-0,536 <i>-0,20</i>	7,436 <i>0,90</i>	-48,428 <i>-0,51</i>	-0,251 <i>-0,17</i>	7,432 * <i>1,83</i>	-25,161 *** <i>-3,38</i>	-0,328 <i>-0,48</i>
Net interest margin $t-1$	-2,092 <i>-1,10</i>	-4,229 <i>-0,78</i>	0,061 <i>0,09</i>	-2,345 <i>-1,06</i>	-0,234 <i>-0,01</i>	0,215 <i>0,40</i>	-0,745 <i>-0,56</i>	4,062 * <i>1,82</i>	0,398 * <i>1,72</i>
Return on assets $t-1$	2,579 <i>0,64</i>	-1,814 <i>-0,34</i>	-1,110 <i>-1,63</i>	3,056 <i>0,88</i>	-7,664 <i>-0,43</i>	-1,224 <i>-1,61</i>	3,922 ** <i>2,19</i>	-4,040 <i>-1,27</i>	-0,601 * <i>-1,94</i>
Cost-to-income $t-1$	0,097 <i>0,44</i>	0,164 <i>0,64</i>	-0,054 <i>-0,99</i>	0,093 <i>0,66</i>	0,289 <i>0,49</i>	-0,055 * <i>-1,75</i>	0,028 <i>0,32</i>	0,124 <i>0,82</i>	-0,003 <i>-0,23</i>
Net loans to total assets $t-1$	1,636 *** <i>4,08</i>	-2,015 ** <i>-2,33</i>	-0,386 *** <i>-4,54</i>	1,702 *** <i>4,01</i>	-2,427 <i>-0,97</i>	-0,373 *** <i>-3,62</i>	0,599 *** <i>3,30</i>	-0,612 * <i>-1,85</i>	-0,127 *** <i>-4,34</i>
D2004	-8,956 <i>-1,20</i>	-36,012 <i>-1,17</i>	-3,567 <i>-1,22</i>	-15,6 <i>-1,4</i>	-36,0 <i>-0,6</i>	-3,8 <i>-1,5</i>	-1,0 <i>-0,1</i>	-14,6 <i>-1,2</i>	0,7 <i>0,6</i>
D2005	-10,791 <i>-0,93</i>	-32,382 <i>-1,11</i>	-5,705 * <i>-1,75</i>	-15,4 <i>-1,4</i>	-55,3 <i>-0,6</i>	-6,0 ** <i>-2,4</i>	7,1 <i>1,1</i>	-26,2 ** <i>-2,2</i>	2,3 * <i>2,0</i>
D2006	-7,352 <i>-0,58</i>	-23,103 <i>-0,79</i>	-4,621 <i>-1,27</i>	-7,0 <i>-0,5</i>	-43,9 <i>-0,4</i>	-4,8 * <i>-1,8</i>	12,2 * <i>1,8</i>	-28,2 ** <i>-2,2</i>	2,7 ** <i>2,2</i>
D2007	-8,704 <i>-0,63</i>	-	-5,103 <i>-1,27</i>	-8,7 <i>-0,7</i>	-59,9 <i>-0,4</i>	-5,4 ** <i>-2,1</i>	9,4 <i>1,3</i>	-37,3 *** <i>-2,7</i>	1,3 <i>1,0</i>
D2008	-0,878 <i>-0,06</i>	-	-8,697 ** <i>-2,11</i>	4,1 <i>0,2</i>	-100,4 <i>-0,4</i>	-9,3 ** <i>-2,4</i>	16,2 ** <i>2,1</i>	-63,9 *** <i>-4,2</i>	-2,0 <i>-1,3</i>
D2009	-13,166 <i>-0,87</i>	-40,883 <i>-1,36</i>	-8,154 * <i>-1,86</i>	-11,5 <i>-0,8</i>	-85,5 <i>-0,5</i>	-8,8 ** <i>-2,2</i>	16,3 ** <i>2,2</i>	-52,0 *** <i>-3,5</i>	-2,1 <i>-1,4</i>
Constant	-27,3 <i>-0,30</i>	534,4 ** <i>2,56</i>	61,2 ** <i>2,02</i>	-15,4 <i>-0,21</i>	930,7 <i>0,55</i>	58,8 * <i>1,78</i>	-61,4 <i>-1,39</i>	450,1 *** <i>5,17</i>	36,1 *** <i>4,32</i>
Fixed-effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Number of observations	1.211	1.241	1.210	1.180	1.222	1.178	1.180	1.222	1.178
Number of banks	323	342	322	323	342	322	323	342	342
R2 within	0,127	0,083	0,236	0,076	.	0,223	0,000	0,000	0,000
R2 between	0,153	0,019	0,452	0,108	0,010	0,453	0,013	0,031	0,174
R2 overall	0,176	0,019	0,429	0,114	0,007	0,434	0,039	0,002	0,214

Notes: All regressions include bank fixed-effects. Peers are defined as the $j \neq i$ banks operating in the same country and in the same year as bank i . Columns 1, 2 and 3 show the results obtained when peer liquidity choices are considered directly in the regressions, i.e., not addressing the reflection problem. Columns 4 to 6 show the results of three 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 columns 1, 2 and 3 of Table 3, respectively. Columns 7, 8 and 9 show the first stage estimation results for these three instrumental variables regressions. The Tier 1 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. The variables in this table are included in the Bankscope database.

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

	Interaction with other banks - country year rivals (without IV)			Interaction with other banks (country year rivals) - IV = predicted values of rivals' liquidity ratios			First-step regressions			
	Loans to customer deposits	Interbank ratio	Liquidity ratio	Loans to customer deposits	Interbank ratio	Liquidity ratio	Loans to customer deposits	Interbank ratio	Liquidity ratio	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	
Before the crisis										
Peer effects	0,011 <i>0,67</i>	0,074 <i>0,46</i>	0,439 *** <i>3,32</i>	0,936 <i>0,54</i>	0,803 <i>0,27</i>	0,453 <i>0,49</i>	-0,217 <i>-0,90</i>	-0,148 <i>-0,68</i>	0,231 * <i>1,76</i>	
Including macro variables										
Peer effects	0,247 *** <i>2,90</i>	-0,055 <i>-0,42</i>	0,202 ** <i>2,06</i>	-0,611 <i>-0,75</i>	-0,955 <i>-0,19</i>	0,211 <i>0,36</i>	0,331 *** <i>2,88</i>	-0,045 <i>-0,51</i>	0,281 *** <i>3,80</i>	
Dependent variable: changes in liquidity ratios										
Peer effects	0,091 * <i>1,72</i>	0,124 <i>1,52</i>	0,170 ** <i>2,30</i>	-1,406 <i>-0,56</i>	0,954 <i>0,77</i>	9,451 <i>0,10</i>	-0,139 <i>-0,95</i>	-0,279 * <i>-1,68</i>	0,008 <i>0,10</i>	
All variables as first differences										
Peer effects	0,066 <i>0,94</i>	0,090 <i>0,80</i>	0,268 *** <i>2,66</i>	-1,776 <i>-0,63</i>	0,344 <i>0,27</i>	11,942 <i>0,14</i>	-0,136 <i>-0,93</i>	-0,264 <i>-1,59</i>	0,012 <i>0,14</i>	
Only banks using IFRS accounting standards										
Peer effects	0,209 *** <i>3,17</i>	0,157 <i>1,40</i>	0,187 * <i>1,94</i>	-0,064 <i>-0,12</i>	6,723 <i>0,10</i>	1,337 <i>0,15</i>	0,404 *** <i>2,92</i>	-0,013 <i>-0,10</i>	0,023 <i>0,26</i>	
Removing banks with asset growth above 50%										
Peer effects	0,210 *** <i>2,84</i>	0,127 <i>1,17</i>	0,254 *** <i>2,98</i>	-1,352 <i>-0,41</i>	-5,487 <i>-0,33</i>	0,483 <i>1,02</i>	0,096 <i>0,70</i>	-0,047 <i>-0,36</i>	0,344 *** <i>4,33</i>	

Notes: Peers are defined as the $j \neq i$ banks operating in the same country and in the same year as bank i . Each line shows the coefficients for these peer effects for different robustness tests. The pre-crisis period refers to the years 2002-2006. The macro variables included in the second group of regressions are the short-term interest rate, the change in the consumer price index, real GDP growth and credit growth (using IMF/IFS data). In the third group of regressions, the dependent variable was first-differenced, whereas in the fourth group this procedure was applied to all the variables. Columns 1, 2 and 3 show the results obtained when peer liquidity choices are considered directly in the regressions, i.e., not addressing the reflection problem. Columns 4 to 6 show the results of three 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 columns 1, 2 and 3 of Table 3, respectively. Columns 7, 8 and 9 show the first stage estimation results for these three instrumental variables regressions.

All the regressions use the same control variables as those reported in Table 6. All regressions include bank fixed-effects.

Table 8 - Regressions on peer effects in liquidity strategies - robustness on peer group definition

	Interaction with other banks - country year rivals (without IV)			Interaction with other banks (country year rivals) - IV = predicted values of rivals' liquidity ratios			First-step regressions		
	Loans to customer deposits	Interbank ratio	Liquidity ratio	Loans to customer deposits	Interbank ratio	Liquidity ratio	Loans to customer deposits	Interbank ratio	Liquidity ratio
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Lagged peers									
Peer effects	0,095 ** <i>2,01</i>	0,003 <i>0,05</i>	0,013 <i>0,15</i>	-0,438 <i>-0,61</i>	-3,402 <i>-0,51</i>	0,007 <i>0,01</i>	0,346 *** <i>2,86</i>	-0,074 <i>-0,58</i>	0,231 *** <i>2,86</i>
Peers as other banks (in other countries) in the same quartile									
Peer effects	0,238 <i>1,17</i>	-0,108 <i>-0,33</i>	-0,147 <i>-1,06</i>	0,349 <i>1,10</i>	-0,242 <i>-0,37</i>	0,786 * <i>1,84</i>	1,032 *** <i>13,09</i>	0,441 *** <i>12,94</i>	0,890 *** <i>10,46</i>
Large banks (4th quartile in each country)									
Peer effects	0,003 <i>0,05</i>	0,193 ** <i>2,35</i>	0,040 <i>0,63</i>	0,099 <i>0,52</i>	0,810 ** <i>2,28</i>	0,135 <i>0,82</i>	1,157 *** <i>6,31</i>	0,719 *** <i>4,01</i>	1,022 *** <i>6,06</i>
Only larger banks (3rd and 4th quartiles)									
Peer effects	0,262 *** <i>3,38</i>	0,221 * <i>1,96</i>	0,228 *** <i>2,81</i>	-0,807 * <i>-1,72</i>	0,586 * <i>1,83</i>	0,333 <i>1,00</i>	0,514 *** <i>3,59</i>	1,167 *** <i>4,60</i>	0,532 *** <i>4,81</i>
Only smaller banks (1st and 2nd quartiles)									
Peer effects	0,199 *** <i>2,97</i>	-0,091 * <i>-1,91</i>	0,128 <i>1,64</i>	3,951 <i>0,69</i>	0,699 <i>0,87</i>	-0,103 <i>-0,04</i>	0,103 <i>0,73</i>	-0,384 *** <i>-2,64</i>	0,082 <i>0,75</i>
Only larger banks (top 5 in each country)									
Peer effects	0,047 <i>1,44</i>	0,383 *** <i>3,61</i>	0,261 ** <i>2,33</i>	0,418 ** <i>1,99</i>	0,887 <i>1,51</i>	-0,030 <i>-0,14</i>	0,632 *** <i>4,34</i>	0,563 ** <i>2,17</i>	0,801 *** <i>5,08</i>
Only larger banks (banks classified as SIFIs)									
Peer effects	-0,491 ** <i>-2,36</i>	0,025 <i>0,46</i>	0,369 ** <i>2,24</i>	-0,146 <i>-0,06</i>	0,115 * <i>1,69</i>	-0,992 <i>-0,31</i>	0,026 <i>0,44</i>	2,081 *** <i>4,98</i>	0,105 <i>0,48</i>
Only larger banks (banks that belong to the Euribor panel)									
Peer effects	-0,275 <i>-0,78</i>	-0,236 <i>-1,51</i>	0,178 <i>0,80</i>	0,772 <i>0,97</i>	-1,344 <i>-0,38</i>	1,260 <i>1,41</i>	0,565 *** <i>2,89</i>	0,075 <i>0,43</i>	0,478 ** <i>2,32</i>
Euro area as one peer group									
Peer effects	0,198 ** <i>2,35</i>	0,201 <i>1,38</i>	0,410 *** <i>3,98</i>	0,210 <i>0,72</i>	1,072 <i>0,63</i>	0,263 <i>0,57</i>	0,837 *** <i>6,88</i>	0,184 <i>1,50</i>	0,392 *** <i>5,64</i>
Banks with similar liquidity ratios (cluster)									
Peer effects	0,670 *** <i>13,09</i>	0,920 *** <i>65,28</i>	0,222 *** <i>4,22</i>	0,333 *** <i>5,60</i>	0,690 ** <i>1,99</i>	0,196 *** <i>3,20</i>	1,446 *** <i>11,13</i>	-0,161 <i>-1,02</i>	1,584 *** <i>28,00</i>
Banks with similar characteristics (cluster)									
Peer effects	0,260 *** <i>4,02</i>	0,044 <i>0,40</i>	0,239 *** <i>4,80</i>	0,404 *** <i>4,13</i>	-0,082 <i>-0,19</i>	0,304 *** <i>6,72</i>	1,136 *** <i>20,78</i>	0,327 *** <i>7,45</i>	1,867 *** <i>43,65</i>
Small banks following large banks (4th quartile)									
Peer effects	0,262 *** <i>2,95</i>	0,116 <i>1,42</i>	-0,123 <i>-1,36</i>	0,108 <i>0,39</i>	-0,310 <i>-1,01</i>	0,078 <i>0,35</i>	0,782 *** <i>6,90</i>	0,846 *** <i>5,31</i>	0,930 *** <i>5,89</i>
Small banks following large banks (top 5)									
Peer effects	0,036 <i>0,29</i>	0,068 <i>0,51</i>	-0,006 <i>-0,13</i>	-0,568 <i>-1,24</i>	-0,556 <i>-0,92</i>	-0,224 <i>-1,26</i>	0,350 *** <i>5,68</i>	0,422 *** <i>3,62</i>	1,054 *** <i>7,09</i>
Small banks following large banks (SIFI list)									
Peer effects	-0,130 <i>-1,62</i>	-0,067 <i>-0,46</i>	0,039 <i>0,50</i>	-0,011 <i>-0,03</i>	-0,382 <i>-0,74</i>	0,297 <i>0,90</i>	0,538 *** <i>9,46</i>	0,895 *** <i>4,96</i>	0,327 *** <i>4,28</i>
Small banks following large banks (Euribor panel)									
Peer effects	0,260 <i>0,88</i>	-0,087 *** <i>-3,22</i>	0,120 <i>1,50</i>	0,582 <i>1,35</i>	0,231 <i>0,84</i>	0,660 *** <i>2,73</i>	0,633 *** <i>9,01</i>	1,107 *** <i>24,34</i>	0,657 *** <i>8,85</i>

Notes: Peers are defined as the $\#i$ banks operating in the same country and in the same year as bank i . Each line shows the coefficients for these peer effects for different robustness tests. Bank quartiles were defined based on banks' total assets. Top 5 refers 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. Ten cluster groups were defined for banks with similar liquidity indicators and with similar characteristics (using the explanatory variables presented in Table 3). Columns 1, 2 and 3 show the results obtained when peer liquidity choices are considered directly in the regressions, i.e., not addressing the reflection problem. Columns 4 to 6 show the results of three 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 columns 1, 2 and 3 of Table 3, respectively. Columns 7, 8 and 9 show the first stage estimation results for these three instrumental variables regressions.

All the regressions use the same control variables as those reported in Table 6. All regressions include bank fixed-effects.

Figure 1

Empirical distribution of the ratio between loans and customers deposits

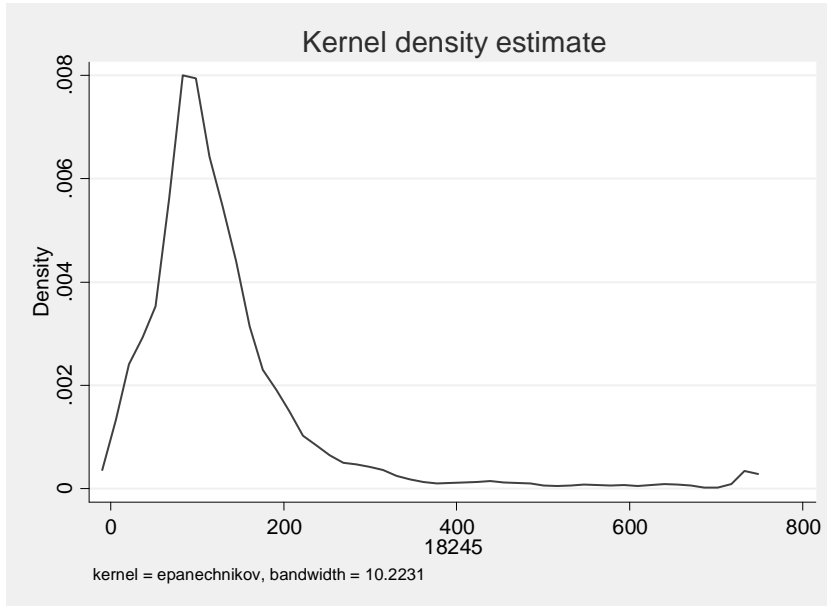


Figure 2

Empirical distribution of the ratio between loans and customers deposits - by year

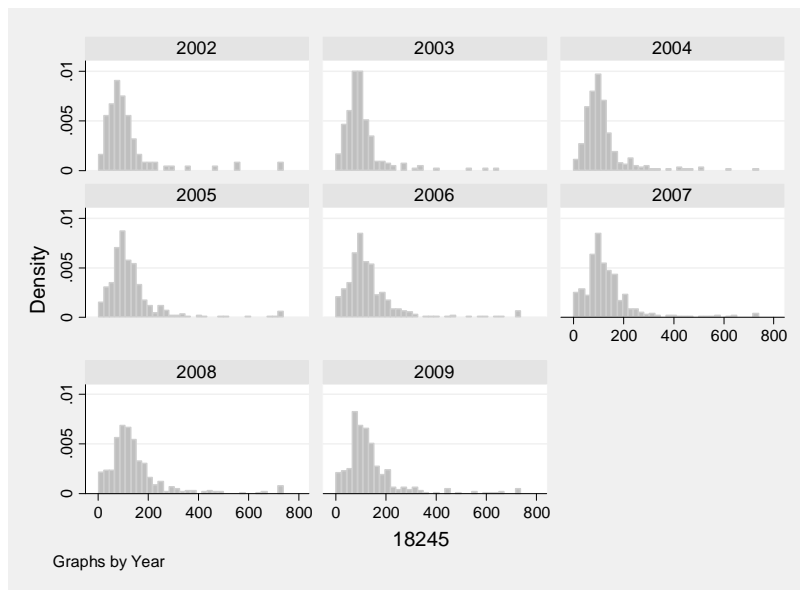
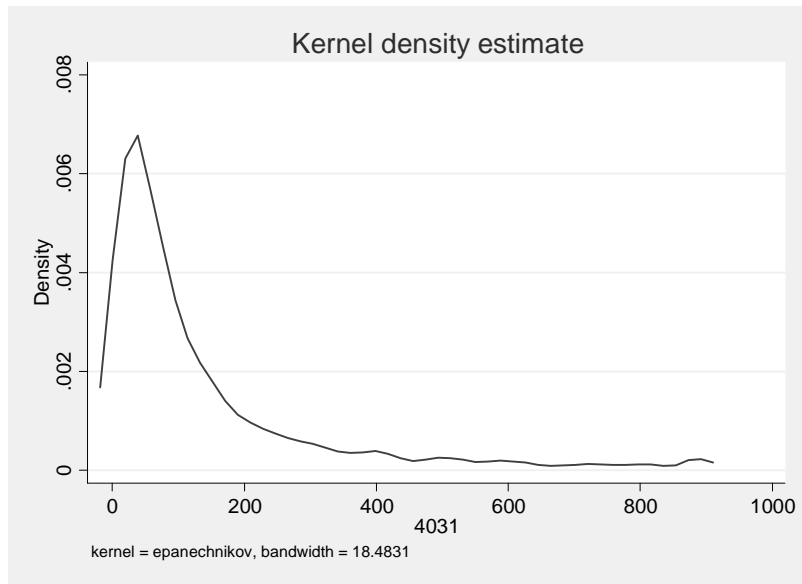
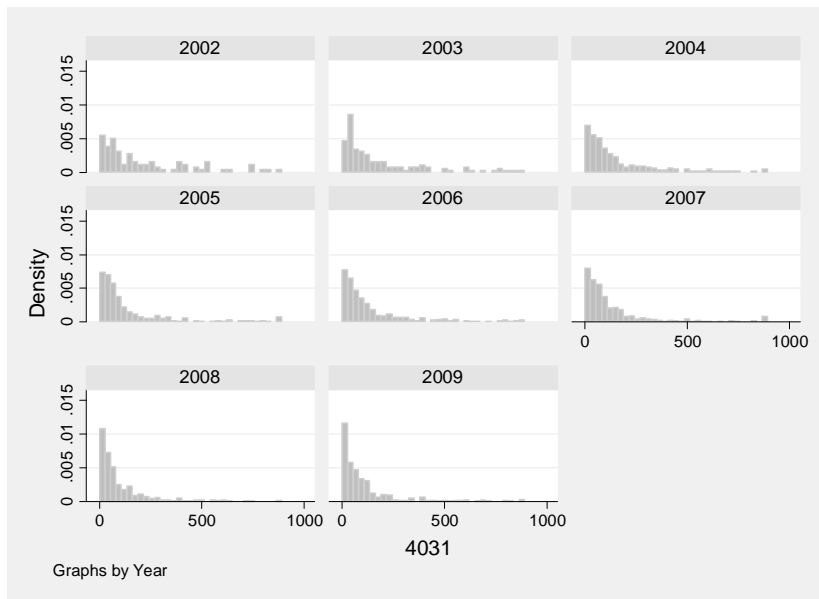


Figure 3
Empirical distribution of the interbank ratio



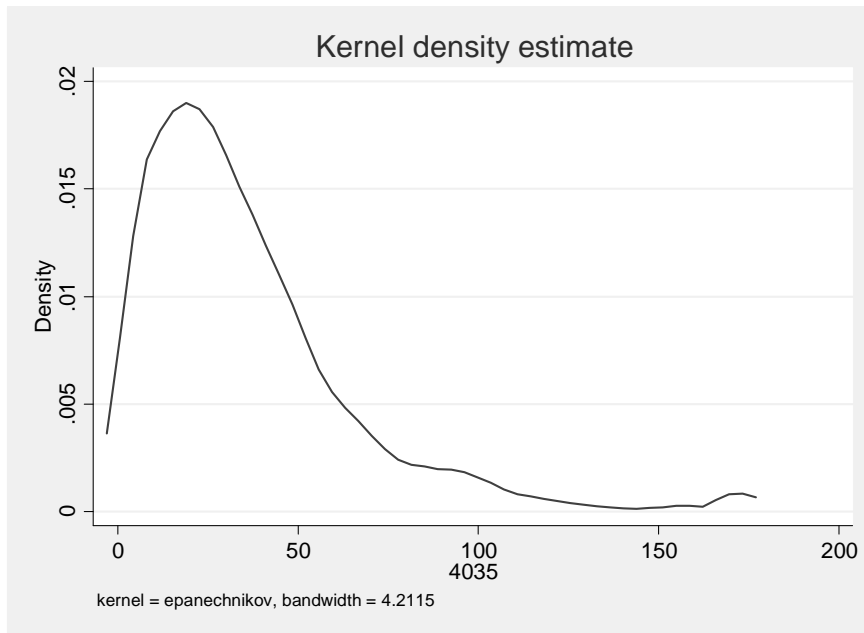
Note: The interbank ratio is defined as interbank assets as a percentage of interbank liabilities (loans to other banks as a percentage of loans from other banks).

Figure 4
Empirical distribution of the interbank ratio - by year



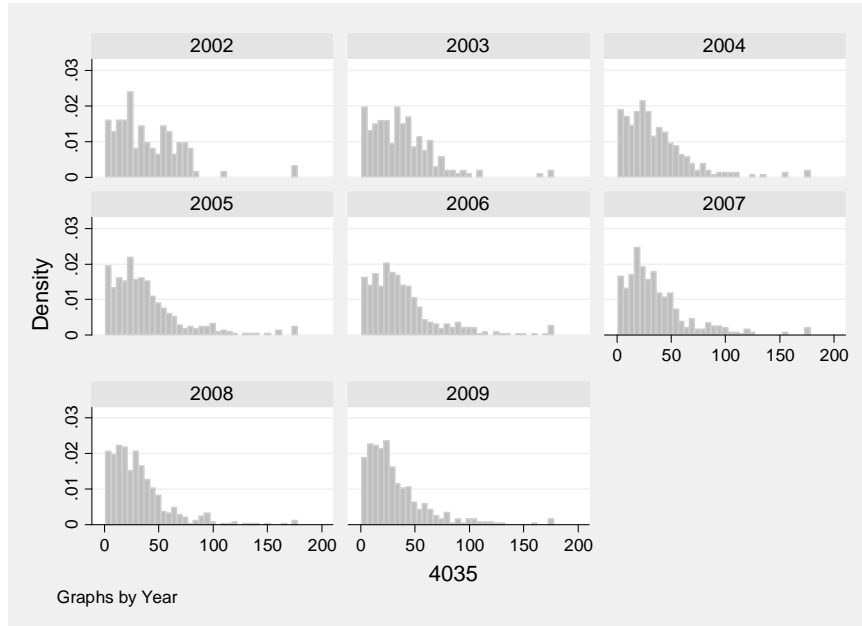
Note: The interbank ratio is defined as interbank assets as a percentage of interbank liabilities (loans to other banks as a percentage of loans from other banks).

Figure 5
Empirical distribution of the liquidity ratio



Note: 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.

Figure 6
Empirical distribution of the liquidity ratio - by year



Notes: 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.

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