Liquidity Risk and Collective Moral Hazard*

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

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1. Introduction

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

In this paper, we contribute to fill this gap by empirically analyzing the way banks manage their liquidity risk. More specifically, we analyze the determinants of banks' liquidity risk management choices, explicitly considering potential strategic interactions among banks. This issue has important 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 (Acharya, Mehran, and Thakor 2016; Acharya and Yorulmazer 2007; 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 will likely be rescued in case of distress. These collective risk-taking strategies may be optimal from an individual perspective, as they should allow banks to increase profitability without increasing the likelihood of bankruptcy, due to the explicit or implicit commitment of the lender of last resort. Hence, these risk-taking strategies may be mutually reinforcing in some circumstances. This collective behavior transforms a traditionally microprudential dimension of banking risk into a macroprudential risk, which may ultimately generate much larger costs to the economy.

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

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

We obtain strong and consistent evidence of collective risk-taking behaviors in liquidity risk management. We are aware that to perfectly estimate the magnitude of peer effects we would need a fully experimental setting, which is not available when studying banks' behavior. Thus, to further minimize the perils of peer effects estimation (Angrist 2014), we run exhaustive robustness tests, including the use of alternative identification strategies and other peer group definitions. Our main results remain valid, supporting the existence of significant peer effects between banks in their liquidity risk management strategies.

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

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

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

This paper is organized as follows. We begin by reviewing the expanding literature on bank's funding liquidity risk and its regulation, in section 2. In section 3 we discuss several indicators of banks' liquidity risk and characterize the data set 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 important question in our paper: do banks take into account peers' liquidity strategies when making their own choices on liquidity risk management? In section 6 we summarize our main findings and discuss their policy implications.

2. Related Literature

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

The 2008 global financial crisis placed liquidity risk in the spotlight and made it clear that something was missing in the international regulatory consensus (Bouwman 2014, Vives 2014). While banks voluntarily hold buffers of liquid assets to manage the risks associated with the maturity gap between assets and liabilities (Acharya, Mehran, and Thakor 2016; Acharya, Shin, and Yorulmazer 2011; Allen and Gale 2004a, 2004b; Bouwman 2014; Calomiris, Heider, and Hoerova 2013; Farhi, Golosov, and Tsyvinski 2009; Feinman 1993; Gale and Yorulmazer 2013; Rochet and Vives

2004; Tirole 2011; and Vives 2014), these buffers will hardly ever be sufficient to fully insure against a bank run or a sudden dry-up in wholesale markets.

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

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

The moral hazard problem associated with the existence of a safety net provided by a lender of last resort is further aggravated

[1]Many authors discuss the importance of imposing minimum holdings of liquid assets (Acharya, Shin, and Yorulmazer 2011; Allen and Gale 2004a, 2004b; Farhi, Golosov, and Tsyvinski 2009; Gale and Yorulmazer 2013; Ratnovski 2009, 2013; Rochet and Vives 2004; Santos and Suarez 2018; Tirole 2011; and Vives 2014). However, Wagner (2007b) shows that, paradoxically, holding more liquid assets may induce more risk-taking by banks. Freixas, Martin, and Skeie (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.

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

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

[2] Citigroup's former CEO, Charles Prince, has been repeatedly quoted as 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."

However, the market failure behind regulation is not linked to a too-big-to-fail problem, but rather to a too-correlated-to-fail problem, as banks adopt excessive maturity mismatches together with correlated risks.

Acharya, Mehran, and Thakor (2015) and Acharya and Yorulmazer (2007) also discuss bailouts when there are many potentially correlated failures. Acharya, Shin, and Yorulmazer (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, Babus, and Carletti (2012) show that when banks make similar portfolio decisions, systemic risk increases, as defaults become more correlated. Jain and Gupta (1987) find (weak) evidence on bank herding during a crisis period. Brown and Dinç (2011) provide evidence that governments are more likely to bail out a bank when the whole banking system is in distress, using a sample of banks from twenty-one emerging markets in the 1990s. Perotti and Suarez (2002) prove the existence of strategic interactions between banks, though their results support the existence of strategic substitutions rather than strategic complementarities. They show that if banks expect to obtain larger rents if their competitors fail, their speculative lending decisions are strategic substitutes. Collective risk-taking incentives and strategic complementarities are also discussed by Acharya (2009), Acharya and Yorulmazer (2008), Barron and Valev (2000), Boot (2011), Malherbe (2014), Rajan (2006), Tirole (2011), van den End and Tabbae (2012), and Vives (2014).

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

Silva (2017) also documents peer effects in liquidity risk, though our papers differ in several dimensions. While Silva (2017) makes an effort to understand if the estimated peer effects have effects on overall financial stability, we focus on understanding where these peer effects come from, by exploring interactions between different groups of banks.[3]

3. How to Measure Liquidity Risk?

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

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

3.1 Data

Given that one of our objectives is to assess the extent to which banks take each others' choices into account when managing liquidity risk, we must 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

[3]There are at least two other important differences between the papers. First, we consider that peer effects are mainly driven by common beliefs about the possible intervention of a lender of last resort (Ratnovski 2009). As such, we consider that our empirical strategy to deal with the estimation of peer effects is more adequate for the purpose of our study than that used in Silva (2017), in which a foreign parent bank holding group influences the decisions of its domestic subsidiary, thus generating partially overlapping peer groups. Second, Silva (2017) uses data up to 2014, while our analysis is based on data up to only 2009. We believe that extending the sample for the 2010–14 period might bias the estimation of peer effects, as the Basel Committee issued its first guidelines on the new liquidity regulation that would be part of Basel III in 2010 (Basel Committee on Banking Supervision 2010). We should thus expect that banks began to change their liquidity ratios in the same direction simultaneously in reaction to the new Basel rules, which could lead to an over-estimation of peer effects.

Table 1. Banks' Characteristics

	N	Mean	Min.	P25	P50	P75	Max.
Total Assets	17,620	21,200	92	295	659	2,183	772,000
Total Capital Ratio	10,211	14.5	7.3	11.3	12.9	15.6	44.5
Tier 1 Ratio	9,851	12.6	4.7	9.5	11.2	13.9	41.6
Net Interest Margin	17,561	3.7	0.3	3.0	3.8	4.4	10.4
Return on Assets	17,596	0.9	−4.9	0.5	1.0	1.3	5.1
Cost to Income	17,510	67.1	27.4	56.7	65.0	74.2	165.1
Net Loans to Total Assets	17,509	63.0	5.1	55.1	66.4	75.2	90.6

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

format, so as to ensure the comparability of variables across countries. Savings and investment banks are not included in the data set, as they usually have different liquidity risk profiles and funding strategies. Using these filters, we obtain data for almost 3,500 banks during eight years, for forty-five countries.[4] Excluding banks without information on total assets, we obtain 17,643 bank-year observations.

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

3.2 Liquidity Indicators

In table 2 we present summary statistics on liquidity risk for the banks included in the sample. As discussed by Tirole (2011),

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

Table 2. Liquidity Indicators: Summary Statistics

A. Global Summary Statistics									
	N	**Mean**	**Min.**	**P25**	**P50**	**P75**	**Max.**		
Liquidity Creation	17,620	9.1	−35.7	−4.8	4.8	22.1	69.2		
NSFR	17,618	115.1	27.8	106.7	121.2	129.9	155.1		
B. Liquidity Indicators Over Time (Mean)									
	2002	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**Total**
Liquidity Creation	2.7	2.5	3.8	6.9	13.0	13.7	13.9	24.9	9.1
NSFR	122.2	122.6	119.9	116.9	109.4	108.5	108.2	104.5	115.1

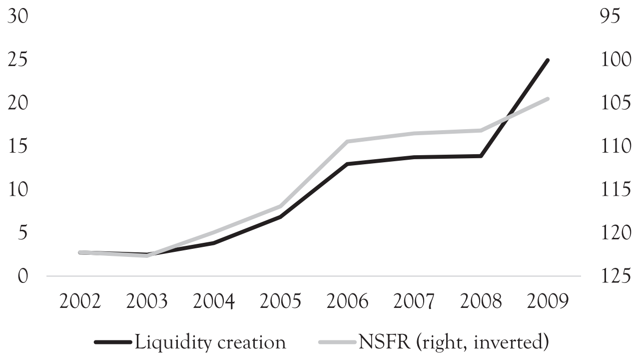
Notes: Liquidity creation is a proxy of the liquidity indicator proposed by Berger and Bouwman (2009). The higher this variable is, the more liquidity a bank is creating, i.e., the larger is its maturity transformation role. NSFR is an approximation of the net stable funding ratio defined in Basel III,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

liquidity cannot be measured by relying on a single variable or ratio, given its complexity and the multitude of potential risk sources. Ideally, a complete liquidity indicator would rely on the overall liquidity mismatch between assets and liabilities. However, the data necessary for such an indicator is usually not publicly available. Nevertheless, some approximation is feasible. Taking that into account, we focus our analysis on two indicators that offer an encompassing view of banks' liquidity risk: (i) *liquidity creation* and (ii) *net stable funding ratio*.

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

$$\begin{aligned}
&Liquidity_creation \\
&\quad = \{1/2 * Illiq_assets + 0 * Semi_liq_assets - 1/2 * Liq_assets\} \\
&\qquad + \{1/2 * Liq_liabilities + 0 * Semi_liq_liab. - 1/2 * Illiq_liab.\} \\
&\qquad - 1/2 * Capital.
\end{aligned}$$

Figure 1. Liquidity Indicators Over Time (Mean)



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

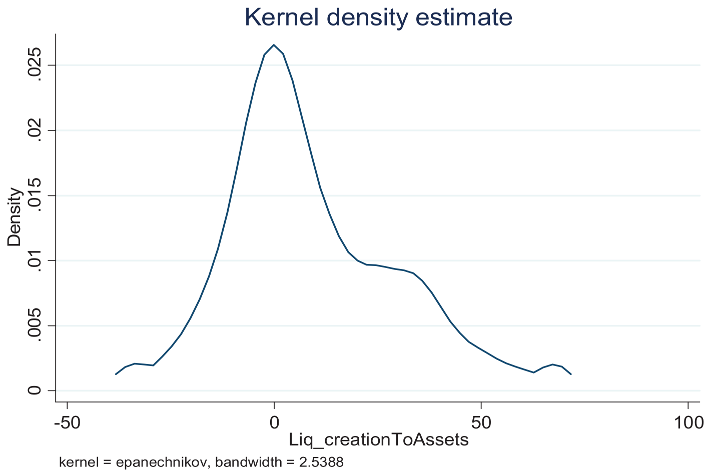
Liquidity creation increased steadily during the sample period, including during the crisis years (figure 1). Actually, its highest value was recorded in 2009, thus showing that banks continued to create liquidity even during the global financial crisis. However, this also implies that liquidity risk increased during this period, according to this indicator. However, it is important to note that this indicator continued to increase during the crisis because banks' total assets contracted more than liquidity creation itself.

Figure 2 shows that this variable exhibits some dispersion during our sample period.

In turn, the net stable funding ratio (NSFR) included in the Basel III package is a structural ratio designed to address liquidity

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

Figure 2. Empirical Distribution of the Liquidity Creation Ratio



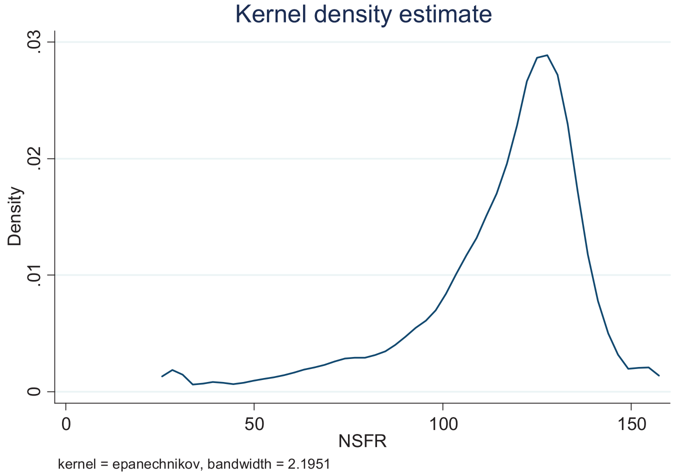
Notes: Liquidity creation is a proxy of the liquidity indicator proposed by Berger and Bouwman (2009). The higher this variable is, the more liquidity a bank is creating, i.e., the larger is its maturity transformation role. See the data appendix for further details.

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 percent. The higher this ratio is, the more comfortable is the institution's liquidity position. Though the available data do not allow for the accurate computation of this indicator, a rough approximation is possible.[6]

The NSFR showed some deterioration in the run-up to the crisis. Figure 3 shows that most banks record high values in this ratio. It is important to stress that this indicator is an approximation of the indicator proposed by the Basel Committee. As such, the 100 percent minimum threshold defined for this ratio for prudential purposes cannot be considered for our indicator.

[6]Please see the data appendix for further details.

Figure 3. Empirical Distribution of the NSFR



Notes: NSFR is an approximation of the net stable funding ratio defined in Basel III, which considers the available stable funding as a percentage of the required stable funding (i.e., assets that need to be funded). See the data appendix for further details.

The two liquidity indicators used in our analysis offer an encompassing view of banks' liquidity risk because they contain information from all assets and liabilities.

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

4. How Do Banks Manage Liquidity Risk?

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

$$\begin{aligned} Liqx_{it} = {} & \alpha_0 + \alpha_i + \alpha_{nt} + \beta_1 Capital_{it-1} + \beta_2 Banksize_{it} \\ & + \beta_3 Profitability_{it-1} + \beta_4 Cost\_inc_{it-1} \\ & + \beta_5 Lend\_spec_{it-1} + \beta_6 (Liq - x_{it-1}) + i_t + \varepsilon_{it}, \end{aligned} \tag{1}$$

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

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

Table 3. Determinants of Liquidity Indicators

Dependent Variable →	**Liquidity Creation**	**NSFR**
	(1)	**(2)**
Total Capital Ratio$_{t-1}$	−0.14	0.07
	(−1.56)	(0.85)
Log Assets$_t$	−5.87***	−2.69**
	(−4.96)	(−2.46)
Net Interest Margin$_{t-1}$	−1.37***	2.11***
	(−3.96)	(5.95)
Return on Assets$_{t-1}$	0.68*	−1.43***
	(1.81)	(−3.66)
Cost-to-Income$_{t-1}$	0.08***	−0.04**
	(3.72)	(−2.10)
Net Loans to Total Assets$_{t-1}$	0.29***	0.11**
	(6.72)	(2.03)
Loans to Customer Deposits$_{t-1}$	−0.02**	−0.08***
	(−2.01)	(−5.77)
Liquidity Ratio$_{t-1}$	0.23***	0.04
	(7.90)	(1.36)
Liquidity Creation$_{t-1}$	—	−0.14***
	—	(−4.22)
NSFR$_{t-1}$	−0.15***	—
	(−5.31)	—
D2004	−3.74***	2.10***
	(−10.36)	(5.36)
D2005	−3.66***	1.13**
	(−8.58)	(2.55)
D2006	−7.35***	4.49***
	(−21.51)	(11.57)
D2007	−9.08***	4.79***
	(−23.22)	(12.18)
D2008	−11.59***	5.08***
	(−27.44)	(13.43)
Constant	−593.2***	355.24***
	(−15.33)	(9.92)
Number of Observations	7,020	7,020
Number of Banks	1,738	1,738
R2 Within	0.366	0.160
R2 Between	0.139	0.165
R2 Overall	0.103	0.138
Fraction of Variance Due to Bank FE	0.998	0.984

Notes: All regressions include country-year fixed effects, bank fixed effects, and robust standard errors. t-statistics are in parentheses. The total capital ratio is calculated according to the regulatory rules defined by the Basel Committee. Net interest margin is defined as net interest income as a percentage of earning assets. Return on assets is computed as net income as a percentage of average assets. The cost-to-income ratio is computed as banks' operational costs (overheads) as a percentage of income generated before provisions. Liquidity creation is a proxy of the liquidity indicator proposed by Berger and Bouwman (2009). The higher this variable is, the more liquidity a bank is creating, i.e., the larger is its maturity transformation role. NSFR is an approximation of the net stable funding ratio defined in Basel III, which considers the available stable funding as a percentage of the required stable funding (i.e., assets that need to be funded). These two variables are negatively correlated (i.e., more liquidity risk is associated with higher liquidity creation and lower NSFR) and are defined in detail in the data appendix. ***, **, and * indicate significance at the 1 percent, 5 percent, and 10 percent level, respectively.

$Banksize_{it}$ is measured by the log of assets. Larger banks might show poorer liquidity indicators for two reasons. First, larger banks can more easily have access to markets and might thus afford to hold less liquid assets. Second, larger banks are often perceived as too big to fail, thus having fewer incentives to have very prudent (and costlier) liquidity risk management strategies. Indeed, Dinger (2009) and Kashyap, Rajan, and Stein (2002) find that larger banks hold fewer liquid assets, though Aspachs, Nier, and Tisset (2005) find no significant effects for U.K. banks.

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

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

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

$(Liq - x_{it})$ refers to the other liquidity indicators, i.e., $x_{it} \neq -x_{it}$. Given that liquidity risk is hard to capture using one single indicator, as discussed above, we consider that it is important to control for the other liquidity indicators, as they jointly characterize the risk profile of each institution.

All variables are lagged by one period to mitigate concerns of simultaneity and reverse causality.

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

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

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

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

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

Finally, it is worth noting that much of the variation in liquidity ratios cannot be attributable to the observed financial ratios. Indeed, as shown in table 3, bank fixed effects account for a very large fraction of the variance. This result is entirely consistent with evidence obtained by Gropp and Heider (2010) regarding the determinants of banks' capital ratios. These authors find that unobserved time-invariant bank fixed effects are ultimately the most important determinant of banks' capital ratios.

5. Are Other Banks' Decisions Relevant?

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

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

5.1 The Reflection Problem and Identification Strategies

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

$$\begin{aligned} Liqx_{it} = {} & \alpha_0 + \alpha_i + \alpha_{nt} + \beta_0 \sum_{j \neq i} \frac{Liqx_{jt}}{N_{it} - 1} + \beta_1 Capital_{it-1} \\ & + \beta_2 Banksize_{it} + \beta_3 Profitability_{it-1} + \beta_4 Cost\_inc_{it-1} \\ & + \beta_5 Lend\_spec_{it-1} + \beta_6 (Liq - x_{it-1}) + i_t + \varepsilon_{it}, \end{aligned} \tag{2}$$

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 the baseline specification, the peer banks are all the other banks operating in the same country, which share common beliefs about the lender of last resort. The coefficient β_0 captures the extent to which banks' liquidity choices reflect those of the peer group. Recall that we are controlling for bank, time, and country-year fixed effects.

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

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

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

First, we use as instruments 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. To ensure that the instrument is valid, the predicted values of peer banks should be highly correlated with the average of the observed liquidity indicators, our potentially endogenous variable. More importantly, for the exclusion restriction to hold, the predicted values should 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.

Given that the instrumental variable is a linear combination of observed bank characteristics, we believe that the exclusion restriction holds. The coefficients sustaining this linear combination come from a regression in which we explore the role of bank characteristics in explaining liquidity ratios. A bank with a given amount of

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

capital, with a given return on assets, etc., is expected to have a certain liquidity ratio. This should not be contaminated by the effect of peer choices.

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

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

$$\begin{aligned} Liqx_{it} = {} & \alpha_0 + \alpha_i + \alpha_{nt} + \beta_0 \sum_{j \neq i} \frac{Liqx_{jt}}{N_{it} - 1} + \beta_1 Capital_{it-1} \\ & + \beta_2 Banksize_{it} + \beta_3 Profitability_{it-1} + \beta_4 Cost\_inc_{it-1} \\ & + \beta_5 Lend\_spec_{it-1} + \beta_6 (Liq - x_{it-1}) + i_t + \varepsilon_{it}. \end{aligned} \tag{3}$$

The peer effects, $\sum_{j \neq i} \frac{Liqx_{jt}}{N_{it}-1}$, i.e., the average liquidity indicators of peers, are instrumented by the predicted values of liquidity ratios for these peers $\left(\sum_{j \neq i} \frac{Liq\_predx_{jt}}{N_{it}-1} \right)$, as shown in the first-step equation:

$$\begin{aligned} \beta_0 \sum_{j \neq i} \frac{Liqx_{jt}}{N_{it} - 1} = {} & \alpha_0 + \alpha_j + \alpha_{nt} + \gamma_1 \sum_{j \neq i} \frac{Liq\_predx_{jt}}{N_{it} - 1} \\ & + \beta_1 Capital_{jt-1} + \beta_2 Banksize_{jt} \\ & + \beta_3 Profitability_{jt-1} + \beta_4 Cost\_inc_{jt-1} \\ & + \beta_5 Lend\_spec_{jt-1} + \beta_6 (Liq - x_{jt-1}) + i_t + \varepsilon_{it}. \end{aligned} \tag{4}$$

The predicted values Liq_predx_{jt} are obtained from a bank-level equation in which we consider the entire set of bank characteristics:

$$\begin{aligned} Liq\_predx_{it} = {} & \alpha_0 + \alpha_i + \alpha_{nt} + \beta_1 Capital_{it-1} + \beta_2 Banksize_{it} \\ & + \beta_3 Profitability_{it-1} + \beta_4 Cost\_inc_{it-1} \\ & + \beta_5 Lend\_spec_{it-1} + \beta_6 (Liq - x_{it-1}) + i_t. \end{aligned} \tag{5}$$

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

As before, we define the benchmark peer group as the banks operating in the same country and in the same year. These are the banks that are more likely to engage in collective risk-taking behaviors due to implicit or explicit bailout expectations. Let us suppose that in a given country several banks engage in funding liquidity strategies that are deemed as overall risky (e.g., excessive reliance on short-term debt to finance long-term assets, large funding gaps, or persistent tapping of interbank markets). If several banks engage

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

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

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

in these strategies simultaneously, there is naturally an increase in systemic risk. As discussed by Ratnovski (2009) and Rochet and Tirole (1996), 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, other banks will likely follow very soon, thus becoming too many to fail (Acharya and Yorulmazer 2007). Given this incentive structure, a given bank in that country clearly has 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 restriction and test other possible peer groups.

Using the two approaches, we are able to identify peer effects, after having dealt with the reflection problem through the use of instrumental variables. However, given that identification hinges on the quality of the instrument, we considered alternative approaches, discussed in detail in section 5.2.2. These include using another instrument inspired by the social multiplier approach proposed by Glaeser, Scheinkman, and Sacerdote (2003) and Sacerdote (2011).

5.2 Empirical Results

Table 4 presents the results of the first instrumental-variable approach in the estimation of peer effects in liquidity risk management.

In the first two columns we present the results of the estimation of equation (2). Hence, in these columns the peer effects are included in the regressions without properly addressing the reflection problem discussed before. When running this simple, yet possibly biased, estimation, we find strong evidence of positive peer or herding effects in individual banks' choices for the two liquidity indicators. The riskier are the funding and liquidity strategies of other banks in a given country, the riskier will tend to be the choices of each bank individually. However, as discussed above, these preliminary estimates may

Table 4. Regressions on Peer Effects in Liquidity Strategies

	Bank Peer Effects: Country-Year Peer Group (without IV)		Bank Peer Effects: Country-Year Peer Group (IV = Predicted Values of Rivals' Liquidity Ratios)			
			Second Step		First Step	
	Liquidity Creation	NSFR	Liquidity Creation	NSFR	Liquidity Creation	NSFR
	(1)	(2)	(3)	(4)	(5)	(6)
Peer Effects	0.81***	0.43***	0.56***	0.36	0.92***	0.24***
	(18.62)	(7.54)	(9.02)	(1.08)	(31.28)	(7.21)
Total Capital Ratio$_{t-1}$	−0.19**	0.08	−0.18***	0.08	0.03	−0.02
	(−2.29)	(0.91)	(−3.63)	(1.51)	(1.15)	(−0.83)
Log Assets$_t$	−1.73	−2.86**	−3.02***	−2.80***	−2.86***	0.87***
	(−1.61)	(−2.56)	(−4.95)	(−4.77)	(−10.22)	(3.47)
Net Interest Margin$_{t-1}$	−1.08***	1.90***	−1.17***	1.94***	−0.29***	0.41***
	(3.26)	(5.28)	(−5.71)	(7.18)	(−2.76)	(4.39)
Return on Assets$_{t-1}$	0.56	−1.34***	0.60***	−1.36***	−0.05	−0.19*
	(1.59)	(−3.46)	(2.60)	(−5.25)	(−0.39)	(−1.85)
Cost-to-Income$_{t-1}$	0.05***	−0.04*	0.06***	−0.04***	0.02***	−0.02***
	(2.64)	(−1.81)	(4.43)	(−2.80)	(2.79)	(−2.93)
Net Loans to Total Assets$_{t-1}$	0.26***	0.12**	0.26***	0.12***	0.04**	−0.01
	(6.34)	(2.18)	(9.17)	(3.72)	(2.54)	(−0.99)
Lons to Customer Deposits$_{t-1}$	0.00	−0.08***	0.00	−0.08***	−0.02***	0.00
	(0.43)	(−6.02)	(−0.51)	(−10.95)	(−6.33)	(0.63)
Liquidity Ratio$_{t-1}$	0.12***	0.05*	0.15***	0.05**	0.12***	0.04***
	(4.34)	(1.90)	(6.72)	(2.22)	(11.05)	(−4.50)
Liquidity Creation$_{t-1}$	—	−0.13***	—	−0.13***	—	−0.04***
	—	(−3.79)	—	(−5.92)	—	(−4.65)

(*continued*)

Table 4. (Continued)

	Bank Peer Effects: Country-Year Peer Group (without IV)		Bank Peer Effects: Country-Year Peer Group (IV = Predicted Values of Rivals' Liquidity Ratios)			
			Second Step		First Step	
	Liquidity Creation	NSFR	Liquidity Creation	NSFR	Liquidity Creation	NSFR
	(1)	(2)	(3)	(4)	(5)	(6)
$NSFR_{t-1}$	−0.12***	—	−0.13***	—	−0.03***	—
	(−4.53)	—	(−7.58)	—	(−3.84)	—
Constant	69.7	72.8	−137.2**	119.3	−100.9***	587.8***
	(1.27)	(1.31)	(−2.44)	(0.54)	(−3.84)	(39.78)
Number of Observations	7,019	7,019	7,012	7,012	7,012	7,012
Number of Banks	1,737	1,737	1,736	1,736	1,736	1,736
F-test	127.9	37.7	—	—	785.0	308.7
R2 Within	0.477	0.186	0.467	0.186	0.705	0.484
R2 Between	0.329	0.501	0.095	0.524	0.399	0.555
R2 Overall	0.331	0.455	0.055	0.471	0.313	0.494

Notes: All regressions include year, country-year, and bank fixed effects. t-statistics are in parentheses. Peers are defined as the $j \neq i$ banks operating in the same country and in the same year as bank i. Columns 1 and 2 show the results obtained when peer liquidity choices are considered directly in the regressions, i.e., not addressing the reflection problem. Columns 3 and 4 show the results of the instrumental-variables regressions (one for each liquidity indicator), where the instruments are the predicted values of peers' liquidity ratios. These predicted values result from the estimation of the regressions in table 3. Columns 5 and 6 show the first-stage estimation results for these three instrumental-variables regressions. The total capital ratio is calculated according to the regulatory rules defined by the Basel Committee. Net interest margin is defined as net interest income as a percentage of earning assets. Return on assets is computed as net income as a percentage of average assets. The cost-to-income ratio is computed as banks' operational costs (overheads) as a percentage of income generated before provisions. Liquidity creation is a proxy of the liquidity indicator proposed by Berger and Bouwman (2009). The higher this variable is, the more liquidity a bank is creating, i.e., the larger is its maturity transformation role. NSFR is an approximation of the net stable funding ratio defined in Basel III, which considers the available stable funding as a percentage of the required stable funding (i.e., assets that need to be funded). These two variables are negatively correlated (i.e., more liquidity risk is associated with higher liquidity creation and lower NSFR) and are defined in detail in the data appendix. ***, **, and * indicate significance at the 1 percent, 5 percent, and 10 percent level, respectively.

not be dealing adequately with the endogeneity problem underlying the estimation of peer effects.

The second group of columns (3–4) displays our main empirical results when explicitly dealing with the endogeneity problem created by considering peer effects. When we use the predicted values of peers' liquidity indicators as instruments, we conclude that the results presented in the first columns are no longer significant for the NSFR. For liquidity creation, peer effects continue to be strongly statistically significant. We obtain a coefficient of 0.56, meaning that one standard deviation in the average liquidity creation of peer banks will increase the liquidity creation of a given bank by 0.56 standard deviations. The different results obtained when the endogeneity problem is addressed are an indication that neglecting endogeneity in peer effects may lead to biased and incorrect results.

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

Table 5 shows the results using our second identification strategy, based on Leary and Roberts (2014). Even though the subsample of listed banks used to compute this alternative estimation of peer effects is much smaller than the original (roughly one-quarter), we are still able to obtain statistically significant peer effects. In this case, the results are significant not only for liquidity creation but also for the NSFR. However, the statistical significance of the results is weaker. In terms of economic significance, the peer effects coming from the NSFR are very similar to those obtained from liquidity creation in table 4 (0.59, compared to 0.56 in table 4). However, the magnitude of the peer effects for liquidity creation is much larger with this identification strategy (1.28). Nevertheless, it is important to note that this coefficient is more imprecisely estimated, due to the lower statistical significance.[9]

[9]The sample used in table 5 is much smaller than that used in table 4. The difference in the significance and magnitude of peer effects between these two tables could thus be due to the difference in the way peer effects are measured

Table 5. Regressions on Peer Effects in Liquidity Strategies Using an Alternative Identification Strategy (Leary and Roberts 2014)

	Bank Peer Effects: Country-Year Peer Group (without IV)		Bank Peer Effects: Country-Year Peer Group			
			Second-Step Regressions		First-Step Regressions	
	Liquidity Creation	NSFR	Liquidity Creation	NSFR	Liquidity Creation	NSFR
	(1)	(2)	(3)	(4)	(5)	(6)
Peer Effects	0.53***	0.48***	1.28*	0.59**	0.00***	0.01***
	(4.31)	(5.31)	(1.70)	(2.00)	(−3.71)	(9.52)
Total Capital Ratio$_{t-1}$	−0.69***	0.43***	−0.66***	0.44***	−0.06	−0.06
	(−4.23)	(3.50)	(−5.21)	(4.21)	(−1.35)	(−1.61)
Log Assets$_t$	−2.57	−2.32	−1.85	−2.20**	−0.96**	−1.16***
	(−0.76)	(−1.61)	(−1.26)	(−2.00)	(−2.09)	(−3.13)
Net Interest Margin$_{t-1}$	−0.31	2.55***	−0.11	2.59***	−0.25	−0.46***
	(−0.32)	(4.72)	(−0.19)	(5.88)	(−1.34)	(−3.07)
Return on Assets$_{t-1}$	1.11	−1.98***	1.73**	−2.04***	−0.82***	0.58***
	(1.41)	(−3.46)	(2.15)	(−4.57)	(−4.51)	(4.01)
Cost-to-Income$_{t-1}$	0.11***	−0.06*	0.13***	−0.06***	−0.03***	0.01*
	(2.66)	(−1.82)	(3.86)	(−3.05)	(−3.52)	(1.75)
Net Loans to Total Assets$_{t-1}$	0.28***	0.28***	0.26***	0.29***	0.02	−0.05**
	(3.02)	(3.21)	(3.70)	(4.75)	(0.87)	(−2.39)
Loans to Customer Deposits$_{t-1}$	−0.02	−0.16***	0.03	−0.16***	−0.07***	0.02**
	(−0.56)	(−5.18)	(0.56)	(−7.75)	(−7.06)	(2.51)
Liquidity Ratio$_{t-1}$	0.31***	0.01	0.22**	0.01	0.13***	0.02
	(3.69)	(0.21)	(1.97)	(0.26)	(6.51)	(1.01)
Liquidity Creation$_{t-1}$	—	−0.28***	—	−0.28***	—	0.03**
	—	(−5.07)	—	(−7.37)	—	(1.99)

(*continued*)

Table 5. (Continued)

	Bank Peer Effects: Country-Year Peer Group (without IV)		Bank Peer Effects: Country-Year Peer Group			
			Second-Step Regressions		First-Step Regressions	
	Liquidity Creation	NSFR	Liquidity Creation	NSFR	Liquidity Creation	NSFR
	(1)	(2)	(3)	(4)	(5)	(6)
NSFR_{t-1}	−0.17***	—	−0.14***	—	−0.03**	—
	(−2.75)	—	(−2.93)	—	(−2.18)	—
Constant	−300.2*	185.4**	437.8	115.1	−987.7***	652.3***
	(−1.80)	(2.30)	(0.59)	(0.58)	(−56.12)	(46.40)
Number of Observations	1,986	1,986	1,986	1,986	1,986	1,986
Number of Banks	428	428	428	428	428	428
R2 Within	0.492	0.319	0.453	0.318	0.000	0.000
R2 Between	0.010	0.073	0.056	0.441	0.131	0.610
R2 Overall	0.001	0.063	0.050	0.407	0.053	0.494

Notes: All regressions include year, country-year, and bank fixed effects. t-statistics are in parentheses. Peers are defined as the $j \neq i$ banks operating in the same country and in the same year as bank i. Columns 1 and 2 show the results obtained when peer liquidity choices are considered directly in the regressions, i.e., not addressing the reflection problem. Columns 3 and 4 show the results of the instrumental-variables regressions (one for each liquidity indicator), where the instruments are the idiosyncratic component of peer banks' equity returns (computed as the difference between the bank's returns and those of the S&P banks index in a given year). Columns 5 and 6 show the first-stage estimation results for these three instrumental-variables regressions. The total capital ratio is calculated according to the regulatory rules defined by the Basel Committee. Net interest margin is defined as net interest income as a percentage of earning assets. Return on assets is computed as net income as a percentage of average assets. The cost-to-income ratio is computed as banks' operational costs (overheads) as a percentage of income generated before provisions. Liquidity creation is a proxy of the liquidity indicator proposed by Berger and Bouwman (2009). The higher this variable is, the more liquidity a bank is creating, i.e., the larger is its maturity transformation role. NSFR is an approximation of the net stable funding ratio defined in Basel III, which considers the available stable funding as a percentage of the required stable funding (i.e., assets that need to be funded). These two variables are negatively correlated (i.e., more liquidity risk is associated with higher liquidity creation and lower NSFR) and are defined in detail in the data appendix. ***, **, and * indicate significance at the 1 percent, 5 percent, and 10 percent level, respectively.

5.2.1 Who Follows Whom: Alternative Peer Group Definitions

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

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

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

An additional possibility is to consider that banks focus on peer groups outside borders, implying that the lender of last resort may not be the only factor motivating 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

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or to the different sample used. To clarify this issue, we estimated our baseline peer effect estimation (table 4) using the sample of listed firms used for the estimation of the results reported in table 5. The results using this smaller sample are broadly consistent with those of table 4, thus suggesting that the differences in the results come mainly from identification strategy used rather than from the decrease in sample size.

Table 6. Regressions on Peer Effects in Liquidity Strategies—Robustness on Peer Group Definition

	Bank Peer Effects: Country-Year Peer Group (without IV)		Bank Peer Effects (with IV): Second-Step Regressions	
	Liquidity Creation	NSFR	Liquidity Creation	NSFR
	(1)	(2)	(3)	(4)
Baseline				
Peer Effects	0.81***	0.43***	0.56***	0.36
	(18.62)	(7.54)	(9.02)	(1.08)
Lagged Peers				
Peer Effects	0.38***	0.03	0.74***	0.79
	(5.83)	(0.65)	(6.00)	(0.67)
Peers as Other Banks (in Other Countries) in the Same Quartile				
Peer Effects	0.82***	0.21***	0.30	−0.11
	(9.50)	(3.59)	(1.22)	(−0.39)
Large Banks (Fourth Quartile in Each Country)				
Peer Effects	0.40***	0.27***	0.10	0.35***
	(5.97)	(4.40)	(0.33)	(5.05)
Large Banks (Fourth Quartile in the Sample)				
Peer Effects	0.30***	0.23***	1.60*	0.21*
	(4.83)	(4.12)	(1.67)	(1.69)
Only Larger Banks (Third and Fourth Quartiles)				
Peer Effects	0.63***	0.39***	0.59***	0.33**
	(10.45)	(7.38)	(6.64)	(2.46)
Only Smaller Banks (First and Second Quartiles)				
Peer Effects	0.75***	0.34***	0.98**	0.16
	(12.19)	(4.14)	(1.98)	(1.50)
Only Larger Banks (Top Five in Each Country)				
Peer Effects	0.15*	0.17**	−0.04	0.26
	(1.78)	(2.27)	(−0.12)	(1.27)
Only Larger Banks (Banks Classified as SIFIs)				
Peer Effects	−0.03	0.21	−0.27	0.48
	(−0.14)	(1.11)	(−0.52)	(1.27)
Only Larger Banks (Banks that Belong to the EURIBOR Panel)				
Peer Effects	0.46**	0.17*	−0.37	0.38*
	(2.55)	(1.70)	(−0.38)	(1.87)

(*continued*)

Table 6. (Continued)

	Bank Peer Effects: Country-Year Peer Group (without IV)		**Bank Peer Effects (with IV): Second-Step Regressions**	
	Liquidity Creation	**NSFR**	**Liquidity Creation**	**NSFR**
	(1)	**(2)**	**(3)**	**(4)**
Excluding Larger Banks (Top Five in Each Country)				
Peer Effects	0.76***	0.40***	0.58***	−0.55
	(14.15)	(6.40)	(9.01)	(−0.81)
Small Banks Following Large Banks (Fourth Quartile)				
Peer Effects	0.59***	−0.01	−0.41**	−0.15**
	(7.41)	(−0.24)	(−2.35)	(−2.15)
Small Banks Following Large Banks (Top Five)				
Peer Effects	−0.84***	−0.30***	−1.38***	−0.27***
	(−9.66)	(−7.13)	(−4.33)	(−5.71)
Small Banks Following Large Banks (SIFI List)				
Peer Effects	−0.47***	0.00	−1.84***	0.33***
	(−5.82)	(−0.01)	(−14.06)	(3.42)
Small Banks Following Large Banks (EURIBOR Panel)				
Peer Effects	−0.21***	−0.03	−0.86***	−0.30***
	(−3.41)	(−0.51)	(−9.77)	(−4.92)

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

all the other banks of the same size quartile, regardless of their country of origin. This seems to be implausible, as peer effects are not statistically significant in any of the indicators analyzed. Collective risk-taking strategies seem to play a role mainly at the national level, possibly reflecting common lender of last resort beliefs previously discussed.

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

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

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

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

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

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

Given these results, another important dimension to test is whether small banks tend to replicate the behavior of the larger banks. These smaller banks are those that could benefit more from engaging in collective risk-taking strategies, as argued above, most notably when larger banks are already taking more risk, thereby increasing the likelihood of systemic distress (Dávila and Walther

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

2017). Using different definitions of small and large banks, we obtain evidence of significant peer effects. However, in contrast to what we could expect initially, we obtain negative peer effects in some specifications for liquidity creation and for the NSFR in most specifications. This means that, in these cases, small banks actually decrease liquidity risk when the largest banks are increasing it. Collective risk-taking strategies are not prevalent among the smaller banks. These banks do not seem to replicate liquidity risk management strategies between themselves, nor replicate those of the largest banks.

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

5.2.2 Robustness Analysis

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

Table 7 reports some of the most important tests conducted. All the estimations were performed without and with instrumental variables, in columns 1–2 and 3–4, respectively.

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

First, we consider an adapted version of our identification strategy based on the social multiplier proposed by Glaeser, Scheinkman, and Sacerdote (2003) and Sacerdote (2011). The basic idea is to

Table 7. Regressions on Peer Effects in Liquidity Strategies—Robustness

	Bank Peer Effects: Country-Year Peer Group (without IV)		Bank Peer Effects (with IV): Second-Step Regressions	
	Liquidity Creation	NSFR	Liquidity Creation	NSFR
	(1)	(2)	(3)	(4)
Baseline				
Peer Effects	0.81***	0.43***	0.56***	0.36
	(18.62)	(7.54)	(9.02)	(1.08)
Peer Effects Using Predicted Values (without IV)				
Peer Effects	0.51***	0.09	—	—
	(8.32)	(1.06)		
Accounting for Predicted Regressors with Bootstrapped Standard Errors				
Peer Effects	0.81***	0.43***	0.56***	0.34
	(17.13)	(7.62)	(4.74)	(0.81)
Before the Crisis				
Peer Effects	0.46***	0.12	0.35***	0.33*
	(5.24)	(1.54)	(2.74)	(1.94)
Removing Banks with Asset Growth above 50 Percent				
Peer Effects	0.79***	0.39***	0.53***	0.42***
	(17.94)	(7.00)	(7.97)	(2.60)
Excluding U.S. Banks				
Peer Effects	0.24***	0.19***	−1.87	0.28*
	(2.92)	(2.94)	(−1.47)	(1.95)
Excluding Smaller Countries (Less than Fifty Observations)				
Peer Effects	0.84***	0.46***	0.56***	0.25
	(18.78)	(7.06)	(10.60)	(1.06)
Western Europe Banks				
Peer Effects	0.24**	0.19***	−10.43	0.24
	(2.45)	(2.79)	(−0.42)	(0.43)
Eastern Europe Banks				
Peer Effects	0.20	0.13	0.28	0.25*
	(1.59)	(1.22)	(0.26)	(1.73)
U.S., Canada, and Western Europe Banks				
Peer Effects	0.79***	0.43***	0.63***	0.23
	(13.12)	(6.60)	(8.78)	(1.47)
Excluding Countries More Directly Affected during the Global Crisis				
Peer Effects	0.21**	0.15**	−1.35	0.18
	(2.41)	(2.06)	(−1.48)	(1.18)

(continued)

Table 7. (Continued)

	Bank Peer Effects: Country-Year Peer Group (without IV)		Bank Peer Effects (with IV): Second-Step Regressions	
	Liquidity Creation	NSFR	Liquidity Creation	NSFR
	(1)	(2)	(3)	(4)
Euro Area as One Peer Group				
Peer Effects	0.85***	0.47***	1.29***	4.00
	(18.87)	(7.49)	(10.47)	(0.68)
Without Country-Year Fixed Effects				
Peer Effects	0.81***	0.43***	0.43***	0.36
	(18.62)	(7.54)	(3.46)	(1.08)
With Country and Year Fixed Effects (Random-Effects Estimation)				
Peer Effects	0.78***	0.37***	0.46***	0.02
	(19.34)	(6.95)	(5.21)	(0.11)
Without Liquidity Controls				
Peer Effects	0.81***	0.41***	0.54***	0.25
	(19.91)	(6.90)	(8.58)	(0.44)
Controlling for Leverage (instead of Capital Ratio)				
Peer Effects	0.76***	0.46***	0.66***	0.23***
	(21.44)	(9.97)	(16.09)	(3.50)
Only after 2004				
Peer Effects	0.89***	0.53***	0.58***	0.45**
	(20.90)	(9.01)	(6.41)	(2.31)
Lagged Dependent Variables				
Peer Effects	0.76***	0.42***	0.55***	0.00
	(18.14)	(7.90)	(8.87)	(0.00)
Peers Weighted by Size				
Peer Effects	0.82***	0.44***	0.51***	0.27
	(18.04)	(7.41)	(4.33)	(0.81)

Notes: Peers are defined as the $j \neq i$ banks operating in the same country and in the same year as bank i. t-statistics are in parentheses. Each line shows the coefficients for peer effects for different robustness tests. In the regressions with bootstrapped standard errors, two year dummies had to be excluded. The pre-crisis period refers to the years 2002–06. Countries considered as most directly affected by the global financial crisis include the United States, Iceland, Greece, Ireland, Portugal, Spain, and Italy. Columns 1 and 2 show the results obtained when peer liquidity choices are considered directly in the regressions, i.e., not addressing the reflection problem. Columns 3 and 4 show the results of the instrumental-variables regressions, where the instruments are the predicted values of peers' liquidity ratios. These predicted values result from the estimation of the regressions in table 3. All the regressions use the same control variables as those reported in table 5. All regressions include year, country-year, and bank fixed effects. ***, **, and * indicate significance at the 1 percent, 5 percent, and 10 percent level, respectively.

use the peer group average of the predicted values arising from the regressions on liquidity determinants directly in the peer effects regressions (equation (1)), instead of using them as instruments for the peer effects.[11] The results of this alternative estimation approach confirm the existence of peer effects, though only for liquidity creation.

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

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

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

U.S. banks represent slightly more than three-quarters of the sample. In order to ensure that the results are not influenced by this, we exclude all U.S. banks from the estimation. In this case, we obtain statistically significant effects only for the NSFR. In addition, we also estimate the regressions separately for Western and Eastern European banks, and for U.S., Canadian, and Western European banks together. The results are not statistically significant when only Western European banks are considered and are marginally significant for Eastern European banks. All this suggests that collective

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

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

risk-taking strategies in the run-up to the crisis were more prevalent among U.S. banks.

Furthermore, we exclude the countries more directly affected by the global financial crisis from the regressions (United States, Iceland, Greece, Ireland, Portugal, Spain, and Italy). When banks from these countries are excluded, we obtain no evidence for collective risk-taking strategies, suggesting that the countries more severely hit by the crisis were indeed those where these behaviors were more prevalent.

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

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

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

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

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

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

Table 8. Peer Effects by Year

	Bank Peer Effects: Country-Year Peer Group (IV = Predicted Values of Rivals' Liquidity Ratios) Second-Step Regressions		Bank Peer Effects: Country-Year Peer Group (IV = Idiosyncratic Equity Returns) Second-Step Regressions	
	Liquidity Creation	**NSFR**	**Liquidity Creation**	**NSFR**
	(1)	**(2)**	**(3)**	**(4)**
Full Sample	0.56***	0.36	1.28*	0.59**
	(9.02)	(1.08)	(1.70)	(2.00)
2003	0.52***	0.14*	0.61	−5.54
	(8.44)	(1.92)	(1.60)	(−0.35)
2004	0.38***	0.18**	−3.75	−2.36*
	(4.89)	(2.04)	(−0.59)	(−1.77)
2005	0.51***	0.03	1.51	0.34
	(6.49)	(0.44)	(0.74)	(0.37)
2006	0.68***	−0.04	0.80	3.08
	(12.93)	(−0.94)	(1.01)	(0.30)
2007	0.74***	−0.08*	0.28	0.43**
	(14.01)	(−1.66)	(0.85)	(2.51)
2008	0.76***	0.09**	−0.10	0.38
	(14.18)	(2.02)	(−0.29)	(1.28)
2009	0.13	0.21***	−3.49	0.73***
	(1.25)	(3.69)	(−0.87)	(3.42)

Notes: t-statistics are in parentheses. Each line shows the coefficients for peer effects for different years. All the regressions use the same control variables as those reported in table 4. All regressions include year, country-year, and bank fixed effects. ***, **, and * indicate significance at the 1 percent, 5 percent, and 10 percent level, respectively.

5.2.3 Peer Effects by Year

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

In terms of statistical significance, when we consider as instruments the predicted values of liquidity indicators (columns 1 and 2), there were peer effects in almost all years in liquidity creation, with the exception of 2009. The results are somewhat weaker for the

NSFR. When we use the idiosyncratic component of equity returns as an instrument as in Leary and Roberts (2014), thereby focusing on a smaller subsample of publicly listed banks, the results are slightly weaker, though there is still statistically significant evidence of peer effects in the NSFR (columns 3 and 4).

Looking at the economic significance of the estimated peer effects, some interesting conclusions may be drawn. Peer effects were greater in the years immediately before the global financial crisis. For instance, in 2007 the peer effects estimated for liquidity creation were 0.74, which compares with an average estimate for the whole sample of 0.56. This suggests that there were indeed observable collective risk-taking behaviors right before the global financial crisis, which possibly made banks more vulnerable to the shocks they later faced. It is also interesting to note that there were significant peer effects during the crisis years, when banks were simultaneously reshaping their balance sheets to manage risks in the new environment in which they were operating, marked by heightened funding pressures and deleveraging incentives.

6. Concluding Remarks and Policy Implications

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

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

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

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

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

Data Appendix

Table 9. Definition of Liquidity Indicators

	Liquidity Creation		NSFR
	Classification	**Weights**	**Weights**
Assets			
Residential Mortgage Loans	SL	0	0.65
Other Mortgage Loans	SL	0	0.65
Other Consumer/Retail Loans	SL	0	0.85
Corporate and Commercial Loans	1	0.5	0.85
Other Loans	1	0.5	0.85
Less: Reserves for Impaired Loans/NPLs			−1.00
Net Loans			
Loans and Advances to Banks	SL	0	0.50
Reverse Repos and Cash Collateral			0.00
Trading Securities and at FV through Income			0.50
Derivatives			0.50
Available for Sale Securities			0.50
Held to Maturity Securities			1.00
At-Equity Investments in Associates			1.00
Other Securities			1.00
Total Securities	L	−0.5	
Investments in Property	1	0.5	1.00
Insurance Assets	1	0.5	1.00
Other Earning Assets	1	0.5	1.00
Total Earning Assets			
Cash and Due from Banks	L	−0.5	0.00
Foreclosed Real Estate	1	0.5	1.00
Fixed Assets	1	0.5	1.00
Goodwill	1	0.5	1.00
Other Intangibles	1	0.5	1.00
Current Tax Assets	1	0.5	1.00
Deferred Tax Assets	1	0.5	1.00
Discontinued Operations	1	0.5	1.00
Other Assets	1	0.5	1.00
Total Assets			
Liabilities			
Customer Deposits: Current	L	0.5	
Customer Deposits: Savings	L	0.5	
Customer Deposits: Term	SL	0	
Total Customer Deposits			0.85
Deposits from Banks	L	0.5	0.00
Repos and Cash Collateral	L	0.5	0.00
Other Deposits and Short-Term Borrowings	L	0.5	0.00

(continued)

Table 9. (Continued)

	Liquidity Creation		NSFR
	Classification	**Weights**	**Weights**
Total Deposits, Money Market and Short-Term Funding			
Total Long-Term Funding	1	−0.5	1.00
Derivatives	L	0.5	0.00
Trading Liabilities	L	0.5	0.00
Total Funding			
Fair Value Portion of Debt	SL	0.0	0.00
Credit Impairment Reserves	SL	0.0	0.00
Reserves for Pensions and Other	SL	0.0	0.00
Current Tax Liabilities	SL	0.0	0.00
Deferred Tax Liabilities	SL	0.0	0.00
Other Deferred Liabilities	SL	0.0	0.00
Discontinued Operations	SL	0.0	0.00
Insurance Liabilities	SL	0.0	0.00
Other Liabilities	SL	0.0	0.00
Total Liabilities			
Pref. Shares and Hybrid Capital Accounted for as Debt	1	−0.5	1.00
Pref. Shares and Hybrid Capital Accounted for as Equity	1	−0.5	1.00
Total Equity	1	−0.5	1.00
Total Liabilities and Equity			

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

$$Liquidity\_creation = \{1/2 * Illiq\_assets + 0 * Semi\_liq\_assets - 1/2 * Liq\_assets\}$$
$$+ \{1/2 * Liq\_liab. + 0 * Semi\_liq\_liab. - 1/2 * Illiq\_liab.\} - 1/2 * Capital.$$

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

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

$$NSFR = \frac{Available\_stable\_funding}{Required\_stable\_funding} * 100.$$

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

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