The Quarterly Review of Economics and Finance 66 (2017) 302–313

Contents lists available at ScienceDirect

The Quarterly Review of Economics and Finance

journal homepage: www.elsevier.com/locate/qref

Measuring heterogeneity in bank liquidity risk: Who are the winners and losers?

Soula Jean-Loup*

Strasbourg University & LaRGE Research Center, France

ARTICLE INFO

Article history:
Received 22 December 2015
Received in revised form 7 March 2017
Accepted 7 April 2017
Available online 17 April 2017

JEL classification:
E51
G21
G28
G32

Keywords:
Bank risk management
Liquidity risk
Systemic risk

ABSTRACT

The 2007–2009 crisis stressed the importance of liquidity for banks. Aggregate liquidity indices provide an account of financial market liquidity conditions. However, these indices do not illustrate how banks individually are affected by such conditions. Similarly, balance sheet indicators only reflect degrees of potential bank exposure to liquidity shocks. Using a risk factor model, we present a way of measuring bank sensitivity to liquidity risk. Our results indicate that liquidity risk is a specific risk, and we shed light on heterogeneities among banks in terms of their exposure to liquidity risk. Liquidity conditions can hinder or benefit banks, and banks can also be insensitive to such conditions. We document large variations in exposure levels across the 2008 and 2011 crises. Larger size and higher capital levels insulate banks from aggregate liquidity risk. However, deposit shares, wholesale funding reliance and funding gaps affect only those banks benefiting from aggregate liquidity risk. These ratios reveal bank liquidity production levels. This suggests that market discipline applies to liquidity production, but only for less risky banks in cases of liquidity crisis. Thus, market discipline appears to be one-sided. This reinforces the necessity of liquidity requirements for all banks as illustrated from the Basel III liquidity ratios.

1. Introduction

Bank overexposure to liquidity risk can have dramatic effects on the stability of financial systems and the economy. The 2007–2008 crisis revealed the disruptive effects of liquidity risk (e.g., Allen & Carletti, 2008; Brunnermeier, 2009). Banks relying on short-term funding suffered from higher short-term interest rates and lower degrees of funding availability (e.g., Cornett, McNutt, Strahan, & Tehranian, 2011). Some banks could not even rollover their short-term debt, threatening their solvency. Nevertheless, not all banks were affected to the same extent by fluctuations in market-wide liquidity conditions (e.g., Craig, Fecht, & Tümer-Alkan, 2015). This therefore raises questions concerning cross-sectional variations in bank risk as aggregate liquidity conditions change. This calls for a measurement of individual bank sensitivity to aggregate liquidity conditions. Indeed, the literature uses two main measures of liquidity risk. A first strand of the literature uses individual bank features describing potential bank exposure to liquidity shocks. These measures, which are based on balance sheet elements, assess either asset liquidity or funding stability. A second strand of the literature considers aggregate liquidity risks associated with money markets. Aggregate liquidity conditions are measured based on interbank rates or spreads. Almost no measure considers the direct effect of aggregate liquidity on individual bank liquidity risk. Therefore, this article measures individual bank exposure to liquidity shocks in consideration of aggregate liquidity conditions. Our objective is to develop a stronger understanding of how banks respond individually to aggregate liquidity risks.

This paper contributes to the literature by introducing a measure of bank exposure to aggregate liquidity conditions. We use a risk factor model as our framework. The model allows one to compute bank sensitivity to daily variations in aggregate liquidity conditions. The sample consists of listed banks across the euro area for 2005–2012.

A first result indicates that liquidity risk is mainly an idiosyncratic risk in calm markets. However, during the 2007–2008 and 2011 crises, banks faced systemic liquidity shocks, as runs occurred in most components of money markets. Liquidity risk thus tended to become systematic. A second result indicates that there is a high degree of heterogeneity across banks in terms of their exposure to liquidity conditions. Bank risk is either positively or negatively affected by general liquidity conditions: aggregate liquidity either reduces or increases bank stock volatility. Moreover, many banks are not affected by aggregate liquidity. Consequently, liquidity risk

* Correspondence to: Institut d'Etudes Politiques, Université de Strasbourg, 47 Avenue de la Forêt Noire, 67082 Strasbourg Cedex, France.
E-mail address: jlsoula@unistra.fr

http://dx.doi.org/10.1016/j.qref.2017.04.006
1062-9769/

at the bank level reflects overly idiosyncratic decisions in terms of funding and asset liability management. However, this heterogeneity across banks decreases during liquidity crises, as most banks become negatively affected by market-wide liquidity conditions.

The paper then looks at indicators of bank exposure to liquidity risk. Our intention is to develop a stronger understanding of relationships to bank liquidity risk. Indeed, these indicators are mainly used by regulators to contain effects of aggregate liquidity conditions on bank liquidity risk (e.g., Basel III liquidity requirements). They are also currently used to assess bank liquidity creation (Berger & Bouwman, 2009). We find that the share of deposits in total funding tends to increase exposure to liquidity risk. Moreover, reliance on wholesale funding and the scale of the funding gap limits exposure to liquidity risk. However, these effects only apply for banks positively affected by liquidity conditions, i.e., whose risk measured by stock price volatility decreases as aggregate liquidity conditions deteriorate. Thus, investors consider risks associated with liquidity creation only for those banks positively affected by aggregate liquidity changes. We interpret this as reflecting a flight-to-quality behavior, as investors consider only the liquidity creation by the strongest banks, i.e., banks benefiting from aggregate liquidity. This is also consistent with benefits associated with liquidity hoarding. For banks that are negatively affected (for which risk increases as liquidity conditions deteriorate), market participants do not consider liquidity production. They likely anticipate receiving public support when needed. This belief is based on size and capitalization, which decrease exposure to liquidity risk. As capitalization helps banks face credit losses, we identify a relationship between bank liquidity and solvency risk.

The paper is organized as follows. Section 2 reviews the literature on bank liquidity risk measures. Section 3 introduces the risk factor model used to develop our individual measure of bank exposure to aggregate liquidity and specifies the variables used. Section 4 presents the results and analyses the liquidity risk measure. Section 5 studies relationships between balance sheet measures of liquidity risk and the measure of bank exposure to liquidity risk based on a Tobit model with friction. Section 6 presents our robustness check results; Section 7 concludes.

2. Literature review

Liquidity risk reflects a bank's potential to become unable to settle obligations with immediacy over a specific horizon by using available liquid assets and cash or by incurring new debt at a reasonable price (Drehmann & Nikolaou, 2013). The literature on bank liquidity risk mostly addresses balance sheet measures of liquidity risk and measures of liquidity conditions affecting all banks on interbank and money markets separately.

First, the literature studies bank potential exposure to liquidity risk based on three balance sheet characteristics: the stability of funding, the liquidity of assets, and the funding gap between assets and liabilities.

The stability of funding represents the proportion of stable liabilities used by banks to fund their assets. Deposit withdrawals or short-term lender decisions not to rollover their funding represent a loss of funding. This possibility represents a rollover risk (Acharya, Gale, & Yorulmazer, 2011). To this extent, bank liquidity refers to the capacity to raise funds at a reasonable cost at short notice. The stability of funding is approached by accounting for ratios representing the share of short-term funding over total funding or of interest expenses over total deposits, with the latter ratio being used to proxy funding costs (Dietrich, Hess, & Wanzenried, 2014). These ratios are currently known as core deposit ratios, non-core funding ratios, and brokered deposit ratios.

The liquidity of assets represents a second element of balance sheet exposure to liquidity risk. Indeed, liquid assets constitute a buffer that insures banks against rollover risks. However, the liquidity of assets is closely linked to market liquidity (Brunnermeier & Pedersen, 2009). When market liquidity dries up, banks can experience difficulties when attempting to sell specific assets without significant losses. Various ratios gauge the amount of liquid assets or cash such as the net short-term asset ratio, current ratio, acid test ratio, and government securities ratio. Asset liquidity is usually measured using the share of customer loans over total assets (Pagratis & Stringa, 2009), the reserve balance at the central bank (Acharya & Merrouche, 2012) or the daily change in bank reserve deposits (Cocco, Gomes, & Martins, 2009), among other measures.[1]

Funding gaps are the third type of accounting indicator. Funding gaps represent the difference or proportion of illiquid assets funded by demandable debt. They are approached for instance as customer loans minus short-term liabilities over customer loans (Aikman et al., 2011), as money lent to banks over money borrowed from banks, as customer loans over short-term liabilities, as liquid assets over short-term liabilities, or as liquid assets over total debt (Pagratis & Stringa, 2009).

These individual micro-level measures of bank liquidity risk present banks' potential capability to withstand fluctuations in funding liquidity, all things being equal. Nevertheless, these measures are unable to account for bank effective capacities to withstand liquidity shocks. They bear at least four shortcomings. First, balance sheet measures do not account for bank capacities to access funding sources during liquidity shocks. Bank capacities to fund themselves are not only expressed as public balance sheet variables. Bank access to funding can also depend on dimensions such as bank reputation, the diversification of bank funding sources, or central bank policies. Second, the comparison of balance sheet measures between banks and across time is not straightforward. From the previous argument, the same level of a given measure for several banks does not necessarily denote the same degree of exposure to liquidity risk. Similarly, when an accounting indicator has the same value at two different points in time, this does not imply that exposure to liquidity risk is the same. Third, balance sheet measures lack frequency, as they are dependent on yearly or at best quarterly data and are backward looking measures. They also fail to provide a precise assessment of bank individual liquidity risk across time, and especially when examining stressed liquidity conditions in financial markets. These stress events usually last for a few weeks or months. Finally, it is difficult to understand the interactions between various accounting indicators. Each balance sheet measure underlines a different aspect of bank potential exposure to liquidity risk, with no measure encompassing all of them.

Second, the literature considers measures of liquidity conditions for the banking sector. These aggregate liquidity measures are relatively frequent but at the macro level. These measures are often referred to as systemic liquidity measures. However, Hong, Huang, and Wu (2014) note that there is no commonly accepted definition of systemic liquidity risk. Drawing on Kaufman and Scott's (2003) definition of systemic risk, systemic liquidity risk can be defined as the risk or probability of breakdowns in the entire money market as opposed to breakdowns in individual components. This is evidenced by comovements among most or all parts of the money market. Systemic liquidity risk manifested during the 2007–2008 financial crisis through a general drying up of money market liquidity. The literature documents runs that occurred from 2007 to 2008 in asset-backed securities markets (Brunnermeier, 2009) such as

[1] Acharya and Merrouche (2012) also use the reserve balance at the central bank to account for liquidity hoarding among large settlement banks in the UK occurring during the subprime crisis of 2007–2008. Cocco et al. (2009) find that banks with a larger imbalance in reserve deposits tend to borrow funds from banks with which they have a relationship and to pay lower interest rates than they would otherwise.

the asset-backed commercial paper market (Covitz, Liang, & Suarez, 2013), the repurchase agreement market (Gorton & Metrick, 2012), federal funds markets (Afonso, Kovner, & Schoar, 2011), and other interbank markets (Acharya & Merrouche, 2012). Moreover, some banks such as Northern Rock faced runs from retail depositors (Shin, 2009) or from non-deposit creditors such as Bear Stearns and IndyMac.

Systemic liquidity risk is commonly measured using market liquidity indices such as interbank rate spreads. Spreads such as the Euribor or Libor minus government yield rates of the same maturity (e.g., Cornett et al., 2011; Hong et al., 2014; Hong & Wu, 2012) or interbank rates minus Overnight Indexed Swap (OIS) rates (e.g., Hui, Genberg, & Chung, 2011) are widely used. Market liquidity risk can also be studied based on repo haircuts as is done in Gorton and Metrick (2012).[2] Finally, Schwarz (2014) proposes a measure of market liquidity computed as the spread between German sovereign bonds and German KfW agency bonds.[3] Both bonds share the same degree of credit risk, as they are both explicitly guaranteed by the federal government. Consequently, the yield spread reflects aggregate liquidity conditions.[4]

Finally, some studies have presented individual bank measures of liquidity risk in attempting to account for balance sheet characteristics and funding conditions of financial markets. Some authors have used bank bid or paid liquidity prices of the Eurosystem's weekly main refinancing operations (MRO) (e.g., Abbassi, Fecht, & Weber, 2013; Craig et al., 2015; Drehmann & Nikolaou, 2013). However, the data from which they are computed are not publicly available. Brunnermeier, Gorton, & Krishnamurthy (2012) propose a Liquidity Mismatch Index (LMI) computed as a sum of balance sheet items weighted by their market liquidity based on repo haircut and interbank rates. Berger and Bouwman (2009) develop a similar measure of liquidity creation by banks that involves weighting assets and liabilities of balance sheets according to their liquidity levels. Severo (2012) uses the approach that is most similar to ours. His paper measures bank exposure to systemic liquidity conditions based on bank equity return sensitivity to systemic liquidity risk. However, Severo (2012) uses this measure to estimate the cost for public authorities to provide liquidity support to banks.

3. Methodology

3.1. A factor model of bank returns and volatility

Using a risk factor model, we measure individual bank exposure to liquidity conditions. The measure determines the sensitivity of volatility in bank stock returns to an aggregate liquidity risk factor. Factors models have been widely applied in the banking sector. These models analyze common risk factors that drive bank returns. Baele, De Bruyckere, De Jonghe, and Vander Vennet, (2015) review the literature on models including factors thought to be relevant for banks. More particularly, some authors have included liquidity risk factors in return models. Hess and Laisathit (1997) take the interest rate of three-month federal agency securities minus the interest rate of three-month U.S. Treasury bills as a liquidity risk factor. Dewenter and Hess (1998) use three-month unregulated time deposits minus the discount rate on three-month Treasury bills. Schuermann and Stiroh (2006) use the commercial paper spread to proxy liquidity risk. However, all of these authors find little explanatory power for liquidity risk. Consequently, liquidity risk does not appear to be a priced systematic risk factor.

Still, liquidity risk may influence total bank risk levels. We thus select a model that characterizes the influence of liquidity risk on either systematic risk or total risk. By expanding the market model to include an aggregate liquidity risk factor, we measure the sensitivity of total variations in bank returns to liquidity risk. We estimate this return model using an ARCH(1) process. We model the sensitivity of bank stock return volatility to aggregate liquidity risk. Using this model, we consider both idiosyncratic and market channels of liquidity risk affecting banks (Allen, Carletti, & Gale, 2009). Indeed, bank liquidity risks can be divided into idiosyncratic and systematic liquidity risks. Systematic liquidity risks relate to bank exposure to aggregate common liquidity conditions. This occurs during a liquidity shock when the price every bank pays to finance itself on the wholesale market increases or when banks cannot refinance their maturing debt. Idiosyncratic liquidity risk reflects all bank funding decisions that can be diversified away by investors, as these decisions are independent across banks. A return model based on an ARCH(1) process can account for this dichotomy between idiosyncratic and systematic components of liquidity risk.

Following (Severo, 2012), the stock returns of bank *i* from period t−1 to t follow the model shown below[5]:

$$r^i(t) = \alpha^i + \beta^i_m r_m(t) + \beta^i_L SL(t) + e^i(t)\sigma^i(t) \quad (1)$$

$$\sigma^i(t)^2 = \exp(\omega^i_0 + \omega^i_L SL(t)) + \gamma^i \varepsilon^i(t-1)^2 \quad (2)$$

where

$e_i \sim N(0, 1)$

The first equation expresses bank *i*'s stock return $r^i(t)$ as a function of the market return $r_m(t)$ and aggregate liquidity risk factor $SL(t)$. The second equation models the volatility of bank *i*'s stock returns. Volatility is affected by parameter (ω^i_L), which measures the sensitivity of bank *i* stock return volatility to aggregate liquidity risk. The exponential form of conditional heteroskedasticity prevents the emergence of negative volatility values.

This model allows one to characterize the nature of bank liquidity risk as either specific or systematic. The two parameters facilitating the analysis of bank *i*'s liquidity risk in this model are ω^i_L and β^i_L. Parameter ω^i_L estimated in the second equation is a measure of bank *i*'s individual exposure to liquidity risk. A positive (negative) ω^i_L value denotes that bank *i* loses (benefits) from aggregate liquidity conditions. Indeed, the volatility of its stock returns increases with aggregate liquidity risk. A bank can for example be a net borrower (lender) on the interbank market and pay (get) a higher price for funding liquidity. Parameter β^i_L captures the liquidity risk premium of bank *i*'s risk. Parameter ω^i_L includes both systematic and idiosyncratic components of bank liquidity risk. Parameter β^i_L represents the systematic component of bank liquidity risk. A situation involving a significant parameter ω^i_L and non-significant parameter β^i_L would denote that the systematic component of bank *i*'s liquidity risk is absent. Consequently, bank liquidity risk would present a specific risk.

3.2. Hypotheses

Consistent with the literature previously mentioned, we do not expect liquidity risk to be priced most of the time. Regarding the

[2] Gorton and Metrick (2012) find a correlation between the change in the LIBOR-OIS and changes in repo rates.

[3] Kreditanstalt für Wiederaufbau is a German governmental development bank.

[4] Schwarz (2014) uses this measure of market liquidity to disentangle the liquidity component from the credit component in LIBOR-OIS and sovereign bond spreads. She finds that the liquidity component represents more than two-thirds of the widening in these spreads at the start of the 2007–2009 crisis.

[5] The only difference between Severo's (2012) model and ours is that we do not include control variables in Eqs. (1) and (2). This does not alter the results.

liquidity parameters, we expect to observe insignificant parameters β_L on average but also significant parameters ω_L (hypothesis 1).

We expect to observe heterogeneity in bank sensitivity to aggregate liquidity conditions (hypothesis 2). Some banks should lose while others should benefit from liquidity risk.

On the one hand, during periods of liquidity crisis, banks should be negatively affected by liquidity conditions. Indeed, they may not be able to refinance themselves at a reasonable cost despite central bank and government liquidity support schemes. Such schemes were expanded after the beginning of the crisis, starting with ECB liquidity support for the interbank market starting in August 2007. Banks should then be immune to aggregate liquidity shocks. Nevertheless, banks can lose as a result of aggregate liquidity risks due to the stigma associated with receiving public support. The literature underscores that banks receiving liquidity support from public authorities can suffer from stigma effects (Philippon & Skreta, 2012; Ennis & Weinberg, 2013). Furthermore, short-term depositor runs can occur.

On the other hand, banks can benefit from liquidity conditions for two main reasons. In contrast to normal conditions, liquidity crisis conditions can be characterized by the occurrence of liquidity hoarding behaviors by market participants and/or an increase in counterparty risk concerns. Dried up money markets can be accompanied by the hoarding of liquid assets by banks, which has been empirically shown (e.g., Aspachs, Nier, & Tiesset, 2005; De Haan & Van den End, 2013). Two theoretical causes for such hoarding behaviors have been proposed. First, banks can hoard liquid assets for strategic reasons (Acharya, Gromb, & Yorulmazer, 2012; Diamond & Rajan, 2009). Second, banks can hoard liquid assets for precautionary reasons (Allen et al., 2009; Caballero & Krishnamurthy, 2008). Dried up aggregate liquidity could also be explained by an increase in counterparty risk perceived by market participants (Heider, Hoerova, & Holthausen, 2015). Asymmetric information on counterparty credit risk leads to higher interest rates or to complete drying-up of the interbank market. Adverse selection in interbank markets was observed during the 2007–2008 crisis (Afonso et al., 2011; Angelini, Nobili, & Picillo, 2011).

3.3. Data description

We build an unbalanced panel dataset for 2005–2012 based on daily observations of bank stock returns obtained from Datastream. Our sample includes data on listed commercial, savings and cooperative banks across the euro area. Following Schuermann and Stiroh (2006), we do not count any bank return observations for a given year when more than 150 observations of daily returns are missing for a given year. After cleaning the data, we obtained a sample covering 85 banks from twelve countries across the euro area for 2005–2012.

Data for the one-period return of the market factor are estimated using daily national stock market return indexes relevant to the domestic market of each bank. Table A3 in Appendix shows the number of banks by country and the national stock market indices. To proxy aggregate liquidity, scholars often use measures of liquidity for the interbank market. A commonly used measure is the spread between banks' and government borrowing rates (Christensen, Lopez, & Rudebusch, 2014; Haq & Heaney, 2012; Hong & Wu, 2012). As our sample is composed of banks of the euro area, we use the three-month Euribor rate. As for government borrowing rates, we use the three-month rate of euro-area AAA-rated member state yield curves computed by the ECB. We thus compute a Euribor-euro area AAA yield spread for a three-month maturity period. One of the main criticisms of spreads between banks and government borrowing rates concerns the fact that they contain both liquidity and credit risk components (e.g., Gyntelberg & Wooldridge, 2008; Schwarz, 2014), and especially in the context of a liquidity crisis affecting banks as shown by Angelini et al. (2011). We thus correct for bank credit risk by subtracting the Euribor-euro area AAA three-month spread from the CMA European Bank 5-year CDS Index provided by Datastream, which has standardized both distributions. We do not take the liquidity of bank CDS into account, as when working with CDS data, liquidity is less of a concern (Bijlsma, Lukkezen, & Marinova, 2014; Bongaerts, De Jong, & Driessen, 2011). Working with spread rather than rate, we control for the term structure of risk-free interest rate. The five-year CDS spread is the most liquid CDS contract. In spite of their maturity mismatch, both the Euribor three-month rate and the five-year CDS index should on average move in the same direction, responding to new information about banks' creditworthiness (Tölö & Jokivuolle, 2015).

Table 1
Descriptive statistics on ω_L per year.

Year	2005	2006	2007	2008	2009	2010	2011	2012
Obs.	73	74	78	80	78	79	80	79
Mean	−0.44	−0.71	0.15	0.31	0.24	0.26	0.67	0.08
Median	0	0	0	0.34	0	0	0.75	0
Std. dev.	3.22	1.72	0.41	0.30	0.42	1.21	0.71	0.32

Table 1 presents the number of observations, means, medians and standard deviations of ω_L. Non-significant ω_L values at the 10% level are set to zero.

Table 2
Descriptive statistics on β_L per year.

Year	2005	2006	2007	2008	2009	2010	2011	2012
Obs.	73	74	78	80	78	79	80	79
Mean	−0.59	−1.29	−0.18	−0.09	−0.10	0.54	0.15	0.03
Median	0	0	0	0	0	0	0	0
Std. dev.	5.73	3.47	0.58	1.14	1.68	1.51	2.45	1.34

Table 2 presents the number of observations, means, medians and standard deviations of β_L. Values are multiplied by 1000. Non-significant β_L values at the 10% level are set to zero.

4. Results

4.1. Descriptive statistics of liquidity parameters

The model from Eqs. (1) and (2) is estimated for each bank and for each year from 2005 to 2012. Descriptive statistics on the distribution of liquidity parameters ω_L and β_L are presented in Tables 1 and 2. Non-significant liquidity coefficients are set as equal to zero, as they correspond to banks that are not exposed to aggregate liquidity risk.

The parameters ω_L are on average negative before the beginning of the 2007–2008 liquidity crisis and are positive thereafter (Table 1). Liquidity conditions represent the cost of liquidity in the interbank market. On average, during the pre-crisis period, bank stock volatility decreased with liquidity costs. Higher liquidity costs reinforced bank income and decreased total risk levels. Thus, banks on average benefited from a relatively efficient allocation of liquidity in a booming interbank market. However, since the 2007–2008 crisis, banks have been on average impeded by aggregate liquidity, as indicated by the positive value of ω_L. Higher liquidity costs decreased incomes and increased stock returns as banks were viewed as riskier. In addition to this mean effect of liquidity conditions, the standard deviation reveals heterogeneity in bank sensitivity to liquidity risk: banks have negative or positive parameters ω_L.

Furthermore, this heterogeneity has evolved over time. We observe a substantial reduction in heterogeneity through the lower dispersion of ω_L during periods of liquidity stress. During liquidity crises, banks benefiting from aggregate liquidity conditions benefited relatively less. Banks in need of liquidity were relatively less hampered. The central bank's intervention as a substitute for the interbank market may have eased bank funding conditions, and especially for banks that were most exposed.[6] Still, more banks were sensitive to aggregate liquidity during the crisis, as the median denotes a lower proportion of ω_L equal to zero in 2008 and 2011.

The parameters β_L are valued at very close to zero for the whole 2005–2012 period (Table 2). This is consistent with the literature finding that liquidity risk is generally not a priced factor (Section 3). This confirms our first hypothesis. Still, the sensitivity of bank returns to liquidity conditions decreased in absolute value from 1.29 in 2006 to 0.09 in 2008. Similarly, the dispersion of β_L declined since the beginning of the liquidity crisis from 3.47 in 2006 to 0.58 in 2007. This suggests that the link between aggregate liquidity conditions and bank returns is significant for a larger number of banks in times of liquidity stress. This is due to the systemic nature of liquidity shocks. Liquidity decline in the money markets affected a large majority of banks that in turn experienced difficulties financing themselves. The diversity of liquidity risk positions within the interbank system declined and the correlation between bank liquidity risks increased.

4.2. Univariate analysis of liquidity parameters ω_L

We now focus our analysis on parameter ω_L. Indeed, parameter β_L is typically non-significant, which is consistent with the literature on bank risk factors. According to the literature, liquidity risk is not typically a systematic risk (Hess & Laisathit, 1997; Dewenter & Hess, 1998; Schuermann & Stiroh, 2006). As parameter ω_L denotes the sensitivity of individual bank susceptibility to aggregate liquidity risk, bank liquidity risk is typically a specific risk accounted for by ω_L. The absence of a systematic component of bank liquidity risk may be attributable to market participants believing that the central bank and governments would help banks in cases of systemic liquidity shock.

We perform a univariate analysis by comparing group means. As noted above, non-significant ω_L is set to zero. The estimate ω_L is not normally distributed as the Kolmogorov Smirnoff test indicates. Thus, Welch and Levene's tests are used to compare distributions of ω_L. Corresponding results are shown in Table 3 below.

First, we break the sample into two periods: 2005–2007 and 2008–2012. These periods, respectively, correspond to the pre-crisis and liquidity crisis periods. We investigate how exposure to liquidity risk has evolved across time. From comparing means of ω_L for all banks of the euro area for 2005–2007 and 2008–2012, a statistically significant difference is observed between the two means (Table 3). Before the liquidity crisis of 2005–2007 had occurred, banks benefited on average from aggregate liquidity conditions as denoted by the negative mean of ω_L. By contrast, once the liquidity crisis had begun in 2008, banks on average were negatively affected by aggregate liquidity risk. Furthermore, a significant difference in the standard deviation of ω_L is found between the two periods. ω_L volatility decreased after the start of the 2007–2008 crisis. This is consistent with our observation of more heterogeneity in ω_L before the crisis than afterwards (Section 4.1). Thus, the systemic liquidity event characterized by a strong deterioration of liquidity conditions changed the average sensitivity of bank total risk to aggregate liquidity.

Second, we evaluate whether the measure accounts for potential differences in terms of exposure to liquidity risk across bank size. The sample is divided into small and large banks. The literature indeed shows that large banks are more heavily exposed to liquidity risk than small banks. Large banks tend to enjoy better access to financial markets (Cocco et al., 2009). They tend to be charged less for interbank loans (Furfine, 2001; Akram & Christophersen, 2010). Finally, large banks tend to hold a lower share of liquid assets on their balance sheets (Bunda & Desquilbet, 2008; Vodova, 2013). By contrast, small banks typically focus on traditional intermediation and finance themselves relatively less from financial markets or the central bank (Berger & Bouwman, 2009). Thus, small banks should be less sensitive to aggregate liquidity. Then, we should expect to observe higher positive values of ω_L for large banks than small banks. Large banks are defined as those occupying the highest decile of banks ranked by total assets at the start of the period of observation in 2005 (Jokipii & Milne, 2008). Twelve banks of 85 are considered to be large. Our results indicate that the average ω_L value is higher for large banks than for small banks, but the difference is not significant (Table 3). However, ω_L dispersion is significantly stronger for small banks.

Table 3
Descriptive statistics of ω_L for separately large/small banks and 2005–2007/2008–2012 periods.

	Obs	Mean	F-value	Std. dev.	F-value
2005–2007	225	−0.32	19.24***	2.12	45.76***
2008–2012	396	0.31		0.71	
Large banks	96	0.22	2.25	0.81	3.80**
Small banks	525	0.06		1.51	
Small banks 2005–2007	189	−0.34	13.65***	2.27	45.13***
Small banks 2008–2012	336	0.28		0.73	
Large banks 2005–2007	36	−0.22	16***	0.96	5.04**
Large banks 2008–2012	60	0.48		0.56	
Large banks 2005–2007	36	−0.22	0.28	0.96	4.74**
Small banks 2005–2007	189	−0.34		2.27	
Large banks 2008–2012	60	0.48	5.63**	0.56	0.22
Small banks 2008–2012	336	0.28		0.73	

The table above reports the mean and standard deviation of parameter ω_L split into two distinctive groups six times. The table presents tests of significant differences in ω_L means for 2005–2007 and 2008–2012 for large and small banks with each divided across the two periods. Tests are based on Welch's test statistics. Tests on significant differences in group variances of ω_L are based on Levene's test on variance homogeneity.

* Denote that the subsamples differ significantly from one another at the 10% levels.

*** Denote that the subsamples differ significantly from one another at the 1% levels.

** Denote that the subsamples differ significantly from one another at the 5% levels.

On average, large and small banks have both been negatively affected by the liquidity crises. The average, ω_L became positive and significantly higher from 2008 to 2012 relative to the 2005–2007 period for both large and small banks. Similarly, ω_L dispersion significantly declined for both large and small banks. Both large and small banks were affected by liquidity crises in a similarly negative way. However, they were not affected to the same extent. Indeed, from 2005 to 2007, both large and small banks on average benefited from liquidity conditions and average ω_L values between them did not differ significantly. Small banks still show significantly higher levels of heterogeneity, as the standard deviation of their ω_L is higher. However, from 2008 to 2012, large banks were more negatively affected by liquidity risk than small banks, as their average ω_L is significantly higher. ω_L dispersion does not show any significant difference. The effect of liquidity crises was stronger among large banks than small banks, which is consistent with the literature underscoring the higher exposure of large banks to liquidity risk. Higher levels of large bank exposure to aggregate liquidity are likely due to a higher reliance on money markets. This hypothesis is investigated further in Section 5 below.

4.3. Signs of exposure to liquidity risk (ω_L)

The paragraphs above show heterogeneity across banks in terms of exposure to liquidity risk either as a cross-section or across time.

[6] The ECB provided liquidity support to banks through operations such as long term refinancing operations (LTRO) settled by the ECB in December 2012 and March 2013.

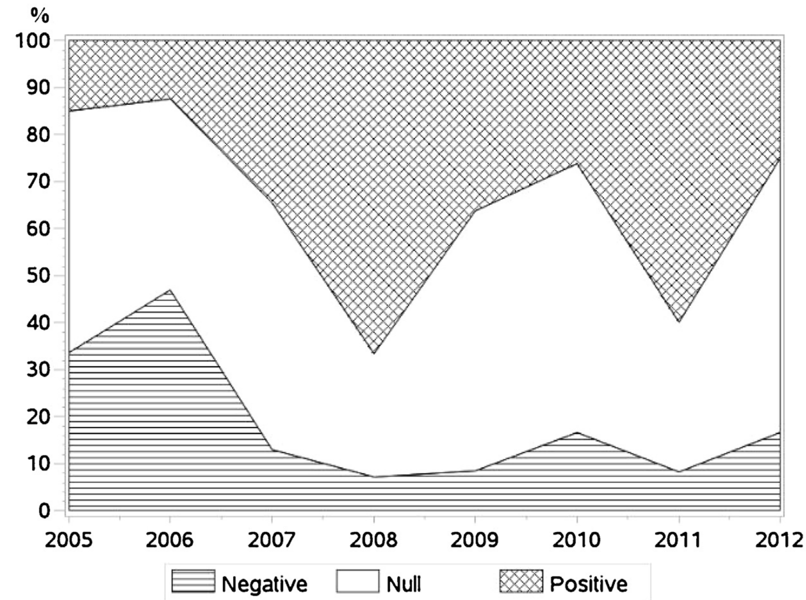

Fig. 1. Frequency of ω_L
The frequency of ω_L is plotted by sign for each year. Frequency is cumulated from negative to positive ω_L values. Non-significant ω_L at the 10% level of significance is set to 0.

The purpose of this section is to analyze the evolution of the distribution of banks across three categories defined by the signs of their ω_L values. As stated in Section 3.1, a ω_L value equal to zero indicates that a bank is insensitive to aggregate liquidity. When ω_L is positive (negative), a bank is negatively (positively) affected by aggregate liquidity risk. Fig. 1 shows the cumulative frequency of the estimated ω_L per sign. Banks insensitive to aggregate liquidity are listed in the central area of the graph while banks negatively (positively) affected are represented at the top (bottom) of the figure.

The proportions of the three types of banks evolved continually over the 2005–2012 period. Total bank sensitivity to aggregate liquidity risk was overwhelmingly either null or negative, respectively, for 51% and 35% of banks on average in 2005. Most banks were thus either not affected or benefited from aggregate liquidity conditions. A peak in negative sensitivity to aggregate liquidity risk was observed in 2006 for 42% of banks from the euro area while only 13% of banks had a positive ω_L the same year. The lower proportion of banks negatively affected by aggregate liquidity risk is interpreted as a result of the stronger liquidity of money markets prior to August 2007. Most banks did not experience difficulties obtaining funding from financial markets during that period, and their total susceptibility was independent from liquidity conditions.

In 2007 and 2008, the proportion of positive ω_L values increased, reaching a peak of 67% of banks in 2008. Consistent with stressed liquidity conditions, most banks observed their total risk increasing as aggregate liquidity deteriorated. Similarly, only two banks had a negative ω_L value in 2008. Furthermore, the proportion of banks insensitive to aggregate liquidity risk dropped from an average of 50% to 30%. These results are consistent with the degradation of aggregate liquidity during the 2007–2008 liquidity crisis starting from July 2007 with the collapse of the market for short-term asset-backed commercial paper.

In 2009 and 2010, bank total risk became less heavily affected by aggregate liquidity risk than it did during the 2007–2008 crisis. The proportion of banks negatively affected by aggregate liquidity (positive ω_L) decreased from 35% during the crisis to 28%. However, a larger proportion of banks was still negatively affected by aggregate liquidity risk than in the pre-crisis 2005–2006 period, when only 13% of banks were negatively affected by aggregate liquidity. The proportion of banks insensitive to aggregate liquidity risk increased to 60%, thus returning to the 2005 pre-crisis level (57%). Thus, relative to the pre-crisis period, the higher proportion of positive ω_L in 2009–2010 is attributed to a lower proportion of negative ω_L values (12%).

The comparable proportion of banks insensitive to aggregate liquidity to the pre-crisis period suggests a reduction of aggregate liquidity risk back to pre-crisis levels. This is consistent with the normalization of bank access to market liquidity. However, the 2007–2008 crisis seemed to have lasting effects on the pricing of bank risk by market participants: more banks were negatively affected by systemic liquidity risk after the crisis than before.

Total bank sensitivity to aggregate liquidity risk then increased in 2011 to levels comparable to those of 2008. This second peak in positive ω_L values signals a second liquidity crisis corresponding to the euro area sovereign debt crisis.

Thus, the measure of bank total risk sensitivity to aggregate liquidity conditions is consistent with the chronology of the crisis. An increasing proportion of banks with positive ω_L signals the occurrence of liquidity stress events. More banks were sensitive to aggregate liquidity risk during the liquidity crises of 2007–2008 and 2011 than during pre- and post-crisis periods. A higher proportion of banks is negatively affected by aggregate liquidity conditions when aggregate liquidity deteriorates. Furthermore, since the 2007–2008 liquidity crisis, market participants have tended to remain cognizant of previously stressed liquidity conditions and to view bank exposure to liquidity conditions more negatively than before the crisis. These results confirm our second hypothesis.

5. Balance sheet determinants of bank sensitivity to aggregate liquidity conditions

A segment of the related literature focuses on accounting measures of bank liquidity risk. In this section, we analyze relationships between bank sensitivity measures to aggregate liquidity risk and balance sheet variables related to bank exposure to liquidity risk. Some of these more detailed variables are at the core of Basel III liquidity requirements designed to limit bank exposure to potential liquidity shocks.

Bank size most likely shapes bank exposure to liquidity risk. Large banks are expected to be more heavily exposed to liquidity risk due to their greater reliance on wholesale markets (Cocco et al., 2009) and holdings of fewer liquid assets (Bunda & Desquilbet, 2008; Vodova, 2013). However, the literature also underscores funding advantages associated with size, namely, relatively privileged access to funding liquidity for large banks. This is attributed to the higher liquidity of more significant debt issues, to more frequent issuances, and to anticipated liquidity support from public authorities in times of distress. Lenders to large institutions anticipate that these will be bailed out during emergencies and require a lower risk premium through more advantageous interest rates (e.g., Akram & Christophersen, 2010; Acharya, Anginer, & Warburton, 2014; Bijlsma et al., 2014). Thus, access to wholesale markets and to liquidity support from central banks or governments should protect banks negatively affected by aggregate liquidity shocks. Consequently, the effects of bank size on bank exposure to liquidity risk are ambiguous.

Leverage may also be related to liquidity risk exposure. Leverage is procyclical. In times of economic growth, money markets are liquid and banks finance the expansion of their balance sheets using short-term funds on wholesale markets (Adrian & Shin, 2010). Thus, more heavily leveraged banks should be more exposed to liquidity shocks. When leverage is computed as equity over total assets, a negative link between leverage and measures of bank liquidity risk is expected.

Funding stability tends to render banks less affected by liquidity risk. Deposits are viewed as a stable funding source due to deposit insurance (e.g., Diamond & Dybvig, 1983; Calomiris & Kahn, 1991; Diamond & Rajan, 2001). According to models of banking theory, insured depositors have no incentives to run on banks. A negative link is expected between deposit shares of total assets and exposure to liquidity risk (ω_L). By contrast, the more banks rely on wholesale funding, the more heavily exposed to liquidity risk they can become. Thus, a positive relationship is anticipated between short-term debt shares of total assets and measures of bank liquidity risk. Holding a buffer of liquid assets also tends to protect banks from liquidity risk, as they can face larger cash outflows. We expect to find a negative link between the proportion of liquid assets of total assets and measures of bank liquidity risk. Finally, funding gaps defined as the share of loans financed with stable funding synthesize both the stability of funding and the liquidity of assets. We expect to find a negative relationship between funding gaps and measures of bank liquidity risk. These last four variables provide an account of bank liquidity creation.

Finally, a positive relationship between liquidity and insolvency risk is proven theoretically (e.g., Eisenbach, Keister, McAndrews, & Yorulmazer, 2014) and empirically (e.g., Imbierowicz & Rauch, 2014). This principle mainly comes from the literature on bank runs. On the one hand, short-term creditors can decide to run based on beliefs on bank assets through sunspot bank runs (Diamond & Dybvig, 1983; Iyer & Puri, 2012). On the other hand, depositors can run based on information on asset risks through fundamental bank runs (Allen & Gale, 2007; Goldstein & Pauzner, 2005). We thus expect to observe a positive relationship between credit risk and exposure to liquidity risk.

5.1. Methodology

One characteristic of the estimated ω_L is the large number of non-significant values set to zero in the previous section. This calls for a regression strategy based on this feature. To estimate the effects of the selected balance sheet features on exposure to liquidity risk, we use a Tobit model with friction introduced by Rosett (1959) as a generalization of Tobin's (1958) model. This model considers the fact that variations in explanatory variables may affect the explained variable if and only if they are large enough, i.e., contributing to the crossing of certain thresholds. This specific feature accounts for the fact that a bank not currently exposed to liquidity risk can become positively or negatively exposed only when its characteristics change sufficiently, hence reflecting the share of banks exhibiting non-significant exposure to aggregate liquidity.

This specification thus assumes that the dependent variable, ω_L, only responds to strong variations in a latent non-observable variable ω_L^*. This market participant behavior may be due to transaction costs that limit transactions relative to desired levels and more generally to stickiness. When parameter ω_L is positive or negative, we are no longer referring to the frictional part of the model and ω_L can be determined by a given set of covariates. However, a parameter ω_L that is equal to zero denotes insensitivity to liquidity conditions.

Let $\omega_{L,it}^*$ be the latent individual liquidity measure of liquidity risk for bank i at time t. Balance sheet characteristics are modeled by a vector x_t of k exogenous variables excluding the constant as shown by Eq. (3):

$$\omega_{L,it}^* = \sum_{j=1}^{k} \beta_j x_{j,it-1} + \varepsilon_{it} \tag{3}$$

The observed individual liquidity measure $\omega_{L,it}$ is modeled as a function of the expected $\omega_{L,it}^*$ according to $\omega_{L,it} = \xi(\omega_{L,it}^*)$. Function $\xi(.)$ maps latent variable $\omega^*{}_L$ to observed variable ω_L. This function is given by Eq. (4):

$$\omega_{L,it} = \begin{cases} \omega_{L,t}^* - \alpha_1, & \omega_{L,t}^* < \alpha_1 \\ 0, & \alpha_1 \le \omega_{L,t}^* \le \alpha_2 \\ \omega_{L,t}^* - \alpha_2 & \alpha_2 < \omega_{L,t}^* \end{cases} \tag{4}$$

5.2. Data and results

The model is estimated using the following balance sheet variables. Bank balance sheet data were extracted from Datastream and Worldscope reports:

- Size = ln(total assets)
- Leverage = equity/total assets
- Deposit share = deposits/total liabilities
- Cash share = cash & due from banks/total assets
- Reliance on wholesale funding = short-term debt/total debt
- Asset liquidity = net loans/total assets
- Funding gap = (net loans − short-term debt)/net loans
- Credit risk = provisions for loan losses/net loans

Table 4 lists descriptive statistics on these balance sheet characteristics. A lag of one year is applied to all of these independent variables. Correlations between all variables used to estimate the model are shown in Appendix Table A1.

The effect of liquidity production and credit risk on bank liquidity risk is most likely dependent on bank liquidity conditions. We thus expect effects on bank liquidity risk to vary depending on whether banks are positively or negatively affected by aggregate liquidity risk. Different parameters of Eq. (4) should reflect effects of liquidity production and credit risk conditional to the sensitivity of bank liquidity risk. The opposite signs of parameters for positive and negative ω_L reflect two possible situations. When parameters are positive for negative ω_L and negative for positive ω_L, then the proxy of liquidity production or credit risk should tend to make

Table 4
Descriptive statistics on bank balance sheet characteristics.

Independent variables	ω_L			
	Negative	Null	Positive	p-Values
N	80	310	231	
Volatility of returns	0.019***	0.021	0.030	0.00
	(0.013)**	(0.021)	(0.017)	0.01
Size	16.46***	17.24	17.58	0.00
	(2.00)	(2.02)	(2.18)	0.44
Leverage	0.09	0.08	0.08	0.51
	(0.09)	(0.07)	(0.07)	0.81
Deposit share	0.45	0.45	0.42	0.19
	(0.19)*	(0.19)	(0.16)	0.06
Cash share	0.02	0.02	0.02	0.92
	(0.01)	(0.03)	(0.02)	0.67
Reliance on wholesale	0.50	0.51	0.52	0.79
funding	(0.29)**	(0.24)	(0.23)	0.02
Asset liquidity	0.71	0.72	0.68	0.11
	(0.17)*	(0.16)	(0.19)	0.10
Funding gap	0.64	0.71	0.63	0.16
	(0.85)	(0.21)	(0.62)	0.23
Credit risk	0.008	0.007	0.007	0.68
	(0.02)*	(0.01)	(0.01)	0.10

Table 4 reports means and standard deviations of bank balance sheets in parentheses. Bank characteristics are values lagged by one period. Data are observed for 2005–2012. Significant mean difference tests are based on Welch's test statistic. Significant variance difference tests of negative, null and positive ω_L are based on Levene's test statistic.

*** Denote that the three samples differ from one another at the 1% levels.
** Denote that the three samples differ from one another at the 5% levels.
* Denote that the three samples differ from one another at the 10% levels.

Table 5
Tobit regressions.

	Estimates	
	Panel A: negative ω_L	Panel B: positive ω_L
α1	−7.917***	–
	(1.73)	–
α2	–	5.568***
	–	(0.81)
Size	0.166**	-0.198***
	(0.08)	(0.04)
Leverage	**−5.808****	**−5.808****
	(2.89)	**(2.89)**
Deposit share	−2.422*	0.134
	(1.44)	(1.05)
Cash share	**−6.51**	**−6.51**
	(4.72)	**(4.72)**
Reliance on wholesale	2.477***	-0.312
funding	(0.93)	(0.68)
Asset liquidity	**−0.284**	**−0.284**
	(0.58)	**(0.58)**
Funding gap	4.713***	-0.282
	(1.61)	(1.04)
Credit risk	**1.959**	**1.959**
	(5.61)	**(5.61)**
Error term	**1.361*****	**1.361*****
	(0.06)	**(0.06)**
Goodness of fit	61%	36%
Obs	521	379

Table 5 presents the results of the Tobit regressions of bank balance sheet variables lagged by one year on ω_L. The regressions are estimated for 2005–2012 and for negative ω_L (panel A) and positive ω_L (panel B). Error terms were subjected to Wald testing and are constrained to be equal. Hence, they are only reported in panel B. Variables in bold present the same parameters for negative and positive ω_L. The goodness of fit measure is the squared multiple correlation between predicted and observed values of ω_L. Standard errors are reported in parentheses.

*** Denote that coefficients are statistically significantly different from zero at the 1% levels.
** Denote that coefficients are statistically significantly different from zero at the 5% levels.
* Denote that coefficients are statistically significantly different from zero at the 10% levels.

banks insensitive to liquidity risk. By contrast, when parameters are negative for negative ω_L and positive for positive ω_L, then the proxy should tend to make banks more sensitive to liquidity risk.

Consequently, we first perform a Wald test on each independent variable to determine whether to impose a restriction of equal slope of upper and lower parts of the model (Fox, 1997). The results are shown in Appendix Table A2. When the test results are not significant, we impose a restriction of equal coefficients on the upper and lower parts. Thus, we impose a restriction of equal coefficients on leverage, cash, asset liquidity, loan loss provisions, and the error term.

The model is estimated for the entire 2005–2012 period. Table 5 shows the estimation results. Estimates in panel A correspond to the estimation with negative ω_L while panel B refers to the estimation with positive ω_L.

We first comment on the results of explanatory variables on which an equality constraint was applied. Leverage computed as equity over total assets has a consistent effect on banks depending on their sensitivity to liquidity risk. Market participants value higher levels of capital to decrease their sensitivity to aggregate liquidity. Leverage tends to decrease (increase) the sensitivity of banks negatively (positively) affected by aggregate liquidity risk. As more capitalized banks rely less on wholesale markets to finance themselves, they depend less on aggregate liquidity. This result provides information on the relationship between liquidity and credit risk. Indeed, capital buffers help banks absorb credit shocks and decrease their insolvency risks. Imbierowicz and Rauch (2014) observed that the interaction between bank liquidity risk and credit risk is dependent on the overall level of bank risk. Rather, conditional to the probability of defaults, the interaction between liquidity risk and credit risk can either mitigate or aggravate the probability of defaults. Here, we further argue that the relationship between liquidity risk and credit risk is dependent on bank sensitivity to liquidity risk. Indeed, capital tends to insulate banks from liquidity risk when they are negatively affected by aggregate liquidity, i.e., banks for which risks measured based on stock volatility increase as aggregate liquidity conditions deteriorate. In addition, capital decreases the volatility of returns of banks insensitive to or positively affected by market wide liquidity, thus increasing benefits in terms of total risk. Regarding cash shares, asset liquidity and credit risk, no significant relationship was observed with ω_L.

Second, we comment on the results of explanatory variables for which no equality constraint was imposed. These parameters are size, the deposit share, reliance on wholesale funding and funding gaps.

Size is significant for all ω_L values. The positive (negative) sign of the estimated parameter for size for negative (positive) ω_L suggests that larger banks are exposed to less liquidity risk. A larger size tends to make banks insensitive to aggregate liquidity conditions. Larger banks with negative ω_L values benefit less from aggregate liquidity. Similarly, for positive ω_L values, larger banks are subjected to higher risk levels with aggregate liquidity. Thus, we observe that market participants value size as a way to insulate banks from aggregate liquidity pressures. This may reflect an incentive for banks to expand enough to benefit from public support under systemic liquidity stress. This suggests that even though larger banks are likely to be more heavily exposed to liquidity risk, the market anticipates public support for banks.

Regarding deposit share, wholesale funding reliance and funding gap relationships to ω_L, such relationships are significant only for banks with negative ω_L values. The estimated parameter for deposit shares is negative. Thus, for banks gaining from aggregate liquidity stress, market participants value a higher deposit share as even more advantageous in terms of total risk. This result is consistent with the literature underscoring the funding advantages of stable deposits. In addition, this result complements the literature, as the effects of deposits are dependent on bank exposure to liquidity risk. Increasing deposits is advantageous for banks benefiting from aggregate liquidity but not for banks negatively affected. Similarly, the estimated parameter for the reliance on wholesale funding is positive. Banks benefiting from the degradation of aggregate liquidity tend to lose this advantage in terms of total risk as they finance themselves relatively more through money markets. This result is consistent with the literature, as wholesale funding increases potential bank exposure to liquidity shocks. Finally, the estimated parameter for the funding gap is positive. A larger funding gap denotes here that a bank finances its loans with more long-term debt. This implies a lower share of short-term debt. This result is in accordance with the literature stressing that more long-term funding reduces exposure to potential liquidity shocks.

Thus, regarding deposit shares, reliance on wholesale funding, and funding gaps, there are asymmetries between positive and negative ω_L. These results provide insight into investors' perceptions of risk. According to these three ratios, investors have perceptions of a bank's business model and more particularly of the intensity of liquidity creation levels. Higher levels of liquidity creation result in higher degrees of liquidity risk (Berger & Bouwman, 2009). Concordantly, riskier banks are more negatively affected by aggregate liquidity (Table 4). However, liquidity creation only affects the sensitivity of banks positively affected by aggregate liquidity changes. This behavior reflects a flight-to-quality behavior as investors consider the liquidity creation of the strongest banks. This is also consistent with motivations behind liquidity hoarding. Indeed, benefits are anticipated from liquidity hoarding either as a strategic or precautionary motive. Banks can benefit from the degradation of aggregate liquidity through profits from fire sales of assets or from needing less wholesale funding (Allen et al., 2009; De Haan & Van den End, 2013). For banks negatively affected by aggregate liquidity, market participants do not view variations in liquidity creation as either aggravating or mitigating bank sensitivity to liquidity risk. Market participants likely believe that these banks should benefit from the support of public authorities when needed. This is consistent with the literature showing that unconditional public support for banks reduces incentives for banks to hold liquidity (Acharya, Shin, & Yorulmazer, 2011). This belief is most likely based on the size and capitalization of banks as indicated by the results shown above. As a result, the market discipline of liquidity creation appears to be one-sided. From a regulatory point of view, this argues in favor of the regulation of liquidity creation through liquidity requirements such as Basel III ratios.

6. Robustness checks

We investigated some alternative specifications as a check on the robustness of our main findings. We estimated a model for alternative aggregate liquidity indices (Section 6.1) and market factor indices (Section 6.2). We also checked for linearity in the relationship between bank returns and aggregate liquidity risk factors (Section 6.3).

6.1. Alternative aggregate liquidity indices

First, we estimate the model from the Euribor euro area AAA spread on maturities for six, nine and twelve months. Furthermore, we use another measure of euro area government borrowing rates: the Eurobenchmark yield curve rate provided through Bloomberg for maturities of 6 and 12 months. For all cases, the relationship between bank returns and the aggregate liquidity index reflects results reported in Section 4.

Table 6
Descriptive statistics of ω_L per year.

Year	2005	2006	2007	2008	2009	2010	2011	2012
Obs.	73	74	78	80	78	79	80	79
Mean	−0.41	−0.93	0.20	0.31	0.21	0.32	0.52	0.07
Median	0	0	0	0.38	0	0	0.53	0
Std. dev.	3.51	1.79	0.44	0.30	0.44	0.99	0.72	0.45

Table 6 presents the number of observations, means, medians, standard deviations, 10th and 90th quantiles, and maximum and minimum values of ω_L. Non-significant ω_L values at the 10% level are set to zero.

Table 7
Descriptive statistics of β_L per year.

Year	2005	2006	2007	2008	2009	2010	2011	2012
Obs.	73	74	78	80	78	79	80	79
Mean	−1.20	−0.72	−0.31	−0.22	−0.12	0.92	0.35	−0.32
Median	0	0	0	0	0	0	0	0
Std. dev.	6.66	2.50	0.95	1.51	2.27	1.88	2.32	1.84

Table 7 presents the number of observations, means, medians, standard deviations, 10th and 90th quantiles, and maximum and minimum values of β_L. Values are multiplied by 1000. Non-significant β_L values at the 10% level are set to zero.

6.2. Alternative market factor indices

Second, another concern relates to what extent composite national market return indexes integrate the banking industry and thus to the effect of aggregate liquidity on bank stock returns. Indeed, larger banks are usually a component of composite national market indices. For instance, French market return index CAC 40 and the German DAX 30 each include three large banks.[7] We determined whether this could explain the quasi-absence of significant β_L values consistent with the literature on risk factor models. To investigate the influence of market index returns on the aggregate liquidity index, we re-estimate the factor model using a market return index excluding banks. As computing composite national market returns while excluding banks is not the aim of this study, we take Eurostoxx ex banks as a market return factor including all sectors but the banking industry.[8] The distribution of negative, null and positive ω_L values estimated (Table 6) reflects our previous results (Section 4). Indeed, the distribution of ω_L (Fig. 2 below) takes the same shape, but the impact of liquidity crises is slightly accentuated as we observe fewer positive ω_L values prior to the crisis of 2006 and more positive values during the crisis. Similarly, the distribution of β_L (Table 7 below) reflects results presented in Section 4. We still observe a few more positive β_L values in 2010 and negative β_L values in 2007 and 2012. Thus, effects of a market factor index excluding banks on bank liquidity risk appear to be negligible.

6.3. Linearity of the relationship between bank returns and the aggregate liquidity factor

Finally, we allow for non-linearity in the relationship between bank returns and the aggregate liquidity factor. Indeed, from the sudden irruption of liquidity crises, one could question the linearity of this relationship. We thus add another regressor to the initial

[7] The CAC 40 index includes BNP Paribas, Crédit Agricole, and Société Générale while the DAX 30 index includes Commerzbank, Deutsche Bank, and Deutsche Postbank.

[8] The Eurostoxx ex bank index is generated by STOXX Limited. It is computed as an index of 261 large, mid-sized and small capitalization companies across 12 Eurozone countries corresponding exactly to the geographical area covered by our sample and excluding stocks from the banking sector.

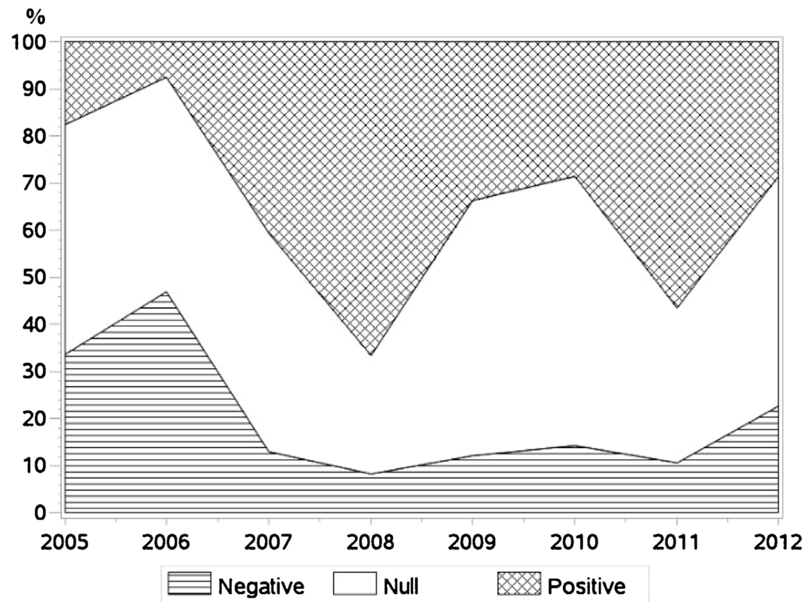

Fig. 2. Frequency of ω_L estimated for Eurostoxx ex banks.
ω_L frequency is plotted by sign for each year. Frequency is cumulated from negative to positive ω_L. Non-significant ω_L values at 10% significance are set to 0.

model: the squared aggregate liquidity index. The following model is thus estimated:

$$r_{i,t} = \alpha_i + \beta_{m,i} r_{m,t} + \beta_{L,i} SL_t + \beta_{L^2,i} SL_t^2 + e_{i,t}\sigma_{i,t} \quad (5)$$

$$\sigma^2{}_{i,t} = \exp(\omega_i + \omega_{L,i} SL_t) + \gamma_i \varepsilon^2{}_{i,(t-1)} \quad (6)$$

where

$e_i \sim N(0, 1)$

However, the cumulative frequencies of squared β_L and ω_L follow the same pattern as that shown in Section 4 (Figs. 1 and 2). The number of significant β_L values (85) remains close to that we observe for the first model (81) while 91 significant $\beta_L{}^2$ values are observed. The results on parameter ω_L remain unchanged.

7. Conclusion

The measure of exposure to aggregate liquidity conditions confirms that liquidity risk is generally considered a specific risk. Our main results also highlight the heterogeneity of exposure to liquidity risk across banks. While some banks benefit from it, others are hampered by or insensitive to liquidity risk. The benefits of liquidity costs could be explained by the liquidity hoarding behaviors of banks either for strategic or precautionary reasons. A second major result concerns the identification of the 2007–2009 and 2011 liquidity crises as heterogeneity declines. However, even during liquidity crises, liquidity risk remained as a specific risk. This suggests that market participants anticipate interventions from public authorities, stressing the efficiency of European Central Bank policies during liquidity crises. Nevertheless, our findings show that size becomes determinant only during liquidity crises. As the literature stresses the importance of accounting for indicators of liquidity risk, we further examined the relationship between them and our measure. Deposit shares, reliance on wholesale funding, and funding gaps denote levels of liquidity production in banks. Our results indicate that market participants value liquidity creation only for banks whose risk decreases with increasing aggregate liquidity risk. Regarding banks negatively affected by liquidity risk, liquidity production has no effect. Market participants likely anticipate support from public authorities. Indeed, higher levels of size and capitalization reduce bank sensitivity. Thus, our measure is in accordance with the literature on accounting measures of liquidity risk. Furthermore, we shed light on perceptions of bank liquidity risks among market participants. As the market discipline of liquidity production appears to be one-sided, this reinforces the need to impose liquidity requirements on all banks such as the Basel III liquidity ratios.

Appendix.

Table A1
Correlations between ω_L and balance sheet variables.

	ω_L	Size	Leverage	Deposit share	Cash share	Wholesale funding	Asset liquidity	Funding gap	Credit risk
ω_L	1	0.082	−0.099	0.021	−0.002	0.029	−0.028	0.021	−0.020
		(0.050)	(0.018)	(0.609)	(0.965)	(0.481)	(0.494)	(0.619)	(0.632)
Size		1	−0.386	−0.288	−0.038	0.150	−0.502	−0.068	−0.055
			(<.0001)	(<.0001)	(0.363)	(0.000)	(<.0001)	(0.104)	(0.184)
Leverage			1	−0.235	−0.040	−0.086	0.302	0.089	−0.088
				(<.0001)	(0.341)	(0.040)	(<.0001)	(0.032)	(0.033)
Deposit share				1	0.328	0.166	0.214	0.324	0.161
					(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
Cash share					1	0.055	−0.017	0.109	0.148
						(0.187)	(0.687)	(0.009)	(0.000)
Wholesale funding						1	−0.333	-0.333	−0.075
							(<.0001)	(<.0001)	(0.070)

Table A1 (*Continued*)

	ω_L	Size	Leverage	Deposit share	Cash share	Wholesale funding	Asset liquidity	Funding gap	Credit risk
Asset liquidity							1	0.445 (<.0001)	0.061 (0.146)
Funding gap								1	0.073 (0.079)
Credit risk									1

Table A1 presents Pearson correlation coefficients and p-values in parentheses between ω_L and balance sheet characteristics such as size = ln(total assets), leverage = capital/total assets, deposit shares = deposits/total assets, cash shares = cash/total assets, wholesale funding = short-term debt/total debt, asset liquidity = net loans/total assets, funding gaps = (net loans − short-term debt)/net loans, credit risk = provisions for loan losses/net loans.

Table A2
Results of the Wald test.

Balance sheet variables	Wald statistics
Size	14.15***
Leverage	1.94
Deposit share	3.20*
Cash share	0.51
Reliance on wholesale funding	4.34**
Asset liquidity	1.63
Funding gap	3.15*
Credit risk	0.03

Table A2 presents the results of our Wald tests on equal coefficients for balance sheet variables of the model between upper and lower parts of the friction model. When the Wald test is not significant, a restriction is imposed on the variable that consists of equal coefficients for the upper and lower parts of the Tobit model.

*** Denote that the tests are statistically significantly at the 1% levels.
** Denote that the tests are statistically significantly at the 5% levels.
* Denote that the tests are statistically significantly at the 10% levels.

Table A3
Geographical distribution of the sampled banks.

Country	Number of banks	National stock market index
Austria	3	ATX
Belgium	2	BEL20
Germany	14	DAX30
Spain	8	IBEX35
Finland	1	OMXH
France	21	CAC40
Greece	9	ATHEX
Ireland	3	ISEQ20
Italy	18	FTSE MIB
Luxemburg	1	LUXX
The Netherlands	2	AEX25
Portugal	3	PSI20

Table A3 presents the number of banks in the sample by country of origin and national stock market indices used to estimate the risk factor model (Eqs. (1) and (2)).

References

Abbassi, P., Fecht, F., & Weber, P. (2013). How stressed are banks in the interbank market? *Deutsche Bundesbank Discussion Paper, 40*.

Acharya, V. V., Anginer, D., & Warburton, A. J. (2014). The End of Market Discipline? Investor Expectations of Implicit Government Guarantees. *SSRN Working Paper*.

Acharya, V. V., Gale, D., & Yorulmazer, T. (2011). Rollover risk and market freezes. *Journal of Finance*, *66*(4), 1177–1209.

Acharya, V. V., Gromb, D., & Yorulmazer, T. (2012). Imperfect competition in the interbank market for liquidity as a rationale for central banking. *American Economic Journal: Macroeconomics*, *4*(2), 184–217.

Acharya, V. V., & Merrouche, O. (2012). Precautionary hoarding of liquidity and interbank markets: Evidence from the subprime crisis. *Review of Finance*, *17*, 107–160.

Acharya, V. V., Shin, H. S., & Yorulmazer, T. (2011). Crisis resolution and bank liquidity. *Review of Financial Studies*, *24*, 2166–2205.

Adrian, T., & Shin, H. S. (2010). Liquidity and leverage. *Journal of Financial Intermediation*, *19*(3), 418–437.

Afonso, G., Kovner, A., & Schoar, A. (2011). Stressed, not frozen: The federal funds market in the financial crisis. *Journal of Finance*, *66*, 1109–1139.

Aikman, D., Alessandri, P., Eklund, B., Gai, P., Kapadia, S., Martin, E., . . . & Willison, M. (2011). Funding liquidity risk in a quantitative model of systemic stability. *Financial Stability, Monetary Policy and Central Banking*, *15*(12), 371–410.

Akram, F. Q., & Christophersen, C. (2010). Interbank overnight interest rates-gains from systemic importance. *Norges Bank Working Paper Series, 11*.

Allen, F., & Carletti, E. (2008). The role of liquidity in financial crises. *Economic policy symposium – Jackson Hole – Federal Reserve Bank of Kansas City*, 379–412.

Allen, F., Carletti, E., & Gale, D. (2009). Interbank market liquidity and central bank intervention. *Journal of Monetary Economics*, *56*, 639–652.

Allen, F., & Gale, D. (2007). *Understanding financial crises*. Oxford: Oxford University Press.

Angelini, P., Nobili, A., & Picillo, M. C. (2011). The interbank market after August 2007: What has changed and why? *Journal of Money, Credit and Banking*, *43*(5), 923–958.

Aspachs, O., Nier, E., & Tiesset, M. (2005). Liquidity, banking regulation and the macroeconomy—Evidence on bank liquidity holdings from a panel of UK-resident banks. *Bank for International Settlements Working Paper*.

Baele, L., De Bruyckere, V., De Jonghe, O., & Vander Vennet, R. (2015). Model uncertainty and systematic risk in US banking. *Journal of Banking & Finance*, *53*, 49–66.

Berger, A. N., & Bouwman, C. H. S. (2009). Bank liquidity creation. *Review of Financial Studies*, *22*, 3779–3837.

Bijlsma, M., Lukkezen, J., & Marinova, K. (2014). Measuring too-big-to-fail funding advantages from small banks' CDS spreads. *CPB Netherlands Bureau for Economic Policy Analysis Discussion Paper, 268*.

Bongaerts, D., De Jong, F., & Driessen, J. (2011). Derivative pricing with liquidity risk: Theory and evidence from the credit defaut swap market. *Journal of Finance*, *76*(1), 203–240.

Brunnermeier, M. K. (2009). Deciphering the liquidity and credit crunch 2007–2008. *Journal of Economic Perspectives*, *23*(1), 77–100.

Brunnermeier, M. K., Gorton, G., & Krishnamurthy, A. (2012). Risk topography. *NBER Macroeconomics Annual*, *26*(1), 149–176.

Brunnermeier, M. K., & Pedersen, L. H. (2009). Market liquidity and funding liquidity. *Review of Financial Studies*, *22*(6), 2201–2238.

Bunda, I., & Desquilbet, J.-B. (2008). The bank liquidity smile across exchange rate regimes. *International Economic Journal*, *22*(3), 361–386.

Caballero, R. J., & Krishnamurthy, A. (2008). Collective risk management in a flight to quality episode. *Journal of Finance*, *63*(5), 2195–2230.

Calomiris, C. W., & Kahn, C. M. (1991). The role of demandable debt in structuring optimal banking arrangements. *American Economic Review*, *81*(3), 497–513.

Christensen, J. H. E., Lopez, J. A., & Rudebusch, G. D. (2014). Do central bank liquidity facilities affect interbank lending rates? *Journal of Business and Economic Statistics*, *32*(1), 136–151.

Cocco, J. F., Gomes, F. J., & Martins, N. C. (2009). Lending relationships in the interbank market. *Journal of Financial Intermediation*, *18*, 24–48.

Cornett, M. M., McNutt, J. J., Strahan, P. E., & Tehranian, H. (2011). Liquidity risk management and credit supply in the financial crisis. *Journal of Financial Economics*, *101*, 297–312.

Covitz, D., Liang, N., & Suarez, G. (2013). The evolution of a financial crisis: Collapse of the asset-backed commercial paper market. *Journal of Finance*, *68*(3), 815–848.

Craig, B. R., Fecht, F., & Tümer-Alkan, G. (2015). The role of interbank relationships and liquidity needs. *Journal of Banking & Finance*, *53*(C), 99–111.

De Haan, L., & Van den End, J. W. (2013). Bank's responses to funding liquidity shocks: Lending ajustment, liquidity hoarding and fire sales. *Journal of International Financial Markets, Institutions & Money*, *26*, 152–174.

Dewenter, K. L., & Hess, A. C. (1998). An International Comparison of Banks' Equity Returns. *Journal of Money, Credit and Banking*, *30*(3), 472–492.

Diamond, D., & Rajan, R. G. (2001). Liquidity risk, liquidity creation, and financial fragility: A theory of banking. *Journal of Political Economy*, *109*(2), 287–327.

Diamond, D. W., & Dybvig, P. H. (1983). Bank runs, deposit insurance, and liquidity. *Journal of Political Economy*, *91*(3), 401–419.

Diamond, D. W., & Rajan, R. G. (2009). The credit crisis: Conjectures about causes and remedies. *American Economic Review*, *99*(2), 606–610.

Dietrich, A., Hess, K., & Wanzenried, G. (2014). The good and bad news about the new liquidity rules of Basel III in Western European countries. *Journal of Banking and Finance*, *44*, 13–25.

Drehmann, M., & Nikolaou, K. (2013). Funding liquidity risk: Definition and measurement. *Journal of Banking & Finance*, *37*(7), 2173–2182.

Eisenbach, T., Keister, T., McAndrews, J., & Yorulmazer, T. (2014). Stability of funding models: An analytical framework. *Economic Policy Review*, *20*(1), 29–47.

Ennis, H. M., & Weinberg, J. A. (2013). Over-the-counter loans, adverse selection, and stigma in the interbank market. *Review of Economic Dynamics*, *16*, 601–616.

Fox, J. (1997). *Applied regression analysis, linear models, and related methods*. Thousand Oaks: C.S. Publications.

Furfine, C. H. (2001). Banks as monitors of other banks: Evidence from the overnight federal funds market. *Journal of Business*, *74*(1), 33–57. Bank for I. S.

Goldstein, I., & Pauzner, A. (2005). Demand-deposit contracts and the probability of bank runs. *Journal of Finance*, *60*(3), 1293–1327.
Gorton, G., & Metrick, A. (2012). Securitized banking and the run on repo. *Journal of Financial Economics*, *104*, 425–451.
Gyntelberg, J., & Wooldridge, P. (2008). Interbank rate fixings during the recent turmoil. *Bank for International Settlements Quarterly Review*, (March).
Haq, M., & Heaney, R. (2012). Factors determining European bank risk. *Journal of International Financial Markets, Institutions & Money*, *22*(4), 696–718.
Heider, F., Hoerova, M., & Holthausen, C. (2015). Liquidity Hoarding and Interbank Market Rates: The Role of Counterparty Risk. *SSRN Working Paper*.
Hess, A. C., & Laisathit, K. (1997). A market-based risk classification of financial institutions. *Journal of Financial Services Research*, *12*(2/3), 133–158.
Hong, H., Huang, J., & Wu, D. (2014). The information content of Basel III liquidity risk measures. *Journal of Financial Stability*, *15*(C), 91–111.
Hong, H., & Wu, D. (2012). The Information Value of Basel III Liquidity Risk Measures. *SSRN Working Paper*.
Hui, C.-H., Genberg, H., & Chung, T.-K. (2011). Funding liquidity risk and deviations from interest-rate parity during the financial crisis of 2007–2009. *International Journal of Finance and Economics*, *16*, 307–323.
Imbierowicz, B., & Rauch, C. (2014). The relationship between liquidity risk and credit risk in banks. *Journal of Banking & Finance*, *40*, 242–256.
Iyer, R., & Puri, M. (2012). Understanding bank runs: The importance of depositor–bank relationships and networks. *American Economic Review*, *102*(4), 1414–1445.
Jokipii, T., & Milne, A. (2008). The cyclical behaviour of European bank capital buffers. *Journal of Banking & Finance*, *32*(8), 1440–1451.
Kaufman, G. G., & Scott, K. E. (2003). What is systemic risk, and do bank regulators retard or contribute to it? *The Independent Review*, *7*(3), 371–391.
Pagratis, S., & Stringa, M. (2009). Modeling bank senior unsecured ratings: A reasoned structured approach to bank credit assessment. *International Journal of Central Banking*, *5*(2).
Philippon, T., & Skreta, V. (2012). Optimal interventions in markets with adverse selection. *American Economic Review*, *112*(1), 1–28.
Rosett, R. N. (1959). A statistical model of friction in economics. *Econometrica*, *27*(2), 263–267.
Schuermann, T., & Stiroh, K. J. (2006). Visible and Hidden Risk Factors for Banks. *Federal Reserve Bank of New York Staff Reports, 252*.
Schwarz, K. (2014). *Mind the gap: Disentangling credit and liquidity in risk spreads*. SSRN Working Paper.
Severo, T. (2012). Measuring Systemic Liquidity Risk and the Cost of Liquidity Insurance. *IMF Working Paper, 12/194*.
Shin, H. S. (2009). Reflections on Northern Rock: The bank run that heralded the global financial crisis. *Journal of Economic Perspectives*, *23*(1), 101–120.
Tobin, J. (1958). Estimation of relationship for limited dependent variables. *Econometrica*, *26*(1), 24–36.
Tölö, E., & Jokivuolle, E. (2015). ECB Working Paper Series, (1809).
Vodova, P. (2013). Determinants of commercial bank liquidity in Hungary. *Financial Internet Quarterly e-Finanse*, *9*(3), 64–71.