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

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Abstract

The 2007-2009 crisis stressed the importance of liquidity for banks. Using a risk factor model, we propose a measure of bank exposure to liquidity risk based on their sensitivity to aggregate liquidity conditions. Results indicate that liquidity risk is a specific risk. Moreover, this measure sheds light on the heterogeneity among banks in terms of exposure to liquidity risk. Banks benefit, lose or are insensitive to liquidity conditions, and we document large variation in exposure across the 2008 and 2011 crises. Larger size and capital levels tend to insulate banks from aggregate liquidity risk. However, deposit share, reliance on wholesale funding and funding gap impact only banks whose risk decreases with increasing aggregate liquidity risk. These ratios indicate the level of liquidity production by banks. This suggests that market discipline applies to liquidity production but only on the less risky banks in case of a liquidity crisis. Thus market discipline appears to be one-sided. To that extent it reinforces the necessity to impose liquidity requirements to all banks, as through the Basel III liquidity ratios.

JEL classification: E51, G21, G28, G32

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1. Introduction

Overexposure of banks to liquidity risk can have dramatic consequences for the stability of the financial system and the economy, as the 2007-2008 liquidity crisis showed (e.g. Allen & Carletti, 2008; Brunnermeier, 2009). The more banks rely on short term financial markets, the more they suffer from higher short term interest rates and lower availability of funding (e.g. Cornett and al., 2011). During the 2007-2008 crisis, some banks could not rollover their short term debt which in turn threatened their solvency. However, all banks were not affected to the same extent by the aggregate fluctuation of market wide liquidity conditions (e.g. Craig and al., 2015). This calls for a proper measurement of bank liquidity risk. The measures used in the literature can be mainly ordered in two categories. A first strand of the literature uses individual bank features describing bank potential exposure to liquidity shocks. These measures are mainly based on balance sheet elements in order to assess asset liquidity or funding stability (Hong & Wu, 2012). A second strand of the literature considers aggregate liquidity risk on money markets. Aggregate liquidity conditions are here measured with interbank rates or spreads. However, it is necessary to account for both dimensions simultaneously, that is to measure bank individual exposure to liquidity shocks taking aggregate liquidity conditions into account.

This paper contributes to the literature by introducing a measure of bank exposure to aggregate liquidity conditions within the framework of a risk factor model. The model allows computing bank sensitivity to daily variation of aggregate liquidity conditions. The sample consists of listed banks from the euro area between 2005 and 2012. Results indicate 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 on most of the components of money markets. Liquidity risk tended to be systemic – thus systematic. Results also indicate that there is a high level of heterogeneity across banks in terms of exposure to liquidity conditions. Indeed, exposure to liquidity risk is either positively or negatively linked to general liquidity conditions with aggregate liquidity respectively either reducing or increasing bank stock volatility. Moreover, a large share of banks is not affected by aggregate liquidity in statistical terms. Heterogeneity across banks decreases during liquidity crises as most of them were negatively affected by market wide liquidity conditions. Thus, liquidity risk at the bank level reflects overly idiosyncratic decisions in terms of funding and assets liabilities management. The paper then confronts the measure to accounting indicators of bank exposure to liquidity risk in order to gain a deep understanding of their relationship with bank liquidity risk. These indicators are currently used to asset bank liquidity creation (Berger & Bouwman, 2009). The share of deposits in total funding tends to increase the exposure to liquidity risk while the reliance on wholesale funding and the funding gap rather reduce the exposure to liquidity risk. However, these effects are concentrated only on banks positively affected by liquidity conditions as their stock's volatility decreases with aggregate liquidity. Thus, investors consider liquidity creation only for banks positively affected by aggregate liquidity. This appears as a flight to quality behaviour as investors consider only the liquidity creation of the strongest banks, that is to say the banks benefiting from aggregate liquidity. This is consistent with the benefits associated to liquidity hoarding. The market prices the risk of lower profitability associated with liquidity hoarding. Regarding banks negatively affected, market participants do not consider liquidity production. They probably anticipate that these banks would benefit from public support, if needed. This belief is based on size and capitalisation which decrease every bank exposure to liquidity risk. As capitalisation helps banks to face credit losses, we identify a relationship between bank liquidity and solvency risks.

The paper is organised as follows. Section 2 reviews the literature on bank liquidity risk measures. Section 3 introduces the risk factor model used to develop the 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 the relationships between balance sheet measure of liquidity risk and the measure of bank exposure to liquidity risk using a tobit model with friction. Section 6 presents some robustness checks; section 7 concludes.

2. Literature review

Liquidity risk is the possibility for a bank to become unable to settle obligations with immediacy over a specific horizon, using available liquid assets and cash or raising new debt at reasonable price (Drehmann & Nikolaou, 2013). The literature on bank liquidity risk mostly handles separately balance sheet measures of liquidity risk evaluating the potential exposure of banks to liquidity risk and measures of liquidity conditions affecting all banks on the interbank markets.

Firstly, the literature inventories the potential linkage between balance sheet characteristics and liquidity risk. Three characteristics have been investigated in order to characterise bank liquidity risk, corresponding to different features: the stability of funding, the liquidity of assets, or 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 the decision of short term lenders not to rollover their funding represent a loss of funding. The possibility for a loss of funding to occur is called rollover risk (Acharya and al., 2011). To that extent, bank liquidity refers to the capacity to raise funds at reasonable cost at short notice. The stability of funding is approached by accounting ratios such as the core deposit ratio, the non-core funding ratio, and the brokered deposits ratio. These ratios represent the share of short-term funding over total funding or interest expenses over total deposits, the latter ratio being used to proxy funding costs (Dietrich and al., 2014).

A second feature of bank individual exposure to liquidity risk is the liquidity of assets. Indeed, liquid assets represent a buffer that insures banks against liquidity risk. Banks can use liquidity buffers to face higher cash outflows than cash inflows. However, the liquidity of assets is closely linked to market liquidity (Brunnermeier & Pedersen, 2009). When market liquidity dries up, banks could experience difficulties 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, the current ratio, the acid test ratio, or the government securities ratio. Asset liquidity is usually measured by the share of customer loans over total assets (Pagratis & Stringa, 2009), the reserve balance with the central bank (Acharya & Merrouche, 2012) or the daily change in the bank reserve deposits (Cocco and al., 2009), among others measures[2].

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

[2] Acharya & Merrouche (2012) use also the reserve balance with the central bank to account for liquidity hoarding of large settlement banks in the UK during the subprime crisis of 2007-2008. Cocco and al. (2009) find that banks with a larger imbalance in their reserve deposits tend to borrow funds from banks with whom they have a relationship and pay a lower interest rate than they would otherwise.

The main advantage of these individual measures of bank liquidity risk is their micro level. They allow approaching a bank potential ability to withstand fluctuation in funding liquidity all things being equal. Nevertheless, these measures may be unable to account for the effective ability of banks to withstand liquidity shocks. They bear at least four shortcomings. First, balance sheet measures do not account for the capacity of banks to access to funding sources during liquidity shocks. The capacity of banks to refund themselves is not only expressed in public balance sheet variables. Bank's access to funding might also depend on dimensions such as their reputation, the diversification of their funding sources, or the central bank policy. Secondly, the comparison of balance sheet measures between banks or across time is not straightforward. Arising from the previous argument, the same level of a given measure for several banks does not necessarily mean the same exposure to liquidity risk. Similarly, the same level of an accounting indicator at two different points in time does not imply the same exposure to liquidity risk. Thirdly, balance sheet measures lack of frequency as they rely on yearly or at best quarterly data. Because of that, they fail to provide a precise assessment of bank individual liquidity risk across time, especially when looking at stressed liquidity conditions on financial markets. These stress events usually last a few weeks or months. Finally, it is difficult to get to grips with the interaction between the 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.

Secondly the literature considers measures of liquidity conditions for the banking sector. These aggregate liquidity measures are then relatively frequent but at the macro level. These measures are often referred to as systemic liquidity measures. However, Hong and al. (2014) note that there is no commonly accepted definition of systemic liquidity risk. Drawing on Kaufman & Scott's (2003) definition of systemic risk, systemic liquidity risk could be defined as the risk or probability of breakdowns in the entire money market, as opposed to breakdowns in individual components. It is evidenced by comovements among most or all parts of the money market. Systemic liquidity risk manifested during the 2007-2008 financial crisis through the general dry up of liquidity on money markets. The literature documents runs that occurred in 2007-2008 on asset-backed securities markets (Brunnermeier, 2009) such as the asset-backed commercial papers market (Covitz and al., 2013), the repurchase agreement market (Gorton & Metrick, 2012), the federal funds markets, (Afonso and al., 2011), and on other interbank markets (Acharya & Merrouche, 2012). Moreover, some banks faced runs from retail depositors such as Northern Rock (Shin, 2009) or from non-deposit creditors on Bear Stearns and IndyMac.

Systemic liquidity risk is commonly measured by market liquidity indices such as interbank rate spreads. Spreads such as Euribor or Libor minus government yield rate of the same maturity (e.g. Cornett and al., 2011; Hong and al., 2014; Hong & Wu, 2012), or an interbank rate minus Overnight Indexed Swap (OIS) rate (e.g. Hui and al., 2011) are widely used. Market liquidity risk can also be approached with repo haircuts as in Gorton & Metrick (2012)[3]. Finally, Schwarz (2014) proposes a measure of market liquidity computed as the spread between German sovereign bonds and German KfW agency bonds[4]. As both bonds share the same credit risk since they are both explicitly guaranteed by the federal government, the yield spread approaches aggregate liquidity conditions[5].

Finally, some studies develops bank individual measures of liquidity risk trying to account both for balance sheet characteristics and funding conditions on the financial markets. Some authors

[3] Gorton & Metrick (2012) find a correlation between the change in the LIBOR-OIS and change in the repo rates.
[4] Kreditanstalt für Wiederaufbau.
[5] 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 of these spreads at the beginning of the 2007-2009 crisis.

use the bidding or paid liquidity price of banks in the Eurosystem's weekly main refinancing operations (MRO) (e.g. Abbassi and al., 2013; Craig and al., 2015; Drehmann & Nikolaou, 2013). However, the data from which they are computed are not publicly available. Brunnermeier and al. (2012) propose a Liquidity Mismatch Index (LMI) computed as a sum of balance sheet items weighted by their market liquidity approached through repo haircut and interbank rates. Close to these measures, Berger & Bouwman (2009) develop a measure of liquidity creation by banks based on weighting assets and liabilities of balance sheet according to their liquidity. Closest to our approach is Severo (2012). His paper measures the exposure of banks to systemic liquidity conditions through the sensitivity of bank equity returns to systemic liquidity risk. Howerver, 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 bank individual exposure to liquidity conditions as the sensitivity of the volatility of bank stock returns to an aggregate liquidity risk factor. Factors models have been widely applied to the banking sector. These models analyse common risk factor driving bank returns. Baele and al. (2015) review the literature of models including factors thought to be relevant for banks. More particularly, some authors have included liquidity risk factors in return models. Hess & Laisathit (1997) thus take as liquidity risk factor the interest rate on three-month federal agency securities minus interest rate on three-month U.S. Treasury bills. Dewenter & Hess (1998) chose the three-month unregulated time deposit minus the discount rate on the three-month Treasury bills. Schuermann & Stiroh (2006) use the commercial paper spread to proxy liquidity risk. However, all find little explanatory power of liquidity risk. As a consequence, liquidity risk does not seem to be a priced systematic risk factor.

Still, liquidity risk may have an effect on bank total risk. We thus chose a model allowing a characterisation of the influence of liquidity risk on either systematic risk or total risk. Expanding the market model to include an aggregate liquidity risk factor, we measure the sensitivity of total variation of bank returns to liquidity risk. We estimate this return model using an ARCH(1) process to model the sensitivity of the volatility of bank stock returns to aggregate liquidity risk. Using this model, we consider both the idiosyncratic and market channels of liquidity risk affecting banks (Allen and al., 2009). Indeed, liquidity risk of banks can be divided into idiosyncratic and systematic liquidity risks. Systematic liquidity risk relates to the exposure of a banks to aggregate common liquidity conditions. It comes forward through a liquidity shock when the price every bank has to pay to finance itself on wholesale market increases or when banks cannot refund their matured debt. Idiosyncratic liquidity risk reflects all the bank funding decisions that can be diversified away by investors because they are independent across banks. The use of a return model following an ARCH(1) process accounts for this dichotomy between the idiosyncratic and systematic components of liquidity risk.

Following Severo (2012), the stock returns of a bank *i* from period t-1 to t follows the model:

$$r^i(t) = \alpha^i + \beta_m^i r_m(t) + \beta_L^i SL(t) + e^i(t)\sigma^i(t) \tag{1}$$

$$\sigma^i(t)^2 = \exp\left(\omega_0^i + \omega_L^i SL(t)\right) + \gamma^i \varepsilon^i(t-1)^2 \tag{2}$$

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 the aggregate liquidity risk factor $SL(t)$. The second equation models the volatility of bank i's stock returns as affected by the parameter (ω_L^i) which measures the sensitivity of bank i's stock returns' volatility to aggregate liquidity risk. The exponential form for the conditional heteroskedasticity avoids negative values for the volatility process.

This model thus allows characterising the nature of bank liquidity risk as either specific or systematic. The two parameters allowing an analysis of a bank *i*'s liquidity risk in this model are ω_L^i and β_L^i. The parameter ω_L^i estimated in the second equation stands for a measure of bank *i*'s individual exposure to liquidity risk. A positive (negative) ω_L^i means that bank *i* loses (benefits) from aggregate liquidity conditions, as the volatility of its stock returns increases with aggregate liquidity risk. The bank is for example net borrower (lender) on the interbank market and pays (gets) a higher price for funding liquidity. The parameter β_L^i captures the liquidity risk premium of bank *i*'s risk. The parameter ω_L^i includes both systematic and idiosyncratic components of bank liquidity risk, while β_L^i represents the systematic component of bank liquidity risk. A situation corresponding to a significant parameter ω_L^i and a non-significant parameter β_L^i would mean that the systematic component of bank *i*'s liquidity risk is absent. As a consequence, bank liquidity risk would be a specific risk.

3.2. Hypotheses

Consistently with the literature previously mentioned, we do not expect liquidity risk to be priced most of the time. Regarding the liquidity parameters, we expect to observe on average insignificant parameters β_L but significant parameters ω_L (hypothesis 1).

However, during a systemic liquidity crisis, we expect liquidity risk to be priced. Indeed, before the 2007-2008 liquidity crisis, liquidity conditions were loose and money market liquidity was not viewed as a source of risk by market participants (e.g. Adrian & Shin, 2010; Borio, 2004). On the contrary, we expect bank risk to be affected by aggregate liquidity during the liquidity crises. Bank risk would increase because of stressed liquidity conditions, which cause difficulties for banks to refund their short term debt at reasonable price on wholesale markets or making it no longer possible. We thus expect to observe higher proportions of significant parameters β_L during periods of systemic liquidity crises (hypothesis 2).

Finally, we expect to observe heterogeneity in bank sensitivity to aggregate liquidity conditions (hypothesis 3). Some banks would lose while others would benefit from liquidity risk. Indeed, on the one hand, during periods of liquidity crisis, banks would be negatively affected by liquidity conditions because they could not refinance themselves at reasonable cost. However, central bank and government liquidity support schemes were settled since the beginning of the crisis, starting with the ECB liquidity support to the interbank market in August 2007. Consequently, banks would then be immunised from aggregate liquidity shocks. However, a possible explanation for banks loosing from aggregate liquidity risk is the stigmatisation from receiving public support and short term depositor's runs. Banks using liquidity support provided by public authorities may have suffered from a stigma effect (Philippon and Skreta, 2012; Ennis and Weinberg, 2013). On the other hand, there are mainly two possible explanations on how banks would benefit from liquidity conditions. In contrast with normal times, a liquidity crisis could be characterised by a liquidity hoarding behaviour by market participants and/or an increase in counterparty risk concerns. The dry up of moneys markets could be accompanied by a hoarding behaviour of liquid assets by banks, as empirically evidenced (e.g. Aspachs and al., 2005; De Haan & Van den End, 2013). Two theoretical motives are proposed to explain bank's hoarding behaviour. On the one hand, banks could hoard liquid assets for a strategic motive (Acharya and al., 2012; Diamond & Rajan, 2009). On the other hand, banks could hoard liquid assets for a precautionary motive (Allen and al., 2009; Caballero & Krishnamurthy, 2008). The dry up of aggregate liquidity could also be explained by an increase in counterparty risk perceived by market participants (Heider and al. 2015). Asymmetric information about counterparty credit risk leads to higher interest rates or to a complete dry-up of the interbank market. Evidences of adverse selection in interbank markets were observed during the 2007-2008 crisis (Afonso and al., 2011; Angelini and al., 2011).

3.3. Data description

We build an unbalanced panel dataset with daily observations on bank stock returns obtained from Datastream from 2005 to 2012. Our sample includes data for commercial, savings and cooperative listed banks from the euro area. Following Schuermann & Stiroh (2006), we drop all bank returns observations of a given year if more than 150 observations of daily returns are missing for a given year. After cleaning the data, the sample is composed of 85 banks from twelve countries of the euro area from 2005 to 2012.

Data for the one-period return of the market factor consist of daily national stock market return index relevant for the domestic market of each bank. Table A3 in the appendix indicates the number of banks by country and the national stock market indices. In order to proxy aggregate liquidity the literature often uses measures of liquidity on the interbank market. A commonly used measure consists of the spread between banks and government borrowing rates (Christensen and al. 2014; Haq & Heaney, 2012; Hong & Wu, 2012). As our sample is composed of banks from the euro area, we take the Euribor three months rate. As for government borrowing rates, we take the three months rate of the euro area AAA rated member states yield curve computed by the ECB. We thus compute a Euribor-euro area AAA yield spread for a three months maturity. One of the main criticisms of spreads between banks and government borrowing rates is that they contain both liquidity and credit risk components (e.g. Gyntelberg & Wooldridge, 2008; Schwarz, 2014), especially in the context of a liquidity crisis affecting banks as evidenced by Angelini and al. (2011). We thus correct for bank credit risk by subtracting to the Euribor-euro area AAA three months spread the CMA European Banks 5 years CDS Index provided by Datastream, having standardised both distributions. We do not take liquidity of bank CDS into account as working with CDS data, liquidity is less of an issue (Bijlsma and al., 2014).

4. Results

4.1. Descriptive statistics of liquidity parameters

The model from equations 1 to 2 is estimated for each bank each year from 2005 to 2012. Descriptive statistics of the distribution of liquidity parameters ω_L and β_L are presented in tables

1 and 2. Non-significant liquidity coefficients are set equal to zero, as they correspond to banks being not exposed to aggregate liquidity risk.

Insert tables 1 and 2

The parameters ω_L are on average negative before the beginning of the 2007-2008 liquidity crisis and positive after (table 1). Liquidity conditions represent the cost of liquidity on interbank market. In the pre-crisis period on average, bank stock's volatility decreased with liquidity cost. Larger liquidity cost reinforced bank income and decreased total risk. Thus banks on average took benefits from a relatively efficient allocation of liquidity on a booming interbank market. However, since the 2007-2008 crisis, banks were on average impeded by aggregate liquidity, as indicated by positive ω_L. Higher liquidity cost decreased incomes and increased stock returns as banks were perceived as riskier.

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

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

The parameters β_L are very close to zero over the whole 2005-2012 (table 2). This is consistent with the literature finding that liquidity risk is in general not a priced factor (section 3). 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 reduced since the beginning of the liquidity crisis going 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 higher number of banks in time of liquidity stress. This is due to the systemic nature of liquidity shock. The liquidity dry up in the money markets hit a large majority of banks who in turn experienced difficulties to finance themselves. The diversity of liquidity risk positions within the interbank system reduced and the correlation between bank liquidity risks increased.

4.2. Univariate analysis of liquidity parameters ω_L

In this subsection, we perform various univariate analysis of the liquidity parameters by comparing group means of parameters ω_L. As previously, non-significant ω_L are set to zero. The estimated ω_L are not normally distributed as the Kolmogorov Smirnoff test indicates. Thus Welch's and Levene's tests are used to compare the distributions of ω_L. Results are displayed in table 3 below.

First, the sample is broken down in two periods, 2005-2007 and 2008-2012. These periods correspond respectively to the pre liquidity crisis and liquidity crises times. We investigate whether the exposure to liquidity risk evolved across time. Comparing means of ω_L for all banks of the euro area for 2005 to 2007 and 2008 to 2012, a statistically significant difference is observed between the two periods' means (table 3). Before the liquidity crisis in 2005-2007, banks benefited on average from aggregate liquidity conditions as indicated by the negative mean of ω_L. On the contrary, after the beginning of the liquidity crisis in 2008, banks on average lost from aggregate liquidity risk. Furthermore, a significant difference in the standard deviation of ω_L is found between the two periods. The volatility of ω_L reduced after the beginning of the 2007-2008 crisis. This is consistent with the observation of more heterogeneity in ω_L before the crisis than after (section 4.1.). Thus the systemic liquidity event characterised by a strong deterioration of liquidity conditions, the disruption of the money markets, changed the average sensitivity of bank total risk to aggregate liquidity.

Second, we investigate potential differences in terms of exposure to liquidity risk across banks with different characteristics. The sample is broken down by size, differentiating between small and large banks. The literature indeed provides evidence that large banks are more exposed to liquidity risk than small banks. Small banks usually focus on traditional intermediation and finance themselves relatively less on the financial markets or from the central bank (Berger & Bouwman, 2009). Thus, small banks would be less sensitive to aggregate liquidity. However, large banks tend to have also a better access to financial markets (Cocco and 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 sheet (Bunda & Desquilbet, 2008; Vodova, 2013). Then we would expect to observe higher positive ω_L for large banks as compared to small banks. Large banks are defined as those in the highest decile of banks ranked by total assets at the beginning of the period of observation in 2005 (Jokipii & Milne, 2008). Twelve banks out of 85 banks are thus labelled as large. Results indicate that the average ω_L is higher for large banks than for small banks, but the difference is not significant (table 3). However, the dispersion of ω_L is significantly stronger for small banks.

On average, large and small banks have both been negatively affected by the liquidity crises. The average ω_L became positive and significantly higher over the 2008-2012 as opposed to the 2005-2007 period for both large and small banks. Similarly, the dispersion of ω_L significantly reduced for both large and small banks. Both large and small banks were affected by liquidity crisis in a similar negative way. However they were not impacted to the same extent. Indeed, over 2005-2007, both large and small banks on average benefited from liquidity conditions and their average ω_L did not differ significantly. Small banks still show significantly more heterogeneity as the standard deviation of their ω_L is higher. However, in 2008-2012, large banks were more negatively affected by liquidity risk compared to small banks, as their average ω_L is significantly higher. The dispersion of ω_L does not show any significant difference. The effect of liquidity crises was stronger on large banks, compared to small banks, which is consistent with the literature underlying the higher exposure of large banks to liquidity risk. The stronger exposure of large banks to aggregate liquidity is probably due to their higher reliance on money markets. This hypothesis will be further investigated in section 5 below.

Third, we distinguish between banks from GIPS and non-GIPS countries[7]. This distinction relies on evidence of deposits withdrawals from banks in countries where the banking system and the public finances were perceived as weak, such as Greece and Ireland (Allen & Moessner, 2012). The hypothesis is that banks from GIPS countries would be more negatively affected by liquidity conditions than banks from other countries, as they could not replace lost deposits with wholesale borrowing. However, no statistically significant difference is found between the distributions of ω_L for banks in GIPS countries and other countries than GIPS (table 3). Both banks from GIPS and non-GIPS countries were negatively affected by liquidity crises. Indeed, their average ω_L became significantly positive and less dispersed over 2008-2012. This

[7] GIPS stands for Greece, Ireland, Portugal and Spain. Non-GIPS stands for the remaining states from the euro area.

confirms that the liquidity crisis was systemic, affecting all banks regardless their size or country of origin. Similarly to what we observe for size, in 2005-2007, the distribution of ω_L for banks from GIPS and non-GIPS countries is not significantly different. However, in 2008-2012, banks from non-GIPS countries were on average significantly more negatively affected than banks from GIPS countries. We then reject our hypothesis. This result could appear as counterintuitive from a theoretical background. However, Ireland and Greece governments spend a lot to support their banking sector while France and Italy almost spend nothing (Maurer and Grussenmeyer, 2015). This could explain the relatively lower sensitivity of banks from GIPS to the liquidity crises.

Insert table 3

We also complete an univariate analysis of parameters β_L. As the Kolmogorov Smirnoff test indicates, the distribution of β_L is not normally distributed either. Welch's and Levene's tests are performed to compare the group means of $\beta_{L.}$ Similar to the distinction operated for ω_L, non-significant β_L are set to zero. Results are displayed in table 4 below.

Similarly to the results obtained for ω_L, parameters β_L became on average significantly positive and less dispersed in 2008-2012, as opposed to 2005-2007. The switch in the sign of the average β_L might result from the liquidity support policy of the ECB and the governments. Nevertheless, on average β_L remain close to zero. The reduction of the dispersion of β_L suggests a more homogenous effect of aggregate liquidity on banks.

Regarding the effect of size on the exposure to liquidity risk, the only significant difference in the distribution of β_L is observed from small banks across the two 2005-2007 and 2008-2012 periods. The average β_L significantly reduced as well as its dispersion. As the average β_L remains positive, small banks tend to benefit less from liquidity conditions during liquidity crises. Small banks are less exposed to liquidity risk as the literature as the results for ω_L above underline. Furthermore, they rely less on the central bank to finance themselves and more on traditional intermediation (Berger & Bouwman, 2009). The liquidity support offered by the central bank during the liquidity crises might have benefited relatively more to large banks. Thus, during the liquidity crises, the systematic component of liquidity risk might have been concentrated on small banks.

Furthermore, over the whole period, β_L is on average positive for GIPS countries and negative for non-GIPS countries. More particularly, this difference is significant only over the 2005-2007 period, while the average β_L is more dispersed for non-GIPS banks. Thus on average, non-GIPS banks are negatively affected by the systematic component of liquidity risk. Besides non-GIPS banks present more heterogeneity in their exposure to liquidity risk. Furthermore, the exposure of non GIPS banks to the systematic component of liquidity risk evolved with the liquidity crises. Over 2008-2012, the average β_L increases, as compared to 2005-2007 but remains negative and its dispersion reduced. This indicates that the systematic component of liquidity risk was soften for non-GIPS banks during the liquidity crises. This might be an effect of the liquidity support from the ECB. The systematic component of liquidity risk thus concentrated on banks from non-GIPS countries before the liquidity crises.

Insert table 4

4.3. Sign of exposure to liquidity risk (ω_L)

The paragraphs above showed the heterogeneity across banks in terms of exposure to liquidity risk, either cross-sectionally or across time. We focus our analysis on parameters ω_L. Indeed, parameters β_L are most of the time non-significant, which is consistent with the literature on bank risk factors. According to the literature, liquidity risk is most of the time not a systematic risk (Hess & Laisathit, 1997; Dewenter & Hess, 1998; Schuermann & Stiroh, 2006). As parameters ω_L stand for the sensitivity of bank total risk to aggregate liquidity risk, bank liquidity risk is most of the time a specific risk accounted for by ω_L. The absence of a systematic component of banks liquidity risk may be explained by the market participants believing the central bank and governments would help banks in case of a systemic liquidity shock.

The purpose of this paragraph is to analyse the evolution of the distribution of banks across three categories defined by the sign of their ω_L. As stated in section 3.1., ω_L equal to zero indicates that the bank is insensitive to aggregate liquidity. If ω_L is positive (respectively negative), the bank is negatively (positively) affected by aggregate liquidity risk. Figure 1 displays the cumulative frequency of the estimated ω_L, according to their sign. Banks insensitive to aggregate liquidity are represented at 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 categories of banks evolved constantly over the 2005-2012 period. Before the 2007-2008 crisis, the sensitivity of bank total risk to aggregate liquidity risk was overwhelmingly either null or negative, respectively for 51% and 35% of banks on average in 2005. A majority of banks was thus either not affected or benefited from aggregate liquidity conditions. The peak of 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 consequence of the stronger liquidity of money markets before August 2007. A majority of banks did not experience difficulties in obtaining funding from financial markets during that period, and their total risk was independent from liquidity conditions.

In 2007 and 2008, the proportion of positive ω_L increased, reaching a peak of 67% of banks in 2008. Consistent with stressed liquidity conditions, a majority of banks saw its total risk increasing as aggregate liquidity deteriorated. Similarly, only two banks had a negative ω_L 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 dry up of the market for short-term asset-backed commercial paper.

In 2009 and 2010, bank total risk became less impacted by aggregate liquidity risk than during the 2007-2008 crisis. The proportion of banks negatively affected by aggregate liquidity (positive ω_L) decreased from 35% in the crisis to 28%. However, a higher proportion of banks is still negatively affected by aggregate liquidity risk than in the pre-crisis 2005-2006 period where only 13% of banks were negatively affected by aggregate liquidity. The proportion of banks insensitive to aggregate liquidity risk increased to 60%, back to the pre-crisis level of 2005 (57%). Thus, compared to the pre-crisis situation, the higher proportion of positive ω_L in 2009-2010 is explained by a lower proportion of negative ω_L (12%).

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

Bank total risk sensitivity to aggregate liquidity risk then increased in 2011 to comparable proportions of 2008. This second peak of positive ω_L 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 liquidity stress events. More banks are sensitive to aggregate liquidity risk during the liquidity crises of 2007-2008 and 2011, as opposed to the pre-crisis and post crisis periods. A higher proportion of banks is negatively affected by aggregate liquidity conditions when aggregate liquidity deteriorates. Furthermore, after the 2007-2008 liquidity crisis, market participants tend to remind previous stressed liquidity conditions and value more negatively bank exposure to liquidity conditions than before the crisis.

Insert figure 1

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

The literature awards a special place to accounting measures of bank liquidity risk. In this section, we analyse the relationships between the measure of bank sensitivity to aggregate liquidity risk and balance sheet variables related to bank exposure to liquidity risk.

Size most likely has an effect on bank exposure to liquidity risk. Large banks are expected to be more exposed to liquidity risk due to their higher reliance on wholesale markets (Cocco and al., 2009) and holdings of fewer liquid assets (Bunda & Desquilbet, 2008; Vodova, 2013). However, the literature also underlines the funding advantage associated with size, namely the relatively privileged access to market liquidity for large banks. This comes from greater liquidity of larger debt issues, more frequent issuances, and the anticipated liquidity support from public authorities in times of distress. Lenders to large institutions anticipate that these will be bailed-out in case of emergency and require a lower risk premium through more advantageous interest rates (e.g. Akram & Christophersen, 2010; Acharya and al., 2014; Bijlsma and al., 2014). Thus, access to wholesale markets and to liquidity support from central banks or governments would protect banks negatively affected by aggregate liquidity shocks. Consequently, the effect of size on bank exposure to liquidity risk is ambiguous.

Leverage could 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 sheet using short-term funds on wholesale markets (Adrian & Shin, 2010). Thus, more leveraged banks would be more exposed to liquidity shocks. Assuming that leverage is computed as equity over total assets, a negative link between leverage and the measure of bank liquidity risk is expected.

Stability of funding tends to make banks less affected by liquidity risk. Deposits are seen as a stable funding source because of deposit insurance (e.g. Diamond & Dybvig, 1983; Calomiris & Kahn, 1991; Diamond & Rajan, 2001; Diamond & Rajan, 2000). In models of banking theory, insured depositors have no incentive to run on banks. A negative link is expected between deposits' share of total assets and exposure to liquidity risk (ω_L). On the contrary, the more banks rely on wholesale funding, the more exposed to liquidity risk they could be. Thus a positive relationship is expected between short term debt share of total assets and the measure of bank liquidity risk. Besides, holding a buffer of liquid assets also tends to protect banks from liquidity risk as they can face larger cash outflows. We hypothesise a negative link between the proportion of liquid assets in total assets and the measure of bank liquidity risk. Lastly, funding gap defined as the share of loans financed with stable funding, synthesises both stability of funding and liquidity of assets. We expect to observe a negative relationship between funding gap and the measure of bank liquidity risk. These last four variables provide a picture of bank liquidity creation.

Finally, a positive relationship between liquidity risk and insolvency risk is evidenced theoretically (e.g. Eisenbach and al., 2014) and empirically (e.g. Imbierowicz & Rauch, 2014). The argument comes mainly from the literature on bank run. On the one hand, short term creditors could decide to run based on beliefs about bank asset through sunspot bank runs (Diamond and Dybvig, 1983; Iyer and Puri, 2012). On the other hand, depositors could run based on information about asset risk through fundamental ban run (Allen and Gale, 2007; Goldstein and Pauzner, 2005). We thus expect to observe a positive relationship between credit risk and the measure of exposure to liquidity risk.

5.1. Methodology

One of the characteristics of the estimated ω_L is the large amount of non-significant values, set to zero in the previous section. This calls for a regression strategy taking into account this feature. To estimate the effects of the selected balance sheet features on the exposure to liquidity risk, we use a tobit model with friction introduced by Rosett (1959) as a generalisation of Tobin (1958). This model incorporates the fact that variations of explanatory variables may have an impact on the explained variable if and only if they are large enough, i.e. contribute to the crossing of some thresholds. Here, this specific feature accounts for the fact that a bank currently not exposed to liquidity risk may become positively or negatively exposed only if its characteristics change sufficiently, hence reflecting the share of banks with a non-significant exposure to aggregate liquidity.

Thus, this specification assumes that the dependent variable, ω_L, only responds to strong variations of a latent non-observable variable ω_L^*. This behaviour of market participants may be due to transaction costs that limit the level of transactions compared to the desired level, and more generally to stickiness. If parameter ω_L is positive or negative, we are outside the frictional part of the model and ω_L might be determined by a given set of covariates. However a parameter ω_L equal to zero reflects the 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 modelled by a vector x_t of k exogenous variables, excluding the constant, as shown by equation (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 modelled as a function of the expected $\omega^*_{L,it}$ according to $\omega_{L,it} = \xi(\omega^*_{L,it})$. The function $\xi(.)$ maps the latent variable ω^*_L to the observed variable ω_L. This function is given by equations (4):

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

5.2. Data and results

The model is estimated with the following balance sheet variables. Banks balance sheet data are extracted from Datastream and are provided by 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 = provision for loan losses / net loans

Table 5 displays descriptive statistics for these balance sheet characteristics. A lag of one year is applied to all these independent variables. Correlations between all variables used to estimate the model are displayed in the appendix table A1.

Insert table 5

The effect of liquidity production and credit risk on bank liquidity risk most likely depends on the situation of the bank regarding liquidity conditions. We thus expect the effect on bank liquidity risk to be different depending on banks being either positively or negatively affected by aggregate liquidity risk. Different parameters for equations (4) would reflect effects of liquidity production and credit risk conditional to the sensitivity of bank liquidity risk. Opposite sign of parameters for positive and negative ω_L reflect two possible situations. If parameters are positive for negative ω_L and negative for positive ω_L, then the proxy of liquidity production or credit risk tend to make banks insensitive to liquidity risk. On the contrary, if parameters are negative for negative ω_L and positive for positive ω_L, then the proxy tends to make banks more sensitive to liquidity risk.

Consequently, in a first step, we perform a Wald test for each independent variable to test whether or not to impose a restriction of equal slope of the upper and lower parts of the model (Fox, 1997). The results are displayed in the appendix table A2. If the test is not significant, we impose a restriction of equal coefficients for the upper and lower parts. Thus we impose a restriction of equal coefficients for leverage, cash, asset liquidity, provision for loan losses, and the error term.

The model is estimated over the whole 2005-2012 period. Table 6 displays the estimation results. The estimates in panel A corresponds to the estimation with negative ω_L while the panel B refers to the estimation with positive ω_L.

Insert table 6

We first comment results for explanatory variables on which an equality constraint was imposed. 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 as decreasing the sensitivity of total risk to aggregate liquidity. Leverage tends to lower (increase) the sensitivity of banks negatively (positively) affected by aggregate liquidity risk. As more capitalised banks rely less on wholesale markets to finance themselves, they depend less on aggregate liquidity. This result provides informations regarding the relationship between liquidity and credit risk. Indeed, capital buffers help banks to absorb credit shocks and decrease their insolvency risk. Imbierowicz & Rauch (2014) observe that the interaction between liquidity risk and credit risk of banks depends on the overall level of bank risk. That is to say that conditional to the probability of default, the interaction between liquidity risk and credit risk can either mitigate or aggravate the probability of default. Here, we further argue that the relationship between liquidity risk and credit risk depends on bank sensitivity to liquidity risk. Indeed, capital tends to insulate banks from liquidity risk if they are negatively affected by aggregate liquidity. Besides, capital reduces the volatility of return of banks insensitive to, or positively affected by market wide liquidity, thus increasing benefits in terms of total risk. Regarding cash share, asset liquidity and credit risk, no significant relationship is observed with ω_L.

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

Size is significant for all ω_L. The positive (negative) sign attached to the estimated parameter for size, for negative (positive) $\omega_{L,}$ suggests that the larger banks, the lower their exposure to liquidity risk. Size tends to make banks insensitive to aggregate liquidity conditions. The larger banks with negative ω_L, the less they benefit from aggregate liquidity. Similarly, for positive ω_L, the larger the banks, the less their total risk increases with aggregate liquidity. Thus we observe that market participants value size as tending to insulate banks from aggregate liquidity pressures. This could reflect an incentive for banks to increase their size and become too big to fail in order to benefit from public support in the eventuality of a systemic liquidity stress. This means that even if larger banks are probably more exposed to liquidity risk, the market integrates the public support to banks.

Regarding the deposit share, the reliance on wholesale funding and the funding gap, their relationship with ω_L is significant only for banks with negative ω_L. The estimated parameter for the deposit share is negative. Thus, regarding banks gaining from aggregate liquidity stress, market participants value higher deposit share as even more advantageous in terms of total risk. This result is consistent with the literature underlying the funding advantage of the stability of deposits. Besides, this result complements the literature as the effect of deposit depends on the exposure of banks to liquidity risk. Increasing deposits is advantageous to banks benefiting from aggregate liquidity but not to 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 relatively lose this advantage in terms of total risk as they finance themselves relatively more on money markets. This result is consistent with the literature as wholesale funding increases bank potential exposure to liquidity shocks. Finally, the estimated parameter for the funding gap is positive. A higher funding gap means here that the bank finances its loans with more long term debt. This implies a lower share of short term debt. This result is concordant with the literature according to which more long term funding reduces exposure to potential liquidity shocks.

Thus regarding deposit share, the reliance on wholesale funding and the funding gap, there is an asymmetry between positive and negative ω_L. These results provides informations regarding investors' perception of risk. Looking at these three ratios, investors get a perception of bank business model and more particularly of the intensity of liquidity creation. By definition, larger liquidity creation results in greater liquidity risk (Berger & Bouwman, 2009). Concordantly, riskier banks are more negatively affected by aggregate liquidity (table 5). However, liquidity creation affects the sensitivity only of banks positively affected by aggregate liquidity. This behaviour appears like flight to quality as investors consider liquidity creation of the strongest banks. This is also consistent with the motivations for liquidity hoarding. Indeed, benefits are anticipated from liquidity hoarding either for a strategic motive or a precautionary motive. Banks would benefit from the degradation of aggregate liquidity through profits from fire sales of assets or needing less wholesale funding (Allen et al. 2009; De Haan & Van den End, 2013). Thus, market participants value the risk of a lower profitability has hoarding liquidity these banks could increase profits from aggregate liquidity shortages. Regarding banks negatively affected by aggregate liquidity, market participants do not perceive variations of liquidity creation as either aggravating or mitigating bank sensitivity to liquidity risk. Market participant probably believe that these banks would benefit from the support of public authorities if needed. This is consistent with the literature underlying that unconditional public support to banks reduces incentive for banks to hold liquidity (Acharya and al., 2011). This belief is most likely based on the size and the capitalisation of banks, as indicated by the results above. As a result, the market discipline of liquidity creation appears to be one-sided. From a regulatory point of view, this argue in favour of a regulation of liquidity creation through liquidity requirements, such as Basel III ratios.

6. Robustness checks

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

6.1. Alternative aggregate liquidity indices

Firstly, we estimate the model with the Euribor – euro area AAA spread on maturities of six, nine and twelve months. Furthermore, we use another measure of euro area government borrowing rates: the Eurobenchmark yield curve rate provided by Bloomberg for maturities of 6 and 12 months. In all cases the relationship between bank returns and aggregate liquidity index is very similar to the results we report in section 4.

6.2. Alternative market factor indices

Secondly, another concern is to what extent composite national market return indexes integrate the banking industry and thus the effect of aggregate liquidity on bank stock returns. Indeed, larger banks are usually a component of composite national market indices. For instance, the French market return index CAC 40 and the German DAX 30 comprise each three large banks[8]. We check if this could explain the quasi absence of significant β_L which is however consistent with the literature on risk factor models. In order to investigate the influence of market indices return on the aggregate liquidity index, we re-estimate the factor model using a market return index excluding banks. As computing composite national market returns excluding banks is not the aim of this study, we take the Eurostoxx ex banks as a market return factor including all sectors but the banking industry[9]. The distribution of the negative, null and positive ω_L estimated (table 8) is very close to our previous results (section 4). Indeed, the distribution of

[8] The CAC 40 index comprises BNP Paribas, Crédit Agricole, and Société Générale while the DAX 30 index comprises Commerzbank, Deutsche Bank, and Deutsche Postbank.
[9] The Eurostoxx ex banks is provided by STOXX Limited. It is computed as an index of 261 large, mid and small capitalisation companies across 12 Eurozone countries, corresponding exactly to the geographical area covered by our sample, excluding stocks from the banking sector.

ω_L (figure 2 below) presents the same shape but the impact of the liquidity crises is slightly accentuated as we observe less positive ω_L before the crisis in 2006 and more during the crisis. Similarly, the distribution of β_L (table 9 below) is close to the results presented in section 4. We still observe a few more positive β_L in 2010 and negative β_L in 2007 and 2012. Thus the effects of a market factor index excluding banks on the measure of bank liquidity risk seem negligible.

Insert table 8, figure 2, table 9

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

Finally, we allow for non-linearities in the relationship between bank returns and the aggregate liquidity factor. Indeed, because of the sudden irruption of liquidity crisis, one could question the linearity of this relationship. We thus add another repressor to the initial model, the squared aggregate liquidity index. The model following model is thus estimated:

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

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

Where

$$e_i \sim N(0,1)$$

However, the cumulative frequencies of squared β_L and ω_L shows the same pattern than in section 4 (figures 1 and 2). The number of significant β_L (85) remains close to what we observe in the first model (81), while 91 significant β_L^2 are observed.

7. Conclusion

The banking literature awards a special place to accounting measures of liquidity risk. However, they provide an imperfect picture of bank exposure to liquidity risk. The measure confirms that liquidity risk is a specific risk. Our main results highlight the heterogeneity of the exposure to liquidity risk across banks. Some banks benefit from it, while others are hampered or insensitive to liquidity risk. Benefits from liquidity cost could be explained by liquidity hoarding behaviour of banks either for a strategic or a precautionary motive. A second main result regards the identification of the phases of the 2007-2009 and 2011 liquidity crises when the heterogeneity reduces. However, even during liquidity crises, liquidity risk remains a specific risk. This suggests that market participants anticipate intervention of public authorities and stresses the efficiency of the European Central Bank policy during the liquidity crises. Nevertheless, findings show that size and the central or peripheral situation of banks within the euro area become determinant only during liquidity crises. As the literature stresses the importance of accounting indicators of liquidity risk, we looked at the relationship between them and our measure. Deposit share, reliance on wholesale funding and funding gap impact the capacity of banks to benefit from liquidity stresses, as perceived by investors. These ratios indicate the level of liquidity production by banks. Thus, results indicate that market participants value the importance of 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 probably anticipate support from public authorities. Indeed, higher levels of size and capitalisation reduce the sensibility of banks negatively affected. Thus our measure is concordant with the literature on accounting measures of liquidity risk. Furthermore, we shed some light on the perception of bank liquidity risk by market participants. As market discipline of liquidity production appears to be one-sided, this reinforces the necessity to impose liquidity requirements to all banks such as the Basel III liquidity ratios.

Appendix

Table A1 Correlation between ω_L and balance sheet variables

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, deposits share = deposits / total assets, cash share = cash / total assets, wholesale funding = short term debt / total debt, asset liquidity = net loans / total assets, funding gap = (net loans – short term debt) / net loans, credit risk = provision for loan losses / net loans.

	ω_L	size	leverage	deposits 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)
deposits 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)
asset liquidity							1	0.445	0.061
								(<.0001)	(0.146)
funding gap								1	0.073
									(0.079)
credit risk									1

Table A2: Results of the Wald test

Table A2 presents the results of the Wald tests of equal coefficients for balance sheet variables of the model between the upper and lower parts of the friction model. When the Wald test is not significant, a restriction is imposed on the variable, consisting of equal coefficients for the upper and lower parts of the tobit model. ***, **and * denote that the tests are statistically significantly at the 1%, 5% and 10% level, respectively.

Balance sheet variables	**Wald statistics**
Size	14.15***
Leverage	1.94
Deposits 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 A3: Geographical distribution of sample banks

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

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
Netherlands	2	AEX25
Portugal	3	PSI20

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Tables / Figures

Table 1: Descriptive statistics of ω_L per year

Table 1 presents the number of observations, mean, median and standard deviation of ω_L. Non-significant ω_L at the 10% level are set to zero.

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 2: Descriptive statistics of β_L per year

Table 2 presents the number of observations, mean, median and standard deviation of β_L. Values are multiplied by 1 000. Non-significant β_L at the 10% level are set to zero.

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 3: Descriptive statistics of ω_L for separately large/small banks, banks from GIPS/non GIPS and 2005-2007/2008-2012 periods

The table reports the mean and standard deviation for the parameter ω_L split in two distinctive groups, eleven times. Tests for significant difference in means of ω_L between large and small banks, banks from GIPS and banks from non-GIPS countries, 2005-2007 and 2008-2012, and the three first groups of banks each one divided along these two periods, are based on Welch's test statistics. Tests for significant difference in group variance of ω_L are based on Levene's test for homogeneity of variance. *** , ** and * denote that the subsamples differ significantly from one another, at the 1%, 5% and 10% level, respectively.

	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	
GIPS countries	163	-0,07	2,51	1,41	0,01
Non GIPS countries	458	0,14		1,43	
GIPS countries 2005-2007	58	-0.53	6.15^{**}	2.17	15.17^{***}
GIPS countries 2008-2012	105	0.19		0.56	
Non GIPS countries 2005-2007	167	-0.25	13.21^{***}	2.10	31.30^{***}
Non GIPS countries 2008-2012	291	0.36		0.75	
GIPS countries 2005-2007	58	-0.53	0.72	2.17	0.02
Non GIPS countries 2005-2007	167	-0.25		2.10	
GIPS countries 2008-2012	105	0.19	5.97^{**}	0.56	0.42
Non GIPS countries 2008-2012	291	0.36		0.75	

Table 4: Descriptive statistics of β_L for separately large/small banks, banks from GIPS/non GIPS and 2005-2007/2008-2012 periods

The table reports the mean and standard deviation for the parameter β_L split in two distinctive groups, eleven times. The values of means and standard deviation are multiplied by 1 000. Tests for significant difference in means of β_L between large and small banks, banks from GIPS and banks from non-GIPS countries, 2005-2007 and 2008-2012, and the three first groups of banks each one divided along these two periods, are based on Welch's test statistics. Tests for significant difference in group variance of β_L are based on Levene's test for homogeneity of variance. ***, ** and * denote that the subsamples differ significantly from one another, at the 1%, 5% and 10% level, respectively.

	Obs	Mean	F-value	Std. dev.	F-value
2005-2007	225	-0.68	8.38***	3.85	10.48***
2008-2012	396	0.11		1.69	
Large banks	96	0.13	1,91	2.30	0,25
Small banks	525	-0.23		2.77	
Small banks 2005-2007	189	0.82	9.15***	3.91	8.30***
Small banks 2008-2012	336	0.09		1.78	
Large banks 2005-2007	36	0.05	0.04	3.50	2.71
Large banks 2008-2012	60	0.18		1.11	
Large banks 2005-2007	36	0.05	1.79	3.50	0.07
Small banks 2005-2007	189	0.82		3.91	
Large banks 2007-2012	60	0.18	0.24	1.11	0.75
Small banks 2007-2012	336	0.09		1.78	
GIPS countries	163	0.08	3.07 *	1.77	1.96
Non GIPS countries	458	-0.27		2.97	
GIPS countries 2005-2007	58	0.09	0.01	0.68	1.28
GIPS countries 2008-2012	105	0.07		2.14	
Non GIPS countries 2005-2007	167	-0.94	9.04***	4.42	12.98***
Non GIPS countries 2008-2012	291	-0.12		1.50	
GIPS countries 2005-2007	58	0.09	8.52***	0.68	3.21*
Non GIPS countries 2005-2007	167	-0.94		4.42	
GIPS countries 2008-2012	105	0.07	0.05	2.14	1.58
Non GIPS countries 2008-2012	291	0.12		1.50	

Figure 1: Frequency of ω_L

Frequency of the ω_L is plotted according to their sign for every year. Frequency is cumulated from negative to positive ω_L. Non-significant ω_L at the 10% level of significance are set to 0.

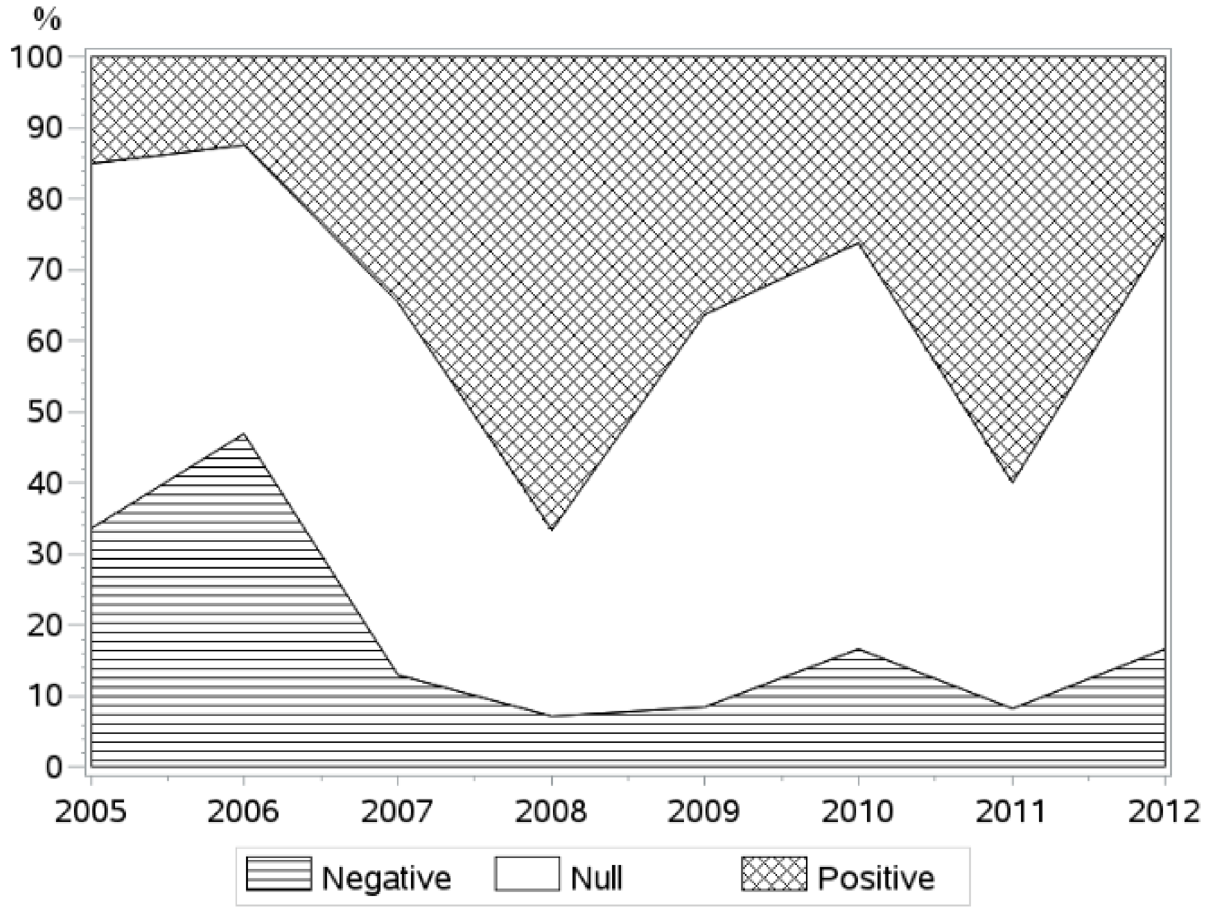

Table 5: Descriptive statistics for banks' balance sheet characteristics

Table 5 reports means and standard deviation in parentheses of banks' balance sheet characteristics. Banks characteristics are values lagged by one period. The data are observed from 2005 to 2012. Tests for significant difference in means are based on the Welch's test statistic. Tests for significant difference in variance of negative, null and positive ω_L are based on the Levene's test statistic. ***, ** and * denote that the three samples differ from one another at the 1%, 5% and 10% level, respectively.

Independent variables	ωL			
	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
Deposits 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 funding	0.50	0.51	0.52	0.79
	(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 6: Tobit regressions

Table 6 present the results for the tobit regressions of banks' balance sheet variables lagged by one year on ω_L. Regression is estimated for the whole 2005-2012, and for negative ω_L (panel A) and positive ω_L (panel B). The error terms were submitted to the Wald test and are constrained to be equal. Hence, they are reported only in panel B. Variable in bold present the same parameters for negative and positive ω_L. Goodness of fit measure is the squared multiple correlation between the predicted and observed values of ω_L. Standard errors are reported in parentheses. ***, **and * denote that the coefficients are statistically significantly different from zero at the 1%, 5% and 10% level, respectively.

	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)**
Deposits share	-2.422*	0.134
	(1.44)	(1.05)
Cash share	**-6.51**	**-6.51**
	(4.72)	**(4.72)**
Reliance on wholesale funding	2.477***	-0.312
	(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 8: Descriptive statistics of ω_L per year

Table 8 presents the number of observations, mean, median, standard deviation, 10th and 90th quantiles, maximum and minimum of ω_L. Non-significant ω_L at the 10% level are set to zero.

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	0,00
Std. dev.	3,51	1,79	0,44	0,30	0,44	0,99	0,72	0,45

Figure 2: Frequency of ω_L estimated with Eurostoxx ex banks

Frequency of the ω_L is plotted according to their sign for every year. Frequency is cumulated from negative to positive ω_L. Non-significant ω_L at the 10% level of significance are set to 0.

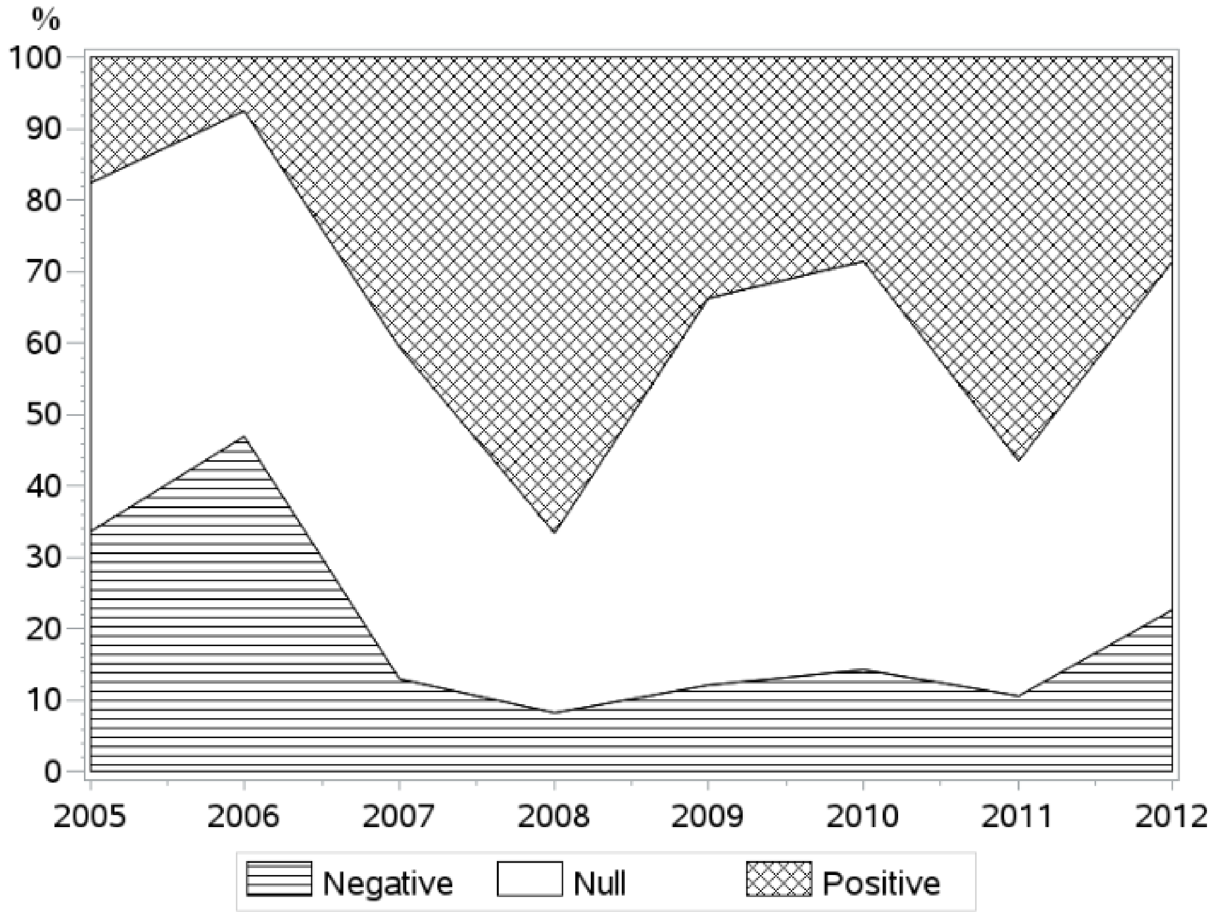

Table 9: Descriptive statistics of β_L per year

Table 9 presents the number of observations, mean, median, standard deviation, 10^{th} and 90^{th} quantiles, maximum and minimum of β_L. Values are multiplied by 1 000. Non-significant β_L at the 10% level are set to zero.

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

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