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ESSAYS ON BANK LIQUIDITY RISK

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PhD in Finance

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ISCAL

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BUSINESS
SCHOOL

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"Progress comes to those who train and train; reliance on secret techniques will get you nowhere."

Morihei Ueshiba

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Resumo

A medida mais adequada para a liquidez das instituições financeiras continua por definir e mantem-se um tema suscetível a diversos estudos e análises, quer por parte das autoridades reguladoras, quer por parte das instituições financeiras quer por parte dos académicos.

Esta tese é assim composta por três artigos de investigação sobre a liquidez nos bancos. O primeiro artigo consta do capítulo 2 e tem como objetivo analisar a evolução da estrutura do balanço dos bancos de 2003 a 2015. O intervalo de tempo inclui uma análise global para todo o período da amostra e os subperíodos de pré-crise, crise e pós-crise. O estudo pretende esclarecer sobre a evolução das demonstrações financeiras dos bancos, identificando possíveis quebras estruturais e padrões, juntamente com a revelação de tendências, através do risco de liquidez. Apesar de todos os estudos e análises realizados, este trabalho contribui para a compilação e sistematização de um painel de dados referente a bancos comerciais a nível mundial. Em relação à liquidez de longo prazo constatou-se que apenas 10% dos bancos comerciais analisados cumprem com as recomendações dos reguladores. Constatou-se também sobre o impacto das variáveis de balanço na liquidez.

O segundo artigo consta do capítulo 3 e tem por objetivo, para o período de 2003 a 2015, esclarecer sobre os determinantes da liquidez. Os resultados da análise evidenciam que o tamanho do banco, a capitalização, a qualidade do crédito, as fontes de financiamento, a rentabilidade e a eficiência podem ter impacto na gestão do risco de liquidez de longo prazo. Constatou-se também que os bancos capitalizados têm uma melhor liquidez de longo prazo que se traduz em instituições mais estáveis e mais aptas a lidar com cenários de crise sistémica.

O terceiro artigo consta do capítulo 4 e tem por objetivo fornecer informação sobre a medição do risco sistémico de liquidez através do "Liquidity Mismatch Index". O resultado da análise efetua permite avaliar o "Liquidity Mismatch Index" como uma medida alternativa para ser utilizada como indicador de risco sistémico de liquidez.

Classificação JEL: G01; G21

Palavras chave: Liquidez; Risco de liquidez; Risco sistémico; Padrões no balanço dos bancos; "Liquidity mismatch Index"; Crise financeira global

Abstract

The most adequate measure for banks liquidity is still to be defined and remains a subject susceptible to various studies and analyzes, by regulatory authorities, financial institutions and academics.

This thesis is thus composed of three research articles on bank liquidity. The first article is in chapter 2 and aims to analyze the evolution of bank balance sheet structures from 2003 to 2015. The scope includes a global analysis for the entire sample period and the pre-crisis, crisis and post-crisis periods. The study aims to clarify the evolution of banks' financial statements, identifying possible structural breaks and patterns, together with the revelation of trends, through liquidity risk. Despite all the studies and analyzes carried out, this work contributes to the compilation and systematization of a data panel referring to commercial banks worldwide. Regarding long-term liquidity, it was found that only 10% of the commercial banks analyzed comply with the recommendations of the regulators. It was also noted the impact of balance sheet variables on liquidity.

The second article is in Chapter 3 and for the period from 2003 to 2015 aims to identify and analyze the liquidity determinants. The results of the analysis show that the size of the bank, capitalization, credit quality, sources of financing, profitability and efficiency can have an impact on the management of long-term liquidity risk. It was also found that capitalized banks have better long-term liquidity, which translates into more stable institutions and better able to deal with systemic crisis scenarios.

The third article is in Chapter 4 and aims to provide information on measuring systemic liquidity risk through the "Liquidity Mismatch Index". The result of the analysis made it possible to consider the "Liquidity Mismatch Index" as a good approach to be used as a measure of systemic liquidity risk.

JEL classification: G01; G21

Keywords: Bank liquidity; Liquidity risk; Systemic risk; Balance sheet patterns; Liquidity mismatch index; Global financial crisis

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1. Introduction

The main purpose of this research is to analyze the liquidity evolution of banks' balance sheet structures along thirteen years from 2003 to 2015. For this purpose, it was built a sample of 645 worldwide commercial banks from 55 countries and this represents over 8.000 values. The timespan includes a global analysis for all the sample period and the sub-periods of pre-crises, crises and post-crises. To better analyze and understand the behavior of the liquidity variables and his determinants, 10 different geographic regions were identified: Europe, USA and Canada, Japan, South America, Africa, Asia, Eastern Europe and Russia, Middle East, Australia and Switzerland.

The study sheds light on the evolution of banks' liquidity through the analysis of banks' balance sheets and through the identification of possible structural breaks and patterns, alongside unveiling trends, through the lens of liquidity risk. The study deploys a large and heterogeneous dataset encompassing multinational commercial banks around the world to define and characterize the structure of banks' balance sheets.

Over the last decades the world has witnessed a number of financial crises: the stock market crash in 1987; the credit crunch in 1992; the Russian debt crisis, the long term capital management collapse in 1998; the dot.com bubble in 2000; and more recently the subprime lending crisis in 2007. These crises were often linked with liquidity issues. In some jurisdictions, as in the U.S., liquidity problems regarding the banking system and the financial markets were at the crux of the crises. The 2007 subprime crisis even entailed a sovereign debt crisis and a liquidity crisis that followed not only in the U.S. but also in Europe and rapidly across the rest of the financial markets across the world.

On one hand, banks are interconnected with all sectors of the economy and so the stability of the financial system affects the society as a whole. On the other hand, banks transform maturities using their short-term liquidity to grant medium and long-term loans and so banks' liquid assets are like blood in our veins. In the absence of bank liquidity, the economy can no longer prosper and might even collapse. And more stressed banks cannot perform the function of transferring risk.

This is why bank liquidity is so important and even more so during crises. The uncertainty of bank liquidity around crises begs for an empirical analysis, to ascertain in what way crises and liquidity risk are interconnected and how do banks behave regarding liquidity. It might be that banks holding more liquid assets as compared to their peers are perceived by the market as less risky and so have lower funding costs, without hurting too much their profitability or more capitalized banks with additional buffers of capital might not need to show high liquidity levels because their stakeholders, both shareholders and clients, might view them as more solid and robust. Whether banks operating lower risk models, e.g. less dependent from wholesale funding, are exempted from abnormal liquid positions, is a question still lacking a clear answer.

This dissertation intends to shed light on the patterns of bank liquidity around the recent crises, namely (i) before the inception of the 2007 subprime crisis (ii) during the subprime and the consequent sovereign debt crisis and the liquidity crisis; and (iii) after the crises.

The subprime crises and their consequences provide a natural experiment for analyzing bank liquidity patterns also in the period when interbank markets simply closed, and liquidity was a problem faced by banks for a significant period. Central banks in Europe and overseas had to come forward as lenders of last resort to ensure stability for the financial markets, and billions were injected in banks both in the U.S and in Europe, at ever low rates. The deleveraging process that followed featured an unprecedented phenomenon as well. Banks around the world had to reshape their balance sheets and cater more closely to their liquidity position. Central bankers, supervisors and rating agencies required banks to regularly disclose their liquidity position and to keep it above new enacted and more stringent regulatory thresholds. Liquidity became as important as bank capital and both have been placing bank operating income under stress, affecting profitability. But banks behave differently during crises and also in 'normal times': some banks even collapsed during the crises (Lehman Brothers is the first too-big-to fail case in the 20th century) and many were resolved. So, an 'average bank' with standard levels of liquidity might not emerge as a benchmark and there must be different reasons for different liquidity positions across banks and jurisdictions.

This study intends to address the questions: What bank liquidity patterns arise around financial crises? And how does liquidity risk evolve? And how do banks behave in the verge of financial crises and bottoming out? And what factors affect liquidity? Most studies have focused on credit crunches, which are a result of liquidity problems and risk management policies exacerbated by the occurrence of crises. This study intends to analyze the origins of such phenomena, as a financial intermediary with liquidity problems can no longer fulfill its function of linking lenders and debtors, at least without dramatic reshuffling and resolve.

The answer to the above research questions can shed light on why some banks in some jurisdictions hold more liquidity and why other banks operate in low levels only to comply with regulatory requirements. Also, banks entered the crises in different circumstances and also behaved differently. This heterogeneity is a rich avenue for research, most importantly because we conduct the analysis both in normal times and before as well as after the crises. The path a particular bank took might be different from its peers' trail and understanding the differences might interest supervisors and regulators, central bankers and the public at large as banks are interconnected with all sectors of the economy.

We cannot discard systemic risk in banking and so intend (i) to come forward with a measure for systemic funding liquidity risk and (ii) analyze the predictive power of determinants of systemic risk. For this purpose, the liquidity mismatch index, a recent approach to systemic liquidity risk, has been used.

In order to answer and clarify the questions presented above, this dissertation is composed by three independent analyzes but interconnected through the concept of liquidity.

The first study "The Structure of Banks Balance Sheet – A Liquidity Risk Approach" has the main purpose of analyzing the evolution of banks' balance sheet structures along the last thirteen years from 2003 to 2015. The timespan includes a global analysis for all the sample period and the sub periods of pre-crises, crises and post-crises. The study intends to shed light on the evolution of banks' balance sheets identifying possible structural breaks, and patterns, alongside unveiling trends, through the lens of liquidity risk.

The second study "Determinants of Liquidity Risk" is part of a broader topic which is the stability of the banking system around the world and focus on the links between the structure of banks' balance sheets and business profiles and liquidity.

The third study "Liquidity Mismatch as Systemic Measure" focus on to provide insights into the measurement of systemic liquidity risk through banks balance sheet data and asset and liability management with the expectation of offer additional ideas on the bank's systemic funding liquidity risk. This study also contributes to the application of real data from banks financial statements.

2. Banks Balance Sheet Structure – A Liquidity Risk Approach

2.1. Introduction

Since the beginning of the twenty-first century, academicians and managers have closely analyzed and discussed transformations in financial institutions. Most people are aware that the banking businesses need to be reinvented because their products are exhausted and new players have appeared in the market that have advantages in terms of structure costs. In addition, tighter regulations have slowed financial institutions' production of reports, adding additional costs imposed by each country's authorities (Brunnermeier et al., 2012; European Central Bank [ECB], 2012; Balachandran, 2015).

Liquidity risk and its impact on banks was already familiar to academicians and managers, but the best proof of this risk's significance was its inclusion and corroboration in the document issued by Basel III in 2010 (Basel Committee on Banking Supervision [BCSB], 2010). This report reinforced the need for risk analysis, and ways to monitor liquidity and its significant changes were introduced that could help banks deal more effectively with the concept of risk and the relationships between factors associated with it.

In the last century and beginning of this century, risky strategies produced important results for financial institutions in an era in which the dematerialization of money gained prominence and large quantities of money were generated without involving physical forms. As a result, the last three decades have included several liquidity crises (Chen, 2016). This new reality has transformed not only banks' financial statements but also their more in-depth analyses of liquidity risk management processes, contractual maturity of assets and liabilities, and their respective remuneration rates (ECB, 2012).

These changes are part of a context of expected growth, which has led managers and institutions to take on multiple responsibilities regarding the same assets. As can be expected, in adverse economic environments, this approach has contributed to efforts to break down the relevant set of assets that were once the basis for the creation of many holdings' results. This process includes risks and complexities within international banks' funding and liquidity management, which became a part of the public's reality in recent global financial crises. A reduction in liquidity has, consequently, occurred in major bank financing and foreign exchange swap markets, leading to considerable maturity gaps between currencies and increased pressure on banks' balance sheets (ECB, 2012).

According to the European Banking Authority (EBA) (2015), banks' business models can involve inappropriate funding structures that are more affected by crises than models that depend less on unstable funding sources. Thus, regulators have asked banks to return to the golden rule of banking expressed by the net stable funding ratio (NSFR), which ensures that long-term assets are refinanced through long-term liabilities (Deutsche Bundesbank, 2008).

This reality underpinned the 2007–2009 subprime mortgage crisis, which, in the most simplistic terms, was caused by an economic crisis that increased unemployment and led borrowers to default on credit obligations. Their mortgages were guaranteed by various securitized assets, but the latter's actual value was insufficient to meet all the banks' responsibilities. In this subprime lending crisis, liquidity dried up as banks became less willing to lend to individuals, businesses, other banks, and capital market participants.

The recent crisis led to the disclosure of less generally known details about banks' activities. Lo (2009) and McCarthy et al. (2010) report that regulators admitted that no information was available to assess banks' real activities accurately. Thus, regulators had difficulty assessing the banking sector's level of risk, thereby preventing appropriate, timely reactions to banking problems during the mortgage crisis. Borio and Drehmann (2009) and Song and Thakor (2010) also assert that this situation occurred due to banks' increased size and complexity, as well as financial products' intricacy.

The importance of liquidity during crisis situations is supported by the theory of financial intermediation, which posits that creating liquidity is a key reason why banks exist. These institutions create liquidity by financing relatively illiquid assets, such as loans to individuals and companies with relatively liquid liabilities, such as individuals and firms' deposits. Holmstrom and Tirole (1998) and Kashyap et al. (2002) suggest that banks also create off-balance sheet liquidity through loan commitments and liquid funds obligations. The cited authors observe that bank liquidity creation can also have real effects, especially if a financial crisis disrupts the generation of liquidity.

A financial crisis is a natural event that allows experts to analyze more closely how capital affects banks' competitiveness. In normal economic contexts, capital has many effects on these institutions—some of which counteract each other, which makes drawing conclusions quite challenging. For example, capital helps banks deal more effectively with risk but also reduces the deposit insurance put option's value. In crises, the risks become higher, and the capacity for risk absorption through capital becomes paramount. High-capital banks are better protected against shocks during crises, so these institutions can potentially gain advantages over smaller banks (ECB, 2012).

The most recent global financial crisis was positive in that it alerted experts to aspects that, until then, were known to be controlled by financial institutions. These features were somewhat constrained by required procedures that were only complied with because of regulations

(Andrievskaya, 2012). Aspects such as liquidity risk management, maturities management, and the risk of mismatch should have been better controlled.

Ayadi et al. (2016) mention the need to include business models in the prudential objectives of regulatory frameworks mainly to make sure that different risk characteristics within banking systems are more adequately taken into consideration. Grossmann and Scholz (2017) argue that banks' business model can be an additional indicator of emerging risks. In 2015, the EBA (2014) started including business models in its Pillar 2 analysis in order to cover different risk profiles. However, Grossmann (2017) reports that "the EBA analysis is for significant European institutions only, which excludes non-European or less significant institutions."

The Basel III agreement thus increased the regulatory demands for high-quality capital, to which a capital buffer was added. Two indexes were also been created—one for leverage and the other for liquidity coverage. These regulatory requirements focused on proposals that envisaged three areas to be modified: capital regulation, liquidity, and leverage. Basel III's goal is to strengthen the banking sector's resilience by providing tools to deal with issues crucial to financial systems and, consequently, to the economy, avoiding the risks posed by the recent international financial crisis.

Due to this crisis, the banking industry learned—and was forced—to adopt new risk analyses and control procedures. In recent years, banks have been subjected to unprecedented regulation, which has also forced them to make large investments in the relevant systems. These institutions recognize the severity of the crisis's effects and the lasting damage it has inflicted on funding markets, which has motivated banks to conduct reviews of their risk management procedures. These practices have a common element that translates into changes in the way these institutions are financed, which, on a qualitative level, have been necessarily incremental (ECB, 2012).

Modifications can be seen in financing's composition and liquidity management at a collective level. Different kinds of banking business models, such as wholesale or trading, entail higher funding cost risks related to equity than the retail banking model does. These observations are based on banks' balance sheet structure and their choice of funding sources, as well as mismatches between assets and liabilities or banks' ratings (Grossmann and Scholz, 2017).

The present research's main goal was to analyze the evolution of banks' balance sheet structures over the 13 years starting with 2003 and ending with 2015. This timespan facilitated an analysis of the entire period under study and its pre-crisis, crisis, and post-crisis sub-periods. The study sought to shed light on changes in these institutions' balance sheets by identifying possible structural breaks and patterns, as well as identifying trends, from the perspective of liquidity risk. A large, heterogeneous dataset was used that encompassed multinational banks around the world in order to define and characterize bank balance sheets' structure.

To assess liquidity, the research focused on two main liquidity measures as dependent variables: Basel III's NSFR and short-term funding ratio (STFR) (Vazquez and Frederico, 2015). In addition, the current study used the liquidity-mismatch index (LMI) proposed by Brunnermeier et al. (2013) and updated by Bai et al. (2018). The leverage ratio (LR) incorporated in the present research was computed as shareholders' capital over total assets (Vazquez and Frederico, 2015).

The current study is the first to use data on commercial banks worldwide and thus to conduct this kind of analysis and obtain results that highlight liquidity patterns across banks. This research identified and examined their liquidity's evolution, structural liquidity, and liquidity leverage throughout the years under study.

The rest of the paper is structured as follows. Section two presents the literature review, after which section three describes the data, methods, and variables. Section four reports the results, and section five offers conclusions.

2.2. Literature review

Some definitions are needed before the relevant literature on financial institutions' balance sheets and the impacts of various forms of liquidity risk management can be presented.

Although generic definitions are present in the relevant textbooks, this study used the definition developed by the Committee on the Global Financial System as reported in Mesquita's (2010) "Funding Patterns and Liquidity Management of Internationally Active Banks" :

> *Funding* can be defined as the sourcing of liabilities. Funding decisions are usually, but not exclusively, taken in view of actual or planned changes in a financial institution's assets. The funding strategy sets out how a bank intends to remain fully funded at the minimum cost consistent with its risk appetite. Such a strategy must balance cost efficiency and stability. A strategy which targets a broader funding base may entail higher operating and funding costs, but through diversity [this approach] provides more stable, reliable funding. One which focuses efforts on generating home currency funding may prove more reliable in adverse times but entail higher costs in normal markets. The balance of cost and benefit will reflect a range of factors. Accordingly, *funding risk*

essentially refers to a bank's (in)ability to raise funds in the desired currencies on an ongoing basis.

The cited author continues with a definition of liquidity management:

> *Liquidity management* is the management of cash flows across an institution's balance sheet (and possibly across counterparties and locations). It involves the control of maturity/currency mismatches and the management of liquid asset holdings. A bank's liquidity management strategy sets out limits on such mismatches and the level of liquid assets to be retained to ensure that the bank remains able to meet funding obligations with immediacy across currencies and locations, while still reflecting the bank's preferred balance of costs (e.g., of acquiring term liabilities or holding low-yielding liquid assets) and risks (associated with running large maturity or currency mismatches). Accordingly, *liquidity risk* refers to a bank's (in)ability to raise sufficient funds in the right currency and location to finance cash outflows at any given point in time.

These interpretations of key concepts indicate that financing and liquidity management could be interrelated. Mesquita's (2010) conceptualizations suggest that all banking transactions have implications for banks' financing needs and liquidity management. The process of transforming banks' maturities leaves these companies exposed and vulnerable to institution-specific and market-related cash flow risks. The likelihood of liquidity stress events has a direct impact on banks' cash flow because these events test their ability to react to and cope with shocks. This process should lead managers to evaluate not only the adequacy of their financing strategies and liquidity management but also these features' consistency under stress conditions. The way banks define and manage their financing strategy shapes their liquidity management needs so that the risks embedded in the chosen strategy translate into risks that liquidity management must control.

Another important term defined above is liquidity risk. This risk is caused by mismatches between cash flows of revenues and payments that are out of sync with each other in time or amount. Because of their transformation functions, banks can convert short-term deposits into long-term loans, so these institutions are often exposed to liquidity risks (BCBS, 2008) that may affect markets and financial systems.

According to Pasiouras and Kosmidou (2007), the definition of liquidity risk applied to European Union (EU) banks is currently the share of illiquid assets covered by short-term liabilities. Nikolaou (2009), in turn, suggests that liquidity risk is the situations in which banks have problems raising the funds requested by clients. Farag et al. (2014) define banks' liquidity risk as when they do not have the necessary funds or collateral to handle withdrawals.

Liquidity risk can thus be split into two forms: funding and market liquidity risks. The former risk is related to an inability to provide funds or issue liabilities to obtain cash, while the latter risk is related to an inability to sell assets (European Systemic Risk Board, 2014). Market liquidity risk assumes that banks are unable to buy or sell assets quickly at any moment (BCBS, 2008; Adalsteinsson, 2014). If, at a specific point in time, these institutions have a short-term ability to settle obligations immediately in order to prevent illiquidity (Drehmann and Nikolaou, 2013), then funding liquidity is present. Funding liquidity risk is, however, the inability to settle quickly and efficiently longer-term expected and unexpected obligations without affecting current bank activities (Soprano, 2015).

Adalsteinsson (2014) asserts that the availability of funding sources on the liability side is closely linked to asset-related market liquidity risk, and, in crisis situations, banks will have to pay more for funding. In addition, liquidity risk cannot be dissociated from other types of risk such as credit, operational, and market risks (BCBS, 2008). Vazquez and Frederico (2015) confirmed a positive relationship between liquidity risk and banks' default risk, reporting that banks with weaker funding liquidity before 2007 were subsequently exposed to a higher risk of default.

Mesquita (2010) also refers to the recent crisis' disproportionate impact on the international retail markets, which highlighted the advantages of stable financing based on customer attraction strategies. This policy helped some international banks with decentralized financing structures deal with the crisis relatively quietly. However, even international banks with decentralized structures recognize that reputational risks can trigger contagion within banking groups in a crisis scenario. The application of various business models within a set of decentralized and centralized institutions is likely to be a source of systemic resilience, provided that the associated financing models are sufficiently diversified.

Experts have also confirmed that changes in international banks' management and liquidity financing can become more comprehensive and rapid if the modifications are driven by regulations. The authorities' implementation of rules and regulations implies a uniform adaptation of all banks' operations to legal requirements, causing these institutions to move in a similar direction, which may diminish the supposed benefits of banks following diverse models. The increased competition can also make customer deposits less stable as a source of financing.

Some studies have examined the expansion of credit among multinational banks, including, among others, De Haas and van Lelyveld (2010), who analyzed the determinants of credit growth in multinational bank subsidiaries. The cited authors identified macroeconomic determinants such as gross domestic product (GDP) growth (i.e., a positive impact), unemployment rate (i.e., a negative impact), and inflation (i.e., a negative impact) as being the most important. De Haas and van Lelyveld (2010) further found evidence of domestic capital markets' existence as subsidiaries with financially strong parent companies were able to expand their lending faster with a lesser impact on their resistance to financial recession contagion. In these situations, the assumption of the parent firm's support was mentioned as merely associated with expanded lending, but this finding suggests that domestic markets' characteristics can play an essential role in a centralized multinational banking model. However, De Haas and van Lelyveld (2010) also found that, when subsidiaries are not autonomous operations, these banks may be affected by adverse developments in other parts of the group operating in various geographical areas.

According to Mesquita (2010), most banks defended the financing and liquidity management approach taken in the pre-crisis period. These institutions continued to consider their own model cost-effective and resilient. Few banks anticipated making sweeping changes to their pre-crisis strategies. Nonetheless, some reactions were possibly emerging that could have implications for future developments in the global financial system. These patterns were noticeable but not uniform across all banks in all jurisdictions, suggesting the existence of centrifugal and centripetal forces that may underlie the availability of financing and liquidity management options.

Another important aspect is the relationship between banking and financial market crises. This question is addressed by Berger and Bouwman (2008), who point out that banking and market crises differ in that banking crises are preceded by positive abnormal liquidity creation while market-related crises are usually preceded by the generation of negative abnormal liquidity. Bank liquidity creation declines and increases during crises, thereby probably aggravating and improving crises' effects. Berger and Bouwman (2008) further found evidence that higher capital has served large banks well in banking crises, during which they have improved their share of the liquidity creation market and increased their profitability.

In addition, highly rated banks have enjoyed above-average stock returns that are significantly higher than those of lower rated institutions during bank crises. These benefits have not been maintained or only to a lesser extent in market-related crises and normal periods. Conversely, high capital adequacy ratios appear to help small banks improve their market share in liquidity creation during bank and market-related crises and normal times, and these institutions' ability to sustain post-crisis results has been verified. Similar patterns have been observed during normal periods for smaller banks (Berger and Bouwman, 2008).

Most researchers argue that financial crises have their roots in the transformation of banking systems over the years (Gordon, 2010), which promotes changes in banks' funding patterns and business models. In pre-crisis periods, the abundance of liquidity sustains the leverage process in financial systems. Banks commonly reuse assets to generate new liquidity, and financial innovations occupy an important place in this process because of the exponential growth in derivatives markets and movement of a large volume of loans into capital markets through securitization and loan sales.

Since 2008, Europe and the US's bank failures have stimulated a finely-tuned regulatory response based on how individual banks' decisions regarding the size of their liquidity and capital buffers at the recent crisis's beginning were not related to their risk taking. In addition, most regulators' perception is that bank failures' costs extended beyond shareholders' interests (Brunnermeier, 2009). Academicians and policymakers have done their homework as well, arguing in favor of introducing a complementary macroprudential framework to safeguard financial stability at a systemic level (Hanson et al., 2011).

Given the new regulatory environment, institutions now need to anticipate the latest rules. Most notably, the introduction of Basel III liquidity guidelines has changed banks' funding practices by requiring stronger liquidity buffers and more diversified funding sources (BCSB, 2010a). Regulatory and supervisory entities have developed international initiatives to define liquidity standards for internationally active banks linked with LRs and to revise Basel III capital requirements.

Thus far, empirical research on the connections between bank liquidity and capital buffers and the probability of failure has been negligible. The studies conducted based on the structure proposed by Basel III have concluded that stricter regulations on liquidity and leverage will likely diminish the probability of systemic bank crises (BCBS, 2010a). Other studies using microdata on US banks have found support for the idea that banks with higher asset liquidity, stronger reliance on retail insured deposits, and larger capital buffers are less vulnerable to failure (Berger and Bouwman, 2010; Bologna, 2011).

Regarding regulatory and supervisory frameworks, Basel III proposed the use of two prudential ratios of liquidity: the liquidity coverage ratio (LCR) to promote banks' resilience to liquidity risk in the short term and the NSFR to strengthen resilience over a one-year horizon. To ensure a hard minimum capital requirement, Basel II introduced the LR, which is indifferent to the structure of risk-weighted assets in banks' balance sheets (BCSB, 2010a).

Due to the complexity of their business, legal structures, and operations across borders, global banks are important to financial systems and extremely challenging to manage. These institutions benefit from macroeconomic and monetary conditions in specific geographical regions (Griffith-Jones et al., 2002; Garcia-Herrero and Vazquez, 2007). Global banks may also exploit their internal capital markets to generate funding liquidity and capital between units.

Risk is inherent in any business activity, and the banking sector cannot escape this rule. The literature includes earlier studies that analyzed banks' role as risk transformers when they issue risk-free deposits to finance risky loans (Diamond, 1984). Notably, the amount of liquidity created may not coincide with the amount of risk transformed, so liquidity creation must be specifically studied to address various research questions and respond to political interests (Berger and Bouwman, 2009).

Allen and Gale (2004) state that liquidity creation can increase bank losses because the associated processes are related to the transformation of more illiquid assets in order to meet customers' liquidity demands. Brunnermeier and Pedersen (2008) analyzed the links between market and funding liquidity in a unified framework that sought to explain stylized facts. The cited authors concluded that market liquidity can dry up suddenly. Tirole (2011) reviewed the recent literature on liquidity, suggesting that changes have occurred in banks' demand for liquidity, determinants of aggregate liquidity, and market liquidity breakdowns. The latter breakdowns in the securitization and interbank markets have also been explained by Dang et al. (2009) based on information theory.

Some studies have found evidence of a relationship between liquidity creation and capital. Horvath et al. (2014) examined this connection through analyses of empirical research on risk's impact on banks' capital buffers. The liquidity risk hypothesis states that, the higher the level of liquidity creation, the greater the liquidity risk is for banks. Banks should, therefore, strengthen their solvency because capital acts as a buffer against customers' unexpected withdrawal of deposits. This hypothesis implies a positive relationship between liquidity creation and bank capital.

The liquidity substitution hypothesis proposed by Distinguin et al. (2013), in contrast, predicts a negative relationship between liquidity creation and banking capital. In the moments when banks experience higher illiquidity, they should consider specific net liabilities to be stable sources of financing and replace capital with these stable liabilities. Banks thus cannot strengthen their capital when they have a lack of liquidity, as defined in the new Basel rules. Distinguin et al. (2013) used a set of simultaneous equations to investigate the relationship between banks' regulatory capital and their liquidity measured by equity positions, based on a sample of commercial banks listed in Europe and the US from 2000 to 2006. The cited authors argue that the creation of liquidity and banking capital are closely interrelated, a concept that coincides with the financial fragility-crowding out hypothesis (i.e., higher capital ratios imply less liquidity creation).

However, unlike the liquidity risk hypothesis, this theoretical approach suggests that banks lower their regulatory capital ratios when they create more liquidity. As noted by Distinguin et al. (2013), capital has negative effects on the creation of liquidity, and increased liquidity creation causes a reduction in bank capital. Various other studies of the relationship between liquidity creation and bank capital have concluded that a significant negative relationship exists between liquidity creation and regulatory capital (Distinguin et al., 2013; Horvath et al., 2014; Fu et al., 2016).

Casu et al. (2018) analyzed this same relationship in the Eurozone. The cited authors used an indicator related to the new liquidity requirements established by Basel III—the inverse of the NSFR—applying this to a sample of 7,275 observations from 1999 to 2013. Casu et al.'s (2018) results confirm a significant, inverse bi-causal relationship between capital and liquidity creation.

Gropp and Heider (2010) verified that, before the mortgage crisis, substantial heterogeneity existed in the level of banks' capital in various countries, which could not be explained by capital requirements but instead was related to banks' specific features. The Deutsche Bundesbank's (2008) monthly report states that banks at the time mainly used funding instruments from repo, unsecured interbank, securitization, and currency swap markets to get financing. This means that these institutions broken the golden rule of banking and refinanced long-term assets with unstable short-term liabilities. To address this problem, the BCBS (2014) introduced the NSFR, which seeks to identify the existence of differences in maturities.

Business model analysis provides the market, regulators, and clients a better understanding of banks' financial and economic performance, risk behavior, and governance. This approach is a useful way to monitor banks' actions and their contribution to systemic risk, and the resulting information can be valuable from a regulatory and market management perspective (Ayadi and de Groen, 2014). The models suggested by Roengpitya et al. (2014) cover retail and wholesale banks mainly dedicated to loan activities and trading banks focused on trading and investment activities using capital market funding. The two former types of banks have the same business objectives, but they may have different financing strategies. While retail banks focus on customer deposits, wholesale banks use more banking and non-current liabilities for refinancing purposes. Roengpitya et al. (2014) examined eight balance sheet ratios that represent strategic management decisions. These ratios are related to banks' share of loans, traded securities, deposits, and wholesale and interbank debt.

Hryckiewicz and Kozłowski (2015) observe that banks' business models have changed and become more heterogeneous than before, which is especially true of global banks. The asset and liability structure of institutions such as the Union Bank of Switzerland, Internationale Nederlanden Groep, Deutsche Bank, and Citibank follow an investment banking model, consisting mainly of trading assets and market funding. Chinese and Japanese banks such as the Industrial and Commercial Bank of China, Sumitomo Mitsui, and Mitsubishi UFJ have chosen to develop a trading asset structure while simultaneously maintaining a more traditional structure of their liabilities. Norwegian or Austrian banks have retained a more diversified approach in terms of both assets and liabilities. Brazilian banks mostly have a traditional banking structure. Hryckiewicz and Kozłowski (2015) found proof that banks' asset structure was responsible for systemic risk before the subprime mortgage crisis, whereas these institutions' liability structure was responsible for the crisis itself.

According to Mergaerts and Vander Vennet (2016), differences exist between banks' business models that are based on their management's long-term strategic decisions related to balance sheet structure, business activities, risk taking, and liquidity. No matter which business model is used by banks, their organization is necessarily based on their balance sheet's asset and liability structure. For this reason, Grossmann and Scholz (2017) used gross loans, interbank borrowing, and wholesale debt as key ratios to identify the funding cost risks of banks' business models. The cited authors found that:

> [T]he risk of higher refinancing costs, when absorbed by equity, has different impacts on bank business models. Retail banks, especially small and medium-sized ones, bear significantly lower funding cost risks relative to equity before and after the financial crisis than wholesale and trading banks in our sample.

2.3. Data, methods, and variables

As financial intermediaries, banks increase the flow of credit in the economy by financing relatively illiquid assets with relatively liquid liabilities (Diamond and Rajan, 2001). In the process of granting illiquid loans, these institutions provide households with insurance against idiosyncratic consumption patterns, and, at the same time, individuals provide liquidity in the form of deposits (Elsas, 2010). Thus, banks function as the main providers of liquidity by investing 1 euro of net liabilities in 1 euro of illiquid assets. However, higher liquidity values can expose these institutions to the risk of customers suddenly withdrawing their deposits. The 2007–2009 global financial crisis exposed weaknesses in market liquidity management and financing risk in individual banks, with significant consequences for entire systems' financial stability.

As a result of the most recent crisis the BCBS issued new regulations for banks (i.e., Basel III), in which they are required to meet standard values for two quantitative liquidity ratios: the LCR and NSFR. The latter requires banks to maintain a stable financing profile in terms of the composition of their assets and off-balance sheet activities. This index limits overconfidence in financing short-term retail segments and encourages a more accurate evaluation of all items' financing risk (BCBS, 2010).

The NSFR is defined as the amount of available stable funding relative to the amount of required stable funding, which should be at least 100% on an on-going basis. Basel III revised the Basel Accords to enhance capital's quantity and quality. Tier 1 capital (i.e., going-concern capital) includes Common Equity Tier 1 (CET1) and is the common stock held by banks or other financial institutions. CET1 is a capital measure introduced in 2014 to protect the financial system from a crisis. The expectation is that all banks should meet the minimum required CET1 ratio of 4.50% by 2019, as well as additional Tier 1 and Tier 2 capital (i.e., gone-concern capital). CET1 capital must be at least 4.5% of risk-weighted assets (RWAs), whereas Tier 1 capital must be at least 6% of RWAs. Total capital (i.e., Tier 1 plus Tier 2 capital) must always be at least 8.0% of RWAs.

In addition, Basel III established the capital conservation buffer—comprised of CET1—above the regulatory minimum capital requirement, bringing the total common equity standard to 7%. The introduction of this buffer implies that banks, at least in normal periods, should operate with a minimum capital of 10.5% of their total RWAs. National authorities may also require a countercyclical capital buffer that varies between 0 and 2.5%. Finally, the BCBS decided to institute a simple, transparent, and non-risk based LR, which is calibrated to function as a credible supplementary measure of the required risk-based capital (BCSB, 2010).

Critics have pointed out that one of the main arguments against the NSFR is that it can be extremely restrictive and undermine the traditional role of banks in terms of liquidity and maturity transformation, which could lead to a shortage of long-term loans. This issue may have real consequences for the NSFR. The literature shows that the relationship between liquidity creation and bank capital is still unclear but suggests that these could be closely interrelated. The argument thus can be made that bank capital may affect banks' ability to create liquidity, while liquidity creation can influence banks' solvency (Grossmann and Scholz, 2017).

Another major element of the Basel III framework and its implementation in the EU is the new LR, which divides banks' supervisory Tier 1 capital (i.e., the numerator) by its total exposure (i.e., the denominator). This ratio is one of the most important new metrics introduced in response to the financial crisis of 2007–2009. The LR is defined in the Bank for International Settlements's documents as the capital measure divided by the exposure measure, with a 3% minimum requirement. Subsequently, some jurisdictions (e.g., the United States [US]) have specified higher ratios of 5% or 6% for systemically significant global banks.

Tier 1 capital is used as the capital measure, which is mostly common equity and some additional Tier 1 capital (e.g., preferred stock). The exposure measure, in turn, is the total of on-balance sheet exposures, derivatives exposures, securities finance transaction exposures, and off-balance sheet items. Capital ratios usually are based on capital divided by risk-weighted assets, but the LR intentionally does not distinguish between safer or riskier assets. Initially, the LR was a supplementary feature that could be applied to individual institutions at the discretion of supervisory authorities (i.e., Pillar 2). At the end of 2017, the BCBS decided to make the provisional 3.0% target ratio a binding minimum requirement from 2018 onwards (Smith et al., 2017). According the *Official Journal of the European Union* (2019):

> [C]redit institutions are required to satisfy the applicable minimum capital requirements ('Pillar 1 requirements') at all times. This includes a CET1 capital ratio of 4.5 %, a Tier 1 capital ratio of 6% and a total capital ratio of 8% as provided for by Article 92 of Regulation (EU) No 575/2013.

The present study analyzed banks' balance sheets and business models to define their profiles in terms of liquidity and capital buffers in conjunction with balance sheet structure. The organization of these institutions' balance sheets has evolved over time and around the globe. Banks also choose to be different from each other (Roengpitya et al., 2014), which makes a comprehensive analysis of banks worldwide necessary to clarify these organizations' commonalities and differences.

2.3.1. Data

After the initial data analysis, the entire sample was filtered, and 645 commercial banks were selected for this research. The Bankscope database used covers non-offshore commercial banks around the globe, with total assets over 100,000,000 euros from 2003 to 2015. This sample facilitated an examination of bank balance sheet dynamics in three different periods (i.e., pre-crisis, crisis, and post-crisis). The crisis period is the years of the subprime mortgage crisis as defined by the US National Bureau of Economic Research, which include 2007 to 2009. Vazquez and Frederico (2015) also consider the crisis period as falling between the end of 2007 to 2009. However, data interpretation considerations required the inclusion of different stages of the global financial crisis, namely, the crisis between 2007 to 2009, the wider financial crisis from 2008 to 2010, and the sovereign debt crisis between 2011 and 2013 (Bayer et al., 2017).

The data were downloaded from the Bankscope database because it provides comprehensive coverage of banks worldwide. Balance sheet data were given a standardized format after adjustments were made for differences in accounting and reporting standards across countries (see Table 2.1).

2.3.2. Methodology

2.3.2.1. Data analysis: bank liquidity patterns

This study focused on analyzing and understanding the patterns within series of homogeneous groups of banks, based on descriptive statistics, correlations, and estimation models, after the data were collected from banks' balance sheets, compiled, analyzed, and interpreted. The research involved evaluating the relationships between ratios that served as proxies for banks' profiles and liquidity patterns, which were linked to homogeneous groups in the sample and sub-samples defined by geographical areas. This study's most important contribution is that it is the first to use data on global commercial banks worldwide, which provided an overall view of these banks' liquidity patterns, as well as a better understanding of these institutions' behavior during the three periods analyzed: pre-crisis, crisis, and post-crisis.

The research was based on two main liquidity measures as dependent variables, namely, Basel III's NSFR and STFR (Vazquez and Frederico, 2015). In addition, this study used the LMI proposed by Brunnermeier et al. (2013) and updated by Bai et al. (2018). To measure leverage, the LR was computed as shareholders' capital over total assets (Vazquez and Frederico, 2015). The present research sought to highlight liquidity patterns across banks by identifying and analyzing these patterns' evolution and structural liquidity and leverage throughout the periods in question.

Most researchers agree that the recent financial crisis had its roots in the banking system's transformation over the years (Gordon, 2010), which promoted changes in banks' funding practices and business models. In the pre-crisis period, a profusion of liquidity was present that supported the leverage process across financial systems as a reaction to a growth cycle and supervisors' capital requirements. Bank managers commonly reused assets to generate new liquidity, and financial innovations played a paramount role in this process. All these trends encouraged exponential growth in derivatives markets and the shifting of huge amounts of loans into capital markets through securitization and loan sales. In a nutshell, banks have diversified not only their activities but also their funding sources and their assets' composition, namely, how liquid their assets are (Ayadi and de Groen, 2014). Diversification is now one of the most frequently used and better understood concepts in finance.

The current study relied on a methodology consistent with Basel III formulations, using the NFS, LR, and STFR. To measure bank liquidity and leverage, the following measures were applied:

- NSFR
- STFR
- LMI
- LR

The NSFR measures the proportion of long-term illiquid assets funded with liabilities, which are either long-term or deemed to be stable. This ratio is the relationship between the weighted sum of various types of bank liabilities (L_i) and assets (A_j), represented by Equation (2.1):

$$NSFR = \frac{\sum_i w_i L_i}{\sum_j w_j A_j} \tag{2.1}$$

The weights w are bound between 0 and 1. They reflect the relative stability of balance sheet components. For assets, larger weights are assigned to less liquid positions, and, for liabilities, larger weights are assigned to more stable sources of funding (Vaquez and Frederico, 2015). Regulations require that banks operate with an NSFR higher than one. Due to granularity in banking assets and liabilities, this ratio is not publicly available, but the ratio can be computed adequately.

The STFR was used to measure liquidity, which is computed by dividing liabilities with less than one year of residual maturity (i.e., deposits and short-term funding) by total liabilities, as shown in Equation (2.2):

$$STFR = \frac{STL}{TL} \tag{2.2}$$

The LMI measures the mismatch between assets' market liquidity and liabilities' funding liquidity (Krishnamurthy et al., 2016). This measure facilitates the calculation of liquidity based on the gap between assets and liabilities. The calculation is defined in Equation (2.3) as follows:

$$LMI_t^i = \sum \gamma_t A_j, x_t^i A_j + \sum \gamma_t L_i, x_t^i L_{ki} \tag{2.3}$$

The LMI for bank i at a given time t is the net assets and liability liquidity, in which assets $x_t^i A_j$ and liabilities $x_t^i L_i$ are balance sheet items that vary over time depending on their asset class (j) or liability class (i). The weights are defined by $\gamma_t A_j$ for assets, and the weights should have values between 0 and 1. For liabilities, $\gamma_t L_i$ is used, with values falling between –1 and 0 (Bai et al., 2018).

Calculating the assets and liabilities weights for LMI has been discussed by various authors (Bai et al. 2016; Krishnamurthy et al., 2016). In the real world, the data needed to calculate these weights for each bank are inaccessible as banks are unwilling to publish this information (Krishnamurthy et al., 2016). For academic purposes, consistency can be maintained by using the symmetric values defined by Basel III as the assets and liabilities weights, which are then used to calculate the NSFR as suggested by Vazquez and Frederico (2015).

The LR measures the proportion of shareholders' equity to assets by dividing equity capital by assets (Vazquez and Frederico, 2015), as shown in Equation (2.4):

$$LR = \frac{EC}{A} \tag{2.4}$$

A higher NSFR and LR imply lower bank liquidity risk.

2.3.2.2. Estimation model

Liquidity is the dependent variable Y_i measured by the NSFR, STFR, and LMI. The regressions carried out included bank-level financial statements' structure as the independent variables X_i, determined by the years between 2003 and 2015. To facilitate the regressions and identify more accurately the variables' impacts in the three periods in question (i.e., pre-crisis, crisis, and post-crisis), independent regressions were performed for each period.

To analyze liquidity's evolution and behavior, this study included the following independent variables:

– Gross loans: loans reported on balance sheet totals (assets)
– Interbank borrowing: deposits from other banks included in balance sheet totals (liabilities)
– Wholesale debt: other deposits plus short-term borrowing plus long-term funding according to balance sheet totals (liabilities)
– Interbank lending: loans and advances to other banks reported in balance sheet totals (assets)
– Customer deposits: clients' deposits included in balance sheet totals (liabilities)

- Stable funding: customer deposits plus long-term funding appearing in balance sheet totals (liabilities)
- Trading exposure: trading liabilities according to balance sheet total (liabilities)

To represent the banks' business model and its impact on liquidity risk, the regression model included dummies that represent the three business models selected for this purpose: retail, wholesale, and trading. This choice was based on Grossmann and Scholz's (2017) findings. The regression model is represented by Equation (2.5):

$$Dep_{it} = f\left(Bank_{it}; Model_{it)}\right) \tag{2.5}$$

in which Dep_{it} represents the dependent variable calculated for bank *i* in year *t* (i.e., the NSFR, STFR, and LMI). $Bank_{it}$ stands for the set of bank specific characteristics (i.e., gross loans, interbank borrowing, wholesale debt, interbank lending, customer deposits, stable funding, and trading exposure). $Model_{it}$ represents bank business model dummies (i.e., retail, wholesale, and trading).

For each dependent variable (i.e., the NSFR, STFR, and LMI), the baseline Equation (2.6) is:

$$\begin{aligned} Dep_{it} = {} & \alpha + \beta_1 GL_{1,it} + \beta_2 IB_{2,it} + \beta_3 WD_{3,it} + \beta_4 IL_{4,it} + \beta_5 CD_{5,it} + \beta_6 SF_{6,it} \\ & + \beta_7 TE_{7,it} + \beta_8 Dummy1_{8,it} + \beta_9 Dummy2_{9,it} \\ & + \beta_{10} Dummy3_{10,it} + \delta_i + \mu_{it} \end{aligned} \tag{2.6}$$

in where Dep_{it} stands for the dependent variable ratios (i.e., banks' liquidity ratio *i* at time *t*). X_{it} is the explanatory variable vector of bank *i* at time *t*, while α is the intercept/constant term and β_k is the coefficient that represents the explanatory variables slope. In addition, μ_{it} is the random error term (scalar quantity), and δ_i represents the fixed effect. Subscript *i* is the cross section (banks), and *t* represents the time series' dimensions (years).

2.3.2.3. Variables

The banks' financial statements obtained from Bankscope enabled the calculation of the liquidity risk ratios as dependent variables in order to analyze liquidity risk. Based on bank-level data for the 645 commercial banks in the final sample and the period from 2003 to 2015, the NSFR was calculated using Equation (2.1). The STFR as a proxy of LCR was estimated with Equation (2.2), and the LMI was calculated by applying Equation (2.3).

The independent variables used in this research (see section 3.2.2) coincide with those included in studies related to banks' business models because these variables explain banks' balance sheet structure better. Researchers have also shown that these variables can be grouped into homogeneous clusters of banks that reflect the associated banks' models. The balance sheet ratios selected interpret and reflect strategic management choices (Ayadi and de Groen, 2014; Roengpitya et al., 2014; Grossmann and Scholz, 2017).

As mentioned previously, the three bank business models (i.e., retail, wholesale, and trading) were represented by dummy variables. The procedure followed to separate the sample by bank business models was based on Grossmann and Scholz's (2017) research and followed Roengpitya et al.'s (2014) suggestions. The criteria for the three models were:

- Retail bank: gross loans ≥ 50% of balance sheets' total net derivatives, with customer deposits ≥ 50%, or gross loans ≥ 35%, with customer deposits ≥ wholesale debt and interbank borrowing and investment activities < 20%
- Wholesale bank: gross loans ≥ 50%, with wholesale debt and interbank borrowing ≥ customer deposits, or gross loans ≥ 35%, with wholesale debt and interbank borrowing ≥ customer deposits and investment activities < 20%
- Trading bank: investment activities ≥ 20% or interbank lending and investment activities ≥ gross loans

In the regression model, the value 1 meant that bank *i* in year *t* was included in the relevant bank model, while a 0 value meant that bank *i* in year *t* was not included in that bank model.

2.4. Research results

Data collection and processing was one of this research project's greatest challenges. Out of a universe of more than 17,000 banks of various types, the final sample analyzed contained 645 commercial banks as a result of the criteria's interaction. For example, the biggest institutions were selected and niche and off-shore banks were excluded because they would have a detrimental effect on the analyses. Overall, an accurate representation of the banking sector affects commercial banks most strongly, which is why this study focused on them.

Due to the long timespan covered by the data sample (i.e., 13 years) and apparently only one credible data source (i.e., Bankscope), the data were collected in two stages: from 2003 to 2011 and from 2012 to 2015. Thus, many banks used different identification codes over time, which required special care to homogenize the data.

Even with only 645 banks, more than 8,000 lines of data were gathered for each bank variable for the regression model. This volume of information was the study's second biggest challenge, including finding a double entry model that could support this level of data.

2.4.1. Patterns' evolution

The sample covering 13 years (i.e., 2003 to 2015) included information that permitted conclusions to be drawn about the banks' behavior in the pre-crisis, crisis, and post-crisis periods. Based on the results shown in Figures 2.1 to 2.28, the trends and patterns in banks' balance sheet structure could be identified, as well as the relevant liquidity variables.

A global analysis (see Tables 2.2 and 2.3 below and Figures 2.1 and 2.17 above) revealed that only 10% of the banks had an NSFRs above 1%, which is the minimum value recommended by regulations (Vazquez and Frederico, 2015). The results verify that 90% of the banks had indices ranging from 0.58% to 1%. This observation shows that, in general, the commercial banks analyzed did not comply with the minimum proposed by regulators for long-term liquidity. The NSFR refers to long-term liquidity risk, so a higher NSFR means lower bank liquidity risk.

However, an analysis of the time series by sub periods revealed that, in the pre-crisis period (see Table 2.3 and Figure 2.5 above), the percentage of banks with an NSFR lower than 1% was 80% and 90% of the banks' values were concentrated between 0.70% and 1.15%. These results indicate that, during this period, short-term liquidity were the banks' main concern probably due to strong market activity. This strategy's impact on bank liquidity is obvious.

In the subsequent crisis period (see Table 2.3 and Figure 2.9 above), the percentage of banks with an NSFR of less than 1% increased to 90% of the analyzed institutions. NSFRs of between 0.69% and 1% represented 91% of these commercial banks. Due to the crisis and more active interventions by authorities, the number of banks with low level NSFRs increased, which makes sense because the banks' main concern become how to become stronger and avoid the financial crisis. Therefore, commercial banks reduced new loans and acquired more stable funds.

Finally, in the post-crisis period (see Table 2.3 and Figure 2.13 above), the results show a reduction of long-term liquidity in institutions, with 93% of banks presenting NSFR levels below 1%. Most institutions' rates fell between 0.69% and 1% (96%). Commercial bank managers clearly thought the storm had passed, so they started to recover their money. By this time, major central banks were offering financial assistance to banks in order to improve the economy's growth. This aid consisted of credit lines with much lower interest rates, which promoted an increase in liquidity in financial systems. Once again, these findings indicate a recovery from a time in which the main concern was maintaining sufficient levels of short-term liquidity so that the third period reflected how economic growth had returned and investments were made in the economy. Table 2.2 and Figure 2.25 above provide an overview of the NSTR by period, indicating that, before the crisis, structural funds were higher than in the post-crisis period since bank management were still unaware of this requirement.

Table 2.4 below and Figures 2.2 and 2.18 above show the values calculated for the LR. An analysis of this rate's behavior provides complementary information on banks' liquidity in the period from 2003 to 2015. A high LR implies an increase in capital, and, because capital is a stable fund, this implies less liquidity for commercial banks. To achieve this study's objectives, the total capital requirements were considered rather than only the LR requirements.

Overall, if regulatory requirements' values are used as a reference point, the results reveal lower level LRs. In the sample as a whole, 35% of the banks had an LR below 7%, but, in the pre-crisis period (see Table 2.4 and Figure 2.6 above), 14% of the institutions had an LR of less than 5%. This means that the majority of the banks in question had an LR in accordance with regulations. The results obtained for the crisis (see Table 2.4 and Figure 2.10 above) are quite interesting because the percentage of banks with an LR below 3% sank to 6% as a result of supervisory authorities' impositions meant to guarantee banks' stability by strengthening their equity capital. The capital increase was naturally obtained by using the institutions' existing liquidity.

In the post-crisis period (see Table 2.4 and Figure 2.14 above), the data show an increase in the number of banks with an LR below 6% (i.e., almost 21%). The post-crisis LR values climbed to the levels observed in the pre-crisis period, which could mean that bank managers achieved to the same level of required performance seen in the period prior to the crisis by sacrificing long-term stability to increase earnings. Table 2.2 and Figure 2.26 above present all the analyzed periods. Similar to the NSFR, the LR fell between the pre-crisis and post-crisis periods, but Table 2.4 above reveals that more banks were near the regulators' minimum requirements of 8%. Bank managers are obliged to meet these requirements and increase their banks' capital.

The STFR (see Table 2.5 below and Figures 2.3 and 2.19 above) gives an indication of the short-term liabilities' weight in the total liabilities, which works as a liquidity measure. As Table 2.5's information shows, 68% of banks had an STFR above 96% for the entire period under study, providing evidence that short-term funding is commercial banks' main strategy regarding their liabilities. A comparison of the pre-crisis period (see Table 2.5 below and Figure 2.7 above) with the overall period highlights that this indicator's values fell so that only 66% of the banks presented an STFR higher than 96%.

In crisis period (see Table 2.5 and Figure 2.11 above), the STFR dropped down to 74% in the analyzed banks as a whole, providing evidence of banks and their managers' concern about balancing short-term liquidity needs. Given that, in this period, the number of banks with a lower NSFR increased as did the percentage of banks with a higher LR, the results indicate an increase in banks' capital in response to regulators' requirements that sought to end the crisis. During the post-crisis period (see Table 2.5 and Figure 2.15 above), the STFR returned to the pre-crisis levels in which 68% of the banks analyzed had an STFR higher than 96%. This tendency was a return to the pre-crisis management profile, perhaps showing that bank managers still preferred short-term funding to financing assets.

The results in Table 2.2 and Figure 2.27 above verify the STFR's evolution across the three periods. The data confirm the trends empirically with higher values in the pre-crisis, a strong reduction in the crisis period due to fewer available deposits, and a recovery in the post-crisis but to lower levels than the pre-crisis period, which may be related to bank managers' increased concern about regulations.

The liquidity mismatch or liquidity gap analysis was a common topic of discussion in all banks even before the recent financial crisis. Excessive liquidity mismatch is a cause for concern for departments dealing with risk analysis and treasury issues as this problem can lead to wholesale markets' breakdown. Distressed asset sales affect individual banks and financial systems' solvency (Brunnermeier, 2009; Tirole, 2011). No reference values are available for the LMI, so the analysis had to be done bank by bank according to their assets and, in particular, liquidity needs and strategy.

Table 2.6 provides the LMI values for all the periods, which show that overall 94% of the sample had an LMI of 8,286,725,000 euros, but this value alone does not explain banks' liquidity. However, this index's evolution across the three periods reveals that the liquidity gap in the pre-crisis and crisis periods was higher than in the post-crisis period based on the frequency or number of banks. This trend could mean better liquidity management in the post-crisis period. When the analysis focused on cumulative percentage and similar values, the results show that 94% of the banks had more liquidity in the post-crisis period than in the previous periods. Figure 2.28 above clearly shows that liquidity mismatch's evolution meant that effective liquidity increased due especially to more saving deposits and fewer loans. The latter result could indicate more risk aversion.

2.4.2. Country analysis

The rules and regulations imposed on banks, in particular the Basel agreements, produced some homogeneity in NSFR values across countries. Figure 2.21 above provides the NSFR's average value for each country and each period analyzed. Overall, the values are between 0.8 and 1, with higher values in the pre-crisis period, followed by a reduction during the crisis and a recovery in the post-crisis period. The third period presented lower NSFR values than the pre-crisis period did. Because the NSFR is a long-term liquidity ratio, the results show an increase in long-term liquidity risk in the crisis and post-crisis periods due to the short-term use of resources to stimulate economic growth with the help of government policies focused on increasing consumption.

With an overall NSFR average of 0.89%, the banks were, in general, below the minimum Basel III requirements, yet some countries were well above this value, such as Botswana, the Netherlands. Other nations, including the Czech Republic, Germany, Indonesia, India, Japan, Malta, Mauritius, the Philippines, and the US, were quite close to the 1% limit. These findings may mean, on the one hand, more restrictions imposed by the authorities and, on the other hand, managers' stronger focus on maintaining better levels of liquidity in the long term. One exception to the general trends was Japanese banks, which had an NSFR lower than 1 and which were not affected by the 3 periods in question, with all the institutions presenting the same NSFR profile. In the opposite direction, the results identify Australia, Austria, Chile, France, Georgia, Ireland, Kazakhstan, Morocco, Paraguay, Peru, Portugal, the Russian Federation, South Africa, Spain, and Sweden as countries with NSFR values below the global average.

Figure 2.22 above presents the LR values grouped by country, revealing greater differences between countries than for the NSFR. Overall, the LR was an average of 9.8% higher than the total capital (i.e., Tier 1 plus Tier 2 capital), which should be at least 8.0% of RWAs at all times. Additional countercyclical capital buffers varied between 0 and 2.5%. Authorities have always been concerned about capital requirements even before NSFR requirements were defined, which explains the existence of average values closer to the legal limits.

Countries such as Brazil, Bulgaria, Croatia, Italy, Lithuania, Mauritius, the Netherlands, Poland, and Turkey increased their LR during the crisis period. The US banks, instead, significantly decreased their LR levels in the crisis, which could have been caused by capital consumption. Many other nations registered higher LR values in the post-crisis period compared with the previous period, including Australia, Austria, Bangladesh, Botswana, Bulgaria, Canada, China, Colombia, Czech Republic, Hungary, India, Indonesia, the Republic of Korea, Malta, Mauritius, Morocco, the Netherlands, Poland, Portugal, Saudi Arabia, Slovakia, Slovenia, South Africa, Sweden, Thailand, Turkey, and the United Kingdom. Despite these increases, significant decreases in the LR were detected between the pre-crisis and post-crisis periods. Countries such as Azerbaijan, Georgia, Kazakhstan, Lithuania, Peru, Romania, the Russian Federation, Singapore, Switzerland, and the US significantly reduced this ratio, which is why the post-crisis average stayed the same as the crisis period but lower than the pre-crisis period.

The STFR was also used in this study to measure liquidity by dividing liabilities with less than one-year residual maturity by total liabilities. Figure 2.23 above presents the STFR by country and period, revealing that many banks exclusively used short-term liabilities to fund their activities. However, a global mean of 88% indicates that, in the analyzed sample, only 12% of the banks' liabilities were over one year in maturity and banks preferred short-term funding. This raises questions about maturity transformation because the assets and especially loans were at 88% for a long time, which created a problem for banks because the majority of their resources was short-time funding but the applications were not in the same level. This situation resulted in a gap that needed to be properly managed by banks' treasury departments. Across the sample, the differences between the analyzed periods was not significant, but countries such as China, Japan, and the US showed extremely high levels of short-term funding with fewer differences between periods. This kind of funding makes banks dependent on an stable economic environment that ensures normal liabilities and asset rotation, and, if these conditions are not present, the consequence is normally a financial system collapse as happened in 2007 in the US. In contrast, the results confirm that countries such as Brazil, Finland, France, Italy, Spain, and Sweden had lower levels of short-term funding to total liabilities than other countries did, which could indicate a more adequate approach to assets and liabilities.

As discussed in the previous section, maturity mismatch is one of the problems—perhaps the most important one—that arises from differences between assets and liabilities' conditions. Maturity mismatch is when financial institutions' assets and liabilities are misaligned in terms of maturity time. If this difference or gap is significant, then banks have a liquidity issue. The LMI measures the mismatch between assets' market liquidity and liabilities' funding liquidity, facilitating an evaluation of liquidity based on the gap between assets and liabilities.

Given banks' different sizes, Figure 2.24 above provides a better understanding of this problem's impact by showing the LMI with log-normal values. An important point highlighted by this figure is that almost all the countries had a positive increase in the LMI in the post-crisis period, which means banks' real liquidity grew or financial institutions had more liquid assets. However, some countries did not experience an increase in the LMI in this period, including

Ireland, Italy, the Netherlands, Portugal, Slovenia, and Tunisia. According this study's data, the LMI appears to be a good indicator with which to analyze banks' liquidity needs more accurately, as well as to identify the associated risk.

2.4.3. Regression analysis

As explained in section 3.2.2, the regression step used three dependent variables: the NSFR, STFR, and LMI. The independent variables (X_i) were measured for the years between 2003 and 2015. An independent regression was performed for each period to identify the impacts more easily in the three periods in question (i.e., pre-crisis, crisis, and post-crisis). The independent variables were gross loans, interbank borrowing, wholesale debt, interbank lending, customer deposits, stable funding, and trading exposure.

To represent the banks' business model, the regression included model dummy variables that represent the three business models selected for this purpose. The three business models included were retail, wholesale, and trading banks.

2.4.3.1. Statistics

Table 2.11 lists the descriptive statistics for the variables included in this study. The details include the mean, median, maximum and minimum, and standard deviations for the dependent and independent variables.

The NSFR measures the proportion of long-term illiquid assets that are funded with liabilities that are either long term or deemed stable and that reflect the relative stability of balance sheet components. Regulations require that banks operate with an NSFR higher than one. Table 2.11 above includes an NSFR of 0.89 for all the period under study, which means that, overall, the banks analyzed did not comply with regulatory requirements. The proximity between the mean and median implies similarities between the banks in the sample. The standard deviation is 0.15, indicating that the computed values are reliable.

As a liquidity indicator, the STFR is computed by dividing liabilities with less than a one-year residual maturity (i.e., deposits and short-term funding) by total liabilities. The results for this indicator reveal that the bank balance sheets in the sample presents significant short-term liquidity values because the mean is 0.88. Thus, the majority of the banks' liabilities is made up of deposits and short-term funding.

Regarding the LMI, the gap between assets and liabilities meant that this variable had to be divided by total assets. The results verify that liquidity represents 9% of the banks' assets, with this value staying quite close to the median because of similarities between banks.

The results for the independent variable analyses, not unexpectedly, show that loans represent 62% of total assets while customer deposits represent 69% and stable funding 75%. These values confirm that commercial banks' balance sheet patterns do give importance to clients' deposits and loans. If the mean is compared with the median, the weight of loans and deposits is even higher, with the former representing 64% of the assets and the latter 76%. A full statistical analysis of dependent variables by period and county was performed as discussed in sections 4.1 and 4.2.

2.4.3.2. GMM estimation model

The fixed effects and generalized method of moments (GMM) panel data analysis techniques are employed to quantify banking variables with regard to the three liquidity indicators. The GMM method was developed by Arellano and Bond (1991), and it has since been used in panel data regression analyses. This technique's estimators consider the dependent variables' lagged value to be an independent variable, as shown in Equation (2.6). GMM estimation models are especially useful as a way to estimate unbiased partial adjustments and to control endogeneity in banks' specific variables and liquidity indicators. According to Hansen (1982), every estimator in nonlinear or linear models with cross sections, panel data, or time series can be understood as a GMM estimator. Hall (2005) asserts that, when this estimation model is used as a unifying framework to produce inferences in econometrics, the model offers the advantage of being robust in terms of the distribution of errors and more efficient than two-stage least squares.

Econometric results are sensitive to the methodology used in estimations, so robust standard errors (SEs) were included in the fixed effects and GMM estimations. The GMM estimation model applies Equation (2.6) while considering two conditions. First, the variables are calculated based on the initial differences, and, second, the lagged variable and its determinants are the instruments. The first condition eliminates any autocorrelation that exists between individual unobservable effects and explanatory variables, as well as autocorrelation between individual unobservable effects and the lagged variable. The second condition removes any autocorrelation between errors and the lagged variable.

Static panel data analysis tends to produce results plagued by bias and inconsistent estimates. In this study, liquidity indicators were used as dependent variables, so the existence of heterogeneity and correlations between independent variables could become an issue (Harris and Mátyás, 2004). To resolve this problem, the GMM represents solutions as estimation models, which is an appropriate method that creates unbiased, consistent parameter estimations.

The GMM method's assumptions include panel data with few years and many cross-sectional units, the existence of a linear functional relationship, a dynamic dependent variable, and independent variables that are not strictly exogenous, individual fixed effects. In addition, autocorrelation and heteroscedasticity is present in individual units but not between them (Roodman, 2006).

Analysis of the determinants of banks' liquidity commonly rely on multiple regression, which shows independent variables' effects on the selected liquidity indicators, thereby testing the hypotheses formulated. However, determinants that affect financial institutions' liquidity can have a potentially endogenous character, so the GMM estimation model was selected as a more adequate estimation method to control the possible problems of unobservable effects' endogeneity and heterogeneity (Blundell and Bond, 1998).

The GMM regression model's output includes the following. The *R*-squared (R^2) coefficient or adjusted R^2 indicates the percentage of change in an dependent variable in response to changes in an independent variable. The regression's SE provides a measure of the typical distance at which the data points fall from the regression line. The SE is defined in terms of the dependent variable's units. A smaller SE of the regression and smaller residual sum of squares are better results for any model.

Regression coefficients predict the amount and direction of change in an dependent variable due to a unit change in an independent variable. The probability provides the statistical significance of each independent variable individually. If the *p*-value is 0.01 or smaller than 0.01, then the coefficient has a significance level of 1%, and the estimated coefficient is quite strongly significant. If the *p*-value is 0.05 or smaller than 0.05, the coefficient also has a strong significance level at 5%. If the *p*-value is 0.10 or smaller, the coefficient is significant but not as strongly as in the previous two cases.

The Durbin-Watson statistic is an autocorrelation test of the residuals from statistical regression analysis. This statistic always has a value between 0 and 4. A value of 2.0 means that no autocorrelation was detected in the sample. Values from 0 to less than 2 indicate positive autocorrelation, and values from 2 to 4 indicate negative autocorrelation.

The *J*-statistic is used to assess the validity of overidentifying restrictions. The null hypothesis is that the overidentifying restrictions are valid. Similarly to other instrumental variables estimators, the GMM estimator can only be identified if at least as many instruments are used as the number of parameters in the model. In models in which the number of instruments matches the number of parameters, the optimized objective function's value is zero.

If more instruments are used than number of parameters, the optimized objective function's value will be greater than zero.

This form of analysis has been used in various studies of the impact of liquidity determinants on financial institutions (Delechát et al., 2012; Hasanovi and Latic, 2017). In addition, Wuryandani (2012) used a GMM model to analyze credit, savings, and deposits' effects on liquidity. Pascual et al. (2015) used a system-GMM estimator, which was developed for dynamic panel data models to analyze bank-specific and macroeconomic determinants of bank risk. The cited authors concluded that capitalization, profitability, efficiency, and liquidity are inversely related to risk and that wholesale funding by banks appears to increase their risk. Galletta and Mazzù (2019) analyzed liquidity risk drivers and bank business models using a GMM model and verified that bank size increases liquidity risk but capital does not. The cited study's findings reveal that, "for savings banks, income diversification raises the liquidity risk while investment banks[' reliance] … on non-deposit funding decrease the exposure to liquidity risk."

2.4.3.3. Correlations

2.4.3.3.1. NSFR correlations

Table 2.8 above displays the correlations between the NSFR as the dependent variable and the independent variables. None of the latter presents multicollinearity with any of the dependent variables, but the relationship between stable funding and customer deposits has a correlation above 0.8. This value confirms the existence of a strong correlation between these two independent variables, which could be expected for commercial banks. This analysis also verified a strong negative correlation between the wholesale and retail bank business models.

Regarding the correlations' signs, a pattern was detected. All the independent variables based on assets have a negative correlation with the NSFR. This result makes sense because the former variables are related to the consumption of long-term liquidity. All the independent variables based on liabilities have a positive correlation with the NSFR as they are sources of long-term liquidity. An analysis of bank business models showed that the retail model has a positive correlation with the NSFR while the wholesale model has a negative correlation.

2.4.3.3.2. STFR correlations

Table 2.9 above provides the results for the STFR's correlations with the independent variables. None of the independent variables presents multicollinearity with the dependent variable, but customer deposits over total assets has a 0.80 positive correlation, which is at the limit. Between the independent variables, correlations exist that are higher than 0.8, namely, stable funding over total assets' relationship with customer deposits over total assets. This result is not unexpected because, by using commercial banks' data, the majority of stable funding is likely to be clients' deposits. In addition, as observed for the NSFR's correlations, the variables that represent the bank business model have a negative correlation higher than 0.8 between the wholesale and retail models. This finding is important as it confirms the data's accuracy and the existence of two well-defined bank models.

All the variable also have a significance level of 0.01, and a strong negative correlation was found between wholesale debt over total assets and the dependent variable. This connection is to be expected as the latter variable is a short-term indicator and wholesale debt has medium- to long-term maturity. A strong positive correlation exists between the dependent variable and customer deposits over total assets. This last correlation was expected again given a short-term indicator and customer deposits' direct impact on short-term liquidity. Regarding the banks' business model, a positive correlation was detected between the STFR and retail business model and a negative correlation between the STFR and wholesale business model.

2.4.3.3.3. LMI correlations

As mentioned previously, the LMI measures the mismatch between assets' market liquidity and liabilities' funding liquidity (Krishnamurthy et al., 2016). Thus, this index represents a different kind of indicator than the NSFR and STFR, which are both regulatory indicators—one long term and the other short term.

An analyses of the LMI correlations shown in Table 2.10 above confirmed the absence of multicollinearity between this dependent variable and the independent variables. Except for wholesale debt over total assets, the variables have a significance level of 0.01. When compared with the results for the two other dependent variables, however, the correlations present lower values, as well as being almost all negative relationships. Only interbank lending over total assets and the trading business model show a positive correlation of 0.26 for the first and 0.20 for the second.

Because the LMI is an indicator of a mismatch between weighted assets and liabilities, the most significant correlations are this index's negative relationships with gross loans over total assets, customer deposits over total assets, and stable funding over total assets. The only positive relationship is with interbank lending over total assts. Regarding bank business models, the correlations are lower, but the results confirm the existence of a positive correlation with the trading bank business model and a negative correlation with the retail bank business model.

2.4.3.4. GMM model results

GMM regression analysis (Arellano and Bover, 1995) determines how the variation in one variable relates to changes in another variable and what the relationship's direction is between the two variables. Each independent variable is weighted during the regression analysis, and regression coefficients indicate the relative contribution of independent variables to the models' predictive power.

This model is also used to avoid some constraints such as endogeneity and heterogeneity. GMM models have been used in various studies of profitability determinants' impact on bank performance (Dietrich and Wanzenried, 2011; Trujillo-Ponce, 2013). In the present research, regression analysis was carried out three times, namely, one for each dependent liquidity variable (i.e., the NSFR, STFR, and LMI).

2.4.3.4.1. NSFR

Table 2.12 summarizes the estimation model's results for the NSFR. The independent variables were those listed previously (see section 2.3.2.2). A correlation higher than 0.8 means multicollinearity exists, so stable funding and the D2 variable that represents the wholesale bank business model were excluded. To understand the dependent variables' behavior more fully, the model was estimated four times—one for each of the three aforementioned periods and one for the overall period that includes the years between 2005 and 2015. As mentioned previously, the pre-crisis period was between 2005 and 2006, the crisis between 2007 and 2009, and the post-crisis period between 2010 and 2015.

For the overall period and the NSFR, the regression model shows an R^2 of 90% and adjusted R^2 of 89%. These results mean that this model explains 90% of the NSFR's changes and behaviors. The pre-crisis period model has an R^2 of 97% and adjusted R^2 of 94%, which means that this model explains 97% of the NSFR's variation and movement in this period.

The crisis period model has an R^2 of 95% and adjusted R^2 of 92%. These percentages confirm that this model explains 95% of the NSFR's changes and behaviors during the crisis. For the last period analyzed (i.e., the post-crisis years), the model presents an R^2 of 92% and adjusted R^2 of 90%, which shows that this model explains 92% of the NSFR's fluctuations and evolution regarding the last period. The results for all the analyzed periods confirm that the GMM model has good predictive power, and this could be confirmed by the relationships between the dependent and independent variables.

For the overall period (see Table 2.12 above), three variables have no statistical significance as shown by *p*-values higher than 0.1: the CD_TA (customer deposits/total assets), D1 (retail bank business model), and D3 (trading bank business model). Thus, they do not explain the dependent variable. According to Mesquita (2010), increased competition can make customer deposits a less stable source of financing. In additionally, the NSFR is a long-term liquidity ratio, and customer deposits are considered to be short-term funding, which partly explains why customer deposits do not explain the NSFR. Elsas (2010) argues that higher liquidity values may expose banks to the risk of customers' sudden withdrawals of deposits. The global financial crisis of 2007–2009 exposed weaknesses in market liquidity management and individual banks' risk financing, with significant consequences for entire banking systems' financial stability.

Regarding the dummy independent variables for bank business models, the estimation model developed for the present study eliminated these variables from those that explain the NSFR, so banks' business models are not an important variable for long term liquidity. Grossmann and Scholz (2017) suggest that gross loans, interbank borrowing, and wholesale debt are key ratios that identify these business models' funding cost risks:

> [T]he risk of higher refinancing costs, when absorbed by equity, has different impacts on bank business models. Retail banks, especially small and medium-sized ones, bear significantly lower funding cost risks relative to equity before and after the financial crisis than wholesale and trading banks in our sample.

For the overall period, the final model's results reveal that five independent variables have a significance level of 1%, namely, GL_TA, IB_TA, WD_TA, IL_TA, and TE_TA. All these independent variables have a negative relationship with the NSFR and an increase in these determinants reduces long-term liquidity.

Regarding the sub-periods, small differences were detected in the independent variables' significance. The pre-crisis period is associated with a lower number of observations, so the regression model did not generate values for the significance of five independent variables: IB_TA, WD_TA, CD_TA, TE_TA, and D1. For GL_TA, IL_TA, and D3, the model shows a significance level of 1%. In the crisis period, D1 and D3 are not significant, WD_TA has a significance level of 5%, and GL_TA, IB_TA, IL_TA, CD_TA, and TE_TA have a significance level of 1%. In the post-crisis period, IL_TA, D1, and D3 are not significant, GL_TA and CD_TA have a significance level of 5%, and IB_TA, WD_TA, and TE_TA have a significance level of 1%. The pattern consistent across all these periods is the existence of negative relationships between the independent variables and dependent variable, with the exception of CD_TA positive connection in the crisis period.

In the overall period, the gross loans over total assets—as a component of banks' balance sheet assets—have a negative impact of 27% on the NSFR for each change of 1% in GL_TA. In the pre-crisis period, this relationship also has a negative impact of 31%; in the crisis period, a negative impact of 44%; and, in the post-crisis period, an impact of 16%. Thus, the negative impact increased from the pre-crisis to crisis period, culminating in a 44% negative impact on the NSFR for each 1% change in GL_TA. In the post-crisis period, this coefficient shrinks to levels lower than the pre-crisis period.

Loans' maturity indicate whether they are a short-, medium-, and long-term liquidity consumers. According to the GMM model's results, gross loans' impact on long-term liquidity is relatively low compared with the other variables included in this research. A possible explanation for this is that banks used to link loans with the relevant resources. Resources such as clients' deposits or interbank borrowing are part of banks' effective carrying out of duties in terms of liquidity as these resources represent outflows while loans after disbursement represent inflows.

The increased impact observed in the crisis period could be related to a reduction of available resources that uncovered dubious loans. Diamond and Dybvig (1983) confirmed the relationship between liquidity and banks' intrinsic fragility, verifying that liquidity is created when liquid liabilities (e.g., deposits and interbank borrowing) are transformed into illiquid assets (e.g., loans). When this liquidity transformation occurs, a gap between assets and liabilities' maturities is also created, and the expected inflows from loan reimbursements may be desynchronized with outflows from clients' demand deposits. As discussed previously, holding cash and similar resources improves the liquidity ratio, but this strategy also reduces resources, which happens when banks allocate funds to illiquid assets (e.g., loans), thereby reducing liquidity creation.

Angora and Roulet (2011) remark that the relationship between liquidity risk can be measured with the LCR and NSFR, balance sheet indices such as ROA, the natural logarithm of total assets, and the ratio between loans to customers and total loans. Other measure include macroeconomic indicators such as the GDP annual growth rate and spread between the interbank and central bank policy rate. Angora and Roulet (2011) found that banks' liquidity risk ratio has a negative relationship with most variables analyzed, while liquidity measures have a significant positive relationship with macroeconomic variables.

The estimation model for the overall period shows that interbank borrowing over total assets has the greatest impact on the NSFR as the results indicate that a 1% change in IB_TA, with the remaining factors kept constant, causes long-term liquidity to decrease by 93%. The model highlights a reduction in interbank borrowing over total assets in the crisis, followed by a large increase in the post-crisis period. The crisis period had already drained banks' resources, so the interbank market shrank and the impact of interbank borrowing on banks' balance sheets was lower as well. In the post-crisis period, interbank borrowing increased due to central banks' assistance.

As this variable represents loans from other banks, it implies obligations that banks must fulfill. The Deutsche Bundesbank (2018) report referred to earlier mentions that banks that mainly used financial instruments from repo, unsecured interbank, securitization, and currency swap markets became stressed. Along with other researchers, Demirguç-Kunt and Huizinga (2010) found evidence that banks' dependence on the interbank market increases the probability of bankruptcy, with interbank loans representing long-term obligations. Acharya et al. (2011) assert that, when banks rely heavily on the interbank market, increased capital requirements can become a prudential measure to reduce both insolvency and liquidity risks. Aymanns et al. (2016) confirmed a significant negative impact of solvency shocks on banks' funding costs, including a significant effect related to interbank funding costs and sensitivity to stress periods.

Wholesale debt over total assets, in turn, has a negative impact of 33% on the NSFR for each 1% variation in WD_TA. This variable comprises other deposits plus short-term borrowing and long-term funding, which is again a liability in terms of banks' balance sheets. This factor's coefficient decreases in the crisis but increases again in the post-crisis period. As a resource, WD_TA follows the same pattern of behavior as IB_TA. Because more stable funding sources are involved, the negative impact on the NSFR is lower. Calomiris (1999) detected the existence of banks' reliance on wholesale funding to mitigate their vulnerability to liquidity risk, as well as depending on market discipline.

Interbank lending over total assets is another item appearing on the asset side of banks' balance sheet, and IL_TA is an independent variable included in the present study. Similar to the remaining independent variables for the overall period, IL_TA has a negative impact of 14% on the NSFR for each 1% change in the independent variable's coefficient, which makes this variable's effect lower than the determinants with a higher p-value. For the remaining periods, IL_TA's influence grew stronger in the crisis, followed by a decrease in the post-crisis period to an even lower level than in the pre-crisis period. During the crisis period, banks reduced their investment in risky assets (i.e., loans) and increased their available cash liquidity.

The only less risky asset available to those seeking to invest these values were the interbank market. After the crisis, banks returned to their credit and investment activities and thus reduced their liquidity surpluses.

Various studies have documented that cash holdings grew substantially during the 2007–2009 financial crisis, and banks' lending to households and corporations stagnated substantially. Acharya and Skeie (2011) explored the relationship between cash holdings and counterparty risk, analyzing the causes of cash holding in the crisis. Acharya and Merrouche (2013) further showed that a change such as the 2007 financial crisis forces banks to retain more treasury values in order to be ready for exceptional situations. Similar to the gross loans variable, interbank lending requires scheduled reimbursements, which means a predictable inflow that has a lower negative impact on long-term liquidity.

As previously mentioned, customer deposits over total assets' coefficient was not significant in the overall or pre-crisis periods. However, during the crisis, this variable's effect reached a significance level of 1% and, in the post-crisis period, of 5%. This coefficient is the only positive relationship with the dependent variable during the crisis, explaining 20% of the positive variation in the NSFR for each 1% variation in CD_TA. In the post-crisis period, this variable changed so that it had a negative impact of 14% on the NSFR for each 1% shift in CD_TA.

As already noted, Angora and Roulet (2011) analyzed the relationship between liquidity risk—measured by the LCR and NSFR—balance sheet indices (e.g., ROA), the natural logarithm of total assets, and the ratio of customer loans to total loans. The cited study also included some macroeconomic indicators (e.g., GDP annual growth rate) and the spread between interbank and central bank policy rates. Angora and Roulet (2011) found that the liquidity risk ratio has a negative relationship with most indicators they analyzed but that liquidity measures have a significant positive relationship with macroeconomic variables. More specifically, during the crisis, customers increased their savings, and banks had an opportunity to create a long-term liquidity buffer.

The second biggest impact is that of the trading exposure over total assets independent variable, with a decrease of 73% for each 1% change in the NSFR. Similar to IB_TA, TE_TA appears on the liability side in balance sheets since this is an obligation for banks that consume long-term resources. As mentioned earlier in this section, the Deutsche Bundesbank's (2008) working paper stated that banks that mainly used funding instruments from repo, unsecured interbank, securitization, and currency swap markets came under stress.

2.4.3.4.2. STFR

In the present analyses, the NSFR measured the proportion of long-term illiquid assets funded with liabilities, which are either long term or considered stable. The STFR, in turn, is a liquidity ratio calculated by dividing liabilities with less than one-year residual maturity by total liabilities, so this ratio represented short-term liquidity and the STFR was expected to present more symmetrical results than the NSFR.

Table 2.13 summarizes the estimation model's outcomes for the STFR as a dependent variable. The independent variables were initially all those presented in section 3.2.2, but, due to correlations higher than 0.8 indicating multicollinearity, stable funding (SF_TA) and the D2 variables (i.e., wholesale bank business model) were excluded. To understand the dependent variables' movements more fully, the regression was performed four times—one for each period included in this study and for the overall period covering all the years between 2005 and 2015.

In the overall period, the regression model retrieved an R^2 of 95% and adjusted R^2 of 94% for the STFR, which means that this model explains 95% of this dependent variable's changes and movements. For the pre-crisis period, the results include an R^2 of 98% and adjusted R^2 of 95%, so the model explains 98% of the variations and developments in the STFR. In the crisis, the estimation model produced an R^2 of 97% and adjusted R^2 of 95%, showing that this model explains 97% of the fluctuations and movements in the STFR. For the last period analyzed (i.e., post crisis), the model presented an R^2 of 96% and adjusted R^2 of 96%, indicating that this model explains 96% of the changes and trends in the STFR. The results obtained for all periods confirm that the model has good predictive power, which was further corroborated by the relationships between the dependent and independent variables.

The analysis of the overall period (see Table 2.13 above) verified that five coefficients—GL_TA, WD_TA, IL_TA, D1, and D3—had no statistical significance with *p*-values higher than 0.1. Elsas (2010) suggests that higher liquidity values can expose banks to the risk of customers suddenly withdrawing their deposits. The global financial crisis of 2007–2009 exposed individual banks' weaknesses in market liquidity management and financing risk, with significant consequences for entire systems' financial stability. Melese (2015) found that loan growth has a negative but insignificant effect on banks' liquidity. In addition, Alessi (2018) states that credit growth is related to systemic risks and financial stability that surface during extensive banking crises.

Regarding the dummy independent variables for bank business models, the current study's model with the STFR as the dependent variable excluded the dummy variables as they did not explain the STFR's behavior, so bank business models are not important to long-term liquidity. Grossmann and Scholz's (2017) previously mentioned research found that:

> [T]he risk of higher refinancing costs, when absorbed by equity, has different impacts on bank business models. Retail banks, especially small and medium-sized ones, bear significantly lower funding cost risks relative to equity before and after the financial crisis than wholesale and trading banks in our sample.

The final model's results for the overall period show that three independent variables have a significance level of 1%, namely, IB_TA, CD_TA, and TE_TA. IB_TA and CD_TA have a positive relationship with the STFR but TE_TA has a negative connection. Positive relationships mean that increases in these variables strengthens short-term liquidity, while negative links imply that the independent variable's growth reduces short-term liquidity.

Regarding the remaining periods, small differences were observed in the independent variables' significance levels. The pre-crisis period has the lowest quantity of observations, so the regression model did not retrieve statistically significant values for five of the independent variables: IB_TA, WD_TA, CD_TA, D1, and D3. GL_TA, IL_TA, and TE_TA have a significance level of 1%. In the crisis, GL_TA, WD_TA, IL_TA, TE_TA, D1, and D3 are also not significant, although IB_TA and CD_TA have a significance level of 1%. The post-crisis period results show that GL_TA, WD_TA, IL_TA, TE_TA, D1, and D3 are not significant, with only IB_TA and CD_TA having a significance level of 1%. The pattern for all three periods is that, when the coefficients are significant, positive relationships exist between the independent variables and dependent variable.

Gross loans over total assets, which appears on banks' balance sheet as part of assets, has a significant negative impact of 23% on the STFR for each 1% change in GL_TA only in pre-crisis period. Depending on loans' maturity, these are consumers of short-, medium-, and long-term liquidity, but, according to this model's results, the impact on short-term liquidity is negligible. One possible explanation of this finding is that banks formerly linked loans with appropriate resources, and resources such as client deposits or interbank borrowing are part of these institutions' regular obligations in terms of liquidity because they represent outflows. Concurrently, loans after disbursement become inflows. Banks' resources were only lower during the crisis than in the remaining periods, so movements in credit lines were less covered.

Diamond and Dybvig (1983) established that a relationship exists between liquidity and banks' basic fragility since liquidity is created when liquid liabilities are transformed into illiquid assets. This liquidity transformation also creates gaps between assets and liabilities' maturity, and expected inflows from loan reimbursements can be out of sync with withdrawals from clients' demand deposits. Holding cash and other liquid assets improves the liquidity ratio but reduces resources, which also happens when banks allocate funds to illiquid assets such as loans and thus decreases liquidity creation. Angora and Roulet (2011) confirmed a relationship exists between liquidity risk measured using the LCR and NSFR, balance sheet indices such as ROA, the natural logarithm of total assets, and the ratio between customer loans and total loans. The cited research also considered macroeconomic indicators such as the GDP yearly growth rate and the spread between interbank and central bank policy rates. Angora and Roulet (2011) found that the liquidity risk ratio has a negative relationship with most variables analyzed, but the liquidity measure has a significant positive link with macroeconomic variables.

Interbank borrowing over total assets were included in the model of the overall period as this variable is one of three variable affecting the STFR. The model's result indicate that, given a 1% change in IB_TA with the other factors kept constant, short-term liquidity will increase 58%. In the remaining periods, the same tendencies appear with a smaller reduction of 49% of IB_TA during the crisis followed by a substantial increase in the post-crisis period. In the latter, a 1% variation in IB_TA with the other factors kept constant means short-term liquidity will increase by 76%.

In the crisis, banks' resources and thus the interbank market shrank, reducing this component in these institutions' balance sheet as well. Post-crisis interbank borrowing increased due to central banks' assistance, generating more short-term liquidity because banks had more resources available. Vodova's (2011) study found that some indicators, such as the capital adequacy ratio, credit interest rate, non-performing loans, and interbank interest rate, has a positive effect on bank liquidity. In contrast, the financial crisis, inflation, and economic growth negatively influence bank liquidity. Unemployment, margin, interest rate, profitability, and interest rate monetary policy further significantly affect bank liquidity. Aymanns et al. (2016) confirmed that solvency shocks have a significant negative impact on these institutions' funding cost, which is especially important for interbank funding cost and sensitivity to long-term stress.

Wholesale debit over total assets, in all the periods, is not significant for any coefficients analyzed when the dependent variable is short-term liquidity. WD_TA is part of banks' balance sheet liabilities as it is made up of other deposits plus short-term borrowing and long-term funding. Calomiris (1999) reports that banks rely on market discipline and wholesale funding to diminish their vulnerability to liquidity risk. According to Gomes and Khan (2011), these companies' liquidity position is defined by cash and cash equivalents and by how funding is organized and managed. Ultimately, funding liquidity is created when banks have sufficient liquid funds or cash to settle contingent liabilities without using traditional client deposits.

Interbank lending over total assets is another asset that appears on banks' balance sheet and one of the independent variables included in the present model. This variable is only significant in the pre-crisis period, in which IL_TA has a negative impact of 18% on the STFR for each 1% change in the independent variable's coefficient. Interbank lending is mainly deposits made in other banks, thereby representing an outflow that reduces cash liquidity.

Various studies have documented that cash holdings substantially increased during the 2007–2009 financial crisis when banks' lending to households and corporations decreased substantially. Acharya and Merrouche's (2013) results show that changes in the markets such as the recent financial crisis forced banks to retain more treasury values so that these institutions could deal with exceptional situations. Similar to the gross loans variable, interbank lending has scheduled reimbursements, so it generates a predictable flow, yet the disbursements related with lending have a negative impact on the STFR.

Customer deposits over total assets' coefficient has a statistically significant impact in all the periods on short-term liquidity—unlike this variable's effect on the NSFR—although, in the pre-crisis period, information on CD_TA's significance is unavailable. This coefficient has a positive relationship with the dependent variable, namely, 61% in the overall period, 54% in the crisis, and then up again to 70% in the post-crisis period. These movements appear to confirm the hypothesis that customer deposits are an important issue in bank liquidity, but the literature offers varied opinions about the connection between deposits and liquidity. Dinger (2009) asserts that an inverse relationship exists between deposits and bank liquidity. Moussa (2015) states that deposits have an insignificant impact on this liquidity. Bonner et al. (2015) and Singh and Sharma (2016), in contrast, confirmed deposits' positive influence on bank liquidity.

The coefficient of trading exposure over total assets for the overall period reveals a decrease of 37% in the STFR for each 1% variation in TE_TA. In the pre-crisis period, this relationship is significant and positive at the 5% level. For the two remaining periods, the coefficient has no significance in the model. TE_TA is a liability that appears on banks' balance sheet as this variable is an obligation that consumes resources. In addition, trade liabilities are securities held for trading or put up for sale, with a time bucket of up to one year that ensures this variable has an impact on short-term liquidity (Grossmann and Scholz, 2017). The Deutsche Bundesbank (2008) reports that banks become stressed when they mainly use funding instruments from repo, unsecured interbank, securitization, and currency swap markets.

2.4.3.4.3. LMI

The NSFR and STFR are both liquidity ratios—for long-term and short-term liquidity, respectively—while the LMI measures the mismatch between assets' market liquidity and liabilities' funding liquidity (Krishnamurthy et al., 2016). This measure facilitates the calculation of liquidity based on the gap between assets and liabilities. The LMI was included in the present research to assess the dependent variable's relationships and compare the results for a model of liquidity variables based on ratios and a variable of absolute values such as the LMI.

Table 2.14 summarizes this estimation model's results for the LMI. The independent variables are those listed in section 2.3.2.2), but a correlation higher than 0.8 showed multicollinearity was a problem for stable funding and D2, which represents the wholesale bank business model. To clarify the dependent variable's movements, four models were constructed: one for each period included in this study (i.e., a pre-crisis [2005–2006], crisis [2007–2009], and post-crisis period [2010–2015] and the overall period covering all the years between 2005 and 2015.

The regression model's results for the overall period, with the LMI as a dependent variable show an R^2 of 91% and adjusted R^2 of 90%, which means this model explains 91% of the LMI's changes and movements. The pre-crisis has an R^2 of 97% and adjusted R^2 of 94%, so the second model explains 97% of the dependent variable's variations and tendencies. The crisis period estimation model produced an R^2 of 95% and adjusted R^2 of 92%. This result confirms that this third model explains 95% of the LMI's fluctuations and movements during the crisis. Finally, the post-crisis model has an R^2 of 93% and adjusted R^2 of 92%, indicating that this model explains 93% of the dependent variable's changes and shifts. For all the analyzed periods, the results confirm that the model has good predictive power, which was confirmed by the relationships between the dependent and independent variables.

The analysis of the overall period (see Table 2.14 above) verified that two variables, GL_TA and D1, do not have a statistically effect on the LMI, with *p*-values higher than 0.1, so these factors do not explain the dependent variable's behavior. Loans must follow a defined schedule, making their role as determinants of liquidity debatable despite researchers' general consensus of loans' effect on specific aspects of liquidity. An asset must be considered liquid if it can be traded quickly at a low risk and if it has a short maturity (Tsuchida et al., 2016). For example, banks' liquid assets include cash, contingency reserves, short-term securities such as treasury bills, commercial paper, and interbank loans with quite short maturity.

The dummy independent variables for bank business models were excluded from the estimation model because they failed to explain the LMI's behavior during the overall period. As mentioned previously, Grossmann and Scholz (2017) used the key ratios of gross loans, interbank borrowing, and wholesale debt to identify funding cost risks of bank business models. The cited authors found that:

> [T]he risk of higher refinancing costs, when absorbed by equity, has different impacts on bank business models. Retail banks, especially small and medium-sized ones, bear significantly lower funding cost risks relative to equity before and after the financial crisis than wholesale and trading banks in our sample.

For the overall period, the final model's results included that four independent variables have a significance level of 1%: IB_TA, WD_TA, CD_TA, and TE_TA. Two variables were accepted with a significance level of 5%, namely, IL_TA and D3. Except for IL_TA, the other significant independent variables have a negative connection with the LMI (i.e., an increase in these factors reduces bank liquidity).

For the pre-crisis period, only GL_TA was excluded due to its lack of significance, while the remaining variables are significant. In the crisis, GL_TA and D3 are not significant, but TE_TA and D1 have a significance level of 5% and IB_TA, WD_TA, IL_TA, and CD_TA have a significance level of 1%. In the post-crisis period, IL_TA, D1 and D3 are not significant. GL_TA, IB_TA, WD_TA, CD_TA, and TE_TA have a significance level of 1%. The pattern across all the periods is negative relationships between the independent variables and dependent variable, except for IL_TA's positive connection for the overall and crisis periods, as well as D1's positive link for the pre-crisis period and GL_TA's for the post-crisis period.

Gross loans over total assets is thus only significant in the post-crisis period, with a positive impact of 1% on the LMI. According the estimation model's results, loans' impact on liquidity is relatively lower compared with the other variables included in this study. Diamond and Dybvig's (1983) study found a relationship between liquidity and banks' fundamental fragility since liquidity is created when liquid liabilities (e.g., deposits and interbank borrowing) are transformed into illiquid assets (e.g., loans). This liquidity transformation opens up a gap between assets and liabilities' maturity, desynchronizing the expected loan reimbursement inflows with clients' demand deposit outflows. While the liquidity ratio is improved by holding cash and similar liquid assets, this practice also reduces resources because banks allocate them to illiquid assets such as loans, thereby reducing liquidity creation. Delechat et al. (2012) state that, when banks aggressively issue loans, this implies the existence of more illiquid assets.

Vodova (2011) also found that the relationship between the loan growth rate and bank liquidity was negative and significant.

The present estimation model's results show that interbank borrowing over total assets is the variable with the greatest impact on the LMI for the overall period. Thus, the regression model indicates that a 1% change in IB_TA—with the other factors kept constant—will cause the LMI to decrease by 62%. This independent variable has a lower value of 32% in the pre-crisis period, then increases to 71% during the crisis, and shrinks again to 65% in the post-crisis period.

As this variable represents loans from other banks, it is an obligation that banks must fulfill, as well as an outflow that affects bank liquidity negatively. Various authors, including Demirguç-Kunt and Huizinga (2010), have confirmed that banks' dependence on the interbank market increases the likelihood of bankruptcy due to these long-term obligations. Acharya et al. (2011) report that, when these institutions rely heavily on the interbank market, increasing capital requirements can become a prudential measure to counteract both insolvency and liquidity risks. Bianchi and Bigio (2014) assert that liquidity levels depend on the nature of assets and banks' ability to obtain cash from the central bank or from interbank or money market transactions. Finally, Aymanns et al. (2016) found evidence that solvency shocks have a significant negative impact on banks' funding costs, especially interbank funding costs, increasing these companies' sensitivity to periods of stress.

Wholesale debit over total assets has a negative impact of 62% on the LMI for each 1% variation in WD_TA with regard to the overall period. This independent variable comprises other deposits plus short-term borrowing and long-term funding. This determinant's coefficient has a lower value in the pre-crisis period, grows substantially during the crisis to 75% and then falls to 64% in the post-crisis period. As a resource used to regulate banks' balance, WD_TA follows the same behavior patterns as IB_TA.

Calomiris (1999) confirmed that banks rely on both market discipline and wholesale funding to mitigate their vulnerability to liquidity risk. Shen et al. (2009) observe that, when banks depend on wholesale funding and borrowing from open market operations instead of on customer deposits to fund their loans, they are more likely to have liquidity problems. In addition, Acharya and Skeie (2011) state that long-term loans are funded with short-term wholesale deposits, and, when customers withdraw these deposits, reimbursement maturity mismatches appear.

Interbank lending over total assets is another component of banks' balance sheets on the asset side. The overall period's estimation model shows that IL_TA has a positive impact of

1% on the LMI for each 1% fluctuation in this independent variable's coefficient. During the pre-crisis period, IL_TA presents a negative value of 1%, while, in the crisis, this factor returns to having a positive impact of 2% and, in the post-crisis period, IL_TA's coefficient has no significance. During the crisis, banks reduced their investments in risky assets (i.e., loans) to increase their available cash, and the only less risky available asset that these institutions had to boost their liquidity was the interbank market.

Various studies have documented that cash holdings substantially increased during the 2007–2009 financial crisis and that banks' lending to households and corporations stagnated substantially. Acharya and Skeie (2011) explored the relationship between cash holding and counterparty risk by analyzing the causes of cash holdings during the recent financial crisis. Acharya and Merrouche (2013), in turn, confirmed that changes such as the 2007 crisis force banks to retain more treasury values in order to deal with these exceptional situations. Interbank lending entails reimbursements defined by schedules that provide a predictable inflow with a less negative impact on liquidity.

Regarding customer deposits over total assets the present study's model produced a significant negative coefficient for all the periods at a 1% level. In the overall period, CD_TA explains 59% of LMI's negative variation for each 1% change in CD_TA. In the pre-crisis period, the coefficient has the lowest value of all the periods, with 46% of negative variation in the dependent variable. During the crisis, the coefficient's value increases to 68% and, in the post-crisis period, falls to 62%. CD_TA is thus one of the most important coefficients in the estimation model, and, as a bank balance sheet liability, this factor represents a negative cash flow with a negative impact on banks' liquidity.

In general, banks' primary function is to collect deposits as a source of funds. Other kinds of bank resources include subordinated bonds and equity, but these are long term in nature. To improve the asset side of their balance sheet, banks buy fixed assets, hold reserves at the central bank, and give loans to corporations and individuals. Banks' inflows and outflows can create mismatches between assets and liabilities' maturities, thereby creating liquidity risk (Zenios and Ziemba, 2007).

Angora and Roulet (2011) analyzed the relationship between liquidity risk, as measured by the LCR and NSFR, balance sheet indices (e.g., ROA), the natural logarithm of total assets, and the ratio between customer loans to total loans. The cited researchers also included some macroeconomic indicators such as GDP annual growth rate and the spread between interbank and central bank policy rates. Angora and Roulet (2011) also report that the liquidity risk ratio has a negative relationship with most indicators they analyzed, while the liquidity measure has a significant positive connection with macroeconomic variables. Asset and liability management theory postulates that banks must match their liabilities and assets in terms of maturity, currency, and interest rate. This matching must be done by comparing cash inflows and outflows based on behavioral maturity because, while demand deposits can, in theory, be reimbursed at any time, customers usually keep their applications, so, in reality deposits have a considerable, long-term maturity (Fall and Viviani, 2016).

For trading exposure over total assets, the current research's model shows that this independent variable's values are all significant and quite similar in all the periods analyzed. In the overall period, TE_TA experiences a decrease of 40% for each 1% change in the LMI. TE_TA is listed as a liability on banks' balance sheet, which makes this factor an obligation that consumes resources. In the pre-crisis period, the model gives the lowest value to this coefficient of all the periods, followed by an increase in the crisis and a small decrease in the post-crisis period. Similar to other trading assets and liabilities, TE_TA's maturity differ from that of liabilities, and this difference creates mismatches between assets and liabilities' maturities and thus greater liquidity risk (Zenios and Ziemba, 2007). In addition, the Deutsche Bundesbank's (2008) working paper states that banks that mainly rely on funding instruments from repo, unsecured interbank, securitization, and currency swap markets tend to become more stressed.

Regarding the variables of bank business models, only D1 (retail bank) and D3 (trading bank) have a significance level of 1% in the pre-crisis period so that D1's coefficient corresponds with 0.7% for each 1% variation in the LMI and D3 presents 0.01%. In the overall period, D1 has a significance level of 5%, with a coefficient of 0.8%. During the crisis, this independent variable also has a significance level of 5% level, and its coefficient is 0.6%. These results indicate that bank business models are not a particularly important determinant of liquidity.

The ECB (2011) reports that business model characteristics' impact is non-linear and these effects depend on variations according to the level of bank risk involved. According to Altunbas et al. (2011), their examination of the recent crisis underlined how challenging identifying the most adequate risk management strategy for different business models can be. The differences between banks' business models are related to management's long-term strategic decisions regarding balance sheet structure, business activities, risk appetite, and willingness to take liquidity risks (Grossmann and Scholz, 2017).

2.5. Conclusions

Despite all the prior research and analyses performed and findings reported on this topic, the present study's results contribute significantly to the compilation and systematization of panel data on commercial banks worldwide. The final sample comprised systematized information on 645 commercial banks for 13 years, facilitating the identification of a set of indispensable ratios, indicators, and bank balance sheet components that provide a better understanding of and improve knowledge about these banks' behavior. The period under analysis encompassed the biggest financial crisis of the last 100 years. Compared to the existing research, this study covered a significant number of commercial banks over a long period, including three sub-periods: pre-crisis, crisis, and post-crisis.

This comprehensive coverage facilitated an assessment of banks' reactions and behaviors regarding short- and long-term liquidity using three different liquidity measures, three different scenarios, and different geographical areas. The current research also identified and analyzed relationships between banks' balance sheet items and liquidity indicators, regarding which few results have been reported or conclusions drawn previously. These findings provide extensive support for banks and authorities' potential initiatives to control structural liquidity.

More specifically, this study investigated the determinants of short- and long-term liquidity (i.e., the NSFR, STFR, and LMI) and analyzed which kinds of variables affect these indicators and their trends. A review of the recent literature confirmed that researchers have not yet studied the relationships between the above liquidity ratios and banks' balance sheet elements, indicating that this investigation may be the first to define these connections. In addition, the few extant empirical studies reported in the literature on this topic highlight the need for unambiguous results as extremely little is known about how bank business models affect banks' profitability and risk (Hryckiewicz and Kozłowski, 2015).

Regarding these institutions' liquidity patterns, the present results include that only 10% of the banks analyzed had NSFRs above 1% during the period under study, even though this figure is the minimum value recommended by regulations. Thus, an overview of these commercial banks revealed they do not always comply with the minimum rates regulators have defined for long-term liquidity. Vazquez and Federico (2015) found that banks vulnerable in terms of funding liquidity before 2007 were exposed to a higher risk of default after the financial crisis started. The current study's analysis of a time series using three sub-periods showed that, in the pre-crisis period, the percentage of banks with an NSFR lower than 1% was 80%, with 90% of the banks having values between 0.70% and 1.15%. This finding indicates that, before the recent crisis, short-term liquidity was these institutions' main concern. This strategy's impact on bank liquidity is obvious in retrospect.

This research also verified that, during the crisis, the percentage of banks with an NSFR under 1% increased to 90% of the analyzed institutions, with 91% of these institutions having a ratio between 0.69% and 1%. In the post-crisis period, a reduction of long-term liquidity occurred in institutions, with 93% of banks presenting an NSFR level below 1% and 96% of these companies' ratios concentrating between 0.69%% and 1%. The results provide an overview of the NSFR by period, showing that, pre-crisis structural funds were higher than post-crisis funds were and thus that banks' management still remained unaware of this requirement.

Analyses of the total sample revealed that 35% of banks had an LR below 7%, but, in the pre-crisis period, 14% of these institutions had an LR of less than 5%, which means that the majority of the analyzed banks had an LR in accordance with regulations. In the post-crisis period, the LR values returned to the pre-crisis levels, indicating that banks' management returned to the same pre-crisis policy ensuring the desired level of performance by sacrificing long-term stability to increase earnings.

Regarding short-term liquidity in the overall period, 68% of banks had an STFR above 96%, which provides evidence that short-term funding is the main liability strategy followed by commercial banks. In contrast, the pre-crisis period shows a reduction of this indicator to 66%, with many banks presenting an STFR higher than 96%. During the crisis, the STFR dropped down to 74% in the banks analyzed, confirming that these institutions and their managers were concerned about balancing their companies' short-term liquidity needs. The STFR's evolution across all three periods reveals a trend toward a higher value in the pre-crisis years, a strong reduction during the crisis, and a recovery in the post-crisis years but at levels lower than the pre-crisis period.

For the LMI, the movements across the three periods show that a liquidity gap existed in the pre-crisis and crisis periods that decreased in the post-crisis period. An analysis of the frequency or number of banks with gaps indicates better liquidity management in the post-crisis period.

In relation to geographical patterns, some homogeneity in the NSFR was present across countries. A global average NSFR of 0.89% means that overall commercial banks' ratios were below the minimum Basel III requirements. An analysis of the LR by country revealed a larger dispersion of values between countries than was found for the NSFR. Worldwide, the LR was an average of 9.8% higher than the total capital (i.e., Tier 1 plus Tier 2 capital), which should be at least 8.0% of RWAs at all times. The post-crisis average LR maintained the same values as the crisis, but these were lower than in the pre-crisis period. The STFR by country and period verified that these banks exclusively used short-term liabilities to fund their activities. Almost all the countries examined showed a positive increase in the LMI in the post-crisis period, which means either real liquidity increased or financial institutions had more liquid assets.

Regarding the estimation model analysis, the NSFR for the overall period confirmed the existence of three variables—client deposits and two bank business models—that did not have a statistically significant impact on liquidity. Thus, bank business models may not be an important variable in terms of long-term liquidity. Gross loans, interbank borrowing, wholesale debts, interbank lending, and trading exposure have a negative relationship with the NSFR so any increase in these variables reduces long-term liquidity. The pattern for all three periods is negative relationships between the independent variables and this dependent variable. An important finding is that the model highlights interbank borrowing as having the greatest impact on the NSFR in the overall period. In addition, client deposits is the only factor that has a positive connection with long-term liquidity and only during the crisis.

The estimation model for the STFR in the overall period verified the existence of five variables, namely, gross loans, wholesale debt, interbank lending, and two bank business models that do not have an impact on short-term liquidity. In this period, interbank borrowing and customer deposits have a positive relationship with the STFR, while trading exposure has a negative connection. The pattern for all three periods is that, when the coefficients are significant, a positive relationship exists between the independent variables and this dependent variable. Wholesale debit over total assets, in all these periods, is not significant for any coefficient analyzed when the dependent variable is short-term liquidity. Concurrently, customer deposits—unlike its behavior with the NSFR—has a significant positive relationship with short-term liquidity, except for the crisis when this independent variable's significance is unavailable.

Regarding the LMI, the pattern for all three periods is a negative connection between the independent variables and this dependent variable. However, the results verify a significant positive relationship exists with interbank lending for the overall and crisis period. The analyses also revealed that liabilities as a whole have a greater impact on the LMI in the crisis and post-crisis periods, indicating an increase in funding sources without appropriate allocations to assets. The same estimation model showed that loans and bank business models appear to have no effect on bank liquidity.

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Table 2.1. Banks by country included in the sample

Country	
Australia	Lithuania
Austria	Malaysia
Azerbaijan	Malta
Bangladesh	Mauritius
Botswana	Morocco
Brazil	Netherlands
Bulgaria	Paraguay
Canada	Peru
Chile	Philippines
China	Poland
Colombia	Portugal
Côte d'Ivoire	Romania
Croatia	Russia
Czech Republic	Saudi Arabia
Denmark	Singapore
Finland	Slovakia
France	Slovenia
Georgia	South Africa
Germany	Spain
Hungary	Sweden
India	Switzerland
Indonesia	Taiwan, Province of China
Ireland	Thailand
Israel	Tunisia
Italy	Turkey
Japan	United Kingdom
Kazakhstan	United States of America
Korea (Republic of)	

Table 2.2. All periods descriptive statistics

Sample: Pre-Crisis

	NSFR	STFR	LR	LMI
Mean	0.9035	0.8829	0.1016	1,206,774
Median	0.9173	0.9301	0.0821	99,098
Maximum	2.0247	0.9994	0.9241	55,715,029
Minimum	0.2093	0.0000	-0.1183	-51,429,740
Std. Dev.	0.1688	0.1341	0.0815	4,536,078
Skewness	0.1113	-2.2031	4.1579	5
Kurtosis	8.8329	9.1962	29.4561	63
Jarque-Bera	2947.25	5000.37	66525	401875.9
Probability	0.0000	0.0000	0.0000	0.0000
Observations	2076	2076	2076	2580

Sample: Crisis

	NSFR	STFR	LR	LMI
Mean	0.8797	0.8677	0.0948	1,978,150
Median	0.8907	0.9228	0.0846	229,338
Maximum	1.9279	0.9989	0.6340	73,628,746
Minimum	0.2090	0.1876	-0.8584	-67,500,980
Std. Dev.	0.1502	0.1441	0.0642	7,034,823
Skewness	0.2612	-1.7717	-0.3580	5
Kurtosis	8.6118	5.8213	39.8536	50
Jarque-Bera	2361.19	1524.98	100997	190000.4
Probability	0.0000	0.0000	0.0000	0.0000
Observations	1784	1784	1784	1935

Sample: Post-Crisis

	NSFR	STFR	LR	LMI
Mean	0.8933	0.8773	0.0945	3,510,181
Median	0.8964	0.9329	0.0877	337,870
Maximum	2.1022	0.9995	0.7599	248,000,000
Minimum	0.3379	0.0025	-0.1621	-6,305,206
Std. Dev.	0.1369	0.1451	0.0453	13,296,491
Skewness	1.3829	-2.2913	2.1733	9
Kurtosis	14.6620	8.8821	20.9236	104
Jarque-Bera	20931.1	8101.27	49548.1	1690271
Probability	0.0000	0.0000	0.0000	0.0000
Observations	3497	3497	3496	3870

Sample: Global

	NSFR	STFR	LR	LMI
Mean	0.8929	0.8765	0.0966	2,447,895
Median	0.9000	0.9293	0.0858	210,340
Maximum	2.1022	0.9995	0.9241	248,000,000
Minimum	0.2090	0.0000	-0.8584	-67,500,980
Std. Dev.	0.1500	0.1420	0.0621	10,018,895
Skewness	0.6233	-2.1423	3.0272	10
Kurtosis	10.9570	8.1799	39.3239	156
Jarque-Bera	19884.9	13852.6	415640	8349043
Probability	0.0000	0.0000	0.0000	0.0000
Observations	7357	7357	7356	8385

Table 2.3. NSFR histogram for all periods

Global			Pre-Crisis			Crisis			Post-Crisis		
Block	*Frequency*	*Cumulative%*	*Block*	*Frequency*	*Cumulative%*	*Block*	*Frequency*	*Cumulative%*	*Block*	*Frequency*	*Cumulative%*
0.2090	1	0.01%	0.2093	1	0.05%	0.2090	1	0.06%	0.3379	1	0.03%
0.2847	16	0.23%	0.2820	12	0.63%	0.2778	3	0.22%	0.4084	2	0.09%
0.3605	8	0.34%	0.3546	3	0.77%	0.3465	3	0.39%	0.4790	13	0.46%
0.4362	33	0.79%	0.4272	15	1.49%	0.4153	8	0.84%	0.5496	25	1.17%
0.5119	39	1.32%	0.4998	15	2.22%	0.4840	8	1.29%	0.6202	44	2.43%
0.5877	104	2.73%	0.5724	27	3.52%	0.5528	17	2.24%	0.6907	91	5.03%
0.6634	208	5.56%	0.6450	42	5.54%	0.6216	42	4.60%	0.7613	260	12.47%
0.7391	447	11.64%	0.7176	100	10.36%	0.6903	78	8.97%	0.8319	490	26.48%
0.8148	846	23.13%	0.7903	168	18.45%	0.7591	142	16.93%	0.9025	920	52.79%
0.8906	1663	45.74%	0.8629	303	33.04%	0.8278	222	29.37%	0.9730	921	79.12%
0.9663	2127	74.65%	0.9355	491	56.70%	0.8966	408	52.24%	1.0436	496	93.31%
1.0420	1230	91.37%	1.0081	496	80.59%	0.9653	447	77.30%	1.1142	120	96.74%
1.1178	345	96.06%	1.0807	239	92.10%	1.0341	256	91.65%	1.1848	43	97.97%
1.1935	126	97.77%	1.1533	86	96.24%	1.1029	71	95.63%	1.2553	24	98.66%
1.2692	65	98.65%	1.2259	27	97.54%	1.1716	33	97.48%	1.3259	15	99.08%
1.3449	37	99.16%	1.2986	26	98.80%	1.2404	19	98.54%	1.3965	9	99.34%
1.4207	14	99.35%	1.3712	5	99.04%	1.3091	9	99.05%	1.4670	3	99.43%
1.4964	14	99.54%	1.4438	4	99.23%	1.3779	9	99.55%	1.5376	5	99.57%
1.5721	8	99.65%	1.5164	6	99.52%	1.4466	2	99.66%	1.6082	4	99.69%
1.6479	7	99.74%	1.5890	2	99.61%	1.5154	0	99.66%	1.6788	4	99.80%
1.7236	4	99.80%	1.6616	2	99.71%	1.5842	1	99.72%	1.7493	0	99.80%
1.7993	1	99.81%	1.7343	1	99.76%	1.6529	1	99.78%	1.8199	0	99.80%
1.8750	1	99.82%	1.8069	1	99.81%	1.7217	1	99.83%	1.8905	1	99.83%
1.9508	6	99.90%	1.8795	0	99.81%	1.7904	0	99.83%	1.9611	1	99.86%
2.0265	3	99.95%	1.9521	2	99.90%	1.8592	1	99.89%	2.0316	1	99.89%
More	4	100.00%	More	2	100.00%	More	2	100.00%	More	4	100.00%

Table 2.4. LR histogram for all periods

Global			Pre-Crisis			Crisis			Post-Crisis		
Bin	*Frequency*	*Cumulative%*	*Bin*	*Frequency*	*Cumulative%*	*Bin*	*Frequency*	*Cumulative%*	*Bin*	*Frequency*	*Cumulative%*
-0.8584	1	0.01%	-0.1183	1	0.05%	-0.8584	1	0.06%	-0.1621	1	0.03%
-0.7871	0	0.01%	-0.0766	1	0.10%	-0.7987	0	0.06%	-0.1252	1	0.06%
-0.7158	0	0.01%	-0.0349	0	0.10%	-0.7390	0	0.06%	-0.0883	0	0.06%
-0.6445	0	0.01%	0.0068	5	0.34%	-0.6793	0	0.06%	-0.0514	1	0.09%
-0.5732	0	0.01%	0.0485	292	14.40%	-0.6196	0	0.06%	-0.0146	3	0.17%
-0.5019	0	0.01%	0.0902	851	55.39%	-0.5599	0	0.06%	0.0223	12	0.51%
-0.4306	0	0.01%	0.1319	525	80.68%	-0.5002	0	0.06%	0.0592	715	20.97%
-0.3593	0	0.01%	0.1736	203	90.46%	-0.4405	0	0.06%	0.0961	1270	57.29%
-0.2880	1	0.03%	0.2153	96	95.09%	-0.3808	0	0.06%	0.1330	947	84.38%
-0.2167	2	0.05%	0.2569	30	96.53%	-0.3211	1	0.11%	0.1698	375	95.11%
-0.1454	2	0.08%	0.2986	16	97.30%	-0.2614	1	0.17%	0.2067	110	98.26%
-0.0741	5	0.15%	0.3403	12	97.88%	-0.2017	1	0.22%	0.2436	25	98.97%
-0.0028	12	0.31%	0.3820	12	98.46%	-0.1420	0	0.22%	0.2805	16	99.43%
0.0685	2516	34.52%	0.4237	8	98.84%	-0.0824	3	0.39%	0.3174	7	99.63%
0.1398	3757	85.59%	0.4654	1	98.89%	-0.0227	2	0.50%	0.3542	7	99.83%
0.2111	834	96.93%	0.5071	3	99.04%	0.0370	91	5.61%	0.3911	4	99.94%
0.2824	115	98.49%	0.5488	5	99.28%	0.0967	972	60.09%	0.4280	1	99.97%
0.3537	53	99.21%	0.5905	4	99.47%	0.1564	526	89.57%	0.4649	0	99.97%
0.4250	28	99.59%	0.6322	3	99.61%	0.2161	131	96.92%	0.5018	0	99.97%
0.4963	6	99.67%	0.6739	1	99.66%	0.2758	22	98.15%	0.5386	0	99.97%
0.5676	9	99.80%	0.7156	1	99.71%	0.3355	17	99.10%	0.5755	0	99.97%
0.6389	6	99.88%	0.7573	3	99.86%	0.3952	8	99.55%	0.6124	0	99.97%
0.7102	2	99.90%	0.7990	0	99.86%	0.4549	5	99.83%	0.6493	0	99.97%
0.7815	4	99.96%	0.8407	1	99.90%	0.5146	1	99.89%	0.6862	0	99.97%
0.8528	1	99.97%	0.8824	0	99.90%	0.5743	1	99.94%	0.7230	0	99.97%
More	2	100.00%	More	2	100.00%	More	1	100.00%	More	1	100.00%

Table 2.5. STFR histogram for all periods

Global			Pre-Crisis			Crisis			Post-Crisis		
Bin	*Frequency*	*Cumulative%*	*Bin*	*Frequency*	*Cumulative%*	*Bin*	*Frequency*	*Cumulative%*	*Bin*	*Frequency*	*Cumulative%*
0	1	0.01%	0	1	0.05%	0.1876	1	0.06%	0.0025	1	0.03%
0.0400	4	0.07%	0.0400	3	0.19%	0.2200	0	0.06%	0.0424	0	0.03%
0.0800	2	0.10%	0.0800	0	0.19%	0.2525	2	0.17%	0.0823	2	0.09%
0.1199	0	0.10%	0.1199	0	0.19%	0.2849	1	0.22%	0.1222	0	0.09%
0.1599	4	0.15%	0.1599	0	0.19%	0.3174	2	0.34%	0.1621	4	0.20%
0.1999	8	0.26%	0.1999	1	0.24%	0.3498	6	0.67%	0.2019	6	0.37%
0.2399	8	0.37%	0.2399	1	0.29%	0.3823	7	1.07%	0.2418	7	0.57%
0.2799	13	0.54%	0.2798	1	0.34%	0.4147	12	1.74%	0.2817	10	0.86%
0.3198	20	0.82%	0.3198	3	0.48%	0.4472	10	2.30%	0.3216	13	1.23%
0.3598	28	1.20%	0.3598	6	0.77%	0.4797	18	3.31%	0.3614	16	1.69%
0.3998	34	1.66%	0.3998	6	1.06%	0.5121	15	4.15%	0.4013	18	2.20%
0.4398	39	2.19%	0.4398	8	1.45%	0.5446	16	5.04%	0.4412	18	2.72%
0.4798	61	3.02%	0.4797	19	2.36%	0.5770	25	6.45%	0.4811	19	3.26%
0.5197	56	3.78%	0.5197	10	2.84%	0.6095	33	8.30%	0.5210	27	4.03%
0.5597	78	4.84%	0.5597	16	3.61%	0.6419	21	9.47%	0.5608	41	5.20%
0.5997	100	6.20%	0.5997	26	4.87%	0.6744	38	11.60%	0.6007	36	6.23%
0.6397	112	7.72%	0.6396	33	6.45%	0.7068	36	13.62%	0.6406	48	7.61%
0.6797	167	9.99%	0.6796	59	9.30%	0.7393	32	15.41%	0.6805	64	9.44%
0.7196	187	12.53%	0.7196	59	12.14%	0.7717	47	18.05%	0.7203	81	11.75%
0.7596	199	15.24%	0.7596	49	14.50%	0.8042	70	21.97%	0.7602	107	14.81%
0.7996	267	18.87%	0.7996	68	17.77%	0.8366	78	26.35%	0.8001	129	18.50%
0.8396	409	24.43%	0.8395	113	23.22%	0.8691	105	32.23%	0.8400	189	23.91%
0.8795	577	32.27%	0.8795	153	30.59%	0.9015	169	41.70%	0.8799	271	31.66%
0.9195	964	45.37%	0.9195	308	45.42%	0.9340	255	56.00%	0.9197	425	43.81%
0.9595	1675	68.14%	0.9595	425	65.90%	0.9664	327	74.33%	0.9596	855	68.26%
More	2344	100.00%	More	708	100.00%	More	458	100.00%	More	1110	100.00%

Table 2.6. LMI histogram for all periods

Global			Pre-Crisis			Crisis			Post-Crisis		
Bin	*Frequency*	*Cumulative %*	*Bin*	*Frequency*	*Cumulative %*	*Bin*	*Frequency*	*Cumulative %*	*Bin*	*Frequency*	*Cumulative %*
-67,500,980	1	0.01%	-51,429,740	1	0.04%	-67,500,980	1	0.05%	-6,305,206	1	0.03%
-54,869,695	0	0.01%	-47,143,949	0	0.04%	-61,855,790	0	0.05%	3,878,247	3334	86.18%
-42,238,411	2	0.04%	-42,858,158	1	0.08%	-56,210,601	0	0.05%	14,061,700	331	94.73%
-29,607,127	0	0.04%	-38,572,368	0	0.08%	-50,565,412	0	0.05%	24,245,153	67	96.46%
-16,975,843	0	0.04%	-34,286,577	0	0.08%	-44,920,223	0	0.05%	34,428,606	52	97.80%
-4,344,559	3	0.07%	-30,000,786	0	0.08%	-39,275,034	0	0.05%	44,612,059	25	98.45%
8,286,725	7892	94.19%	-25,714,995	0	0.08%	-33,629,845	0	0.05%	54,795,512	17	98.89%
20,918,009	257	97.26%	-21,429,205	0	0.08%	-27,984,656	0	0.05%	64,978,966	4	98.99%
33,549,293	101	98.46%	-17,143,414	0	0.08%	-22,339,467	0	0.05%	75,162,419	5	99.12%
46,180,577	48	99.03%	-12,857,623	0	0.08%	-16,694,278	0	0.05%	85,345,872	8	99.33%
58,811,861	33	99.43%	-8,571,833	0	0.08%	-11,049,089	0	0.05%	95,529,325	8	99.53%
71,443,145	11	99.56%	-4,286,042	0	0.08%	-5,403,900	1	0.10%	105,712,778	4	99.64%
84,074,429	11	99.69%	-251	4	0.23%	241,289	982	50.85%	115,896,231	3	99.72%
96,705,713	9	99.80%	4,285,540	2408	93.57%	5,886,478	814	92.92%	126,079,684	1	99.74%
109,336,997	3	99.83%	8,571,330	85	96.86%	11,531,667	61	96.07%	136,263,138	2	99.79%
121,968,281	3	99.87%	12,857,121	26	97.87%	17,176,856	28	97.52%	146,446,591	0	99.79%
134,599,566	2	99.89%	17,142,912	17	98.53%	22,822,045	10	98.04%	156,630,044	2	99.84%
147,230,850	1	99.90%	21,428,703	9	98.88%	28,467,234	8	98.45%	166,813,497	1	99.87%
159,862,134	2	99.93%	25,714,493	5	99.07%	34,112,423	4	98.66%	176,996,950	1	99.90%
172,493,418	2	99.95%	30,000,284	6	99.30%	39,757,612	5	98.91%	187,180,403	1	99.92%
185,124,702	0	99.95%	34,286,075	7	99.57%	45,402,801	2	99.02%	197,363,856	0	99.92%
197,755,986	1	99.96%	38,571,866	1	99.61%	51,047,990	4	99.22%	207,547,310	2	99.97%
210,387,270	2	99.99%	42,857,656	4	99.77%	56,693,179	8	99.64%	217,730,763	0	99.97%
223,018,554	0	99.99%	47,143,447	3	99.88%	62,338,368	3	99.79%	227,914,216	0	99.97%
235,649,838	0	99.99%	51,429,238	2	99.96%	67,983,557	1	99.84%	238,097,669	0	99.97%
More	1	100.00%	More	1	100.00%	More	3	100.00%	More	1	100.00%

Table 2.7. All periods correlations

	Net Stable Funding Ratio	Leverage Ratio	Short Term Funding Ratio	Money Market Fundind to Total Liabilities	Customer Deposits to Total Liabilities	CAR - Basel Tier 1	Credit Growth	Cost-To-Income Ratio	Bank Size (operating Revenue last year available)	ROE	ROA	Equity Capital to Assets	Non-Interest Income to Total Income	Non-Interest Income to Assets
Net Stable Funding	1													
Leverage Ratio	.071**	1												
Short Term Funding	.086**	-.056**	1											
Money Market	-.276**	.031**	-.183**	1										
Customer Deposits to	.282**	-.072**	.824**	-.553**	1									
CAR - Basel Tier 1	.178**	.497**	.034**	-.044**	.066**	1								
Credit Growth	-.016	.017	.009	.009	.001	-.023	1							
Cost-To-Income Ratio	.027*	.102**	-.026*	-.001	-.016	.191**	.015	1						
Bank Size (operating	-.044**	.271**	.188**	-.164**	.194**	.041**	.013	.063**	1					
ROE	.002	-.013	-.003	-.003	-.007	-.022	-.001	-.244**	-.071**	1				
ROA	.015	.225**	-.045**	.038**	-.066**	.000	-.008	.161**	-.104**	-.015	1			
Equity Capital to	.071**	1.000**	-.056**	.031**	-.072**	.497**	.017	.102**	.271**	-.013	.225**	1		
Non-Interest Income to	-.025*	.038**	-.136**	.077**	-.158**	-.037**	-.010	-.235**	-.046**	.036**	-.003	.038**	1	
Non-Interest Income to	-.080**	.200**	-.285**	.010	-.328**	-.064**	-.016	.004	.068**	.018	.101**	.200**	.158**	1

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Table 2.8. GMM model NSFR correlations

Probability	NSFR	Gross Loans/ Total Assets	Interbank Borrowing / Total Assets	Wholesale debt / Total Assets	Interbank Lending/ Total Assets	Customer Deposits/ Total Assets	Stable Funding / Total Assets	Trading Exposure / Total Assets	D1 - Retail	D2 - Wholesale	D3 - Trading
NSFR	1										
Gross Loans/ Total Assets	-0.2861 **	1									
Interbank Borrowing / Total Assets	-0.5529 **	-0.1294 **	1								
Wholesale debt / Total Assets	-0.3645 **	0.03013 **	0.052044 **	1							
Interbank Lending/ Total Assets	-0.1482 **	-0.4205 **	0.202407 **	0.090802 **	1						
Customer Deposits/ Total Assets	0.49284 **	0.19642 **	-0.53142 **	-0.76623 **	-0.2825 **	1					
Stable Funding / Total Assets	0.5403 **	0.33177 **	-0.61869 **	-0.48197 **	-0.3528 **	0.88883 **	1				
Trading Exposure / Total Assets	-0.1683 **	-0.1801 **	0.152006 **	0.04769 **	0.05715 **	-0.2247 **	-0.2512 **	1			
D1 - Retail	0.31394 **	0.24947 **	-0.33258 **	-0.63504 **	-0.3066 **	0.72579 **	0.61407 **	-0.2205 **	1		
D2 - Wholesale	-0.346 **	-0.0133	0.310415 **	0.677928 **	0.1156 **	-0.6837 **	-0.5165 **	0.09908 **	-0.8706 **	1	
D3 - Trading	-0.0077	-0.482 **	0.110291 **	0.055566 **	0.41202 **	-0.2293 **	-0.3067 **	0.26728 **	-0.4458 **	-0.05233 **	1

** Correlation is significant at the 0.01 level (2-tailed).

Table 2. 9 GMM model STFR correlations

Probability	STFR	Gross Loans/ Total Assets	Interbank Borrowing / Total Assets	Wholesale debt / Total Assets	Interbank Lending/ Total Assets	Customer Deposits/ Total Assets	Stable Funding / Total Assets	Trading Exposure / Total Assets	D1 - Retail	D2 - Wholesale	D3 - Trading
STFR	1										
Gross Loans/ Total Assets	0.10105 **	1									
Interbank Borrowing / Total Assets	-0.1874 **	-0.1294 **	1								
Wholesale debt / Total Assets	-0.7455 **	0.03013 **	0.052044 **	1							
Interbank Lending/ Total Assets	-0.1319 **	-0.4205 **	0.202407 **	0.090802 **	1						
Customer Deposits/ Total Assets	0.80444 **	0.19642 **	-0.53142 **	-0.76623 **	-0.2825 **	1					
Stable Funding / Total Assets	0.5178 **	0.33177 **	-0.61869 **	-0.48197 **	-0.3528 **	0.88883 **	1				
Trading Exposure / Total Assets	-0.2782 **	-0.1801 **	0.152006 **	0.04769 **	0.05715 **	-0.2247 **	-0.2512 **	1			
D1 - Retail	0.59864 **	0.24947 **	-0.33258 **	-0.63504 **	-0.3066 **	0.72579 **	0.61407 **	-0.2205 **	1		
D2 - Wholesale	-0.5867 **	-0.0133	0.310415 **	0.677928 **	0.1156 **	-0.6837 **	-0.5165 **	0.09908 **	-0.8706 **	1	
D3 - Trading	-0.1476 **	-0.482 **	0.110291 **	0.055566 **	0.41202 **	-0.2293 **	-0.3067 **	0.26728 **	-0.4458 **	-0.05233 **	1

** Correlation is significant at the 0.01 level (2-tailed).

Table 2.10. GMM Model LMI Correlations

Probability	LMI_TA	Gross Loans/ Total Assets	Interbank Borrowing / Total Assets	Wholesale debt / Total Assets	Interbank Lending/ Total Assets	Customer Deposits/ Total Assets	Stable Funding / Total Assets	Trading Exposure / Total Assets	D1 - Retail	D2 - Wholesale	D3 - Trading
LMI_TA	1										
Gross Loans/ Total Assets	-0.1924 **	1									
Interbank Borrowing / Total Assets	-0.0335 **	-0.1294 **	1								
Wholesale debt / Total Assets	-0.0119	0.03013 **	0.052044 **	1							
Interbank Lending/ Total Assets	0.26335 **	-0.4205 **	0.202407 **	0.090802 **	1						
Customer Deposits/ Total Assets	-0.264 **	0.19642 **	-0.53142 **	-0.76623 **	-0.2825 **	1					
Stable Funding / Total Assets	-0.3651 **	0.33177 **	-0.61869 **	-0.48197 **	-0.3528 **	0.88883 **	1				
Trading Exposure / Total Assets	-0.0888 **	-0.1801 **	0.152006 **	0.04769 **	0.05715 **	-0.2247 **	-0.2512 **	1			
D1 - Retail	-0.1371 **	0.24947 **	-0.33258 **	-0.63504 **	-0.3066 **	0.72579 **	0.61407 **	-0.2205 **	1		
D2 - Wholesale	0.04105 **	-0.0133	0.310415 **	0.677928 **	0.1156 **	-0.6837 **	-0.5165 **	0.09908 **	-0.8706 **	1	
D3 - Trading	0.2035 **	-0.482 **	0.110291 **	0.055566 **	0.41202 **	-0.2293 **	-0.3067 **	0.26728 **	-0.4458 **	-0.05233 **	1

** Correlation is significant at the 0.01 level (2-tailed).

Table 2.11. GMM model statistics

	NSFR	STFR	LMI_TA	Gross Loans/ Total Assets	Interbank Borrowing / Total Assets	Wholesale debt / Total Assets	Interbank Lending/ Total Assets	Customer Deposits/ Total Assets	Stable Funding / Total Assets	Trading Exposure / Total Assets
Mean	0.8929	0.8765	0.0933	0.6188	0.0617	0.1045	0.0846	0.6890	0.7519	0.0021
Median	0.9000	0.9293	0.0824	0.6402	0.0256	0.0519	0.0549	0.7562	0.7968	0.0000
Std. Dev.	0.1500	0.1420	0.0618	0.1553	0.0910	0.1421	0.0931	0.2086	0.1609	0.0140
Skewness	0.6233	-2.1423	3.0286	-0.7519	2.7845	2.5068	2.3732	-1.2496	-1.5321	10.9426
Kurtosis	10.9570	8.1799	39.3106	6.8634	14.4460	10.1629	12.0093	4.0401	5.7205	157.7250
Jarque-Bera	19 884.88	13 852.62	415 352.50	5 267.93	49 660.78	23 429.77	31 782.47	2 245.94	5 146.21	7 484 361.00
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Observations	7 357	7 357	7 356	7 356	7 356	7 356	7 356	7 356	7 356	7 356

Table 2.12. GMM model NSFR estimation by period

	Global		Pre Crisis		Crisis		Post Crisis	
Variable	Coefficient	Prob.	Coefficient	Prob.	Coefficient	Prob.	Coefficient	Prob.
C	1.1592	0.0000	1.3098	0.0000	1.1085	0.0000	1.1994	0.0000
GL_TA	-0.2690	0.0001	-0.3058	0.0000	-0.4385	0.0000	-0.1641	0.0126
IB_TA	-0.9303	0.0000	-1.0951	NA	-0.7002	0.0000	-1.1163	0.0000
WD_TA	-0.3261	0.0000	-0.7125	NA	-0.1637	0.0161	-0.4245	0.0000
IL_TA	-0.1387	0.0098	-0.0262	0.0000	-0.3065	0.0000	-0.0497	0.4020
CD_TA	0.0239	0.6634	-0.0301	NA	0.2040	0.0007	-0.1362	0.0150
TE_TA	-0.7287	0.0000	-0.5392	NA	-0.7403	0.0003	-0.7188	0.0003
D1	-0.0126	0.2488	-0.0610	NA	0.0035	0.6683	0.0104	0.1791
D3	-0.0135	0.2423	-0.0862	0.0000	0.0231	0.0587	-0.0166	0.2046
AR1	0.5356	0.0000	-0.1281	0.0000	0.1782	0.4667	0.4257	0.0012
AR2	-0.0052	0.9026	-0.0538	0.0000	-0.0854	0.0908	0.0392	0.4915
R-squared	0.9021		0.9740		0.9469		0.9198	
Adjusted R-squared	0.8902		0.9447		0.9181		0.9009	
S.E. of regression	0.0477		0.0368		0.0425		0.0432	
Durbin-Watson stat	2.0098		4.1645		2.8177		2.2801	
Instrument rank	666.0000		528.0000		604.0000		658.0000	
Mean dependent var	0.8911		0.9013		0.8796		0.8939	
S.D. dependent var	0.1439		0.1565		0.1486		0.1373	
Sum squared resid	12.1490		0.6115		1.9490		5.0915	
J-statistic	12.14904		0.611455		1.949001		5.091518	
Prob(J-statistic)	0.79103		1		0.999999		0.9975	

Table 2.13. GMM model STFR estimation by period

	Global		Pre Crisis		Crisis		Post Crisis	
Variable	Coefficient	Prob.	Coefficient	Prob.	Coefficient	Prob.	Coefficient	Prob.
C	0.4213	0.0000	0.4460	0.0000	0.4687	0.0000	0.3538	0.0000
GL_TA	-0.0203	0.2063	-0.2331	0.0000	-0.0116	0.6764	-0.0050	0.7622
IB_TA	0.5799	0.0000	0.8008	NA	0.4874	0.0000	0.7594	0.0000
WD_TA	0.0093	0.9230	0.4874	NA	-0.0301	0.6860	0.0550	0.5322
IL_TA	0.0082	0.7209	-0.1823	0.0000	0.0144	0.4333	-0.0132	0.3956
CD_TA	0.6055	0.0000	0.6541	NA	0.5448	0.0000	0.6956	0.0000
TE_TA	-0.3734	0.0003	0.0516	0.0000	-0.3272	0.1075	-0.1820	0.1742
D1	0.0074	0.3906	0.0393	NA	0.0064	0.3418	-0.0113	0.1350
D3	0.0036	0.7437	0.0477	NA	0.0049	0.3700	0.0174	0.1279
AR(1)	0.5593	0.0000	-0.1286	NA	0.0914	0.7071	0.4591	0.0001
AR(2)	0.0117	0.5981	-0.0222	0.0000	-0.0219	0.7047	0.0600	0.0523
R-squared	0.9459		0.9782		0.9675		0.9644	
Adjusted R-squared	0.9393		0.9536		0.9499		0.9561	
S.E. of regression	0.0359		0.0307		0.0330		0.0306	
Durbin-Watson stat	1.9807		4.1645		2.7979		2.1302	
Instrument rank	667.0000		528.0000		603.0000		658.0000	
Mean dependent var	0.8734		0.8747		0.8653		0.8769	
S.D. dependent var	0.1458		0.1425		0.1473		0.1458	
Sum squared resid	6.8869		0.4254		1.1726		2.5465	
J-statistic	6.886888		0.425354		1.172619		2.546462	
Prob(J-statistic)	0.991046		1		1		0.999979	

Table 2.14. GMM model LMI estimation by period

	Global		Pre Crisis		Crisis		Post Crisis	
Variable	Coefficient	Prob.	Coefficient	Prob.	Coefficient	Prob.	Coefficient	Prob.
C	0.5953	0.0000	0.4845	0.0000	0.6828	0.0000	0.6156	0.0000
GL_TA	0.0081	0.1799	-0.0199	NA	-0.0096	0.3257	0.0142	0.0004
IB_TA	-0.6245	0.0000	-0.3788	0.0000	-0.7094	0.0000	-0.6525	0.0000
WD_TA	-0.6177	0.0000	-0.4063	0.0000	-0.7504	0.0000	-0.6419	0.0000
IL_TA	0.0128	0.0402	-0.0092	0.0000	0.0151	0.0096	-0.0076	0.2790
CD_TA	-0.5922	0.0000	-0.4644	0.0000	-0.6795	0.0000	-0.6170	0.0000
TE_TA	-0.4038	0.0000	-0.3370	0.0000	-0.4080	0.0329	-0.3711	0.0001
D1	0.0019	0.6257	0.0079	0.0000	0.0061	0.0315	0.0007	0.7100
D3	-0.0085	0.0424	0.0018	0.0000	-0.0023	0.4208	-0.0051	0.4097
AR(1)	0.4406	0.0000	-0.1848	0.0000	0.0071	0.9736	0.3945	0.0002
AR(2)	0.0347	0.3446	-0.0218	0.0000	-0.0635	0.4805	0.0467	0.4900
R-squared	0.9086		0.9736		0.9472		0.9340	
Adjusted R-squared	0.8975		0.9438		0.9185		0.9185	
S.E. of regression	0.0165		0.0129		0.0175		0.0129	
Durbin-Watson stat	2.0097		4.1645		3.0351		2.0732	
Instrument rank	666.0000		528.0000		603.0000		658.0000	
Mean dependent var	0.0898		0.0900		0.0910		0.0891	
S.D. dependent var	0.0517		0.0542		0.0614		0.0452	
Sum squared resid	1.4620		0.0745		0.3315		0.4542	
J-statistic	0.0172		0.07453		0.331521		0.454232	
Prob(J-statistic)	1		1		1		1	

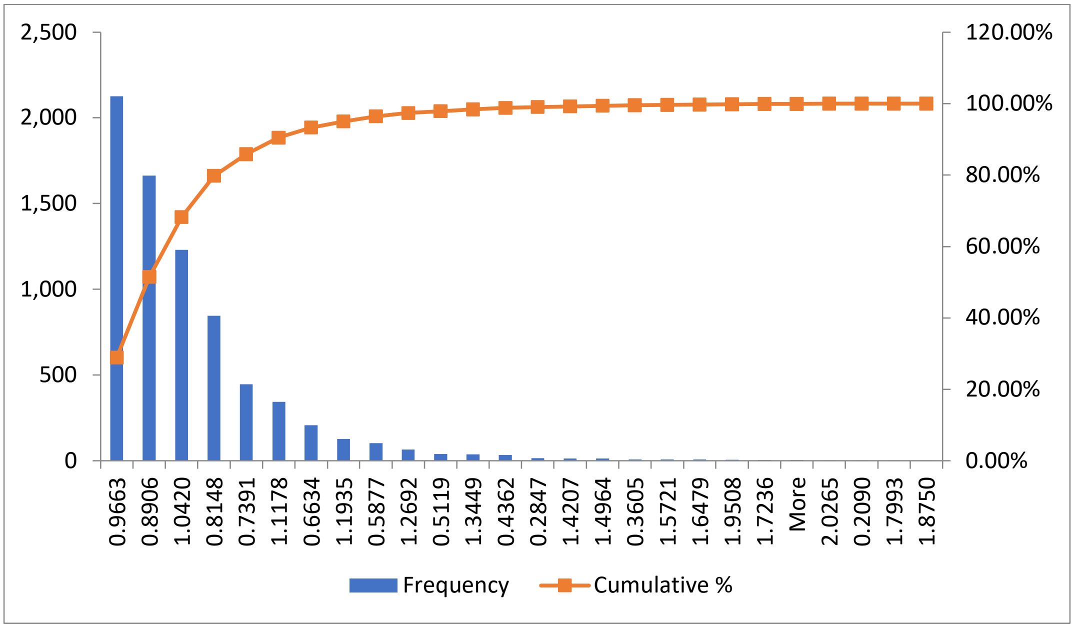

Figure 2.1. NSFR global average (2003–2015)

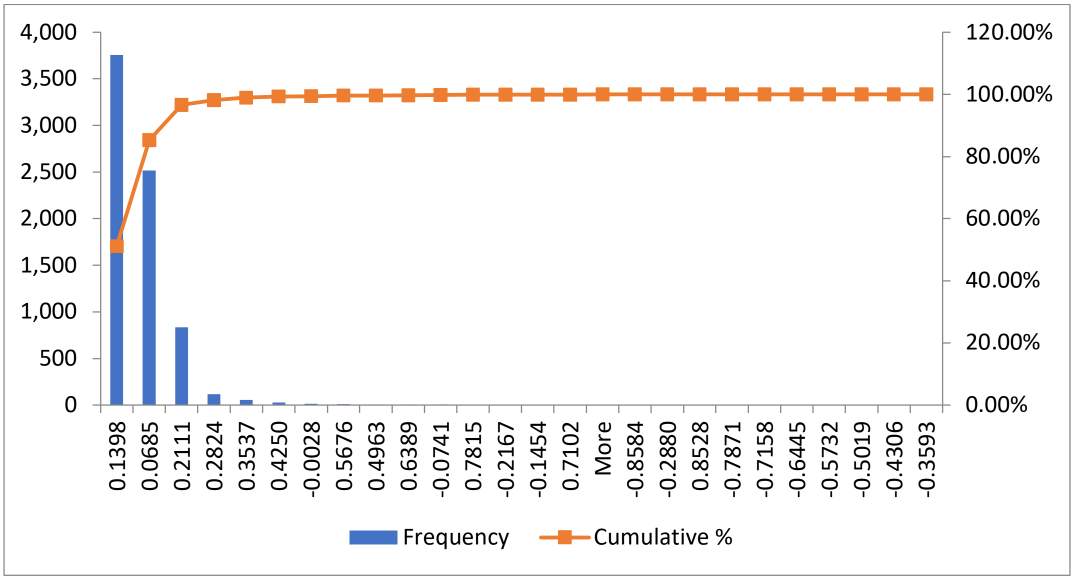

Figure 2.2. LR global average (2003–2015)

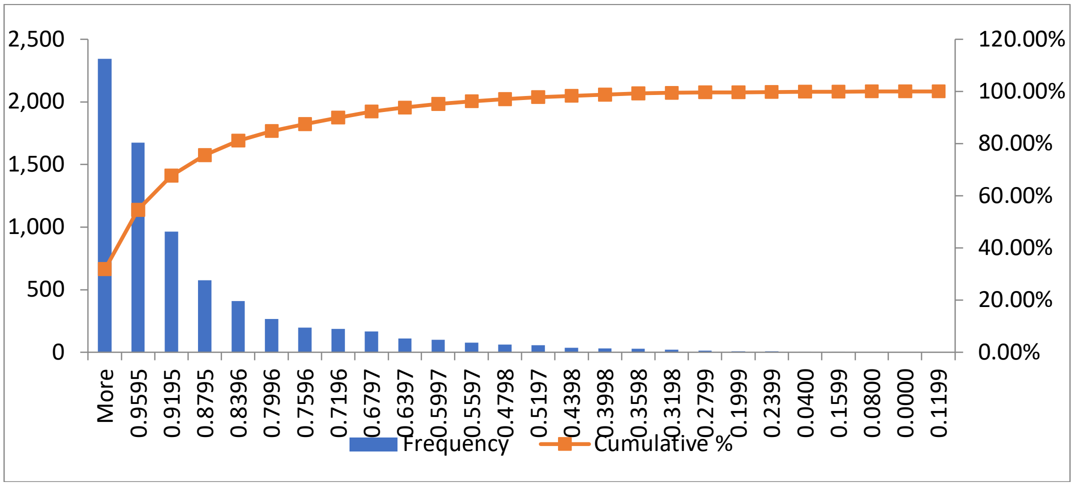

Figure 2.3. STFR global average (2003–2015)

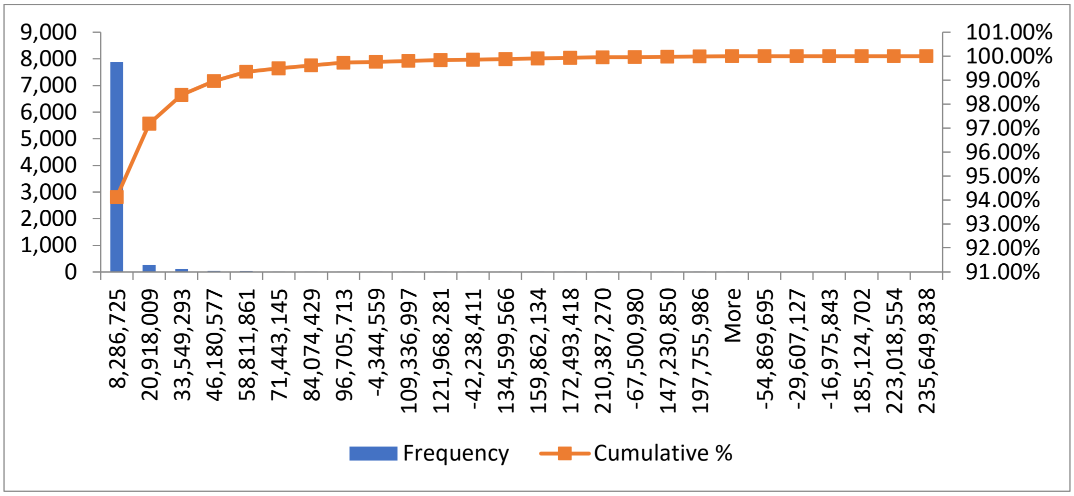

Figure 2.4. LMI global average (2003–2015)

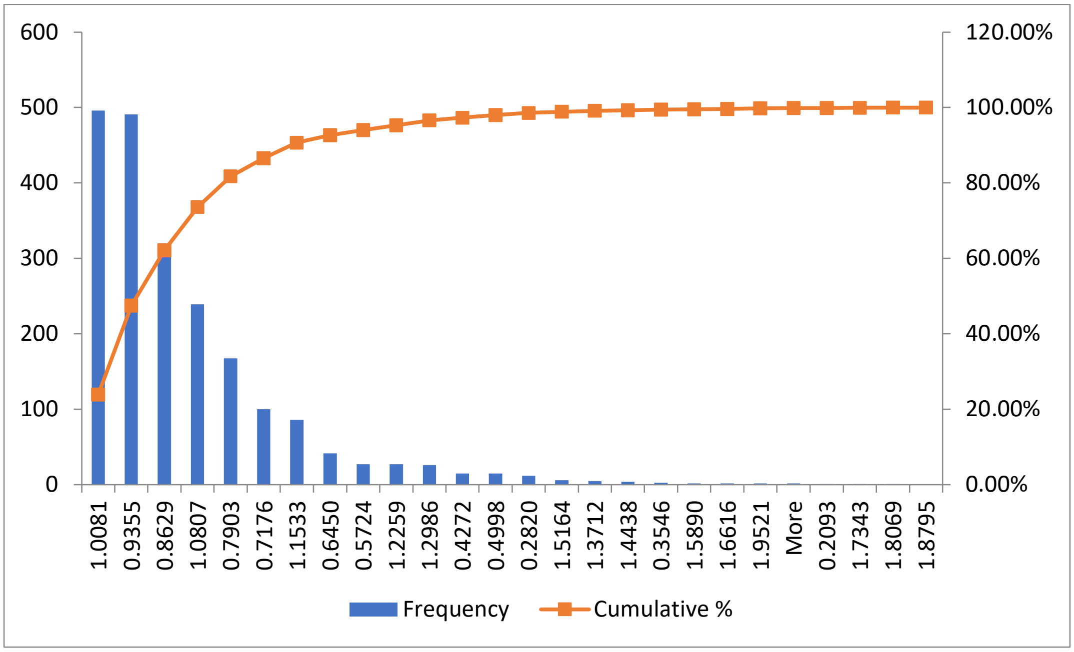

Figure 2.5. NSFR pre-crisis (2003–2006)

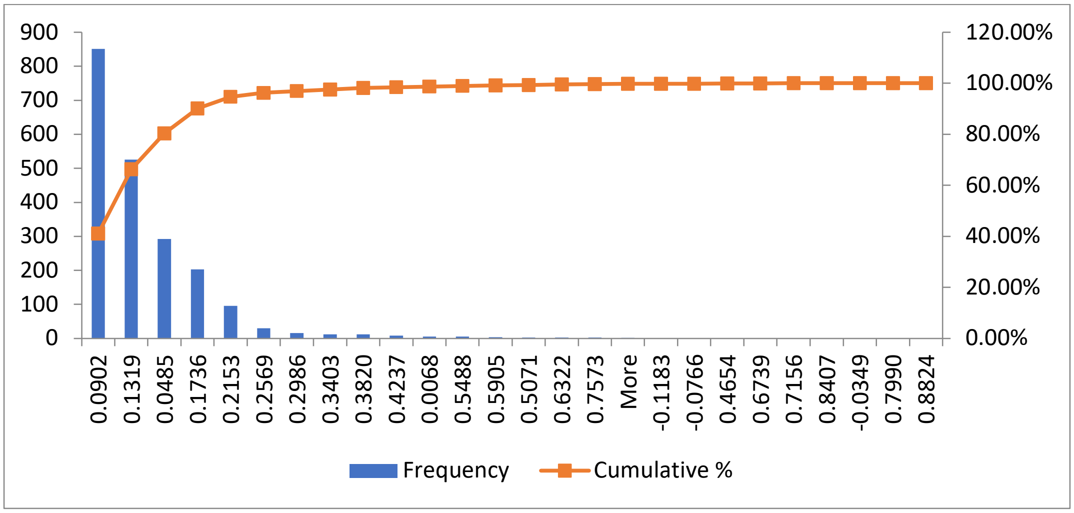

Figure 2.6. LR pre-crisis (2003–2006)

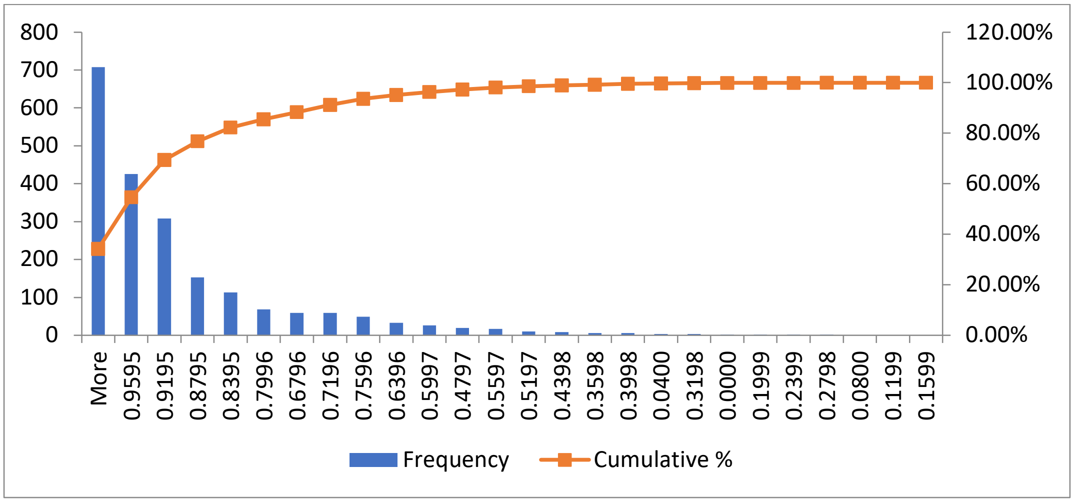

Figure 2.7. STFR pre-crisis (2003–2006)

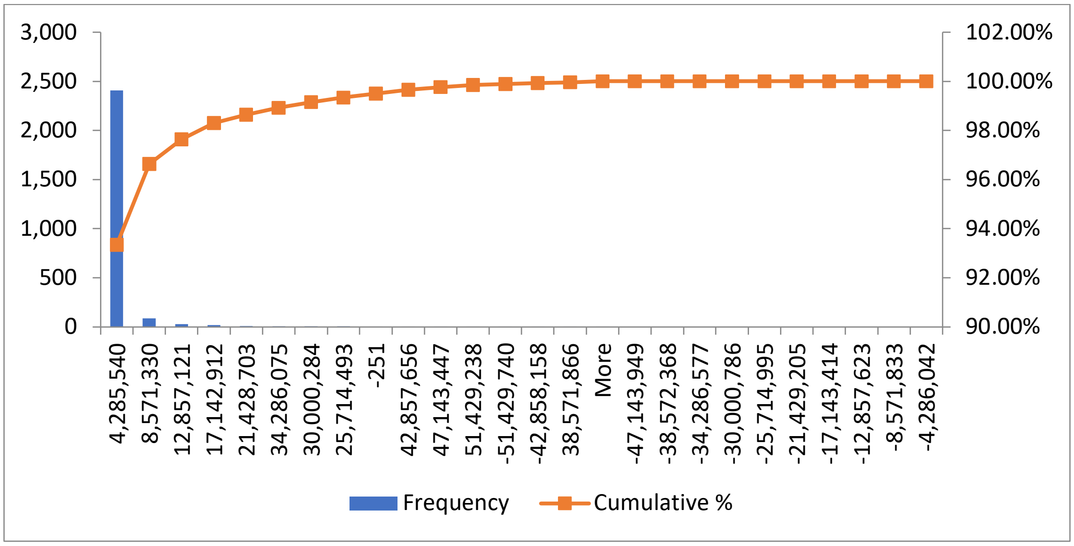

Figure 2.8. LMI pre-crisis (2003–2006)

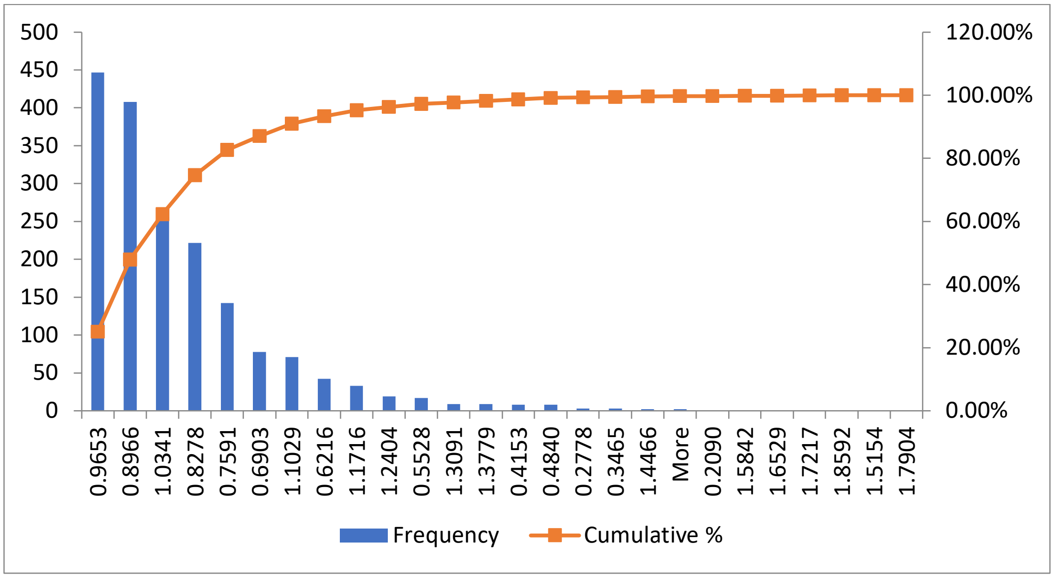

Figure 2.9. NSFR crisis (2007–2009)

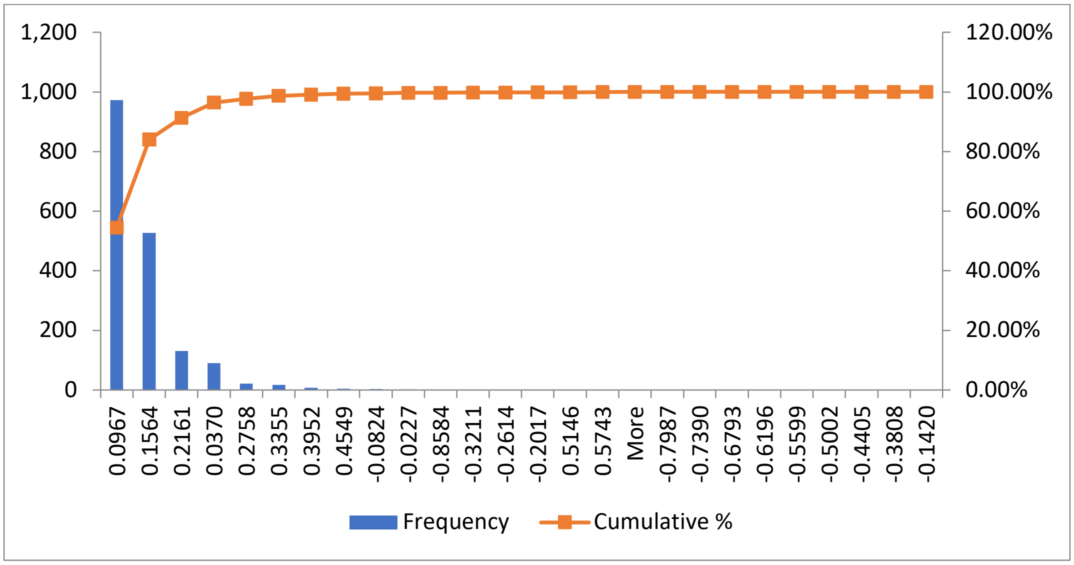

Figure 2.10. LR crisis (2007–2009)

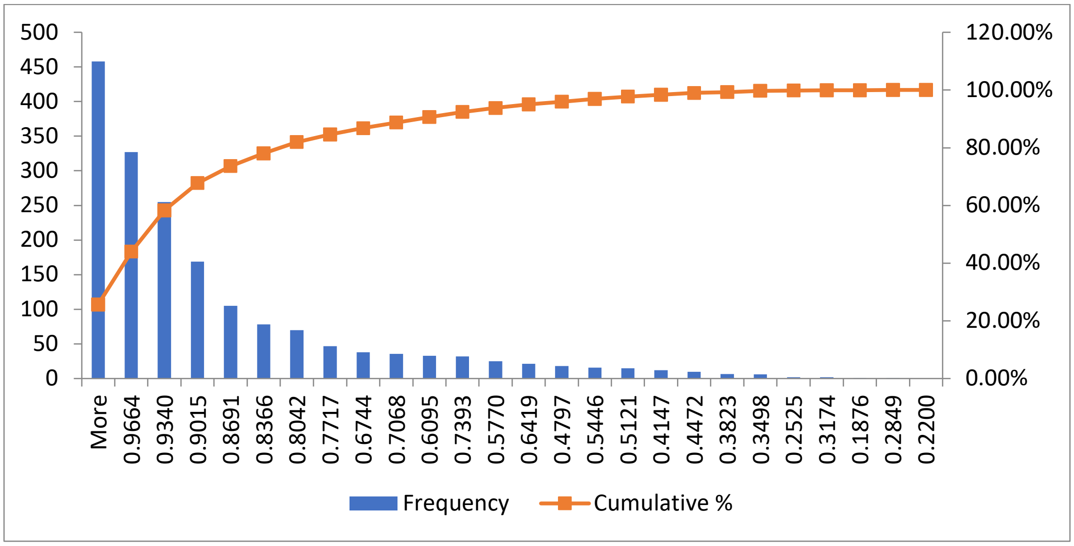

Figure 2.11. STFR crisis (2007–2009)

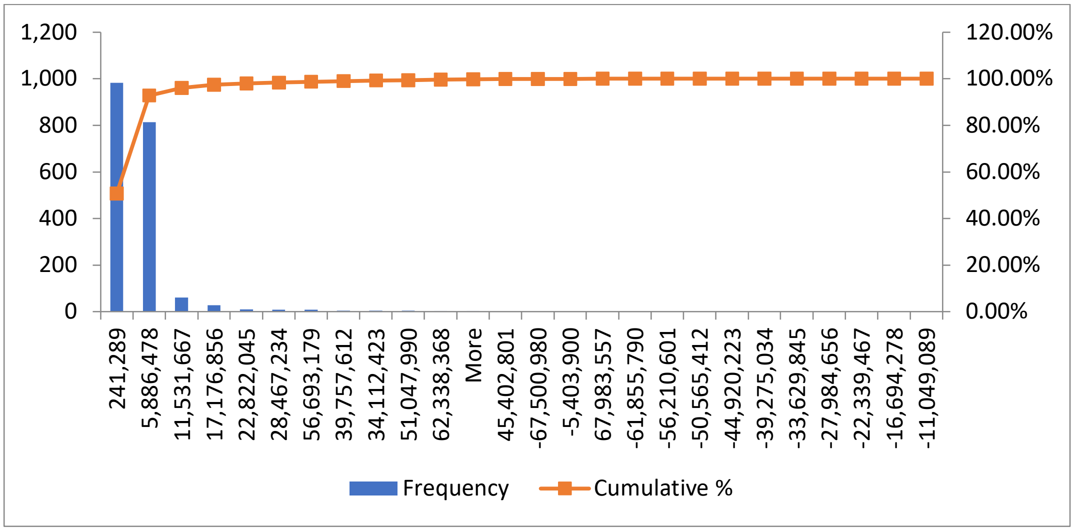

Figure 2.12. LMI crisis (2007–2009)

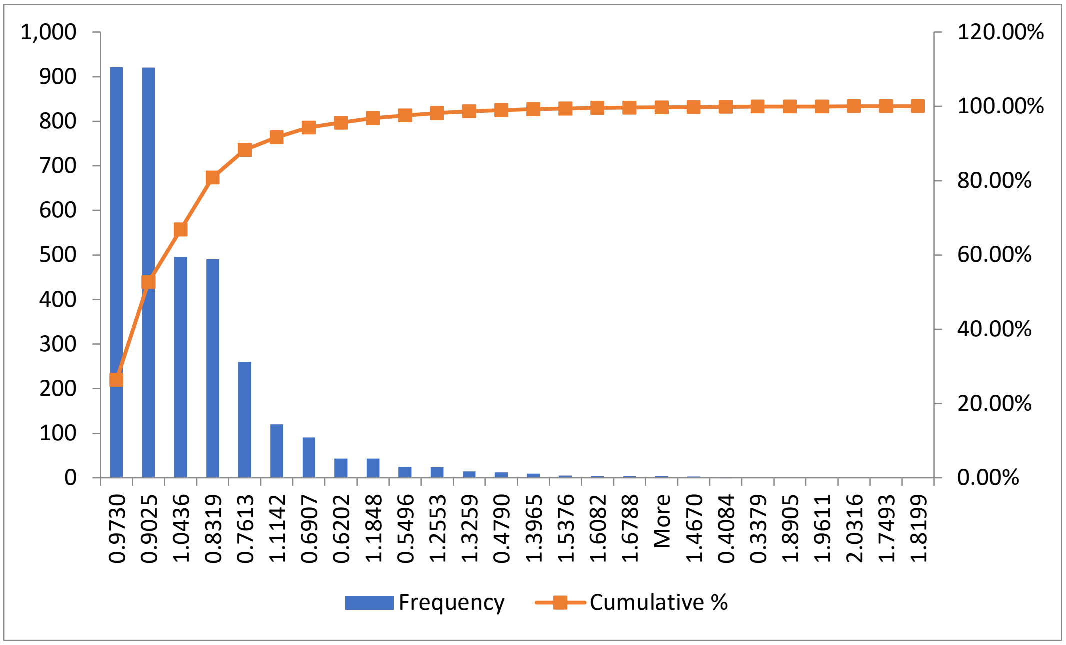

Figure 2.13. NSFR post-crisis (2010–2015)

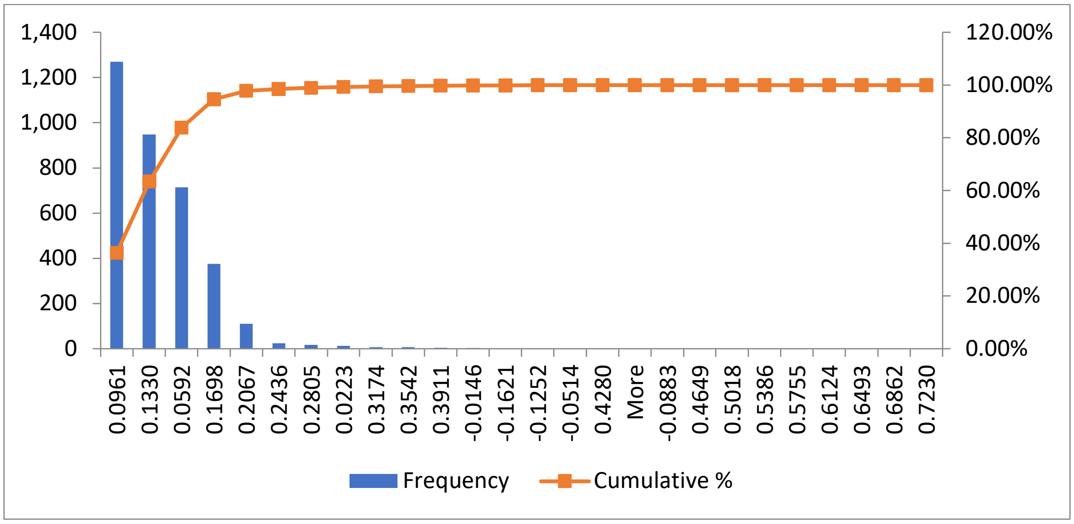

Figure 2.14. LR post-crisis (2010–2015)

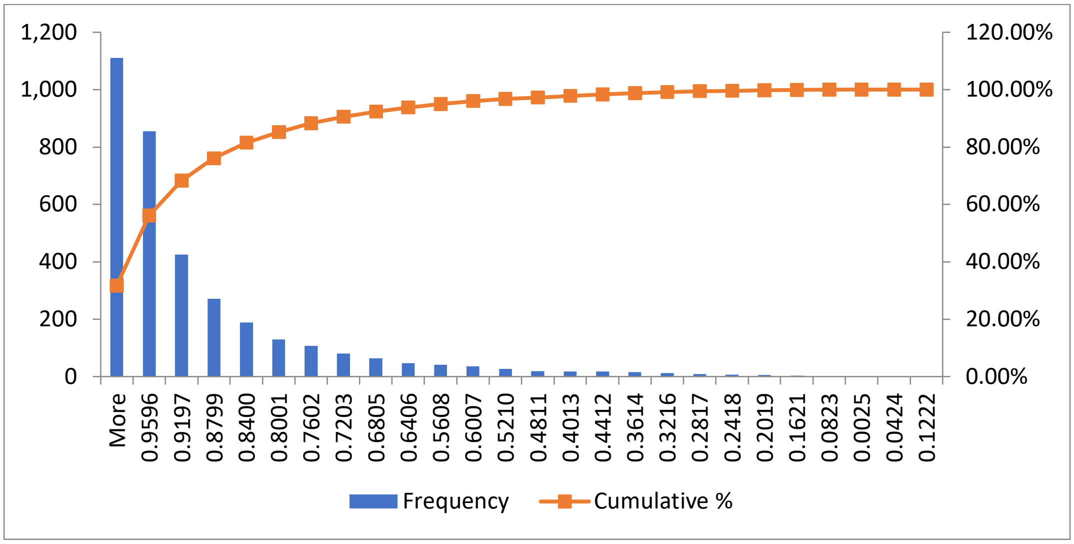

Figure 2.15. STFR post-crisis (2010–2015)

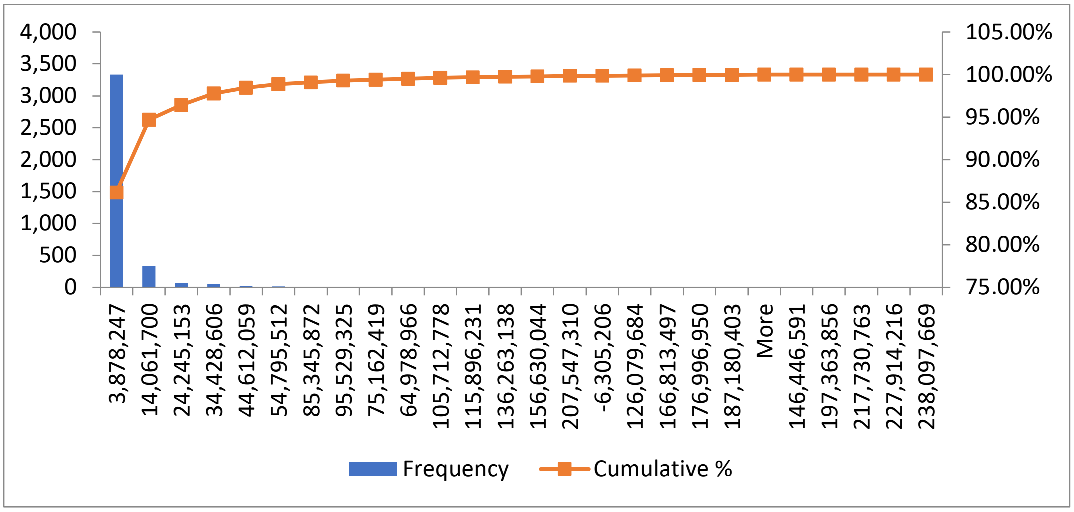

Figure 2.16. LMI post-crisis (2010–2015)

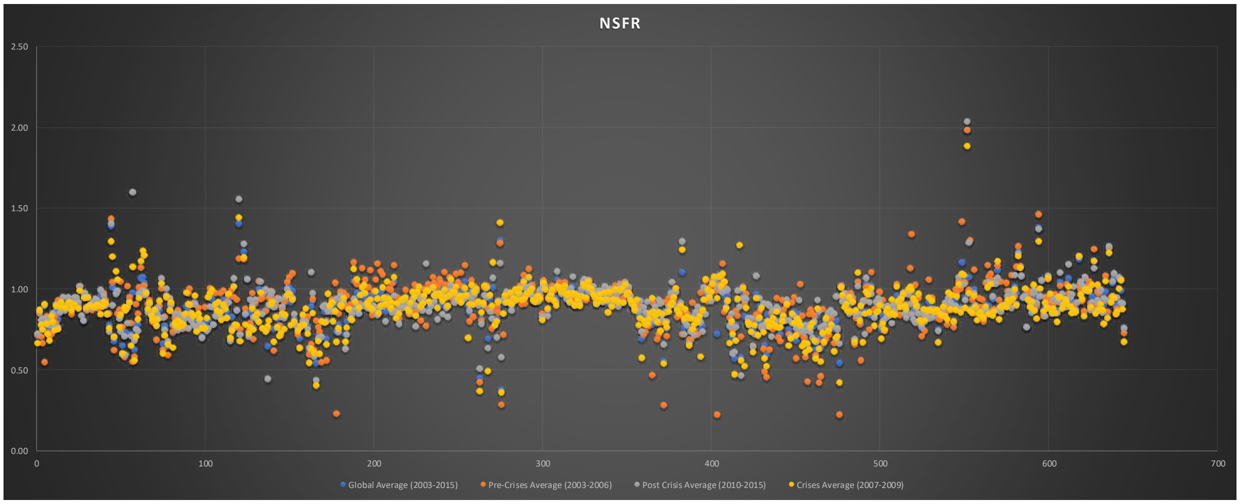

Figure 2.17. NSFR aggregated (2003–2015): average by bank for 645 commercial banks in sample and by period

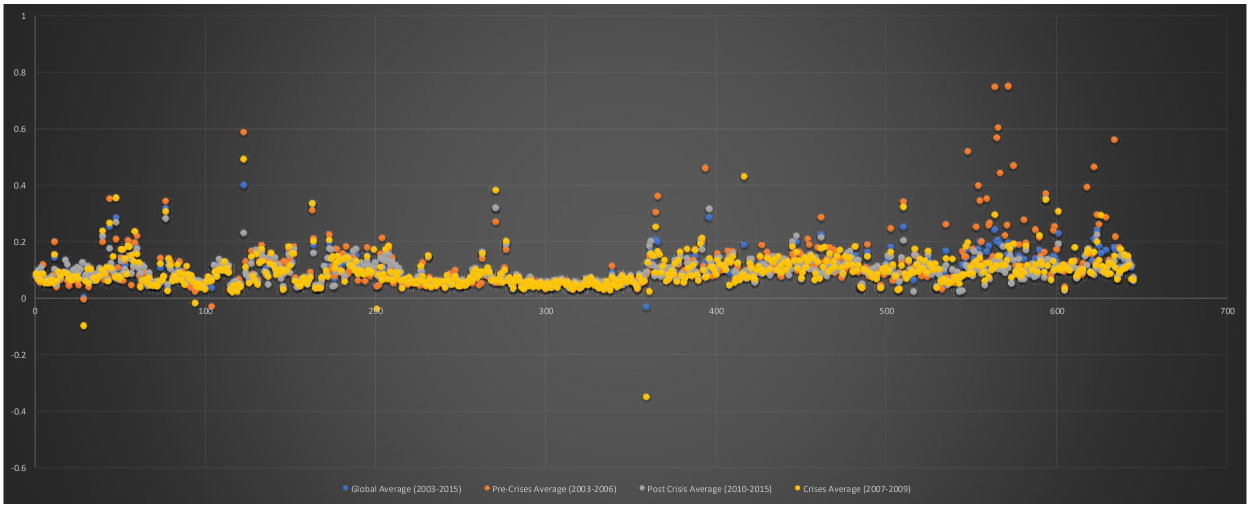

Figure 2.18. LR aggregated (2003–2015): average by bank for 645 commercial banks in sample and by period

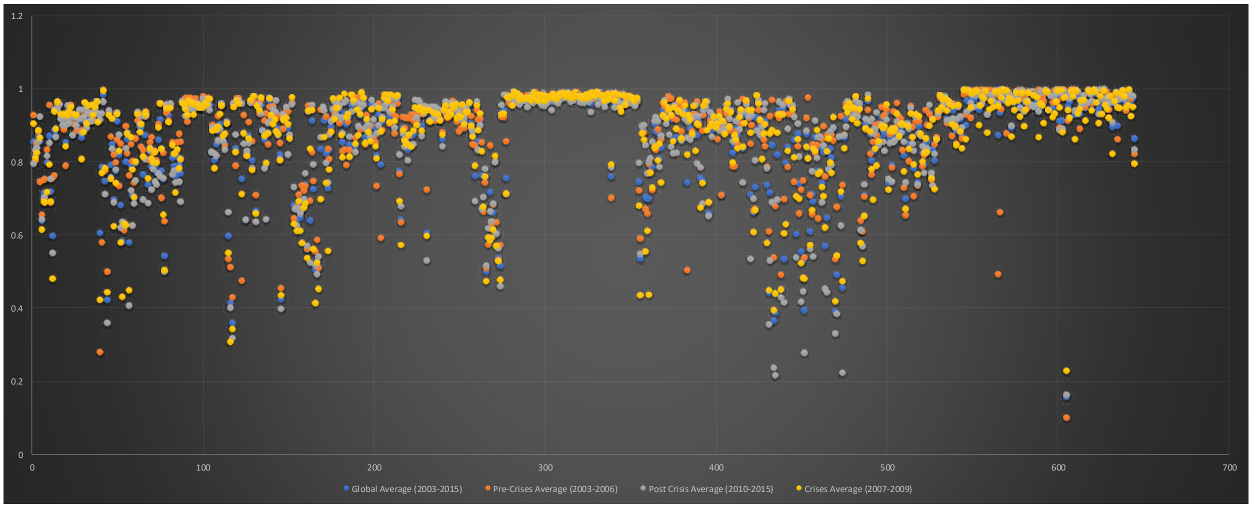

Figure 2.19. STFR: average by bank for 645 commercial banks in sample and by period

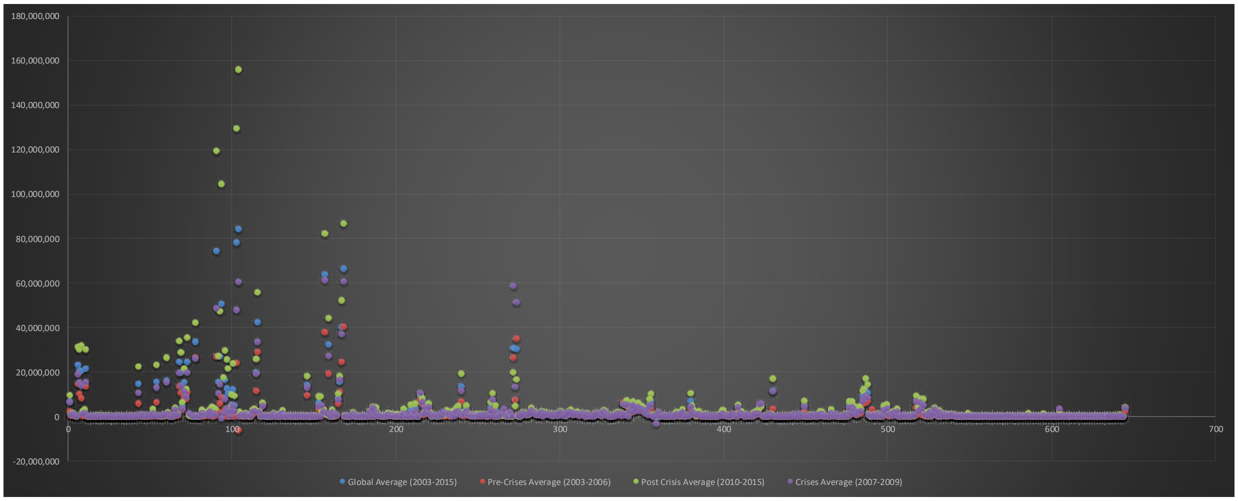

Figure 2.20. LMI aggregated (2003–2015): average by bank for 645 commercial banks in sample and by period

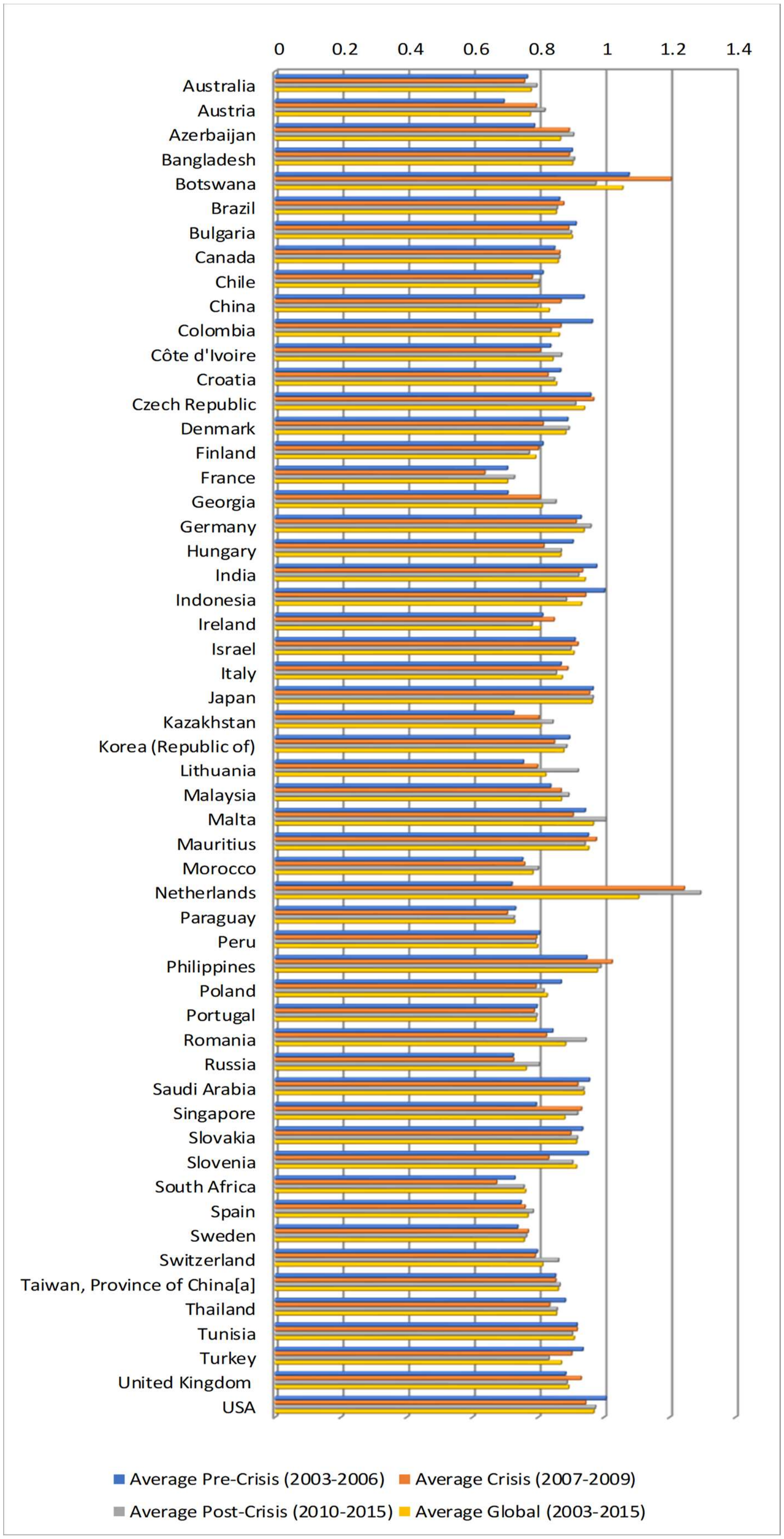

Figure 2.21. NSFR by country (2003–2015): average by country and period

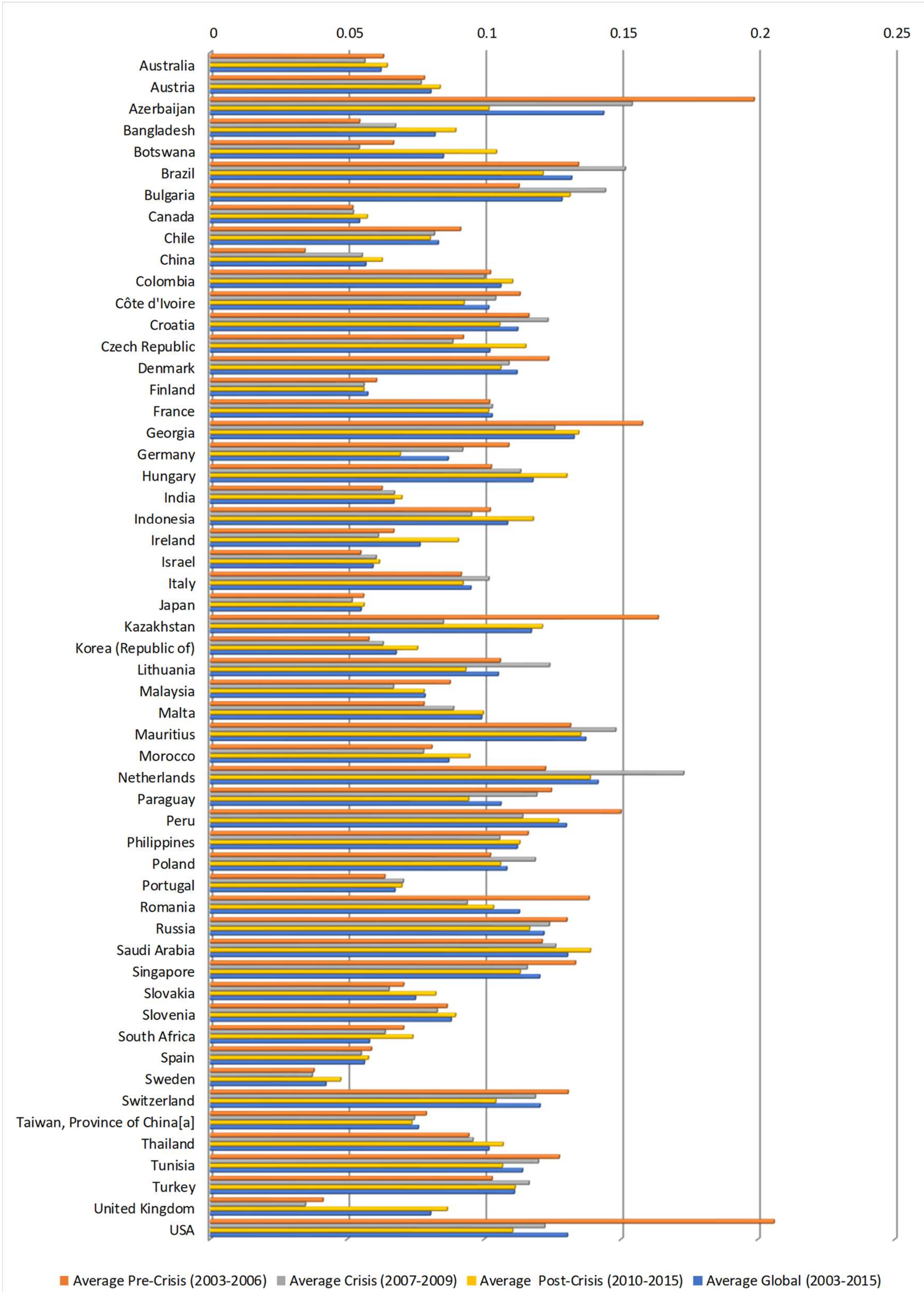

Figure 2.22. LR by country (2003–2015): average by country and period

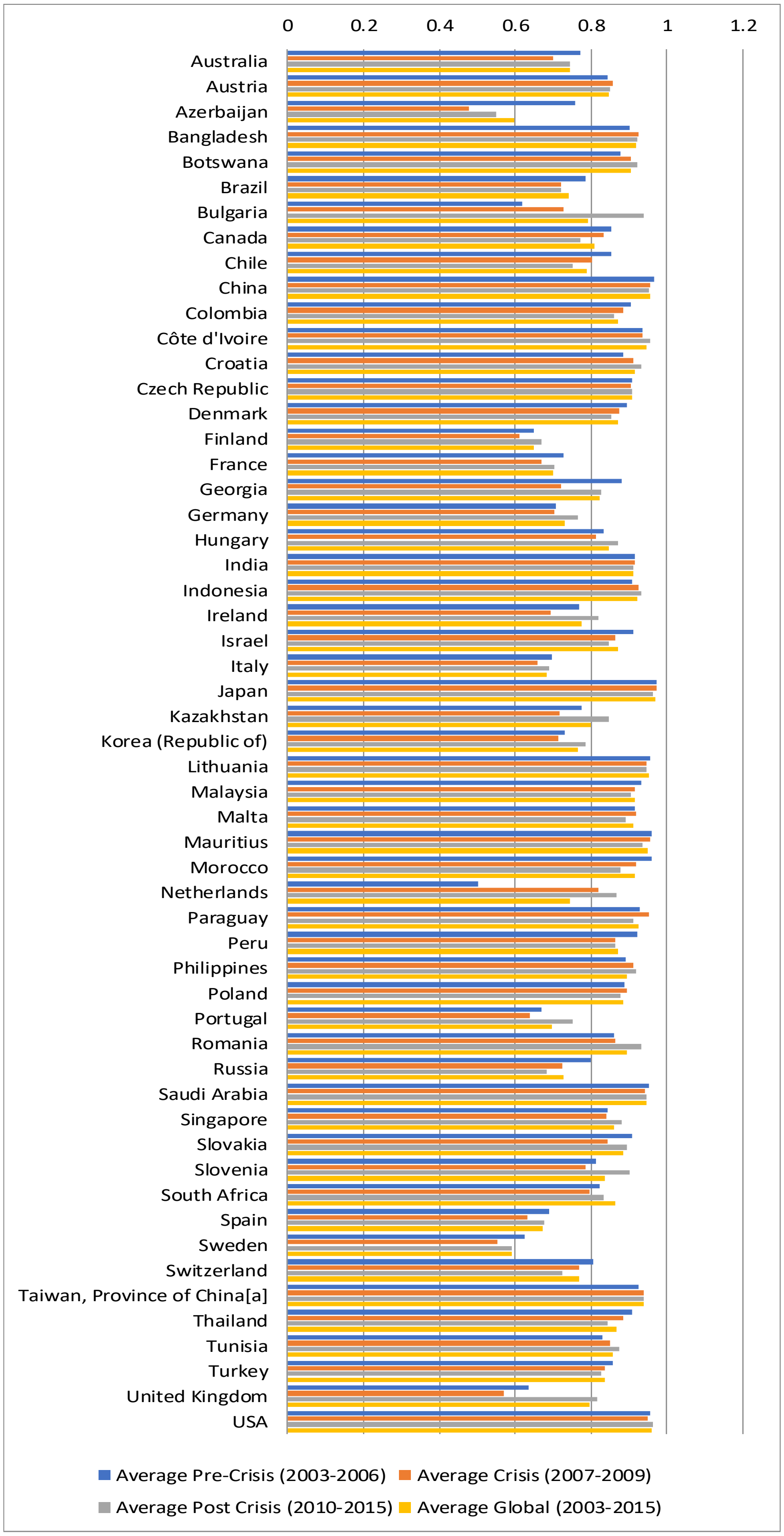

Figure 2.23. STFR by country (2003–2015): average by country and period

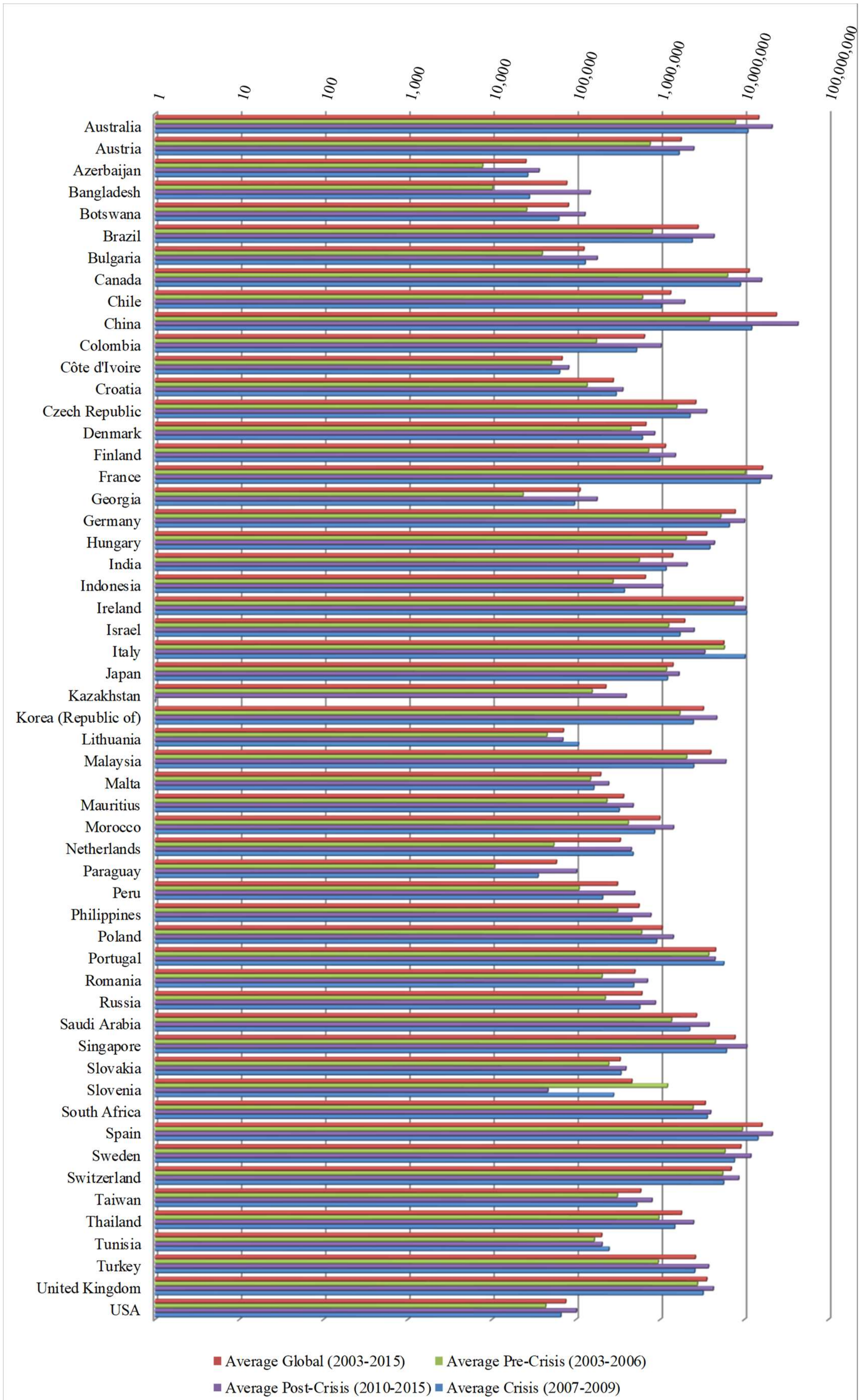

Figure 2.24. LMI by country (2003–2015): average by country and period

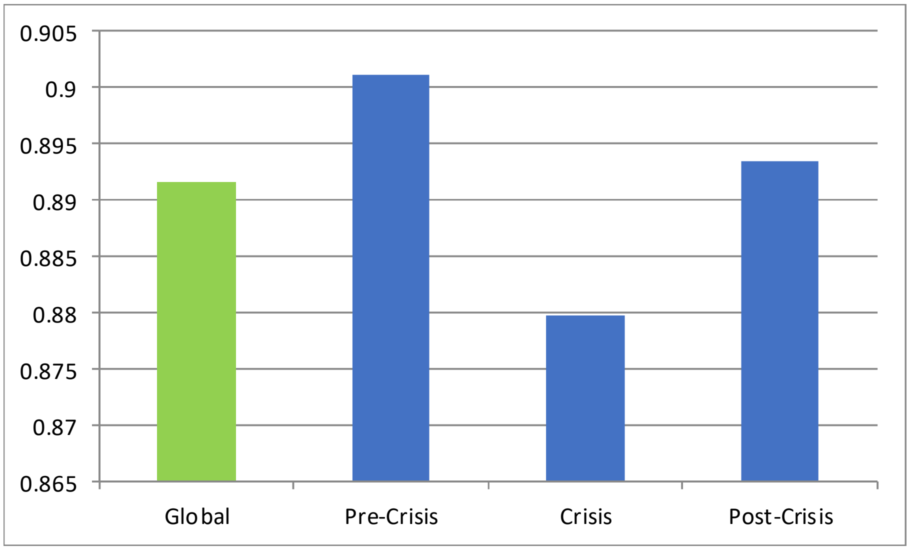

Figure 2.25. NSFR average by period

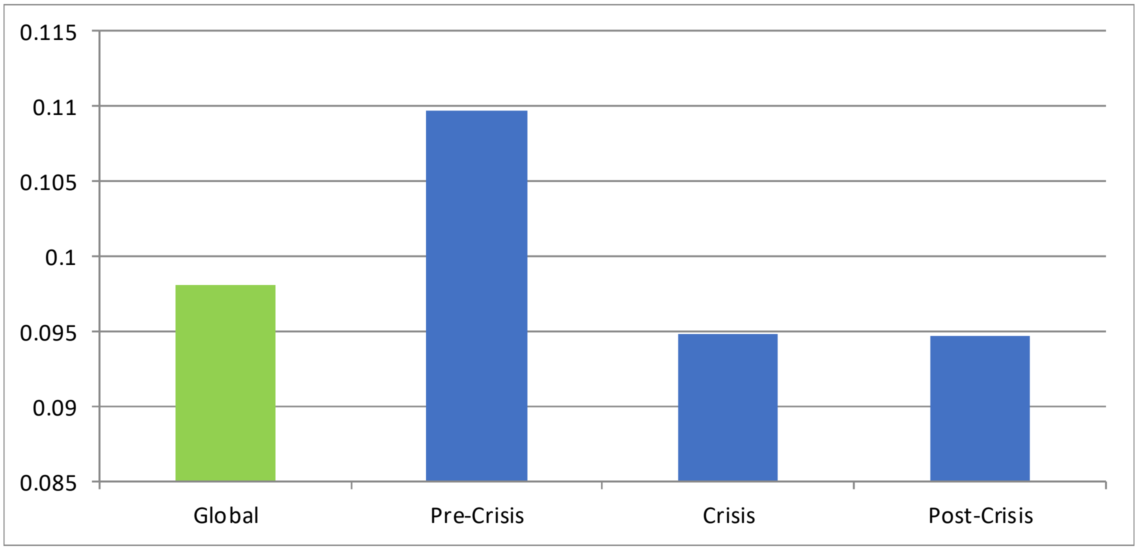

Figure 2.26. LR average by period

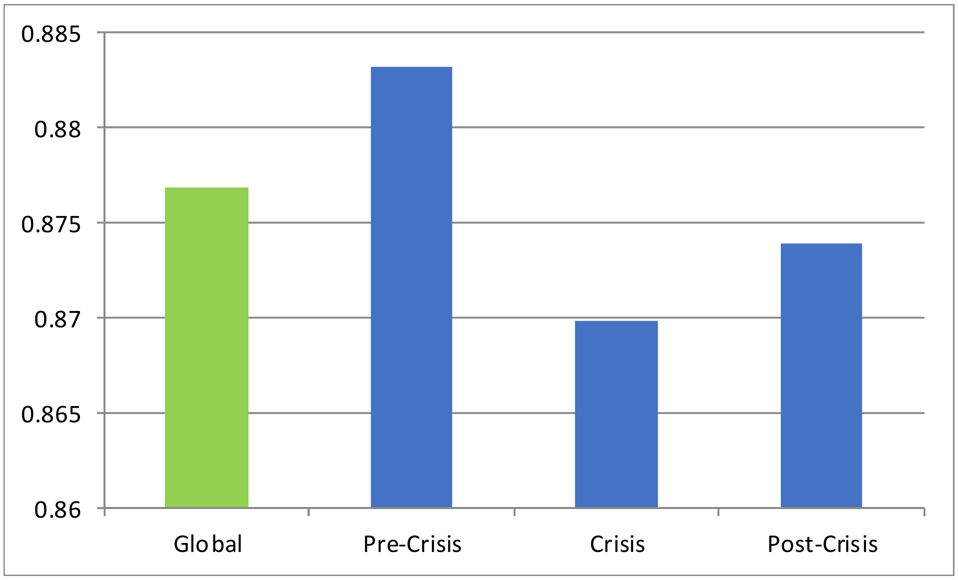

Figure 2.27. STFR average by period

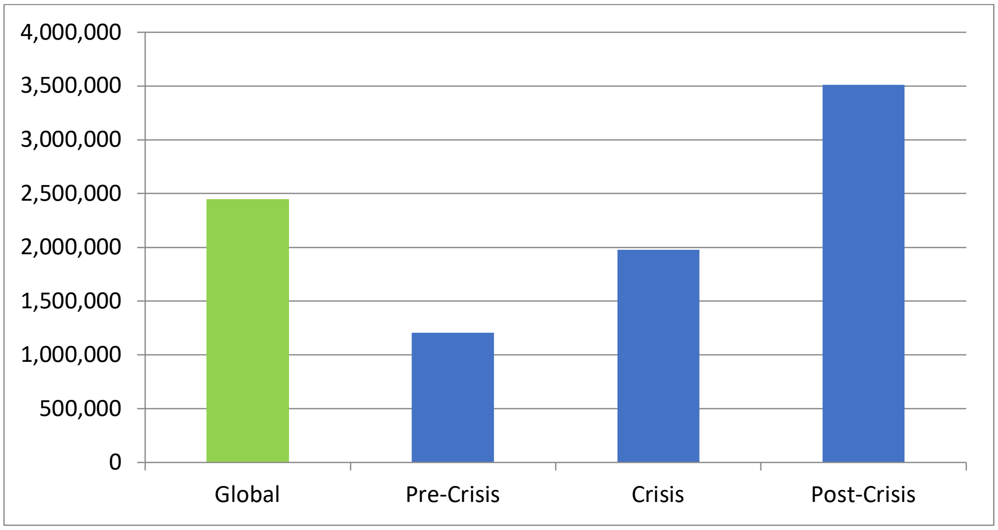

Figure 2.28. LMI average by period

3. Determinants of Liquidity Risk

3.1. Introduction

The ultimate goal of any business is to make a profit. Banks are primed to create value for shareholders and maximize these companies' value. This objective requires a balance between risk and profitability and adequate asset and liability management. Some tradeoffs exist in terms of banks' management of these areas including adequate liquidity, low risk levels, and sufficient capital (Basel Committee on Banking Supervision [BCSB], 2010). Because banks' resources are limited, these institutions' asset and liability management correlates with their liquidity requirements (Vodova, 2013).

As the most recent crisis that affected the financial system showed, liquidity is one of the most vulnerable variables in banking, and liquidity is affected by both exogenous and endogenous factors. One risk associated with liquidity is related to how banks are linked through financial systems and banks' shortage of liquidity can be transmitted to other banks through interbank transactions, thereby causing systemic risk (Gauthier and Souissi, 2010). This contagion effect is what made the central banks willing to make loans to other banks in order to mitigate the crisis's effects that had settled into financial systems.

Various bank management standards have been defined worldwide, many resulting from the guidance provided by these institutions' shareholders. The present study sought to identify banks that have implemented excessive liquidity maintenance strategies to signal the market that their companies have strong liquidity. However, market players do not always interpret this information similarly, and banks' disproportionate liquidity can indicate inefficient liquidity management and thus poor asset and liability control policies put into place at the cost of these institutions' net interest margin and profitability. Banks with excessive liquidity may also suggest poor infrastructure exists in the financial market, which translates into limited payment instruments and segmentation in the interbank market (Tirole, 2011; Delechat et al., 2012; Distinguin et al., 2013; Ratnovski, 2013; Acharya and Mora, 2015; Calomiris et al., 2015).

Experts agree that commercial banks have an important role in financial systems, which explains why these companies are vulnerable to problematic situations such as the 2007–2009 crisis. Global commercial banks are key to funds transference between surplus and deficit agents. Banks, therefore, promote and contribute to a balance between systems' various entities and strengthen countries' overall economic condition.

Global clearing systems need liquidity to keep their day-to-day banking operations working. Banks' inability to meet their clients' daily needs, such as withdrawals from deposits, would cause liquidity shocks. Eventually, these institutions would go bankrupt or begin asset liquidation if they are unable to sustain the liquidity needed to meet clients' demands (Vazquez and Frederico, 2015). Thus, banks' role includes transforming maturities and providing collateral for short-term depositors so that, whenever they need their funds, these are available. In actuality, their money is used to carry out medium- and long-term transactions (Bank for International Settlement, 2008). Maturity mismatch is one reason why banks are especially sensitive businesses.

When examining these institutions' sensitivity to financial systems, in particular, and to the economy, in general, analysts must remember that commercial banks are involved in the lending process. They are basically focused on credit (i.e., counterparty, transaction, consent, and liquidation), market (i.e., interest rate, exchange rate, and liquidity), and operational risks (i.e., process, infrastructure, system, and human resources). To this end, these institutions must concentrate asset and liability management policies on the aforementioned three market risks (Molle, 2008). Liquidity management as a process of optimizing liquidity reserves should maintain a level of liquidity that creates optimum income and minimum liquidity risk. However, banks are not always concerned about this balance because, as companies, their ultimate purpose is profit. At a macroeconomic level, the ideal way to manage asset liabilities implies that the level of liquidity serves monetary policy objectives (Delivorias, 2015).

The current study was based on a sample of 645 listed commercial banks for which information in the Bankscope database was compiled. This research focused on commercial banks because more information was available and the universality of their market actions and market representativity make these institutions more exposed to liquidity effects. The aforementioned database covers commercial banks around the globe that are non-offshore companies with total assets (TAs) higher than 100,000,000 euros, from 2003 to 2015.

The present study's focus is part of the broader topic of banking systems' stability at the international level. The recent crisis has attracted more researchers and practitioners' attention to not only loss-absorbing capacity but also liquidity management. Bank runs appear to be a thing of the past, but they might still pose problems if this threat is not addressed adequately by banks and their supervisors. This research sought specifically to shed some light on the links between banks' balance sheet structure and business profiles, on the one hand, and liquidity, on the other. The study analyzed firm-specific and macroeconomic variables that can have an impact on the long-term liquidity risk of 645 commercial banks worldwide. The investigation covered bank-, country-, and time-specific effects by developing different regression models.

This research's contribution to the knowledge about bank liquidity is important for both academicians and bank professionals. Various theoretical studies appear in the literature on this subject, but few researchers have gathered empirical evidence on banks' liquidity risk determinants based on real data. In addition, the current research focused on a wide 13-year period for 645 commercial banks around the globe that are not from specific geographical zones. The years under analysis ensured the subprime mortgage crisis period and pre- and post-crisis periods were included in the sample.

This study's findings also contribute to the application of Basel III requirements, namely, the net stable funding ratio (NSFR) and leverage ratio (LR) at a time when these were not yet mandatory, providing detailed empirical evidence on liquidity risk determinants. The results provide important insights relevant to regulators, banks, and academicians, including identifying the LR's, non-performing loans' (NPLs), and money market funding's significant impacts on banks' stable funds.

The rest of this paper is structured as follows. Section two presents the literature review, while section three describes the data, methods, and variables. Section four details the results, and section five provides the conclusions.

3.2. Literature review

Liquidity is a construct used in a range of situations and contexts. According to the Bank for International Settlements (BCSB, 2008), liquidity is banks' ability to finance their assets and meet obligations without incurring losses. Usually asset liquidity is used to evaluate how quickly and easily companies can convert their assets into cash or how much more liquid banks are by the amount of cash or near money they have (Berger and Bouwman, 2008). Liquidity risk also has many definitions, such as the probability that companies will not meet their short-term obligations (Petria and Petria, 2009). Other authors have defined liquidity as banks' ability to fund an increase in assets and fulfill commitments on time, without experiencing unacceptable losses (Sheefeni and Nyambe, 2016).

In the banking sector, liquidity has two sides. Banks are responsible for managing their own liquidity and, simultaneously, liquidity creation. The latter helps depositors and companies stay liquid, so a crisis among banks that own liquidity causes liquidity problems in the entire economy. Banks' liabilities are their sources of funds, of which three stand out as more important: deposit accounts, borrowed funds, and long-term funds. On the same side of the balance sheet, capital accounts constitute another source of funds, especially in crisis situations.

Bank assets, in contrast, are obtained with the funds gathered through bank liabilities. Risks arise when banks must meet their obligations if these companies do not have enough cash or assets to convert easily into cash to pay clients. Thus, banks' risk management policies must evaluate the amount of demand deposits versus loans and undrawn credit lines.

Concurrently, investors who purchase securities can use their assets as collateral in the acquisition process. The problem is when the margin required for various securities increases sharply during crises. Brunnermeier and Pedersen (2009) demonstrated that a small negative shock to asset prices can trigger a large decline in wholesale funding due to tightening margin requirements for investment banks.

According Sawada's (2010) investigation of crisis periods, the liquidity shock dealt by depositors' withdrawals causes banks to increase their cash holdings by selling their securities in the financial market, as opposed to liquidating their loans. Keister and McAndrew (2009) found that banks' level of liquidity is determined by central banks' action rather than other banks' behavior. Gulamhussen et al. (2015) further studied the relationship between bank internationalization and risk in the period leading up to the 2007–2008 financial crisis and showed that multinational banks take on more risk.

In addition, Ojo (2010) clarified the significance of risks based on the vital role played by capital adequacy. After examining the Basel Accord principles, the cited author concluded that, besides substantial work needed on asset development, much has yet to be done specifically regarding liquidity risk.

During the recent financial crisis, many institutions experienced important declines in their own assets' value and difficulties in selling these holdings. This trend combined with banks' reduced ability to fund themselves in wholesale funding markets, triggering crashes in these institutions' liquidity. This asset devaluation began with subprime lending's effects in the United States (US). Adrian and Shin (2010) found evidence of a significantly positive correlation between asset growth and the growth in US investment banks' leverage. Vazquez and Federico (2015) report that banks with weaker structural liquidity and higher leverage in the pre-crisis period were more likely to fail during the crisis.

Managing liquidity risk, therefore, involves ensuring banks' own liquidity so that they can maintain their function as liquidity creators. Many factors affect these institutions' liquidity, which, in turn, influences the amount of liquidity created. These determinants have an impact on the balance between liquidity risk and creation, and banks' assets and liabilities are quite important to their ability to find this balance (Madura, 2007).

To identify the specific factors affecting commercial banks' liquidity, Roman and Sargu (2015) studied the determinants of liquidity in Central and Eastern European countries between 2004 and 2011. The cited authors sought to prove that asset quality as measured by the ratio of nonperforming loans to total loans would negatively and significantly affect banks' liquidity. Turning more loans into nonperforming loans would decrease banks' loan operations, which has an impact on their overall liquidity. However, Roman and Sargu (2015) were unable to confirm this hypothesis in any country. The cited researchers instead confirmed a positive association between asset quality and bank liquidity in the Czech Republic, Lithuania, and Romania mainly because of legal requirements.

Evidence against an association between banks' asset quality and liquidity is also provided by Vodavá (2013) and Melese and Laximkantham (2015), who found that asset quality has no statistically significant impact on banking liquidity. Growe et al.'s (2014) study, in contrast, confirmed the association between liquidity and asset quality. The cited researchers' analyses were based on the assumption that poor loan quality leads to poor asset quality and poor asset quality contributes to a low level of liquidity.

In addition, Bonfim and Kim's (2011) findings underline that banks with better capital adequacy present lower liquidity risk exposure. Regarding return on assets (ROA), various researchers, including Pasouras and Kosmidou (2007) and Kosmidou et al. (2008), have asserted that a positive relationship exists between liquidity and bank performance. Both cited studies involved United Kingdom and European Union (EU) countries. In their article, "Bank Liquidity Risk and Performance," Shen et al. (2018) report the results of analyses of banks' ROA and return on equity (ROE) in the US, Canada, France, Taiwan, the United Kingdom, Germany, Japan, Luxembourg, Italy, the Netherlands, Switzerland, and Australia. The cited authors observe that liquidity risk is negatively related to these performance indicators.

Rauch et al. (2010) analyzed liquidity risk determinants and sought to identify factors affecting liquidity creation. The cited research's results show that the most important determinants are macroeconomic variables and monetary policies. However, no evidence was found for a significant relationship between liquidity creation and banks' specific variables such as size and performance. Bunda and Desquilbet (2008) conducted a study of 1,107 commercial banks in 36 emerging economies. The cited authors found that capitalization measured by the ratio between equity and TAs has a significant, positive relationship with all the liquidity measures considered and a significant relationship with inflation and growth rates.

Angora and Roulet's (2011) findings emphasize the relationship between liquidity risk calculated based on the two new liquidity indicators proposed by the Basel Committee (i.e., the CSF and NSFR) and a variety of other indicators. These included, among others, balance sheet indexes such as ROA, the natural logarithm of TAs, and the ratio of customer loans to total loans. Angora and Roulet's (2011) analyses also covered some macroeconomic indicators such as annual gross domestic product (GDP) growth (GDPG) and the differential between the interbank rate and central banks' monetary policy rates. Overall, the cited study's results highlight that the liquidity risk index in question has a negative relationship with most indicators analyzed, including the size of and ratio between regulatory capital and TAs. The liquidity measure, however, has a significant, positive relationship with macroeconomic variables, such as central banks' GDP and monetary policy rates.

Bonfim and Kim's (2011) research focused on European and North American banks from 2002 to 2009 to clarify how banks manage liquidity risk. The cited study considered three different measures of liquidity risk to explain whether these institutions tend to take more risks and follow similar strategies in times of crisis. Bonfim and Kim (2011) also identified liquidity risk determinants, pointing out that the type of liquidity risk relationship and banks' size, performance, and ratio between loans and deposits depend on the kind of liquidity risk measure used. Bank size generally has a positive impact on bank liquidity, while performance measures have an ambiguous relationship with liquidity risk.

In contrast, other researchers have studied bank size and concluded it has a negative impact on liquidity level. Vodová (2013) analyzed liquidity determinants for Hungarian banks from 2001 to 2010, finding that bank size is negatively related to liquidity level. Cucinelli (2013) also reached this conclusion after testing the same variable on a sample of European banks. However, some authors had different results, namely, that bank size positively affects these companies' liquidity level. For example, Melese and Laximikantham (2015) verified that small banks tend to engage in more traditional activities, which produce smaller liquidity ratios.

Shen et al. (2018) further analyzed the determinants of liquidity risk in 12 countries. The cited study's results reveal that liquid assets, external financing, supervision, regulation, and macroeconomic factors influence liquidity risk. In countries with a market-based financial system, liquidity risk correlates negatively with banks' performance. In countries with a bank-based financial system, liquidity risk does not correlate with banks' performance.

Damar et al. (2010) conducted research based on Canadian data and found that banks' access to wholesale funding markets, which was severely impaired during the recent crisis, contributes significantly to a positive correlation between asset and leverage growth. Pontes and Sol Murta (2010), in turn, used two-stage least squares to show that credit growth (CG), government bonds, and financial crises influence bank liquidity. High credit interest rates create impediments to intermediation that create an accumulation of liquidity for banks.

Vodova's (2011) work confirmed that some indicators such as the capital adequacy ratio (CAR) index, credit interest rate, NPLs, and interbank interest rate have a positive effect on bank liquidity. In contrast, the recent financial crisis, inflation, and economic growth negatively influence this liquidity. Unemployment, margins, interest rate, profitability, and interest rate monetary policies also significantly affect bank liquidity.

Regarding macroeconomic effects, Trenca et al. (2015) studied the macroeconomic liquidity determinants of 40 commercial banks in Croatia, Greece, Italy, Portugal, Spain, and Cyprus from 2005 to 2011. The cited authors found that economic growth as measured by GDP has a negative and statistically significant impact on bank liquidity. Trenca et al. (2015) concluded that a higher inflation rate reduces individuals' purchasing power so that they need more money to buy the same products, thus increasing the demand for loans and decreasing bank liquidity risk. Higher inflation also reduces the real rate of return, which means that, given lower yields, banks will not be available to grant credit, thereby expanding their available liquidity.

Berger and Bouwman (2009) report that monetary policies do not have a significant impact on large and medium-sized bank groups that have a market share of around 90%. Conversely, these policies significantly influence small bank groups. In addition, Berger and Bouwman (2009) detected no difference between monetary policies' impacts during crises or normal periods.

3.3. Data, methods, and variables

The present study built on basic financial theory and adopted the Basel III framework, which focuses more closely on liquidity risk to ensure a sound banking system and standard, comparable measures across banks and jurisdictions. The extant literature suggests that the average structural liquidity in banks' balance sheets in the run up to the recent global crisis was close to the target values proposed by Basel III. This research sought to identify the existence of relationships that explain changes in short- and long-term liquidity and to evaluate endogenous and exogenous variables' impacts on liquidity indicators.

The sample comprised commercial banks worldwide that, due to their size and scope, are more subject to liquidity variations. The methodology consisted of identifying variables that offer additional information about the behavior of banks' liquidity. Some studies have concentrated on the same topics, but their research had a narrower focus because a more restricted set of countries and variables were considered.

3.3.1. Data

The first round of analysis filtered out inappropriate banks in the total sample, and 645 listed commercial banks were selected for this study. More information was available for these banks, and the universality of their market actions and representativity meant that these banks are more exposed to liquidity-related impacts. The dataset created covered non-offshore commercial banks around the globe with TAs higher than 100,000,000 euros, from 2003 to 2015. These data facilitated an examination of bank balance sheet dynamics in three different periods (i.e., pre-crisis, crisis, and post-crisis). The data were downloaded from the Bankscope database, which provides a comprehensive coverage of banks worldwide. The balance sheet data were presented in standardized formats after adjusting for differences in accounting and reporting standards across countries (see Table 3.1).

The term "crisis" period is used here to refer to the years officially included in the subprime mortgage crisis. The initial criteria were provided by the US National Bureau of Economic Research, which asserts that this crisis occurred from 2007 to 2009. Vazquez and Frederico (2012) also consider the crisis period as running from the end of 2007 to 2009. However, the present study's data interpretation parameters required the relevant years be divided into the different stages of the global financial crisis, which were the financial crisis between 2007 to 2009, the most serious financial crisis between 2008 and 2010, and the sovereign debt crisis between 2011 to 2013 (Bayer et al., 2017).

Tables 3.2 and 3.3 present the analyzed banks and these institutions grouped by geographical zones. The final sample permitted an analysis of bank balance sheet dynamics in three different periods (i.e., pre-crisis, crisis, and post-crisis). The banks were located in 10 geographical regions: Europe, the US and Canada, Japan, South America, Africa, Asia, Eastern Europe and Russia, Middle East, Australia, and Switzerland. The Bankscope database used provides a comprehensive coverage of banks worldwide. The balance sheet data were given a standardized format that compensated for differences in accounting and reporting guidelines across countries. Both tables include the number of banks, revealing that the largest number of banks in the sample are from Asia, followed by Europe and the US and Canada. Japan alone accounts for 75 banks in the sample and represents 12% of all banks.

3.3.2. Methodology

3.3.2.1. Data analysis: liquidity risk

To measure bank liquidity and leverage, two international regulatory standards were applied:

- NSFR

– LR

The NSFR measures the proportion of long-term illiquid assets funded with liabilities, which are either long term or deemed stable. This ratio is the relationship between the weighted sum of various types of bank liabilities (L_i) and assets (A_j), as shown in Equation (3.1):

$$NSFR = \frac{\sum_i w_i L_i}{\sum_j w_j A_j} \tag{3.1}$$

The weights *w* fall between 0 and 1 (see Table 3.4) according to the range proposed by Basel III regulations. The weights reflect the relative stability of balance sheet components. In the case of assets, larger weights are assigned to less liquid positions, and, in the case of liabilities, larger weights are assigned to more stable sources of funding (Vasquez and Federico, 2012). The NSFR is expressed as a ratio based on the above formula, and this ratio's value must be equal to or exceed 100%. The NSFR compares banks' available stable funding to their required level, which is that banks operate with an NSFR greater than one. The NSFR is not publicly available due to granularity in banking assets and liabilities, but the ratio could be computed adequately to serve the present study's purposes.

The NSFR's main purpose is to promote resilience over a longer time horizon by creating incentives for banks to fund their activities with more stable sources of funding and to ensure that these institutions maintain a stable funding structure. The Basel Committee for Bank Supervision (BCBS) developed the NSFR to promote financial stability by helping to ensure that funding shocks do not significantly increase the probability of individual banks' distress, which is a potential source of systemic risk. This Basel III liquidity measure addresses concerns raised during the subprime mortgage crisis, in which financial institutions suffered mainly from:

– A focus on wholesale funding
– Large amounts of short-term, low-quality liquid assets (i.e., short-term, asset-liability mismatches)

The LR, in turn, measures the proportion of shareholders' equity to assets by dividing equity capital (*EC*) by assets (*A*) funding (Vazquez and Federico, 2012), which is expressed as Equation (3.2):

$$LR = \frac{EC}{A} \tag{3.2}$$

The BCBS introduced an LR in the 2010 Basel III reforms package, and this committee tested the efficacy of a minimum requirement of 3% for the LR from 1 January 2013 to 1

January 2017. This ratio was introduced to reduce the risk related to leverage reduction. The LR is also used to reinforce risk-based capital requirements. Because the NSFR and LR are long-term ratios whose purpose is to ensure banks' future stability, a higher NSFR and LR implies lower bank liquidity risk.

To evaluate the present results' robustness, a set of regressions were run using at least two alternative measures of bank liquidity and capital:

- For liquidity, the short-term funding ratio (STFR) was computed by dividing liabilities with less than a one-year residual maturity (i.e., deposits and short-term funding) by the total liabilities.
- For capital, the Basel Tier 1 CAR was used and defined as the ratio of Tier 1 regulatory capital to risk-weighted assets.

The STFR shows the weight of short-term resources in banks' total resources and facilitates a comparison of short-term assets to evaluate short-term or long-term funding liquidity. According to the BCBS, Tier 1 capital is the core capital that banks must hold in their reserves, which is the primary source of funds and a measure of banks' financial strength. The STFR expresses Tier 1 capital as a percentage of risk-weighted assets.

3.3.2.2. Data analysis: regression

Liquidity risk is the dependent variable measured by the NSFR. The regressions run include bank-level dependent variables, bank-specific independent variables, country variables, and time measured by the number of years between 2003 and 2015. These variables were used to detect different kinds of effects on banks' liquidity level, which were grouped into the following categories:

- Bank fixed effects
- Country fixed effects
- Year fixed effects

To gain a better understanding of liquidity's patterns and dynamics, the following variables were included:

- Bank fixed effects
    - TAs—a measure of bank size
    - LR—a measure of the proportion of shareholders' equity to assets calculated by dividing equity capital by assets

- Tier 1—a key regulatory measure of banks' financial health from the regulators' point of the view, which is a ratio found by dividing Tier 1 capital by risk-weighted assets
- CG—the difference between year *n + 1* and year *n* loans divided by year *n* loans
- NPL—the ratio of the amount of nonperforming loans in banks' loan portfolio to the total amount of outstanding loans these institutions hold
- Money market funding to total liabilities (MML)—the amount of funding received from other banks (i.e., deposits from banks) in the system divided by total liabilities
- ROE—a performance measure obtained by dividing net income by equity
- Cost-to-income ratio (CTI)—operational costs divided by banking products or operating revenues

– Country fixed effects
  - GDPG—a measure of country effects divided by bank liquidity, which was obtained from the World Bank website
  - Consumer price index (CPI)—a measure that examines the weighted average price of a basket of consumer goods and services based on data from the World Bank website
  - Monetary conditions—each country's money market rates (MMRs) obtained from the Bank for International Settlements website

– Year fixed effects
  - Crisis dummy—a variable that identifies the crisis period and includes 2007 to 2009
  - Trend—an additional variable created by using EViews software's trend function to identify time's influence

The most natural choice was to use a traditional ordinary least squares (OLS) regression model to process the panel data, but OLS results can be influenced by outliers and thus can reduce regressions' explanatory power. Thus, a fixed effects model was developed instead, and the new outputs showed that the regressions' explanatory power was increased significantly by using this model.

Regarding the bank fixed effects, TAs were used as a measure of bank size, while the LR functioned as a measure of the proportion of shareholders' equity to assets and the Tier 1 as a regulatory measure. In addition, the CG, NPL ratio, MML, and ROE were combined to form a performance measure—the CTI. Each country's GDPG, CPI, and MMRs were used as the banks' monetary conditions. The above variables were obtained and/or calculated using the data collected from the Bankscope database.

Regarding the country fixed effects, country-specific variables were included to represent each country's macroeconomic and monetary conditions, namely, the yearly average rate of GDPG, MMRs, and the CPI. The GDP and CPI data were obtained from the World Bank website, while the MMR data were taken from the Bank for International Settlement website. If the MMR information was not available on the latter website, each country's central bank website provided the missing data.

The fixed effects regression model is expressed by Equation (3.3):

$$Y_{it} = \beta_1 Bank\ Effects_{1,it} + \beta_2 Country\ Effects_{2,it} + \beta_3 Year\ Effects_{3,it} + \alpha_i + \mu_{it} \tag{3.3}$$

in which $i = 1, \dots n$ and $t = 1, \dots, T$. The α_i are entity-specific intercepts that capture heterogeneities across entities. An equivalent representation of this model can be formulated as Equation (3.4):

$$Y_{it} = \alpha + \beta_1 X_{1,it} + \cdots + \beta_k X_{k,it} + \delta_i + \mu_{it} \tag{3.4}$$

in which Y_{it} represents the dependent variable ratios (i.e., banks' liquidity ratio *i* at time *t*) and X_{it} is the explanatory variable vector of bank *i* at time *t*. In addition, α is the intercept and/or constant term, β_k is the coefficient that represents the explanatory variables' slope, μ_{it} is the random error term (i.e., scalar quantity), and δ_i represents the fixed effect. Subscript *i* stands for the cross section (i.e., banks), and *t* represents the time series dimension (i.e., years). The baseline Equation (3.5) thus is as follows:

$$NSFR_{it} = \alpha + \beta_1 TA_{1,it} + \beta_2 LR_{2,it} + \beta_3 TIER1_{3,it} + \beta_4 CG_{4,it} + \beta_5 NPL_{5,it} + \beta_6 MML_{6,it} + \beta_7 ROE_{7,it} + \beta_8 CTI_{8,it} + \beta_9 GDPG_{9,it} + \beta_{10} CPI_{10,it} + \beta_{11} MMR_{11,it} + \delta_i + \mu_{it} \tag{3.5}$$

To ensure consistency in the econometric analyses and confirm the results, two more models were created: robust regression and generalized method of moments (GMM). Robust regression provides an alternative to least squares regression that works well with less restrictive assumptions. The robust regression technique provides much better regression coefficient estimates when outliers are present in the data. Outliers violate the assumption of normally distributed residuals in least squares regression and tend to distort the least squares coefficients by having more influence than they should. These residuals are difficult to identify since they are much smaller than normal. Models involving various independent variables can often hide outliers from view in scatter plots. Robust regression down-weights the effect of outliers, and, as an iterative procedure, this technique seeks to identify outliers and minimize their impact on the coefficient estimates (Yaffee, 2002).

The GMM, in turn, is a statistical method that combines observed economic data with information on population moment conditions to produce estimates of the economic model's unknown parameters (Hall, 2005). GMM estimators combine the moment conditions with parameters for optimal results, which is the greatest advantage offered by this type of model. To verify short-term impacts, the present study also ran the regression using the STFR as the dependent variable and keeping the independent variables unchanged. In theory, the results should be the inverse of those obtained in the regression with the NSFR as the dependent variable because, while the second ratio refers to long-term liquidity stability, the STFR measures short-term liquidity.

3.3.2.3. Descriptive statistics

To understand more fully the banks' behavior regarding liquidity impacts, the values were aggregated into groups by geographical area and time periods. Segregation by geographical zones was carried out based on 10 options. Europe represents 20% of the sample with 126 banks, and the US and Canada cover 17% of the sample with 112 banks. Japan's banks are 12% of the sample with 73 institutions, while South America represents 8% with 50 banks, Africa 4% with 24 banks, Asia 24% with 156 banks, Eastern Europe and Russia 11% with 73 banks, Middle East 2% with 15 banks, and Australia 1% with 6 banks. Finally, Switzerland contains 1% of the sample with 5 banks.

The analyses considered all the final sample that had an average NSFR lower than one as this would put the ratio below the minimum value proposed by the Basel III regulations. Regarding the period under analysis, the 13 years were also separated into 3 periods: a first period from 2003 to 2006 (i.e., pre-crisis), second period from 2007 to 2009 (i.e., crisis), and third period from 2010 to 2015 (i.e., post-crisis) (Vazquez and Frederico, 2012; Bayer et al., 2017). This division facilitated the identification of the liquidity and capital indicators' behavior in relation to the three macroeconomic scenarios included in the range of years under study and the banks' behavior in reaction to systemic impacts.

Table 3.4 above summarizes the average NSFR and LR by geographic zones, revealing that Japan had the best averages and a lower standard deviation of stable funds and providing evidence of Japanese banks' greater stability and better quality during crises. After Japan comes the US, which, despite being the origin of the subprime mortgage crisis, had an average NSFR in the period under analysis of 0.96. However, the data show more volatility over time, which indicates this indicator was less stable since, unlike Japan, the NSFR shrank in the years prior to the crisis.

Eurozone banks appear in Table 3.4's middle column with an NSFR of 0.85 and a standard deviation of 0.17, which is the highest of the sample. These values show that the stability indicators of medium- and long-term funds did not comply with regulatory requirements, so the volatility was significant, confirming the EU banking system's instability. Swiss banks' results reveal quite similar behavior to Eurozone banks, with an NSFR of 0.78 and the second highest standard deviation at 0.16. This confirms the close relationship between Swiss banks and the remaining financial sector in terms of risk taking.

An analysis of Table 3.5 verified that, of the three periods in question, the one with the best NSFR average was the pre-crisis years, which also show the highest volatility. As expected, this ratio fell during the crisis but recovered in the post-crisis period, with the latter years appearing less volatile. These changes are the result of banks' adjusted balance sheets, and the trends reflect an increase in long-term liquidity in the post-crisis period in response to supervisory authorities' requirements.

In the 13-year period analyzed (see Figure 3.1), the overall average NSFR was consistent with the global financial environment. Between 2003 and 2007, a downward trend can be observed in this medium- and long-term stability indicator, reflecting the institutions' need for stability. The lowest value was reached in 2008 at the peak of the subprime mortgage crisis. Figure 3.1 shows that, in the years after 2008, the NSFR recovered due to the regulatory authorities' more rigorous requirements, the banks' restraint when granting new credit, and the adequate resources bank management ensured were present in applications.

The NSFR was also analyzed from a geographical perspective (see Figure 3.2). At the top of the graph, Japan presents the highest and most stable values for the 13-year period covered by this research. Notably, a slight decline occurred in 2008 that coincided with the subprime mortgage crisis. The lowest NSFR values were found for Eastern European countries and Russia, Australia, and Switzerland.

The evolution of this indicator in the US, where the subprime crisis arose, shows that the NSFR was already entering a downward trend that reached its minimum value in 2008 and that reflected an increase in banks' assets without effective monitoring of their resources. In the following years, between 2008 and 2013, American banks' NSFR rose as a result of restrictions imposed due to the new regulatory recommendations made after the crisis started, which resulted in limits on new credit concessions. Eurozone banks' behavior was similar to that of American banks, much of which was a result of their close relationship. The results reveal a downward trend in the NSFR from 2004 onward, with its lowest value reached in 2008, and a recovery in subsequent years reflecting a growth trend.

Regarding South America and Asia's banks, both showed not only a tendency to experience a reduction in the NSFR but also a certain indifference to the subprime mortgage crisis's effects from the beginning of the period under review (i.e., 2003). This behavior can be explained by the commercial relationship between these institutions and those of the US and Europe. Unlike the North American and European markets, the South America and Asia markets traditionally do not consider mortgage loans to be a primary target, which is another reason why the crisis did not affect them. Non-standard behavior also appears in Switzerland's banks but tending in the opposite direction. Swiss banks had some of the lowest NSFRs. The marked decrease in 2012 was clearly related to the sovereign debt crisis.

Figure 3.3 presents the timeline for the NSFR's evolution between 2003 and 2015. Unsurprisingly, this indicator's smallest value was recorded in 2008, namely, the peak of the subprime mortgage crisis. A more surprising development was that the NSFR shrank beginning with 2003, possibly indicating that banks were alerted to the need to manage their long-term assets and liabilities better. In the years following the crisis, the NSFR recovered but remained stable at levels similar to those recorded in 2006 and far from the 2003 peak levels. The reason for this was a reduction in the differences between short-term assets and liabilities and restrictions on new credit, which increased the short-term capital available and, consequently, liquidity instead of strengthening banks' long-term stable funds.

Banks thus appear to be the economy's feeders due to credit granted to businesses and individuals. The transformation of maturities maintains these institutions viable. However, in the future, banks also need to (1) guarantee customer deposits' stability, (2) diversify into assets that require a smaller volume of stable funds, and (3) generate debt or capital issues whose maturity is more than one year.

The NSFR results can be interpreted as indicating that, while regulatory recommendations suggest the ideal is a value greater than one, the greater this indicator's value, the lower banks' liquidity is. In addition, the higher the long-term stable funds are, the lower the liquidity risk becomes. One of the financial crisis's causes was excessive leverage on and off the balance sheet in the banking system. Banks became increasingly highly leveraged, so the deleveraging process at the height of the crisis created a vicious cycle of losses and reduced credit's availability to the economy.

Overall, the LR in the 10 geographical areas analyzed (see Table 3.4 above) was characterized by significant differences between the banks of the US, South America, Eastern Europe and Russia, Africa, and Switzerland, with the latter showing the best average values. Switzerland also had the highest standard deviation, which indicates financial instability. The next highest was American banks with a standard deviation of 8%, which reflects how severely these banks were affected by the crisis. Japanese banks had the lowest LR, but they were also the second lowest in volatility, which confirms the Japanese financial system's stability.

The LR's higher stability compared with the NSFR can be explained by the way that financial systems—based on Basel I and II—have historically emphasized capital requirements more than liquidity requirements. This policy was reversed by the crisis and Basel III's application. This finding is apparently confirmed by the results shown in Figure 3.4, namely, similar LR values in the pre-crisis, crisis, and post-crisis periods.

The LR's overall global average reveals growth between 2003 and 2006, which is due to the regulators' insistence on compliance with capital ratio guidelines. When the financial system entered the recent crisis, the LR fell sharply between 2006 and 2008 because of capital usage and liquidity requirements. In the following years, this ratio recovered without, however, reaching the pre-crisis figures. In Figure 3.4 above, this evolution can be verified for the 13-year period analyzed. As can be seen from Figures 3.5 and 3.6, a regular pattern of a shrinking LR was present from the beginning in 2003 until the end in 2015.

Once again, Japan appears to be a market in which banks maintain across time the most stable values regarding the BCBS's 3% recommendation. Other Asian banks' LR increased from 8% to almost 10% in the 13 years under analysis, with the most significant variations occurring in the years following the crisis. Eurozone banks kept their average LR stable with only a slight fall in value in the years after the crisis and then a return to previous levels. The biggest impact can be seen on Switzerland's banks, which experienced a continuous decrease in their LR between 2003 and 2012 and only a slight recovery at the end. Despite this drop, Swiss banks presented LR values above the BCBS benchmark, which implies that the variation recorded was the result of adjustments in these institutions' accounting information and which may thus indicate increased liquidity. Despite a lower variation than that shown by Swiss banks, American banks also registered a reduced LR for the period under study. The reason can be said to be the same as for Swiss institutions.

Similar to the NSFR, the LR's evolution reveals that, the greater its value, the lower the banks' liquidity was. The analyses verified that, in the years before the subprime mortgage crisis, the banks had a high LR that shrank during the crisis and grew in the post-crisis period, although values were lower than in the pre-crisis period.

The STFR was used as the liquidity indicator, that is, the relationship between liabilities with less than one-year residual maturity (i.e., deposits and short-term funding) and total liabilities. The STFR shows the weight of short-term resources in total resources and facilitates an evaluation of short-term or long-term funding liquidity. Figure 3.7 confirms the existence of persistent stability across geographical zones in short-term liquidity, which supports the conclusion that client deposits' weight in total liabilities stayed stable throughout the period analyzed. Thus, the crisis cannot be attributed with shaping how banks obtained their resources but rather how these institutions applied their resources.

As was also observed for the NSFR and LR, the STFR's behavior in Switzerland differed from the remaining countries. In the same period (i.e., 2012), Switzerland experienced a sharp fall in this ratio, indicating the banking system's reflex in response to the sovereign debt crisis. The results shown in Figure 3.8 are again similar to those observed for the NSFR and LR, in which a decrease in the STFR occurred between 2003 and 2007, with the lowest value recorded in 2008.

3.3.3. Variables

The BCBS was created to ensure standard regulations and protect the financial system. With the global financial crisis of 2007–2009, the BCBS decided to strengthen banks' soundness by introducing new regulations commonly denoted as Basel III. The measures enacted based on these regulations included three new standard measures as follows:

- CAR—a measure constraining banks' ability to leverage their balance sheets, which is perhaps countercyclical in nature (BCBS, 2010a) especially given these institutions' proclivity for leverage
- Liquidity coverage ratio (LCR)—essentially a measure of banks' exposure to short-run liquidity risk (BCBS, 2013)
- NSFR—a measure of maturity mismatch aimed at promoting more medium- and long-term funding (BCBS, 2010)

The banks' balance sheets and profit and loss statements were obtained from Bankscope, which facilitated the calculation of the above ratios in order to analyze liquidity risk. The NSFR was calculated using Equation (3.1), with the STFR as a proxy for the LCR, and the LR was estimated with Equation (3.2) based on the data for the 645 listed commercial banks in the final sample and the period from 2003 to 2015.

As discussed in section 3.2.2 above, the independent variables included TAs as a measure of bank size, the LR as a measure of the proportion of shareholders' equity to assets, and the Tier 1 as a regulatory measure. In addition, the CG, NPL ratio, MML, and ROE were combined to form a performance measure—the CTI. For the country fixed effects, the GDPG, CPI, and MMRs were used as each country's monetary conditions.

To smooth the variables and reduce outliers, tests were performed with transformations in the variables, such as the application of the mean and/or variance or mathematical functions. After analyzing the transformations' results and applying various regression models, the logarithmic function (*LN*) was chosen for the data processing phase (Trigueiros, 1995; Robert, 2004). Dependent variables underwent the transformation shown in Equation (3.6):

$$NSFR\_LN_{it} = LN(NSFR + 1 - \min(NSFR)) \tag{3.6}$$

Independent variables (*ID*) were subjected to the transformation expressed as Equation (3.7):

$$ID\_LN_{it} = LN(ID + 1 - \min(ID)) \tag{3.7}$$

With these transformed variables, the final regression model assumed the structure represented by Equation (3.8):

$$\begin{aligned} NSFR\_LN_{it} = {} & \alpha + \beta_1 TA\_LN_{1,it} + \beta_2 LR\_LN_{\_2,it} + \beta_3 TIER1\_LN_{3,it} \\ & + \beta_4 CG\_LN_{4,it} + \beta_5 NPL\_LN_{5,it} + \beta_6 MML\_LN_{6,it} \\ & + \beta_7 ROE\_LN_{7,it} + \beta_8 CTI\_LN_{8,it} + \beta_9 GDPG\_LN_{9,it} \\ & + \beta_{10} CPI\_LN_{10,it} + \beta_{11} MMR\_LN_{11,it} + \delta_i + \mu_{it} \end{aligned} \tag{3.8}$$

3.4. Results

The banking business and money market affect bank liquidity's development. This market helps banks manage shortages in or excess liquidity, but the market's structure, instruments' variations, and innovation, regulation, and liquidity conditions influence the money market's development. Liquidity in financial systems determines central banks' monetary policy decisions about how to manage inflation and sustain economic growth. The interbank lending market is an over-the-counter market in which banks can borrow money from or lend money to other banks to manage their liquidity in the short term through daily liquidity gaps.

Regression analysis of panel data involves a longitudinal data structure and parameter estimation in regressions with cross-sectional data. This technique involves applying the least squares method through OLS. Data panel regression is based on a combination of cross-sectional data and time series, in which the same cross-sectional unit is measured at different times and the panel data is from the same individuals observed in specific periods. This study included *T* periods and *N* number of banks, so the panel data had a total observation units of *N x T*.

To underline specific bank characteristics and macro-economic environment factors' impacts on bank liquidity indicators, the NSFR was calculated for the sample of banks. OLS regression analysis was conducted, and the results were verifying by applying robust regression and GMM models.

Data using income, revenue, CG, GDPG, or CPI usually presents negative values that cannot be used with logarithm functions. The log function is one of the most useful transformations in data analysis, which is used to normalize data and perform variance-stabilizing transformations. In addition, this function is useful as a way to reduce outliers' influence on observations involving dependent and/or independent variables. For this reason, the variables were transformed using the normal logarithm presented previously (see Equations [3.7] to [3.18]).

3.4.1. Diagnostic tests of regression model

3.4.1.1. Normality test

To verify the existence of normality, the Jarque-Bera test of normality was run on the data. When residual u_{it} are distributed normally, the Jarque-Bera test statistic should be lower than 5.99, and it should have a p-value over 0.05 (Brooks, 2008). This test is performed under the null hypothesis of normal distribution, and the alternative hypothesis would be that the data are not distributed normally. The results shown in Figure 3.9 for the variable NSFR_LN with a GMM regression confirm that the null hypothesis can be accepted. However, linear panel data regression does not require normally distributed variables (Startz, 2015). For baseline values, normality does not need to be verified.

3.4.1.2. Multicollinearity test

To avoid any problems with multicollinearity, a Pearson correlation analysis was conducted. The baseline estimation's results are presented in Table 3.6 for the original variables and in Table 3.7 for the log-normal transformed data, which show that no multicollinearity exists between the independent variables. A problem with multicollinearity exists when the correlation between two explanatory variables is more than 0.80 or 0.85 (Gujarati and Porter, 2011; Henseler et al., 2015).

3.4.1.3. Autocorrelation test

Autocorrelation describes any correlation between a random variable and itself in the past. Based on the first regression model, Table 3.8's information confirms the presence of autocorrelation since the Durbin-Watson statistic is 0.4118. As a result, a first-order and second-order autoregressive variable were incorporated into the model to eliminate any autocorrelation because the problem was an error function but it lagged until the second period. The adjusted model's results in Tables 3.8 and 3.9 include a Durbin-Watson statistic of around 2—an acceptable value in terms of the null hypothesis.

3.4.1.4. Heteroscedasticity test

Heteroscedasticity is not considered a real problem when working with panel data since panel data is itself a way to solve heteroscedasticity. To eliminate any doubt about heteroscedasticity, the log of all the panel data can be used to verify whether the results with and without a logarithmic data set are quite close to each other. If the errors are not homoscedastic, the OLS estimator is still consistent but no longer optimal. However, the OLS can still be used if White or robust standard errors are applied (Wooldridge, 2003; Heij et al., 2004; Greene, 2008).

3.4.2. Model specification test: fixed versus random effects

Because this study's variables cover multiple banks in different periods, data panel and cross sectional statistical analyses were conducted. In addition, the Hausman test was performed to differentiate between random effects and fixed effects models of the panel data. The fixed effects model under the null hypothesis was selected due to its efficiency.

The latter model assumes that differences between individual banks (i.e., a cross section) can be accommodated via intercepts. To estimate this model based on the panel data, the dummy variable technique was used to capture the differences between intercepting banks. A choice needed to be made of which regression model to use, namely, a common effects, fixed effects, or random effects model, so hypothesis testing was conducted. Various tests can be used to select the most appropriate model, such as the:

- Chow test—determines whether a common effects or fixed effects model is the most appropriate for estimating panel data by showing if the hypothesis is one of two options:

- H_0: If $p > 0.05$, the common effects model is best.
- H_1: If $p < 0.05$, the fixed effects model is chosen.

– Hausman test—confirms whether a fixed effects or random effects model is the most appropriate to estimate panel data by revealing if the hypothesis is one of two options:
  - H_0: If $p > 0.05$, the random effects model is the most suitable.
  - H_1: If $p < 0.05$, the fixed effect model is the best.

– Lagrange multiplier—determines whether a random effects model is better than a common effects model by indicating if the hypothesis is one of two options:
  - H_0: If $p > 0.05$, the common effects model is chosen.
  - H_1: If $p < 0.05$, the random effects model is the most appropriate.

If the Chow test shows that H_1 is valid, a fixed effects model is used. The next step is to run the Hausman test to select between a fixed effects or random effects model. However, if the Chow test confirms H_0 is sound, a common effects model is used. Finally, the Lagrange multiplier can determine if a random effects model is the best option.

3.4.3. Model estimation results

This section presents the results of the estimation model used in this study. The final model was a GMM fixed effects estimation model with a White diagonal. This model was applied to analyze the dependent variable at a global level using the data on 645 banks from 2003 to 2015. Table 3.9 contains the model's results for the dependent variable NSFR and the 11 independent variables designated as determinants to examine long-term liquidity. Of these 11 variables, 8 are firm-specific variables and 3 are macro-economic variables.

Linear regression also involves analyzing the existence of relationship between variables, but this study further sought to determine which variables depend on other variables. In the regression model, the *R*-squared (R^2) shows what percentage of the variables' total variation is explained by the model. The adjusted R^2 measures the net increase of R^2 when a new regressor is included. The Prob(*F*-statistic) is the probability of committing a type I error. This statistic is calculated using Snedecor's *F* distribution.

As shown in Table 3.9 above, the GMM regression presents an R^2 of 99% with a *F*-statistic of 0, which confirms that the model developed has good predictive power. The model's *F*-statistic has a significance level of 1%, which means that all the explanatory variables together can influence the NSFR strongly (i.e., a 99% R^2).

The interpretation of coefficients estimated by multiple linear regression depends on the nature of the model's variables. As a GMM model of time series (i.e., in logarithm) was used in this research, the coefficients represent long-term liquidity's elasticity. Thus, given a 1% increase in the independent coefficient or variable, the NSFR will be influenced by the same percentage of the coefficient. To verify this relationship, the level of probability should be checked. The *p*-value for each variable tests the null hypothesis that the coefficient is equal to zero (i.e., no effect). A low *p*-value (< 0.05) indicates that the null hypothesis can be rejected. In other words, a predictor with a low *p*-value is likely to be a significant addition to the model because changes in the predictor's value are related to changes in the dependent variable. In contrast, a larger (i.e., insignificant) *p*-value suggests that changes in the predictor are not associated with changes in the response variable.

In this study, the NSFR measures the proportion of long-term illiquid assets funded with liabilities that are either long term or deemed stable. The NSFR is a long-term ratio that ensures banks' future stability, so a higher NSFR implies lower bank liquidity risk. The present results indicate that bank size (TA_LN) has a positive, significant impact on banks' long-term liquidity measured by the NSFR. The regression model's results indicate that a 1% increase in TAs—with the remaining factors kept constant—will cause long-term liquidity to increase 4% (see Table 3.9 above).

Sheefeni and Nyambe (2016) define liquidity as banks' ability to fund increasing assets and meet their obligations on time. The BCSB (2008) characterizes liquidity as these institutions' ability to finance their assets and fulfill their obligations without incurring losses. These definitions are consistent with the current study's findings but different from Bonfim and Kim (2011) and Vodová's (2012) results.

In the present research, the LR measures capital adequacy as the ratio of shareholders' equity to assets by dividing equity capital by assets. In Table 3.9 above, this variable's importance is indicated by a positive impact of 41% on the NSFR for each 1% change in the LR. The LR and NSFR represent both structural and long-term regulatory requirements because banks with strong capital are more solid institutions that have better liquidity performance and high levels of capital give banks more room for liquidity. Mazreku et al.'s (2019) study confirmed that capital adequacy is a factor that significantly affects bank liquidity. In addition, Melese (2015) asserts that capital adequacy has statistically significant positive impacts on commercial banks' liquidity.

CG is another significant variable affecting bank liquidity, but this measure only has a small negative impact on the NSFR (i.e., 1.5%). Given a variation of 1% in CG, the NSFR will decrease by 1.5%. The CG process implies assets' consumption (e.g., liquidity depletion), which is one possible explanation for this negative relationship. Because the NSFR is a long-term ratio, it also depends on credit duration's impact on the dependent variables. Melese's (2015) research found that loan growth has a negative but insignificant effect on bank liquidity. Alessi (2018) further reports that CG is related to systemic risks and financial stability so it can become more prominent in systemic banking crises.

The present study used the NPL ratio to verify asset quality's effect on long-term liquidity. If the assets are good quality, liquidity will increase because banks' ability to fulfill their obligations will increase as well. In theory, an increase in NPLs in these institutions' portfolios is a significant financial concern in the banking sector. According to Mazreku et al. (2019), more nonperforming loans reduce the level of banks' liquid assets. However, the current research found that NPLs have a significant positive impact on long-term liquidity, which means an increase of 1% in NPLs will increase the NSFR by 12%. A possible explanation for this is that more NPLs will increase capital requirements and that, as capital increases, long-term funds will also increase, with the NSFR following the same trend.

MML is another specific independent bank variable chosen for this model. The MML was calculated by dividing the amount of funding received by a bank from other banks in the system by the first institution's total liabilities, with attention given to the weight of short-term funding and total liabilities. The results reveal that short-term funding has a significative negative impact on the NSFR so that, for a 1% change in MML, long-term liquidity experiences a 50% negative impact. This finding is quite rational because, if short-term funding is increased, the proportion of more stable funds will decrease in the total capital structure and thus the NSFR falls as well. According Vazquez and Frederico (2012), "stronger structural liquidity is associated with lower reliance on short-term funding—and with money market funding—and positively correlated with deposit funding." This observation was confirmed by the present study's results.

ROE was used to measure bank profitability. As shown by Table 3.9 above, ROE has a small impact on the NSFR. For each 1% of change in ROE, the NSFR will change only 0.5%. Shen et al. (2018) analyzed the ROA and ROE for banks from the US, Canada, France, Taiwan, the United Kingdom, Germany, Japan, Luxembourg, Italy, the Netherlands, Switzerland, and Australia. The cited authors' concluded that liquidity risk is negatively related to these performance indicators. Roman's (2015) study produced similar results regarding the relationship between liquidity and ROE. In addition, Bonfim and Kim (2012) examined

European and North American banks' liquidity, finding that, when these institutions adopt strategies to improve profitability, they become more vulnerable to funding liquidity risk.

The CTI was used to assess bank efficiency in the current research. This ratio is a key financial measure that is particularly important when evaluating banks because it shows companies' costs in relation to their income. The variable CTI_LN has a positive and significant impact on long-term liquidity so that, for each 1% change in CTI, the NSFR will rise 2%. Bonfim and Kim (2012) assert that banks with better efficiency and lower CTIs tend to generate less liquidity and have a larger NSFR.

The current study's macroeconomic variables included the GDPG as a measure of country-level effects on bank liquidity. Trenca et al. (2015) investigated the macroeconomic determinants of 40 commercial banks in Croatia, Greece, Italy, Portugal, Spain, and Cyprus from 2005 to 2011 and found that GDPs have a statistically significant negative impact on bank liquidity. Roulet (2011) also verified that liquidity has a significant positive relationship with GDPs. The current research, in turn, showed that GDPs have a significant negative impact on long-term liquidity, which means that, when the GPD changes 1%, the NSFR shrinks less than 1.5%. This finding is consistent with the literature because long-term bank liquidity decreases with economic growth due to the higher level of investment opportunities during economic expansion, causing banks to increase their profit margins and decrease their liquidity by offering more loans.

3.4.4. Robustness tests

To verify the results' consistency, two kind of robustness tests were conducted. The first involved changing the dependent variables in terms of the STFR and Tier 1. The second test was to add two additional variables to the NSFR's estimation: crisis period and trend. The STFR is a liquidity measure computed by dividing liabilities with less than a one-year residual maturity by total liabilities in order to determine banks' short-term obligations.

According to Basel Tier 1 guidelines, CAR is the ratio of Tier 1 regulatory capital to risk-weighted assets. The BCSB defines Tier 1 capital as the core capital that banks must hold in their reserves, these institutions' primary source of funds, and a measure of banks' financial strength.

Additional variables included a dummy variable for the crisis period, in which 1 is the crisis period from 2007 to 2009 and the remaining years are 0. A trend variable generated by EViews software was also introduced as part of the time analysis.

3.4.4.1. STFR and Tier 1 tests

To verify the robustness of the results, a new set of parallel regressions were estimated using two alternative measures of bank liquidity based on the STFR and Tier 1 to measure capital. The three models are compared in Table 3.10, which presents the baseline GMM model and two additional parallel regressions' results. For both additional estimation models, the adjusted R^2 has values identical to the NSFR regression, which confirms the good predictive power of the two additional regressions and the analyzed data's consistency.

The independent variables TAs, LR, CG, NPLs, ROE, CTI, and GDPG present the same sign for the NSFR and STFR coefficients regarding their relationships' significance. The LR presents a lower coefficient for the STFR compared with the NSFR, which is consistent with the literature since the LR is a measure of stability and, therefore, more closely related to long-term funding. The MML variable has a significant positive relationship with the STFR but a significant negative relationship with the NSFR, which is valid because money market funding leads to short-term requirements, thereby confirming again the estimation models' consistency.

Tier 1 as a regulatory requirement presents the same behavior as the NSFR for TAs, LR, CG, NPLs, ROE, and GDPG. Notably, NPLs have a higher explanation power compared to the NSFR (42% vs. 12%), which comes from Tier 1's greater sensitivity as a capital requirements ratio because an increase in NPLs consumes additional capital. This pattern is consistent with the literature, confirming the models' good predictive power. Money market funding has a significant positive relationship with Tier 1 unlike the NSFR, which has a significant negative connection. Once again, because Tier 1 shows capital requirements' short-term constraints, Tier 1 affects the dependent variable quite broadly, which is consistent with the estimation models. In addition, all three macroeconomic variables have a higher predictive power than Tier 1 because these variables represent regulatory requirements. However, only the macroeconomic variable of GDPG significantly influences the NSFR.

3.4.4.2. Additional variables tests

Table 3.11 compares the baseline estimation model to a parallel model that included the two additional variables of crisis and trend. Similar to the baseline model, the additional model has good predictive power with an adjusted R^2 of 99%, and the coefficient relationships within the two models are consistent.

Regarding the additional variables, crisis presents a significant positive connection, which confirms that the crisis had an impact on long-term funding requirements. The second additional variable, trend, was introduced to clarify the impacts over the 13-year period on the NSFR. The results verify the existence of a significant negative relationship.

Table 3.12 shows the robustness estimation by period for the 13 years of data on the sample of 645 commercial banks, namely, the pre-crisis, crisis, and post-crisis periods. An analysis was conducted to understand the determinants' impacts on the NSFR by period. For all the periods, the adjusted R^2 presents values that confirm the regression's predictive power.

For the overall period, the significant independent variables considered were TAs, LR, Tier 1, NPLs, money market funding, ROE, CTI, GDPG, CPI, and MMRs. All these variables have a significant impact on long-term stable funds, but the LR has an effect of 100%, money market funding 60%, CPI 23%, CTI 18%, GDPG 16%, and NPLs 12%.

The pre-crisis period's adjusted R^2 compared with the remaining periods has a higher value of 81%. In contrast to the overall period in question, only ROE is not significant in the first period, and the other variables still explain the model. The NPLs in this period have an impact of 43%, which means that, for each change of 1%, the effect on the NSFR will be 43%. This variation could be explained by stable funds' additional consumption of capital.

For the crisis period, the model's predictive power is lower, with an adjusted R^2 of 61%. The main changes are the exclusion of 2 of the 3 country variables since CPI and MMRs are no longer significant. The results quite importantly confirm money market funding's significance to the NSFR because the former variable has a significant negative impact in all the periods analyzed and the coefficient has a stable value. In addition, the NPLs have a positive coefficient of 24%. The LR also proved to be an important determinant of the NSFR, showing stable values for all the periods, with an increase between the pre-crisis and crisis periods of up to 97% for each 1% of change.

For the post-crisis period, the results verify important changes when compared with the other periods. Tier 1, CG, NPLs, and ROE are no longer significant independent variables. For the ones that continue to explain the model, all the coefficients have an increased impact on the dependent variable, although LR, MMRs, and money market funding have the highest values. As a result of the crisis, the authorities promoted the application of new requirements to strengthen financial institutions' stable funds, which explains these variables' importance to the liquidity risk measure. Government financial aid further increased levels of liquidity in the financial system, highlighting money market funding and MMRs' significant role in the model.

3.5. Conclusions

Besides the analyses performed and the above findings, the present results contribute to the creation of a long data series related to worldwide commercial banks as the sample created for this study systematized data on 645 commercial banks over 13 years. In addition, a set of indispensable ratios and indicators' values were calculated to understand better—and improve knowledge about—banks' behavior during the period under analysis, which included the biggest financial crisis of the last 100 years. Compared to prior studies, this research thus covered a significant number of commercial banks over a broad period including three sub-periods: the pre-crisis, crisis, and post-crisis periods.

This comprehensive coverage facilitated an assessment of banks' reactions and behaviors regarding long-term liquidity in three different scenarios and thus enabled inferences about the factors and variables that have an impact not only on liquidity but also capital through the application of Tier 1. The findings reported in this paper provide extensive support for banks and authorities' potential initiatives in the areas of structural liquidity and leverage and permit conclusions to be drawn about these areas' complementary nature. This study further investigated the determinants of long-term liquidity risk and analyzed which variables affect the new indicators proposed by the BCSB.

The estimation model results highlight that bank size, capitalization, credit improvement, asset quality, funding sources, profitability, and efficiency can influence long-term liquidity risk management. Regarding country variables, the GDPG has an impact on long-term liquidity, so internal factors have a greater effect on bank liquidity than macroeconomic factors do. When the liquidity measure was changed to the STFR, the results were consistent and similar to the findings obtained when the NSFR was used, which also indicates a relationship between the two measures.

This research further verified that well capitalized banks have a better long-term liquidity that translates into more stable institutions better able to lead other banks during crisis periods—and to survive them. These findings are related to the maintenance of stable bank funds. Another significant result is evidence of NPLs' positive impact on long-term funding ratios, which can be explained by bank reserves in the form of provisions and be created by an increase in bad loans that weaken long-term stability.

In the opposite direction, the results confirm the money market's significant but negative impact on liabilities, which is reflected by long-term funding ratios. This effect implies that an increase in short-term funding from other banks reduces the NSFR because this funding represents short-term liquidity, which institutions use to finance their activities. This tendency was confirmed by the proposed model's behavior.

The analysis of the financial crisis variable in Table 3.11 above verified that this factor affects the NSFR only at a low level. This result may be related to how, in crisis periods, banks focus more on managing their liquidity on a short-term than long-term basis. Overall, the crisis alone is not a sufficiently significant variable in terms of affecting long-term liquidity. The greatest impact on the NSFR is that of other variables that result from crisis situations and indirectly affect the long-term funding ratio, such as banks' capitalization, asset quality, or funding.

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Table 3.1. Stylized balance sheet and weights to compute NSFR

Assets	Wi	Liabilities & Equity	Wi
Loans 100%	100%	Deposits & short term funding	
Gross loans		Total customer deposits	80%
Less: reserves for impaired loans / NPLs		Deposits from banks	0%
Other Earning Assets		Other deposits and short-term borrowings	0%
Other Earning Assets		Other interest bearing liabilities	
Loans and advances to banks	80%	Derivatives	0%
Derivatives	35%	Trading liabilities	0%
Other securities	35%	Long term funding	100%
Remaining earning assets	35%	Other (non-interest bearing)	100%
		Loan Loss Reserves	100%
Fixed Assets	100%	Other Reserves	100%
Non-Earning Assets	100%		
		Equity	100%
TOTAL ASSETS		**TOTAL LIABILITIES & EQUITY**	

Table 3.2. Banks by country

Country	Number of banks
Australia	6
Austria	5
Azerbaijan	1
Bangladesh	27
Botswana	3
Brazil	19
Bulgaria	3
Canada	9
Chile	6
China	17
Colombia	9
Côte d'Ivoire	3
Croatia	12
Czech Republic	1
Denmark	29
Finland	2
France	8
Georgia	3
Germany	9
Hungary	1
India	40
Indonesia	28
Ireland	1
Israel	7
Italy	13
Japan	78
Kazakhstan	10
Korea (Republic of)	4
Lithuania	2
Malaysia	3
Malta	2
Mauritius	2
Morocco	5
Netherlands	1
Paraguay	3
Peru	13
Philippines	12
Poland	13
Portugal	2
Romania	3
Russian Federation	47
Saudi Arabia	8
Singapore	3
Slovakia	5
Slovenia	3
South Africa	1
Spain	7
Sweden	2
Switzerland	5
Taiwan, Province of China[a]	12
Thailand	10
Tunisia	10
Turkey	12
United Kingdom of Great Britain and Northern Ireland	2
United States of America	103
Total	**645**

Table 3.3. Banks by geographical zone

Geographical Zone	Number of Banks
Asia	156
Europe	126
USA and Canada	112
Japan	78
Eastern Europe and Russia	73
South America	50
Africa	24
Middle East	15
Australia	6
Switzerland	5

Table 3.4. Geographical analysis

	NSFR		NSFR_LN		LR		LR_LN	
	Average	**Std**	**Average**	**Std**	**Average**	**Std**	**Average**	**Std**
Europe	0.8523	0.1766	0.5323	0.2245	0.0976	0.0623	0.0798	0.0580
USA and Canada	0.9637	0.1635	0.5468	0.2702	0.1234	0.0852	0.0927	0.0751
Japan	0.9639	0.0559	0.6732	0.0414	0.0551	0.0201	0.0533	0.0186
South America	0.8212	0.1695	0.5029	0.2309	0.1174	0.0620	0.0926	0.0617
Africa	0.8905	0.1345	0.5915	0.1748	0.1021	0.0464	0.0899	0.0463
Asia	0.9128	0.1113	0.5556	0.2319	0.0835	0.0410	0.0683	0.0439
East Europe	0.7911	0.1305	0.5092	0.2027	0.1210	0.0655	0.0996	0.0622
Middle East	0.9245	0.0532	0.6543	0.0277	0.0973	0.0420	0.0921	0.0378
Australia	0.7777	0.0607	0.5748	0.0342	0.0623	0.0086	0.0604	0.0081
Switzerland	0.7895	0.1676	0.4177	0.2723	0.1136	0.1050	0.0749	0.0888
Global	**0.8929**	**0.1500**	**0.5571**	**0.2211**	**0.0966**	**0.0621**	**0.0797**	**0.0006**

Table 3.5. Time analysis

	NSFR		NSFR_LN		LR		LR_LN	
	Average	Std	Average	Std	Average	Std	Average	Std
Pre_Crisis	0.9035	0.1688	0.5147	0.2664	0.1016	0.0815	0.9111	0.4562
Crisis	0.8739	0.1540	0.5789	0.1855	0.0948	0.0642	1.0294	0.3085
Pos_Crisis	0.8930	0.1377	0.5745	0.1993	0.0945	0.0453	1.0143	0.3380
Global	**0.8929**	**0.1500**	**0.5571**	**0.2211**	**0.0966**	**0.0621**	**0.0797**	**0.0006**

Table 3.6. Correlation matrix for baseline variables

		NSFR	TA	LR	TIER1	CG	NPL	MML	ROE	CTI	GDPG	CPI	MMR
NSFR	Correlation	1											
TA	Correlation	-0.195833**	1										
LR	Correlation	0.15921**	-0.210122**	1									
TIER1	Correlation	0.136985**	-0.060211**	0.541135**	1								
CG	Correlation	-0.002572	-0.004181	0.015213	-0.02926	1							
NPL	Correlation	-0.018329	-0.024361	0.052377**	0.01092	0.376856**	1						
MML	Correlation	-0.587882**	0.16421**	0.00145	0.012243	0.007886	0.030426	1					
ROE	Correlation	0.002566	0.028673	-0.004198	-0.000379	-0.000268	-0.011979	0.011273	1				
CTI	Correlation	0.011285	-0.001041	-0.002136	0.024228	0.016981	-0.008062	-0.078264**	-0.112323**	1			
GDPG	Correlation	0.016851	0.032703*	0.002415	-0.032578*	0.0208	-0.013617	0.024533	0.113507**	-0.069922**	1		
CPI	Correlation	-0.062876**	-0.132709**	0.160462**	0.008728	0.030655*	0.057869**	0.05043**	0.048674**	-0.055702**	0.405738**	1	
MMR	Correlation	-0.109403**	-0.05904**	0.180866**	0.072468**	0.034601*	0.055705**	0.147663**	0.072377**	-0.05369**	0.311757**	0.675185**	1

**Correlation is significant at the 0.01 level (2-tailed). *Correlation is significant at the 0.05 level (2-tailed).
This table shows the results of the bivariate test, Pearson Product Moment.

Table 3.7. Correlation matrix for transformed log-normal variables

		NSFR_LN	TA_LN	LR_LN	TIER1_LN	CG_LN	NPL_LN	MML_LN	ROE_LN	CTI_LN	GDPG_LN	CPI_LN	MMR_LN
NSFR_LN	Correlation	1											
TA_LN	Correlation	0.850485**	1										
LR_LN	Correlation	0.523814**	0.31884**	1									
TIER1_LN	Correlation	0.405695**	0.402775**	0.276011**	1								
CG_LN	Correlation	0.233468**	0.215068**	0.231331**	0.120098**	1							
NPL_LN	Correlation	0.20867**	0.179275**	0.190636**	0.021924**	0.035317**	1						
MML_LN	Correlation	0.045005**	0.304174**	0.151778**	0.080382**	0.103761**	0.145328**	1					
ROE_LN	Correlation	0.150882**	0.195885**	0.080762**	0.046436**	0.130097**	-0.033461**	0.071632**	1				
CTI_LN	Correlation	0.578847**	0.454344**	0.437058**	0.222059**	0.176665**	0.198858**	0.03129**	-0.141139**	1			
GDPG_LN	Correlation	-0.07105**	-0.045117**	-0.012293	-0.071805**	0.203962**	-0.029296**	0.032764**	0.210085**	-0.145965**	1		
CPI_LN	Correlation	-0.07875**	-0.09097**	0.101092**	-0.079547**	0.09481**	0.17008**	0.06056**	0.122744**	-0.071169**	0.357863**	1	
MMR_LN	Correlation	-0.105855**	-0.069641**	0.079331**	-0.018971	0.092646**	0.142791**	0.120616**	0.135899**	-0.083704**	0.293084**	0.740371**	1

**Correlation is significant at the 0.01 level (2-tailed). *Correlation is significant at the 0.05 level (2-tailed).
This table shows the results of the bivariate test, Pearson Product Moment.

Table 3.8. Bank liquidity determinants with baseline variables measured by NSFR

	OriginalPanel Least Squares		OriginalPanel Least Squares With Fixed Effects		OriginalPanel Least Squares With Fixed Effects and White Diagonal		OriginalPanel Least Squares With Fixed Effects, White Diagonal and AR Coefficients	
Variable	**Coefficient**	**Prob.**	**Coefficient**	**Prob.**	**Coefficient**	**Prob.**	**Coefficient**	**Prob.**
C			0.9178	0.0000	0.9178	0.0000	0.9190	0.0000
TA_LN	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
LR_LN	4.4480	0.0000	0.3162	0.0000	0.3162	0.0003	0.1983	0.0186
TIER1_LN	0.0072	0.0000	0.0002	0.0705	0.0002	0.3052	0.0004	0.2234
CG_LN	-0.0033	0.1047	0.0000	0.9787	0.0000	0.9581	-0.0007	0.0025
NPL_LN	0.2192	0.0000	0.0048	0.6407	0.0048	0.5312	0.1108	0.0849
MML_LN	-0.0281	0.6077	-0.7056	0.0000	-0.7056	0.0000	-0.7109	0.0000
ROE_LN	0.0682	0.0000	-0.0015	0.5976	-0.0015	0.6472	-0.0023	0.4835
CTI_LN	0.1361	0.0000	0.0007	0.5935	0.0007	0.6166	-0.0010	0.3505
GDPG_LN	2.2188	0.0000	0.1003	0.0036	0.1003	0.0020	0.0194	0.4478
CPI_LN	2.0100	0.0000	-0.0892	0.0963	-0.0892	0.0903	-0.2118	0.0000
MMR_LN	0.2406	0.2055	0.0103	0.8403	0.0103	0.8748	0.2112	0.0021
AR(1)							0.5357	0.0000
AR(2)							-0.0984	0.0002
R-squared	-5.6787		0.8391		0.8391		0.9227	
Adjusted R-squared	-5.6940		0.8148		0.8148		0.9065	
Prob.			0.0000		0.0000		0.0000	
Durbin-Watson stat	0.4118		0.9269		0.9269		2.0887	

Table 3.9. Bank liquidity determinants with transformed log-normal variables measured by NSFR

	Transformed Panel With LN - Panel EGLS (Cross-section weights) With Fixed Effects, White Diagonal and AR		Transformed Panel With LN - Robust Least Squares		Transformed Panel With LN - GMM with Fixed Effects, Cross-Section Weights and White Diagonal	
Variable	**Coefficient**	**Prob.**	**Coefficient**	**Prob.**	**Coefficient**	**Prob.**
C	-0.0316	0.0000			-0.0201	0.0000
LAG1NSFR					-0.0117	0.0000
LAG2NSFR					-0.0058	0.0145
TA_LN	0.0416	0.0000	0.0310	0.0000	**0.0417**	0.0000
LR_LN	0.4539	0.0000	1.0526	0.0000	**0.4060**	0.0000
TIER1_LN	-0.0001	0.7512	0.0045	0.0000	-0.0001	0.8149
CG_LN	-0.0144	0.0000	-0.0032	0.2730	**-0.0153**	0.0000
NPL_LN	0.1232	0.0000	0.1171	0.0000	**0.1182**	0.0000
MML_LN	-0.5139	0.0000	-0.6026	0.0000	**-0.5021**	0.0000
ROE_LN	0.0057	0.0029	0.0196	0.0003	**0.0052**	0.0025
CTI_LN	0.0224	0.0000	0.1830	0.0000	**0.0213**	0.0000
GDPG_LN	-0.0070	0.0409	0.1632	0.0000	**-0.0153**	0.0016
CPI_LN	-0.0031	0.6906	0.2320	0.0000	0.0035	0.7192
MMR_LN	0.0545	0.0001	-0.2677	0.0000	0.0280	0.0769
AR(1)	0.7219	0.0000			0.6774	0.0000
AR(2)	-0.0349	0.0011			-0.0323	0.0096
R-squared	0.9989		0.7130		0.9987	
Adjusted R-squared	0.9987		0.7127		0.9985	
Rw-squared			0.9227			
Adjust Rw-squared			0.9227			
Prob.	0.0000		0.0000		0.0000	
Durbin-Watson stat	2.0379				2.0859	

Note. Estimators with a statistical significance level of 1% are in bold.

Table 3.9. STFR and Tier 1 robustness tests compared

	NSFR_GMM		STFR_GMM		LR_GMM		TIER1_GMM	
Variable	**Coefficient**	**Prob.**	**Coefficient**	**Prob.**	**Coefficient**	**Prob.**	**Coefficient**	**Prob.**
C	-0.0201	0.0000	-0.0227	0.0000	-0.0040	0.0002	0.5674	0.0000
LAG1NSFR	-0.0117	0.0000	-0.0034	0.1311	-0.0029	0.0000	-0.0214	0.5677
LAG2NSFR	-0.0058	0.0145	-0.0015	0.4636	-0.0010	0.1209	-0.0193	0.5452
TA_LN	**0.0417**	0.0000	**0.0399**	0.0000	**0.0058**	0.0000	**0.0377**	0.0000
LR_LN	**0.4060**	0.0000	**0.1641**	0.0000			**4.7244**	0.0000
TIER1_LN	-0.0001	0.8149	**0.0005**	0.0056	**0.0019**	0.0000		
CG_LN	**-0.0153**	0.0000	**-0.0101**	0.0000	**-0.0046**	0.0000	-0.0212	0.0227
NPL_LN	**0.1182**	0.0000	**0.0543**	0.0057	0.0224	0.0494	**0.4173**	0.0016
MML_LN	**-0.5021**	0.0000	**0.0798**	0.0000	**-0.0467**	0.0000	**0.1334**	0.0054
ROE_LN	**0.0052**	0.0025	0.0006	0.7230	**0.0237**	0.0000	0.0390	0.1048
CTI_LN	**0.0213**	0.0000	**0.0190**	0.0000	**0.0114**	0.0000	-0.0108	0.6780
GDPG_LN	**-0.0153**	0.0016	-0.0068	0.0634	-0.0006	0.1534	**-0.3498**	0.0000
CPI_LN	0.0035	0.7192	-0.0040	0.6391	0.0006	0.7265	**0.3531**	0.0014
MMR_LN	0.0280	0.0769	0.0170	0.1864	-0.0039	0.1171	**-0.8939**	0.0000
AR(1)	0.6774	0.0000	0.7459	0.0000	0.5333	0.0000	0.6581	0.0000
AR(2)	-0.0323	0.0096	-0.0297	0.0005	-0.0439	0.0001	-0.0044	0.6527
R-squared	0.9987		0.9975		0.9912		0.9850	
Adjusted R-squared	0.9985		0.9972		0.9901		0.9831	
Prob.	0.0000		0.0000		0.0000		0.0000	
Durbin-Watson stat	2.0859		2.1648		1.9245		2.0729	

Note. Estimators with a statistical significance level of 1% are in bold.

Table 3.10. Additional variables' robustness tests compared

	NSFR_GMM		NSFR_GMM Robustness Test		STFR_GMM Robustness Test		TIER1_GMM Robustness Test	
Variable	**Coefficient**	**Prob.**	**Coefficient**	**Prob.**	**Coefficient**	**Prob.**	**Coefficient**	**Prob.**
C	-0.0201	0.0000	0.0057	0.1246	0.0179	0.0000	1.1468	0.0000
LAG1NSFR	-0.0117	0.0000	-0.0129	0.0000	-0.0061	0.0172	-0.0057	0.9112
LAG2NSFR	-0.0058	0.0145	-0.0052	0.0281	-0.0036	0.0875	-0.0223	0.6155
TA_LN	**0.0417**	0.0000	**0.0416**	0.0000	**0.0395**	0.0000	**0.0410**	0.0000
LR_LN	**0.4060**	0.0000	**0.4202**	0.0000	**0.1908**	0.0000	**4.3506**	0.0000
TIER1_LN	-0.0001	0.8149	**-0.0008**	0.0077	-0.0004	0.0166		
CG_LN	**-0.0153**	0.0000	**-0.0159**	0.0000	**-0.0099**	0.0000	-0.0302	0.0878
NPL_LN	**0.1182**	0.0000	**0.1151**	0.0000	**0.0668**	0.0019	0.1096	0.5978
MML_LN	**-0.5021**	0.0000	**-0.4983**	0.0000	**0.0751**	0.0000	0.2039	0.0216
ROE_LN	**0.0052**	0.0025	**0.0048**	0.0058	0.0006	0.6937	0.0153	0.6619
CTI_LN	**0.0213**	0.0000	**0.0211**	0.0000	**0.0198**	0.0000	0.0812	0.0574
GDPG_LN	**-0.0153**	0.0016	-0.0098	0.2079	0.0065	0.1450	**-0.6786**	0.0000
CPI_LN	0.0035	0.7192	0.0077	0.5167	-0.0134	0.0949	-0.4417	0.0103
MMR_LN	0.0280	0.0769	-0.0106	0.6077	-0.0138	0.3130	-0.1207	0.6754
CRISIS_DUMMY			**0.0025**	0.0004	0.0010	0.0262	**-0.0892**	0.0000
@TREND			**-0.0025**	0.0000	**-0.0032**	0.0000	**-0.0602**	0.0000
AR(1)	0.6774	0.0000	0.6587	0.0000	0.6679	0.0000	0.6740	0.0000
AR(2)	-0.0323	0.0096	-0.0553	0.0000	-0.0409	0.0001	-0.0262	0.0109
R-squared	0.9987		0.9942		0.9966		0.9282	
Adjusted R-squared	0.9985		0.9935		0.9961		0.9190	
Prob.	0.0000		0.0000		0.0000		0.0000	
Durbin-Watson stat	2.0859		2.0701		2.1091		2.0950	

Note. Estimators with a statistical significance level of 1% are in bold.

Table 3.11. Robust estimation by period

	Global		Pre-Crisis		Crisis		Post-Crisis	
Variable	Coefficient	Prob.	Coefficient	Prob.	Coefficient	Prob.	Coefficient	Prob.
TA_LN	**0.030969**	0.0000	**0.033505**	0.0000	**0.03125**	0.0000	**0.02743**	0.0000
LR_LN	**1.052586**	0.0000	**0.910607**	0.0000	**0.970656**	0.0000	**1.157511**	0.0000
TIER1_LN	**0.004534**	0.0000	**0.011299**	0.0000	**0.017356**	0.0000	-0.000112	0.8884
CG_LN	-0.003228	0.2730	0.001863	0.6988	**-0.017734**	0.0095	0.004622	0.2769
NPL_LN	**0.117059**	0.0000	**0.426394**	0.0000	**0.244619**	0.0000	-0.02386	0.2197
MML_LN	**-0.602606**	0.0000	**-0.580182**	0.0000	**-0.599526**	0.0000	**-0.557112**	0.0000
ROE_LN	**0.019599**	0.0003	0.019051	0.1142	**0.017419**	0.0923	0.009745	0.1627
CTI_LN	**0.182993**	0.0000	**0.099687**	0.0000	**0.137788**	0.0000	**0.279107**	0.0000
GDPG_LN	**0.163219**	0.0000	**0.201766**	0.0000	**0.164394**	0.0001	**0.229197**	0.0000
CPI_LN	**0.232029**	0.0000	**0.401959**	0.0000	0.065676	0.2717	**0.487497**	0.0000
MMR_LN	**-0.26767**	0.0000	**-0.331708**	0.0000	-0.130285	0.0289	**-0.635139**	0.0000
Adjusted R-squared		0.712689		0.809698		0.611795		0.685741

Note. Estimators with a statistical significance level of 1% are in bold.

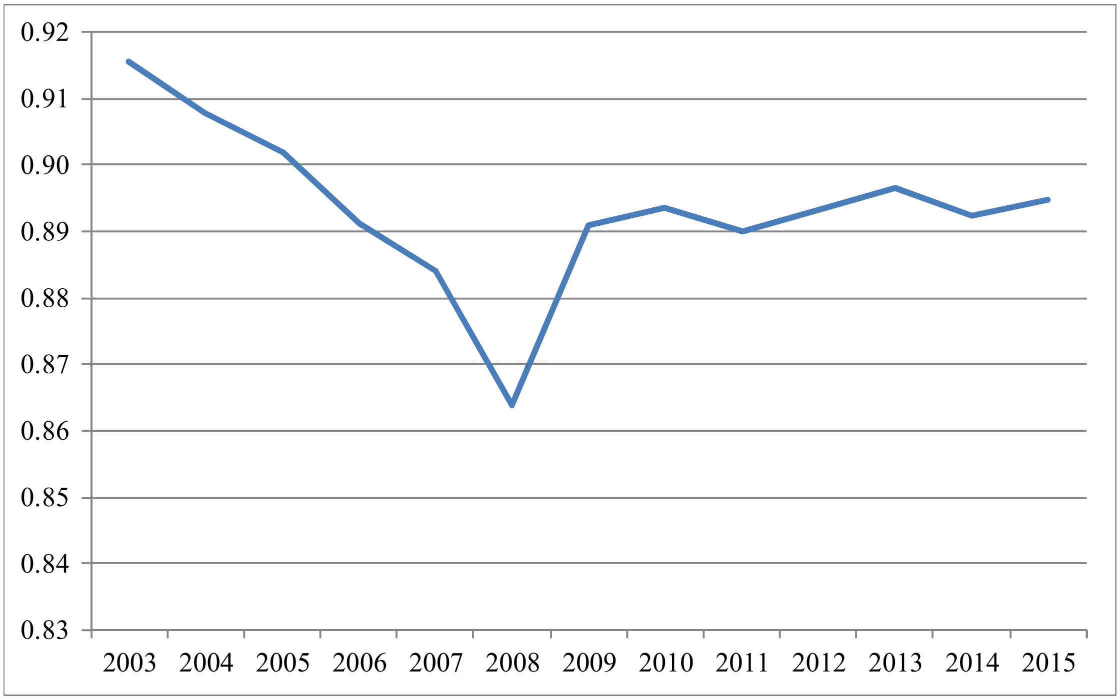

Figure 3.1. NSFR global average

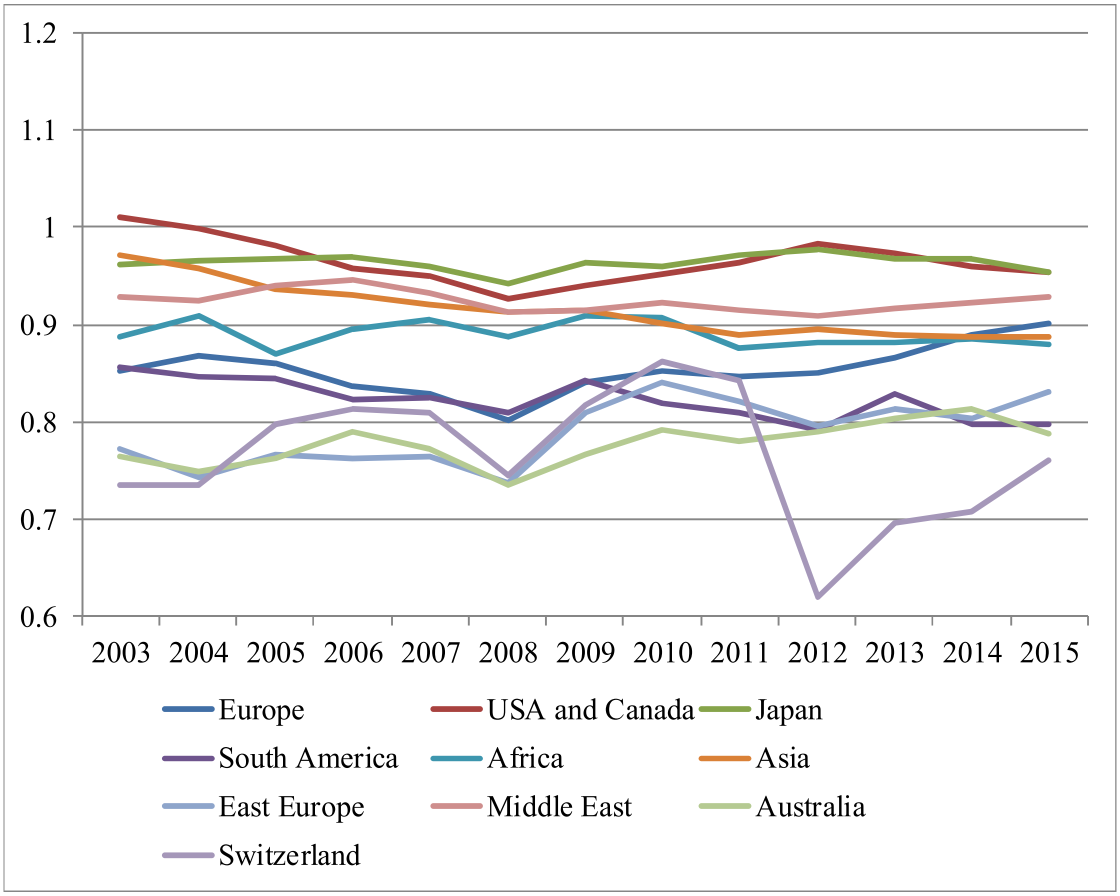

Figure 3.2. NSFR by geographical zone

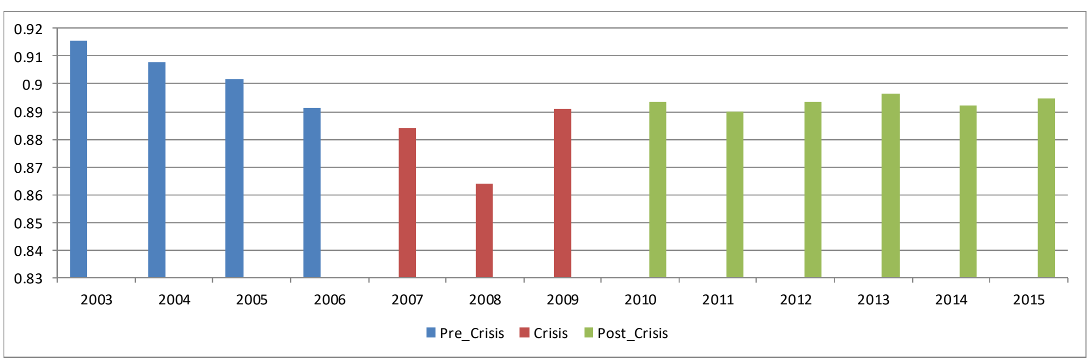

Figure 3.3. NSFR by period

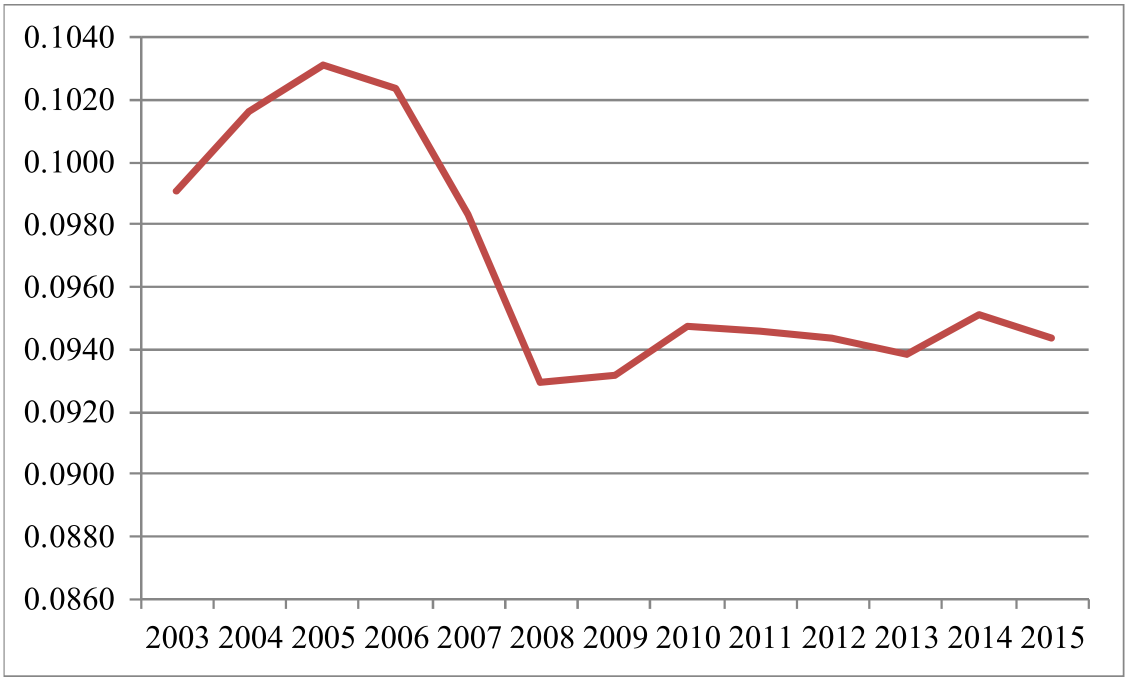

Figure 3.4. LR global average

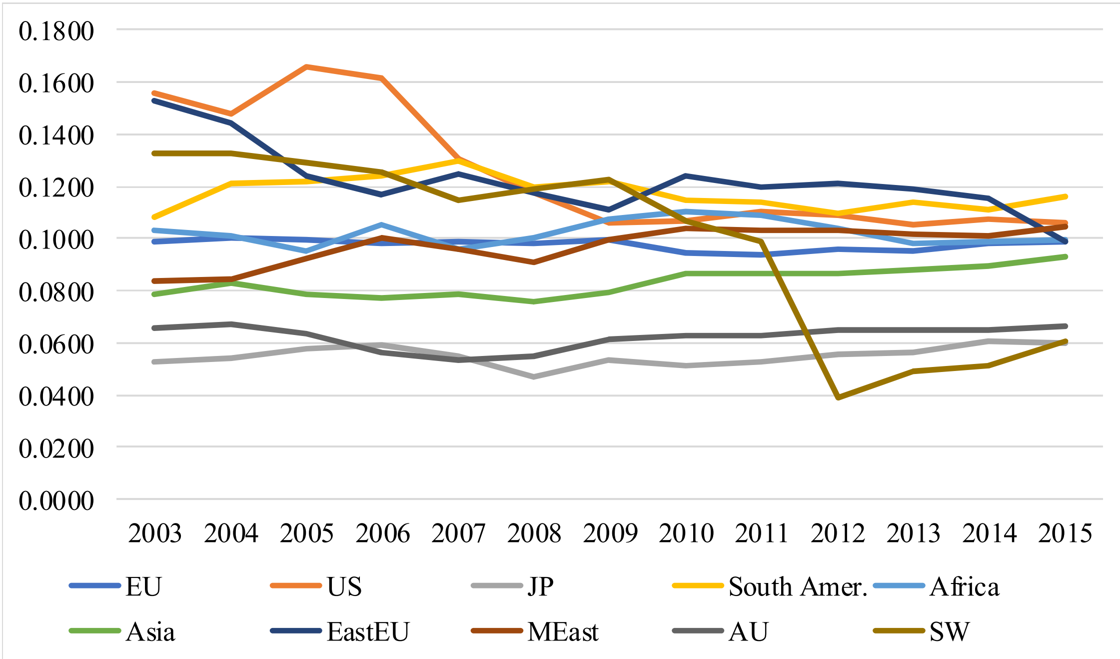

Figure 3.5. LR by geographical zone

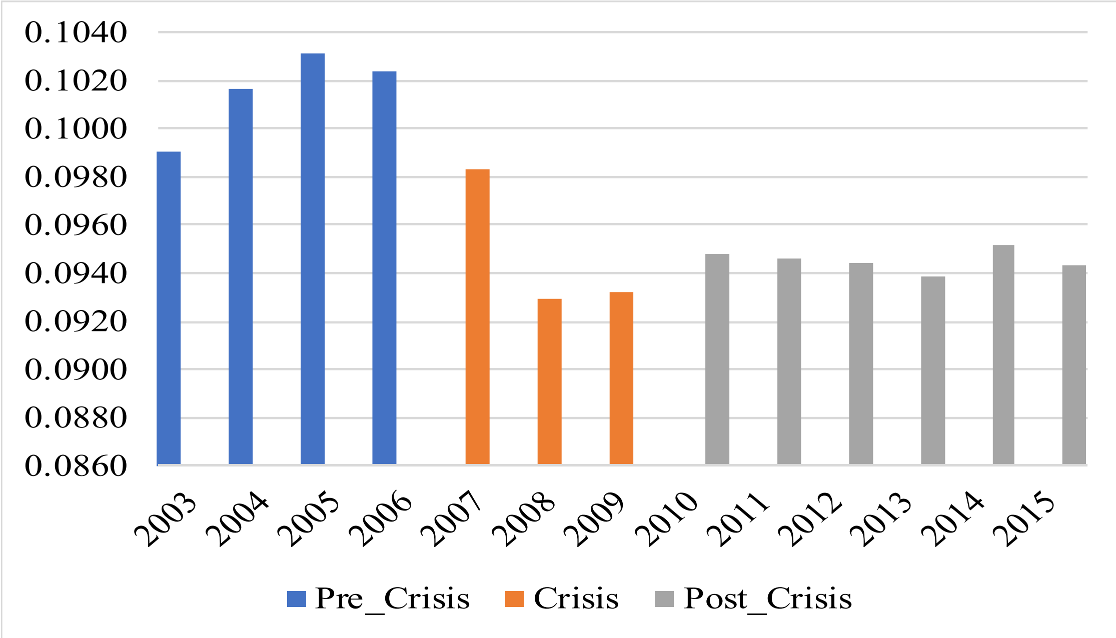

Figure 3.6. LR by period

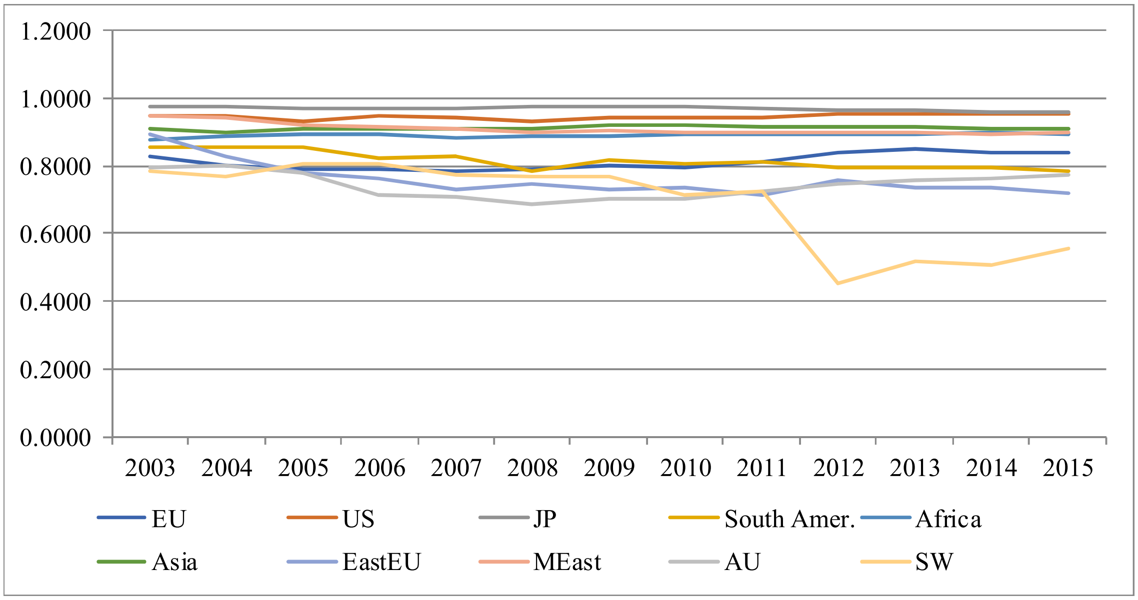

Figure 3.7. STFR by geographical zone

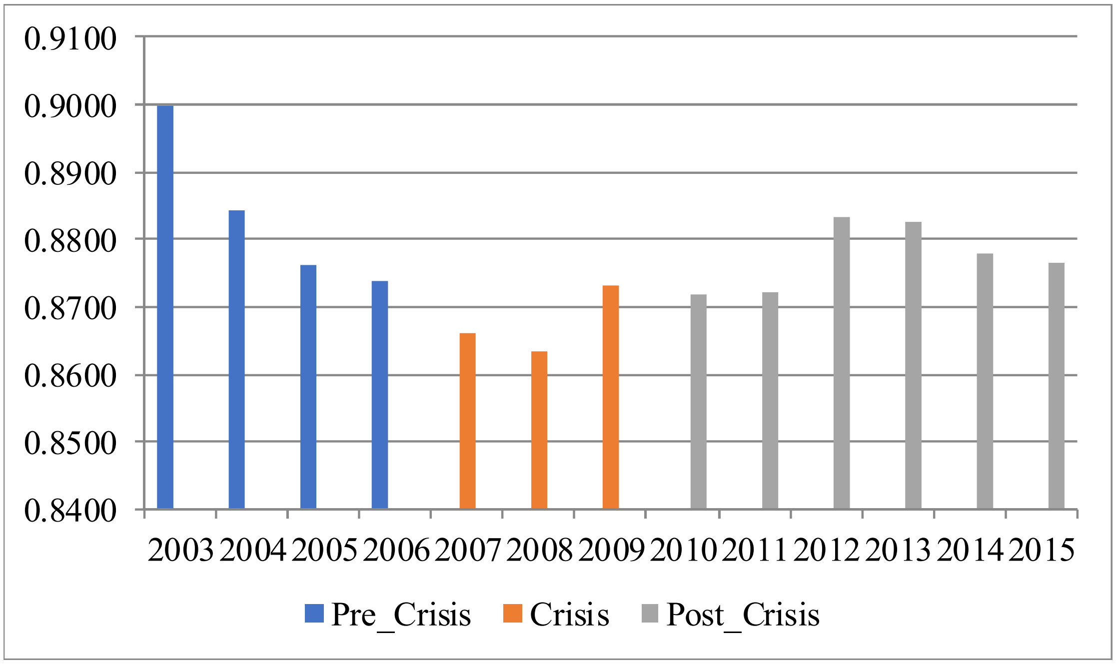

Figure 3.8. STFR by period

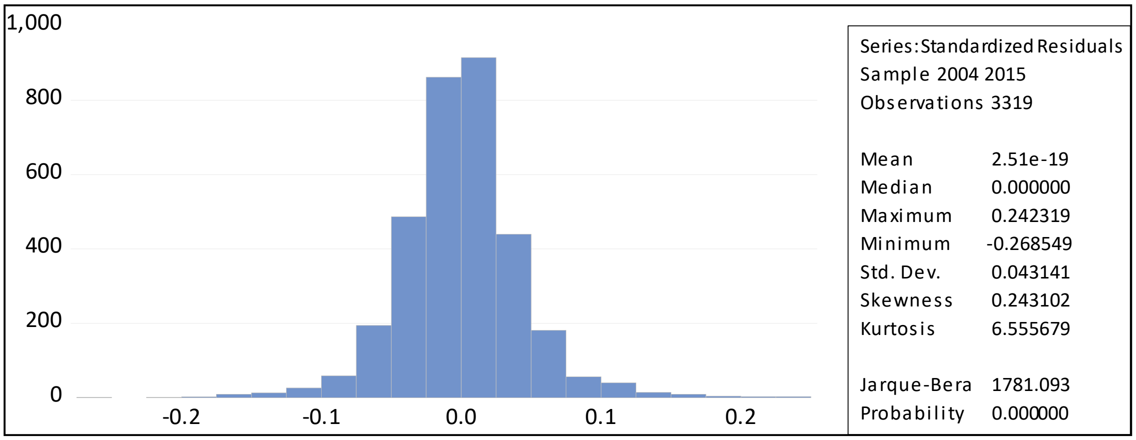

Figure 3.9. NSFR regression: normality test

4. Liquidity Mismatch as a Systemic Measure

4.1. Introduction

The 2007–2009 global financial crisis highlighted the importance of including funding liquidity analyses and controls in systemic risk models. Regulators have striven to contain individual banks' liquidity risk. Whether banks have sufficient incentives to limit risks that can pose problems to other banks or entire financial systems is a question still lacking a straightforward answer (Brunnermeier et al., 2012; Krishnamurthy and Weymuller, 2016). The 2007–2009 crisis showed how individual banks contribute to banking systems' overall risk with these institutions' quite similar diversified portfolios.

Systemic risk is a term whose meaning has changed considerably due to the recent financial crisis. This concept was predominantly understood as the probability of contagion effects that cause default cascades. The crisis revealed that systemic risk can also emerge from other sources such as factors leading to a simultaneous default of several financial institutions or informational spillovers in which bad news about one bank increases all other banks' refinancing costs.

According to the International Monetary Fund's (IMF) (2011) definition, systemic liquidity risk is the "risk of simultaneous liquidity difficulties at multiple financial institutions." The 2007–2009 global crisis underlined the importance of including funding liquidity information in systemic risk models. Houben et al. (2015) define systemic liquidity as having four main features. First, it is conditioned by the current financial cycle phase and is thus an endogenous concept. Second, this liquidity creates a liquidity illusion effect in the financial cycle's upturns. Third, systemic liquidity is driven by the financial sector and markets' interconnectedness, which intensifies liquidity deficits' consequences. Last, this type of liquidity is strongly correlated with capital leverage.

Identifying liquidity risk in organizations, in general, and banks, in particular, has systemic relevance, making it a crucial part of assessing financial stability and enhancing macroeconomic supervision. To monitor liquidity risk, the Basel Committee on Banking Supervision (BCBS) introduced the liquidity coverage ratio (LCR) and net stable funding ratio (NSFR), which were put in place in 2015 and 2018, respectively (BCBS, 2010). Both ratios are important to improving banks' resilience when facing liquidity shocks, but these measures only take into account liquidity risks and their mitigation from a macroprudential perspective.

Excessive reliance on interbank money market financing, as well as common balance sheet exposures, can result in liquidity shocks in one bank that can infect other financial institutions and markets, exacerbating liquidity stress throughout banking systems. These systemic components were underestimated in the period prior to the recent crisis. Comprehensive macroprudential regulations may thus have become necessary to mitigate systemic liquidity risk and minimize banks' propensity to underestimate this risk collectively during economic growth periods (European Central Bank [ECB], 2018).

Debt instruments issued by financial institutions make systems more interconnected, and a high level of intra-financial assets in banks' balance sheets could indicate deterioration in these institutions' capacity to bear liquidity risk (ECB, 2018). Brunnermeier and Pedersen (2009) observe that funding liquidity and market liquidity risk are directly linked, thereby creating systemic liquidity risk. This relationship results from the way markets are often characterized by centralized networks with few liquidity hubs, which are used by various financial institutions, so liquidity shortages disrupt financial systems' liquidity flow and liquidity problems arise (Van Lelyveld and Liedorp, 2006). Widespread contagion occurs when "core liquidity providers" are affected (Gai et al., 2010).

According to Acharya and Mora (2015), banks' failure as liquidity providers was the main reason for the global financial system's fragility during the recent crisis. Links between financial institutions through loans, commitments, asset markets, financial transactions, or other kinds of direct relationships facilitate the contagion process in the financial sector. This problem spreads mainly through money market products that are among banks' most common sources of funding (Hałaj and Kok, 2015). Another important component of systemic liquidity risk is indirect contagion that happens when a financial institution's failure triggers the collapse of other banks with which it is connected. A small market's crash, such as that of the United States' (US) sub-prime credit market in 2007, is a good example of a systemic crisis (European Systemic Risk Board, 2016).

Moral hazard also has an impact on systemic risk, and, due to government intervention seeking to prevent financial systems' collapse, banks do not fully internalize a systemic event's risk (Farhi and Tirole, 2012). Silva (2016) asserts that banks' liquidity and maturity mismatch decisions are strongly affected by competitors' respective choices. The cited author's research provided proof that strategic funding liquidity decisions increase both individual banks' default risk and overall systemic risk. Liquidity problems are the most important determinant of banks' contribution to systemic liquidity risk. Lopez-Espinosa et al. (2012) suggest that short-term wholesale funding is the most important determinant of these institutions' role in increasing global systemic risk.

Liquidity mismatch or liquidity gap analysis was a common topic of discussion in all banks even before the recent financial crisis. Excessive liquidity mismatch is a matter of some concern for banks' risk and treasury departments as it can lead to wholesale markets' breakdown and distressed asset sales that affect individual institutions and financial systems' solvency (Brunnermeier, 2009; Tirole, 2011). In their article entitled "Liquidity Mismatch Measurement," Brunnermeier et al. (2012) argue that what is crucial in liquidity risk assessments is paying attention to liquidity mismatches among asset and liability items. Roberts et al. (2018), in turn, analyzed the relationship between liquidity creation and liquidity resiliency for banking systems using the LCR. The cited researchers verified less liquidity mismatch among compliant banks, finding that the banking sector's overall liquidity creation has decreased, which is consistent with the LCR's objective.

No reference values are available for the liquidity mismatch index (LMI), so analyses using this index must be conducted for each bank according to its assets and especially its liquidity needs and strategies. Bai et al. (2018) developed a version of the LMI that highlights the difference between assets' market liquidity and liabilities' funding liquidity. The cited authors concluded that the proposed LMI provides relevant information about both individual bank's liquidity and the global banking system's liquidity risk.

The present study's main goal was to provide insights into the measurement of systemic liquidity risk based on banks' balance sheet data and their asset and liability management and to offer a fuller understanding of these institutions' systemic funding liquidity risk. Despite the existence of some theoretical literature on this topic, little empirical evidence based on real data is available on bank funding's systemic liquidity risk. This research thus focused on data on a broad 13-year period for 645 commercial banks worldwide rather than for a specific geographical zone. The period analyzed includes the subprime mortgage crisis period and pre- and post-crisis periods. In addition, this study sought to contribute to the application of real data on banks' financial activities provided by the Bankscope database.

The current research's aim was to shed some light into how best to measure liquidity risk through banks' assets and liabilities, Very few researchers have analyzed systemic liquidity risk in terms of asset and liability mismatches (Brunnermeier et al., 2012; Berger and Bouwman, 2017). Until now, the LMI and Basel III liquidity measures have been the measures most frequently analyzed by practitioners and researchers because the LMI focuses on real sources of liquidity risk, namely, market and funding liquidity and liquidity spirals. Notably, Bai et al. (2018) argue that Basel III liquidity measures have no theoretical support as they were implemented before the relevant academic research could be conducted.

The present study analyzed the LMI and compared its performance with Basel III liquidity measures using a generalized method of moments (GMM) model. The empirical findings generated by a comparison of the LMI and NSFR's results facilitate the identification of determinants of liquidity and clarification of how to measure bank liquidity risk's significance in the context of asset and liability mismatches. The new information provided by the results offers regulators, banks, and academics the tools to revisit their liquidity measures and customize them in order to improve their liquidity risk models.

The rest of this paper is structured as follows. Section two presents the literature review. Section three describes the data, methods, and variables. Section four contains the results, while section five provides the conclusions.

4.2. Literature review

Various definitions have been developed for systemic risk, but this research relied on the IMF's (2009) conceptualization. The cited institution states that this is "a risk of disruption to financial services that is (i) caused by an impairment of all or parts of the financial system, and (ii) has the potential to have serious negative consequences for the real economy" (Adler, 2012; Krishnamurthy et al., 2016). Systemic risk has always been the object of study and analysis (Brunnermeier, 2008; Andrievskaya, 2012; Vodová, 2013), but the subprime mortgage crisis in the US ensured that this concept has become quite important to financial institutions and academics.

As a result, in the last 12 years, various authors have proposed models and indicators whose main purpose is to evaluate systemic risk and supply the authorities with evaluation instruments that help regulators monitor liquidity in financial systems (Brunnermeier, 2008; Berger, 2009; Brunnermeier, 2012; Horvàth et al., 2012; Vodová, 2013). Some proposals have used existing microprudential instruments such as the LCR or NSFR. These models have made a macroprudential view more explicit by incorporating countercyclical elements mainly to prevent significant imbalances in banking systems and the real economy (ECB, 2014). Other authors have incorporated macroprudential instruments to complement microprudential regulations (Hardy and Hochreiter, 2014).

Academics and practitioners have taken different routes when addressing systemic risk and ways to limit it. Cetorelli and Goldberg (2011), for example, analyzed how liquidity shocks in the largest banking systems in the 2007–2009 crisis affected emerging economies through cross-border and affiliate lending. Van den End and Kruidhof (2012), in turn, found that, in extreme scenarios, the LCR becomes a strong constraint and interactions between banks behavior and regulators can produce negative externalities. The cited authors report that, with extreme levels of stress, this measure is ineffective, and the last lenders of resources needs to maintain the systems' stability.

Van den End (2016) argues that the loan to deposit (LTD) ratio is less prone to varied interpretations and easier to understand. The LTD ratio considers loans and deposits' intrinsic characteristics, namely, their contractual maturities, so this measure is useful in stress periods, when market participants are more likely to accept direct indicators. Van den End (2016) analyzed 11 eurozone countries, finding that the growing loan volume has been an important factor in increasing the LTD ratio's relevance in recovery processes and raising the LTD to the upper bounds of its value. When the economy slows down, deposit growth is assumed to be an important factor, thereby reducing the LTD ratio to its lower bounds. According to Van den End (2016), the relationship between loans and deposits has long been statistically significant, and the connection is stronger in the LTD cycle's growth phases.

Hardy and Hochreiter (2014) assert that the best solution is a macroprudential liquidity buffer, which can be considered to be a simplified version of the LCR. The macroprudential liquidity buffer's calculation may present problems because systemic liquidity assets that can be sold or used as collateral have to be defined even though this part of the calculation is difficult. In addition, the buffer requires the estimation of a ratio that is the relationship between systemic liquidity assets (i.e., numerator) and liabilities' lower regulatory capital (i.e., denominator). This ratio needs to exceed a minimum requirement, which may be a time-varying covariate. Hardy and Hochreiter's (2014) buffer comprises a concrete functional form that links minimum requirements to growth rates. The macroprudential liquidity buffer serves the same purpose as the LCR, so the buffer can be considered complementary to the NSFR.

Milne (2013) observes that regulators define the upper limit on short-term liabilities of financial intermediaries and the tradable licenses related to this amount, which is then distributed among financial institutions. These short-term liabilities must be monitored, and, if banks are not in compliance with the limit, they must pay a fine. Various authors, such as Ferrara et al. (2016), have concluded that systemic liquidity risk can be reduced by requiring financial institutions to pay attention to their liquidity. Based on a dataset comprised of United Kingdom banks' daily cash flows, short-term interbank funding, and liquid asset buffers, the cited researchers concluded that, if average liquidity requirements are kept at the same level throughout banking systems, systemic risk can be significantly reduced.

Systemic liquidity risk includes both funding and market liquidity risk, which are directly linked to traders' ability to provide market liquidity and are completely dependent on funding's availability. If the markets have insufficient funding, traders will avoid taking capital intensive positions, thereby reducing market liquidity and contributing to systemic liquidity risk. In these situations, financial institutions are more prone to experience financial difficulties when market liquidity disappears due to their inability to exit easily from their current position. Issuers and investors will then choose to reduce their liquidity leverage and thus increase liquidity reserves, extend their own funding, and shorten debt maturities.

For a similar reason, banks seek to increase solvency to improve their funding conditions, and investors want to de-risk their portfolio (Brunnermeier and Pedersen, 2009). When these two different forces conflict, they reduce liquidity leverage, which can promote asset fire sales that precipitate losses in the financial intermediation chain and increase systemic risk. Because liquidity shocks have an impact on solvency, liquidity leverage and capital leverage interact and increase banks' vulnerability to shocks (Puhr and Schmitz, 2014; Schmitz et al., 2017).

McCauley et al. (2010) confirmed a long-term shift toward affiliate lending as opposed to direct cross-border lending but found that direct cross-border credit remains significant for many borrower countries. Bandt et al. (2009), in turn, categorized systemic risks. In the cited authors' classification system, contagion's effects on interbank markets are a systemic risk in the narrowest sense, whereas systemic risk in the broadest sense is characterized as a common financial shock present in many institutions or markets. One approach used to estimate overall systemic risk is to carry out probability distributions and contingent claim analysis (e.g., Lehar, 2005; Huang et al., 2009; Segoviano and Goodhart, 2009). According to these researchers, financial systems can be considered a portfolio of financial institutions for which potential joint losses and distress can be estimated. A drawback of these methodologies is that joint distribution is assumed to be stable over time.

Market data can be useful in international contexts since comparable balance sheet data are difficult to obtain and often only infrequently available. Studies often use these data as a complement to balance sheet-based research because market data can identify contagion channels (Acharya et al., 2010). Examining interbank markets is another way to measure overall systemic risk, as shown by Sheldon and Maurer's (1998) empirical investigation. Aikman et al.'s (2009) study fused funding liquidity risk and a risk assessment model for systemically important institutions, but their analysis only included bank balance sheets' liability side.

Drehmann and Nikolaou (2013) used a more easily implementable empirical approach to estimating liquidity funding risk based on a central bank auction. The spread between the submitted and minimum bid rate in the open market was proposed as a proxy for funding liquidity risk. Liquidity creation is exclusively a feature of banks that consists of transforming liquid liabilities (e.g., client deposits) into illiquid assets (e.g., loans), but, if this process is not well managed, it will generate liquidity mismatches in banks' balance sheets and make these institutions more fragile (Hanson et al., 2015). This process, nonetheless, allows consumers to gain access to goods and services, as well as promoting economic growth. The 2007–2009 global financial crisis, however, forced markets to realize that excessive levels of liquidity mismatch can lead to bank runs (Brunnermeier, 2009; Tirole, 2011). More recent evidence has also shown that banks are trying to deal with the fragility of their client deposit base in order to guarantee their resources' stability (Chen et al., 2019).

Based on a liquidity stress scenario, the LMI measures the mismatch between assets' market liquidity and liabilities' funding liquidity (Brunnermeier et al., 2011). Brunnermeier et al. (2012) focused on whether banks' liquidity mismatches are what truly matters in terms of creating systemic liquidity risk. The cited authors introduced an LMI calculated based on a particular time horizon (i.e., 30 days) and the difference between banks' liquid assets and liquid liabilities. The asset and liability items were given liquidity weights to indicate a particular item's liquidity. This mismatch index needs to be estimated for different scenarios (i.e., nations around the world) with different liquidity weights so that the proposed LMI values' distribution can be identified and liquidity risk assessed using the value at risk technique.

In theory, estimations could be made for the entire international banking system to develop a measure of systemic liquidity risk. A systemic risk metric based on liquidity should capture liquidity imbalances in financial systems as a whole and at the bank level to facilitate comparisons and the construction of a financial crisis indicator. According to Bai et al. (2018), the LMI can be a good indicator of systemic risk as "it can be aggregated across banks to measure the liquidity mismatch of a group of banks or of the entire financial sector." The cited researchers developed an LMI that reveals the difference between assets' market liquidity and liabilities' funding liquidity. Bai et al. (2018) assert that the LMI provides information about both individual banks' liquidity and the global banking system's liquidity risk.

Roberts et al. (2019) found that banks currently rely on the sale or securitization of loans to obtain funding via short-term repos or asset-backed securities. This practice is a liquidity creation process, and both strategies result in liquidity mismatches on bank balance sheets, which requires banks' liquidity management to include the creation of buffers. In recent years, institutions and academics have proposed varied approaches to developing indicators and policy instruments that provide a macroprudential perspective on liquidity regulation in financial systems (ECB, 2018).

4.3. Data, methods, and variables

The present study used the LMI developed by Brunnermeier et al. (2011, 2012). This indicator was chosen because it provides an effective approach to measuring banks' liquidity. The cited authors define the LMI as the "cash equivalent value" of a company in a given country. The assumption is made that the expected liquidity shown on the banks' balance sheet liabilities (e.g., customers deposits) exists and that this resource's use appears on the asset side of balance sheet in the form of loans. This measure captures relevant attributes of bank liquidity such as overall funding liquidity and assets' market liquidity. Brunnermeier et al. (2012) verified that the level of transmission is not important as the key indicator of liquidity risk is the proportion of short-term debt in demandable deposits because banks keep illiquid assets financed by short-term debt. In stressful market environments, this strategy can result in increased systemic risk.

4.3.1. Data

The total sample was filtered, leaving 645 commercial banks to be analyzed. The database covered non-offshore commercial banks around the globe, with total assets (TAs) higher than 100,000,000 euros, from 2003 to 2015. The sample facilitated an examination of banks' balance sheet dynamics in three different periods (i.e., pre-crisis, crisis, and post-crisis). The crisis period was defined as the subprime mortgage crisis years. These were based on the US National Bureau of Economic Research's criteria, which considers this crisis to have occurred from 2007 to 2009. Vazquez and Frederico (2015) also delimit the crisis as the period between the end of 2007 to 2009.

However, the present data's interpretation required that different stages of the global financial crisis be considered, namely, the financial crisis between 2007 to 2009, the overall financial crisis between 2008 and 2010, and the sovereign debt crisis between 2011 to 2013 (Bayer et al., 2017). The data were downloaded from the Bankscope database, which provides a comprehensive coverage of banks worldwide. Balance sheet data were put into standardized formats after adjusting for differences in accounting and reporting standards across countries (see Table 4.1).

Table 4.2 lists the analyzed banks grouped by geographical zones. The final sample reflected banks' balance sheet dynamics in the three different periods under study in 10 geographical regions: Europe, the US and Canada, Japan, South America, Africa, Asia, Eastern Europe and Russia, the Middle East, Australia, and Switzerland. The financial information taken from Bankscope was given standardized formats that compensate for different accounting and reporting standards worldwide.

4.3.2. Methodology

The research focused on examining and understanding each homogeneous bank group's behavior by collecting, compiling, analyzing, and interpreting the empirical data collected from banks' balance sheets. Subsequently, this study evaluated the relationships between ratios proxying banks' profiles and liquidity patterns, which were linked to groups of similar banks and geographical sub-samples.

The LMI and Basel III's NSFR were used to measure bank liquidity risk. The LMI was proposed by Brunnermeier et al. (2012) and updated by Bai et al. (2018) in order to compute liquidity risk through the use of real data on asset liability mismatches provided by banks' balance sheets. This type of analysis is important since each asset and liability contributes to financial institutions' liquidity position (Bai et al., 2018).

As mentioned previously, the LMI measures the mismatch between assets' market liquidity and liabilities' funding liquidity (Krishnamurthy et al., 2016). This measure facilitates the calculation of liquidity based on the gap between assets and liabilities. The calculation is defined in Equation (4.1) as follows:

$$LMI_t^i = \sum \gamma_t A_j, x_t^i A_j + \sum \gamma_t L_i, x_t^i L_i \tag{4.1}$$

The LMI for an entity i at a given time t is the net assets and liability liquidity, in which assets $x_t^i A_j$ and liabilities $x_t^i L_i$ are balance sheet items that vary over time depending on their asset class j or liability class i. The weights are defined by $\gamma_t A_j$ for assets, necessarily presenting values between 0 and 1. Liabilities are represented by $\gamma_t L_i$, with values kept between –1 and 0 (Bai et al., 2018).

The calculation of assets and liabilities' weights for the LMI has been discussed by various authors (Krishnamurthy et al., 2016; Bai et al., 2018). However, the data need to estimate these for each bank are inaccessible in reality as banks are unwilling to publish this information (Krishnamurthy et al., 2016). For academic purposes, consistency in the present study's approach was maintained by using the symmetric value (see Table 4.3) defined by Basel III as the assets and liabilities' weights, which Vazquez and Frederico (2015) also used to estimate the NSFR.

The NSFR proposed by Basel III measures the proportion of long-term illiquid assets funded with liabilities, which are either long term or considered stable. This ratio is the relationship between the weighted total of various types of banks liabilities L_i and assets A_j as shown in Equation (4.2):

$$NSFR = \frac{\sum_i w_i L_i}{\sum_j w_j A_j} \tag{4.2}$$

The weights w are bound between 0 and 1 (see Table 4.3 above) according to the range proposed in Basel III regulations. The weights reflect the relative stability of balance sheet components. In the case of assets, larger weights are assigned to less liquid positions, and, in the case of liabilities, larger weights are assigned to more stable sources of funding (Vazquez and Federico, 2015). Because the ratio compares banks' available stable funding to the required stable funding, regulators require these institutions to operate with an NSFR above one.

The NSFR's main purpose is to promote resilience over a longer time horizon by creating incentives for banks to fund their activities with more stable funding sources and to ensure that these companies maintain a stable funding structure. The BCBS developed the NSFR to support financial stability by helping to ensure that funding shocks do not significantly increase the probability of individual banks' distress—a potential source of systemic risk.

4.3.3. Estimation model

Liquidity risk is represented by the dependent variable Y_i as measured by the LMI and NSFR. The regressions included bank-level dependent variables X_i, bank-specific independent variables, country variables, and time measured by the range of years between 2003 and 2015. To serve the regressions' purposes and identify variables' impacts during the three analyzed periods (i.e., pre-crisis, crisis, and post-crisis) more clearly, independent regressions were conducted for each period. The estimation model was expected to identify different kinds of effects on banks' liquidity risk level.

To develop a better understanding of the patterns and dynamics of these institutions' liquidity risk, the following variables were included:

- TAs as a measure of bank size
- Leverage ratio (LR) as a measure of the proportion of shareholders' equity to assets estimated by dividing equity capital by assets
- Tier 1 as a key measure of banks' financial health from the regulators' point of view obtained by dividing Tier 1 capital by risk weighted assets
- Credit growth (CG) as the difference between years

- Nonperforming loans (NPLs) as the ratio of the amount of nonperforming loans in a bank's loan portfolio to the total amount of its outstanding loans
- Money market funding to total liabilities (MML) as the amount of funding from other banks (i.e., deposits from banks) divided by the financial system's total liabilities
- Return on equity (ROE) as a performance measure obtained by dividing net income by equity
- Cost-to-income (CTI) ratio as operational costs divided by banking products or operating revenues
- Gross domestic product growth (GDPG) as a measure of country effects on banks liquidity, based on data from the World Bank website
- Consumer price index (CPI) as a measure that examines the weighted average of prices of a basket of consumer goods and services, based on data from the World Bank website
- Monetary conditions as each country's money market rates (MMRs) obtained from the Bank for International Settlement website

For each dependent variable (i.e., the LMI and NSFR), the GMM baseline equation becomes the following Equation (4.3):

$$\begin{aligned} Dep_{it} = \ & \alpha + \beta_1 TA_{1,it} + \beta_2 LR_{2,it} + \beta_3 TIER1_{3,it} + \beta_4 CG_{4,it} + \beta_5 NPL_{5,it} \\ & + \beta_6 MML_{6,it} + \beta_7 ROE_{7,it} + \beta_8 CTI_{8,it} + \beta_9 GDPG_{9,it} \\ & + \beta_{10} CPI_{10,it} + \beta_{11} MMR_{11,it} + \delta_i + \mu_{it} \end{aligned} \tag{4.3}$$

in which Dep_{it} represents the dependent variable ratios (i.e., banks' liquidity ratio *i* at time *t*) and X_{it} is the explanatory variable vector of bank *i* at time *t*. In addition, α is the intercept/ constant term, β_k is the coefficient that represents explanatory variables' slope, μ_{it} is the random error term (scalar quantity), and δ_i represents the fixed effect. Subscript *i* represents the cross section (banks), and subscript *t* stands for time-series dimensions (years).

The GMM is a statistical method that combines observed economic data with information on population moment conditions to produce estimates of the economic model's unknown parameters (Hall, 2005). A GMM estimator finds the optimum combination of moment conditions with parameters, which is this model's greatest advantage over other methods.

4.3.4. Variables

The bank financial statements taken from Bankscope facilitated the calculation of the selected liquidity risk ratios, after which these dependent variables could be used to analyze liquidity risk. The analyses were based on bank-level data for the 645 listed commercial banks in the final sample and the years from 2003 to 2015. The LMI and NSFR were calculated by applying Equations (4.1) and (4.2), respectively.

As discussed previously, the independent variables considered for this study were TAs as a measure of bank size, the LR as a measure of the proportion of shareholders' equity to assets, the Tier 1 as a regulatory measure, CG, the NPLs ratio, MML, ROE as a performance measure, and the CTI ratio. The country fixed effects were GDPG and the CPI, while each country's monetary conditions was its MMRs.

To smooth the variables and reduce the number of outliers, the variables need to be transformed. The transformation selected was the logarithmic function (Trigueiros, 1995; Robert, 2004). The LMI and NSFR (i.e., dependent variables) were subjected to the transformations shown in Equations (4.4) and (4.5):

$$LMI\_LN_{it} = LN(LMI + 1 - \min(LMI)) \tag{4.4}$$

$$NSFR\_LN_{it} = LN(NSFR + 1 - \min(NSFR)) \tag{4.5}$$

The independent variables underwent the transformations represented by Equations (4.6) through (4.16):

$$TA\_LN_{it} = LN(TA + 1 - \min(TA)) \tag{4.6}$$

$$LR\_LN_{it} = LN(LR + 1 - \min(LR)) \tag{4.7}$$

$$TIER1\_LN_{it} = LN(TIER1 + 1 - \min(TIER1)) \tag{4.8}$$

$$CG\_LN_{it} = \mathrm{LN}(\mathrm{CG} + 1 - \min(\mathrm{CG})) \tag{4.9}$$

$$NPL\_LN_{it} = \mathrm{LN}(\mathrm{NPL} + 1 - \min(\mathrm{NPL})) \tag{4.10}$$

$$MML\_LN_{it} = \mathrm{LN}(\mathrm{MML} + 1 - \min(\mathrm{MML})) \tag{4.11}$$

$$ROE\_LN_{it} = \mathrm{LN}(\mathrm{ROE} + 1 - \min(\mathrm{ROE})) \tag{4.12}$$

$$CTI\_LN_{it} = \mathrm{LN}(\mathrm{CTI} + 1 - \min(\mathrm{CTI})) \tag{4.13}$$

$$GDPG\_LN_{it} = \mathrm{LN}(\mathrm{GDPG} + 1 - \min(\mathrm{GDPG})) \tag{4.14}$$

$$CPI\_LN_{it} = \mathrm{LN}(\mathrm{CPI} + 1 - \min(\mathrm{CPI})) \tag{4.15}$$

$$MMR\_LN_{it} = \mathrm{LN}(\mathrm{MMR} + 1 - \min(\mathrm{MMR})) \tag{4.16}$$

With these transformed variables, the final regression model assumed the following structure shown in Equations (4.17) and (4.18):

$$\begin{aligned} LMI\_LN_{it} = {} & \alpha + \beta_1 TA\_LN_{1,it} + \beta_2 LR\_LN_{\_2,it} + \beta_3 TIER1\_LN_{3,it} \\ & + \beta_4 CG\_LN_{4,it} + \beta_5 NPL\_LN_{5,it} + \beta_6 MML\_LN_{6,it} \\ & + \beta_7 ROE\_LN_{7,it} + \beta_8 CTI\_LN_{8,it} + \beta_9 GDPG\_LN_{9,it} \\ & + \beta_{10} CPI\_LN_{10,it} + \beta_{11} MMR\_LN_{11,it} + \delta_i + \mu_{it} \end{aligned} \tag{4.17}$$

$$\begin{aligned} NSFR\_LN_{it} = {} & \alpha + \beta_1 TA\_LN_{1,it} + \beta_2 LR\_LN_{\_2,it} + \beta_3 TIER1\_LN_{3,it} \\ & + \beta_4 CG\_LN_{4,it} + \beta_5 NPL\_LN_{5,it} + \beta_6 MML\_LN_{6,it} \\ & + \beta_7 ROE\_LN_{7,it} + \beta_8 CTI\_LN_{8,it} + \beta_9 GDPG\_LN_{9,it} \\ & + \beta_{10} CPI\_LN_{10,it} + \beta_{11} MMR\_LN_{11,it} + \delta_i + \mu_{it} \end{aligned} \tag{4.18}$$

4.3.5. Descriptive statistics

To conduct the analyses, the values were aggregated into groups by geographical area and periods. The geographical zones included 10 areas, of which Europe had 20% of the sample and 126 banks, the US and Canada with 17% and 112 banks, Japan with 12% and 73 banks, South America with 8% and 50 banks, Africa with 4% and 24 banks, and Asia with 24% and 156 banks. In addition, Eastern Europe and Russia had 11% of the sample and 73 banks, the Middle East with 2% and 15 banks, Australia with 1% and 6 banks, and Switzerland with 1% and 5 banks.

The overall period under analysis of 13 years was divided into 3 periods: a first period from 2003 to 2006 (i.e., pre-crisis), a second period from 2007 to 2009 (i.e., crisis), and a third period from 2010 to 2015 (i.e., post-crisis) (Vazquez and Frederico, 2015; Bayer et al., 2017). This division into periods facilitated the identification of liquidity risk indicators' behavior in relation to the three macroeconomic scenarios and banks' reactions in the face of systemic impacts. Tables 4.4 and 4.5 present the mean and standard deviation by geographical zone and period, respectively, for the LMI and NSFR liquidity risk indicators. To understand the relationships more fully, the tables include the ratios' real and transformed values (i.e., obtained with the logarithmic function).

Table 4.4 above summarizes the LMI and NSFR's means by geographical area. These results reveal that Japan had the best average and lowest standard deviation of stable funds, but an analysis of the LMI's absolute values showed a lower level of mismatch exists between assets and liabilities, indicating the values' high dispersion. The US and Canada, despite being the origin of the subprime mortgage crisis, had an average NSFR in the overall period under analysis of 0.96, but greater volatility indicates this indicator was less stable. This geographical area, unlike Japan, experienced a reduction in NSFR values in the years prior to the crisis. The LMI had one of the lowest values, with a higher standard deviation, so this lower value for the absolute LMI value points to the possible existence of lower liquidity in the banking system.

Eurozone banks appear in the middle of Table 4.4 above, with an NSFR of 0.85 and standard deviation of 0.17—the highest in the sample. These results show that this region's stability indicator of medium- and long-term funds did not comply with regulations and the volatility was significant, confirming the financial system's instability. Meanwhile, the LMI's absolute values were better than Japan and the US and Canada, but again the standard deviation is one of the highest. An analysis of the LMI variable verified the same reality as the NSFR did.

Swiss banks behaved quite similarly to European banks, with an NSFR of 0.78 and the second highest standard deviation of 0.16. These results confirm the close relationship between Swiss banks and the remaining financial sector in terms of taking risks. The Swiss banks' LMI presented one of the highest level of mismatches with a higher standard deviation as well.

Australian banks had the best LMI, which represents a liquidity excess and, consequently, lower liquidity risk. African financial institutions appear to have had the lowest level of liquidity mismatch, indicating a lack of liquidity in the continent's financial system. The NSFR values appear to be better given a ratio of 0.89.

The geographical analysis provided evidence of similarities between the LMI and NSFR's descriptive statistics (i.e., in real absolute values). However, when the LMI's (i.e., without transformation) relationship with the NSFR (i.e., without transformation) was examined, this finding was not confirmed.

Table 4.5 above presents the results divided into the three periods, verifying that the years with the best NSFR average were the pre-crisis ones, but this period's values also were the most volatile. As expected, during the crisis, the ratio fell and then failed to recover in the post-crisis period, although the latter showed less volatility. These changes were the result of banks' adjustment of their balance sheets, reflecting an increase in long-term liquidity in the post-crisis period and more stringent requirements established by supervisory authorities.

For the LMI, the lowest value appeared in the pre-crisis period, followed by a progressive increase in liquidity throughout the next two periods. The overall evolution was toward higher liquidity and lower liquidity risk. When the LMI and NSFR are compared, the same trends appeared from the pre-crisis to post-crisis period, that is, an increase in liquidity.

4.4. Estimation model results

To validate the liquidity risk results, a regression was run for the Basel III regulations measure, the NSFR, against its determinants. The estimation model was then compared with the model for the new liquidity risk measure LMI (Brunnermeier et al., 2012; Bai et al., 2018), which included the same determinants and same periods as the NSFR model.

Because this study's data are in a panel format, the regression analysis had to take into account a panel data structure, so the regression's parameter estimation was conducted with a cross section of data. The panel data regression method is a combination of cross-sectional data and time series, in which the same unit of cross section is measured at different times. For this purpose, *T* periods and *N* number of banks were used so that the panel data would have a total of observation units *N x T*. To highlight the impact of banks' specific characteristics and macroeconomic environment factors on banks' liquidity risk indicators, the GMM was used to compute the LMI and NSFR.

Data such as income, revenue, CG, GDPG, or CPI usually present negative values, which cannot be used with the logarithm function. This function is one of the most useful transformations in data analysis in terms of normalizing data and stabilizing variance. The logarithm function is also used to reduce the influence of outlier observations in dependent and/or independent variables. The dependent and independent estimation model variables were transformed by using the normal logarithm, as discussed above (see Equations [4.4] to [4.18]).

4.4.1. Diagnostic tests of regression model

4.4.1.1. Normality test

To verify the existence of normality, the Jarque-Bera test was run. When residual u_{it} are normally distributed, the Jarque-Bera statistics should be lower than 5.99 and should have a p-value over 0.05 (Brooks, 2008). This test is applied under the null hypothesis of normal distribution, and the alternative hypothesis would be that the data are not distributed normally. In the present study, both the LMI and NSFR's values did not show a normal distribution, but panel data linear regression does not require normally distributed variables (Startz, 2015).

4.4.1.2. Multicollinearity test

To avoid any multicollinearity problems, Pearson correlation analysis was conducted. The results for the baseline estimation are presented in Table 4.6 for the LMI and Table 4.7 for the NSFR. For the former dependent variable, the TAs independent variable presents a coefficient higher than 0.85 and, for the NSFR, 0.85, so TAs was excluded from the estimation model. A problem with multicollinearity exists when the correlation between two explanatory variables is more than 0.80 or 0.85 (Gujarati and Porter, 2011; Henseler et al., 2015).

4.4.1.3. Autocorrelation test

Autocorrelation describes the relationship in which a variable had with itself in the past. A first-order and second-order autoregressive variable were incorporated in the estimation model. These variables helped to adjust the model in order to resolve any problems with autocorrelation. For the LMI and NSFR, the Durbin-Watson statistic is around 2, so the null hypothesis of no autocorrelation could be accepted.

4.4.1.4. Heteroscedasticity test

Heteroscedasticity is not considered a real problem when panel data is used. This kind of data is itself a solution for heteroscedasticity. In addition, to address the question of heteroscedasticity, the log of all the data panel can be used to verify if the results with and without the panel data's logarithm are extremely close to each other. If the errors are not homoscedastic, the ordinary least squares estimator is still consistent but no longer optimal. However, ordinary least squares can still be used if White or robust standard errors are applied (Wooldridge, 2003; Heij et al., 2004; Greene, 2008).

4.4.1.5. Results of model estimation

This subsection presents the current study's results based on a GMM fixed effects estimation model with a White diagonal. The regression was applied to the two dependent variables and the global sample of 645 banks for the entire period from 2003 to 2015. Table 4.8 displays the regression results for the dependent variables of LMI and NSFR and the 10 eligible independent variables as determinants in order to analyze systemic liquidity risk. Of the 10 variables, 7 are firm-specific variables and 3 macroeconomic variables. As mentioned previously, the variable TAs was excluded due to multicollinearity.

As presented in Table 4.8 above, the GMM regression produced for both dependent variables an R^2 of 99% and an *F*-statistic of 0, which confirmed that the model developed has good predictive power. The model's *F*-statistic has a significance level of 1%, which means that all the explanatory variables together can influence both the LMI and NSFR at a level of 99%. These results show that for every 1% increase in an independent coefficient or variable, the dependent variables will be changed by the same percentage. In addition, the *p*-value for each independent variable tests the null hypothesis that the coefficient is equal to zero (i.e., no effect). A low *p*-value (< 0.05) indicates that the null hypothesis can be rejected and the predictor is likely to be a significant addition to the model in question because changes in the predictor variable's value are related to changes in the response variable.

In this study, the LMI and NSFR were used to measure the proportion of banks' systemic liquidity risk. Both dependent variables are long-term indicators whose purpose is to ensure these institutions' future stability because higher values for these indicators imply lower bank liquidity risk. The LR measures capital adequacy. Table 4.8 above confirms this variable's importance given its significative positive impact on the LMI and NSFR.

The LR represents structural, long-term regulatory requirements because banks with a strong capital value are more solid institutions who have better liquidity performance and lower risk. Bayazitova and Shivdasani (2012) verified that strong banks opted not to receive money from the government, while equity infusions were provided to institutions with high systemic risk. Mazreku et al. (2019) also concluded that capital adequacy is a factor that significantly affects bank liquidity.

Tier 1 was included in the current study as a regulatory measure. From regulators' point of view, Tier 1 is a measure of banks' financial health. Tier 1 has a significant positive impact on banks' liquidity risk but less so than the other independent variables included in this research. Distinguin et al. (2013) found that a significant positive relationship exists between banks' capital levels and liquidity. Nigist (2015) verified that financial fragility increases when lower levels of capital cause liquidity to grow. According to Kim and Sohn (2017), a negative connection exists between capital and liquidity.

CG is also a bank liquidity measure that has a significant positive link with the LMI and NSFR. However, this independent variable has a smaller impact on the NSFR and a stronger effect on LMI_LN. The CG process implies resource consumption, so, for instance, liquidity consumption can perhaps explain this relationship. Alessi (2018) states that CG is related to systemic risks and financial stability and that CG may emerge in systemic banking crises.

The NPLs ratio was used to verify asset quality's influence on long-term liquidity. If banks have good-quality assets, their liquidity will increase because these institutions' ability to fulfill their obligations will also increase. Mazreku et al. (2019) report that a growth in NPLs reduces banks' level of liquid assets. In the present study, NPLs present a significant positive impact on banks' liquidity risk, with a stronger effect on the LMI than the NSFR, but, in both cases, the NPLs ratio is an important independent variable.

MML was computed by dividing the amount of funding obtained from other banks in the relevant financial system by total liabilities. This variable has a significant positive impact on the LMI. However, MML has a significative but negative effect on the NSFR. Vazquez and Frederico (2015) assert that "stronger structural liquidity is associated with lower reliance on short-term funding—and with money market funding—and positively correlated with deposit funding."

ROE was used in the current research to measure bank profitability. Table 4.8 above shows that ROE has a significant but small impact on the NSFR, but this metric is not significant for the LMI. Shen et al. (2018) analyzed banks' return on assets and ROE in the US, Canada, France, Taiwan, the United Kingdom, Germany, Japan, Luxembourg, Italy, the Netherlands, Switzerland, and Australia. The cited authors concluded that liquidity risk is negatively related to these performance indicators. Bonfim and Kim's (2012) study of European and North American banks' liquidity found that, when banks adopt strategies to improve profitability, these institutions remain more vulnerable to funding liquidity risk.

CTI was used in the present research as a bank efficiency measure. This ratio is important in bank evaluations because it shows companies' costs in relation to their income. In this study, CTI had a significant positive impact on both the LMI and NSFR, with the greatest effect was observed on the former. Bonfim and Kim (2012) confirmed that banks with lower CTI ratios tend to create less liquidity and have larger NSFRs.

Regarding GDPG, the estimation model revealed that this macroeconomic variable does not have a significant effect on either bank liquidity risk variable. Vodová (2011) verified that a negative relationship exists between GDPG and bank liquidity. However, Moussa (2015) found a positive connection between GDPG and bank liquidity buffers. Thus, the literature includes various contradictory positions about GDPG's effect on liquidity. The present study's model excluded GDPG from the set of determinant variables.

Consumer goods and services prices were represented by the CPI. In the estimation model, the CPI exhibited a significant but negative relationship with both liquidity risk measures but had a greater impact on the LMI. For the NSFR, this independent variable had a significance level of 5%, while for the LMI the level was 1%. Rauch et al. (2009) confirmed the existence of a negative connection between inflation and bank liquidity, and Bonner et al. (2015) found that inflation is positively related to bank liquidity buffers.

Monetary conditions were defined as the MMRs for each country. The present analysis verified this independent variable was the only one to show a different relationship with the two dependent variables. The MMRs had no significance for the NSFR, the MMRs' effect on the LMI was significant but negative. Shen et al. (2009) report that an external funding dependence is one cause of liquidity risk. According to Munteanu (2012), an external funding dependence is negatively related to bank liquidity buffers.

4.5. Conclusions

This study covers a significant number of commercial banks over a longer period that includes pre-crisis, crisis, and post-crisis sub-periods. This broad coverage facilitated an assessment of banks' reactions and behaviors in terms of liquidity risk in three different macroeconomic scenarios, thus allowing inferences to be made about the factors and variables that have an impact on systemic liquidity. The findings provide extensive support for banks and authorities' potential initiatives related to structural liquidity.

This study included the LMI as a systemic liquidity risk measure computed for a sample of 645 commercial banks worldwide, which added a dimension to the analyses not yet addressed given that other similar academic research has normally focused on specific geographical areas. Basel III introduced the NSFR as a systemic liquidity risk measure that this study applied in order to verify that a more recently developed liquidity measure, the LMI, can be used as a systemic risk measure. The analyses compared a GMM estimation model's results for both liquidity risk variables.

The descriptive statistics generated and geographical analyses confirmed the existence of similarities between the LMI and NSFR. However, these results were based on real absolute values, so, when the LMI's (i.e., without transformation) relationship with the NSFR (i.e., without transformation), the results appeared to be different. The analyses that included a time perspective revealed that the LMI's lowest value was in the pre-crisis period, with liquidity progressively increasing over the next two periods and the overall evolution leading to higher liquidity and lower liquidity risk. A comparison of the LMI and NSFR's results verified that they show the same trend from the pre-crisis to post-crisis period, that is, an increase in liquidity.

The regression model for the LMI and NSFR confirmed that they present the same behavior in relation to the independent variables classified as determinants. Of the 10 determinants used in the estimation model, CG is not significant for the LMI and NSFR, ROE is nonsignificant only for the LMI, and monetary conditions are not significant only for the NSFR. The remaining independent variables are significant, presenting the same behavior for both the LMI and NSFR.

Another important finding is the capital requirements' strong impact on the dependent variables. This independent variable was represented in the study by the LR. The regression model highlighted this variable as having the strongest relationship with both systemic liquidity risk ratios.

This research thus explored the LMI's application as a systemic liquidity risk measure. The results are in line with recent studies such as that of Bai et al. (2018), who "suggest that this aggregate LMI is a useful barometer for a macroprudential assessment of systemic risk." Future research could expand on the present study by analyzing cross-border samples to compare international financial systems with single banks and create a classification of individual banks' systemic risk.

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Table 4.1. Countries included

Country	
Australia	Lithuania
Austria	Malaysia
Azerbaijan	Malta
Bangladesh	Mauritius
Botswana	Morocco
Brazil	Netherlands
Bulgaria	Paraguay
Canada	Peru
Chile	Philippines
China	Poland
Colombia	Portugal
Côte d'Ivoire	Romania
Croatia	Russia
Czech Republic	Saudi Arabia
Denmark	Singapore
Finland	Slovakia
France	Slovenia
Georgia	South Africa
Germany	Spain
Hungary	Sweden
India	Switzerland
Indonesia	Taiwan, Province of China
Ireland	Thailand
Israel	Tunisia
Italy	Turkey
Japan	United Kingdom
Kazakhstan	United States of America
Korea (Republic of)	

Table 4.2. Banks by geographical zone

Geographical Zone	Number of Banks
Asia	156
Europe	126
USA and Canada	112
Japan	78
Eastern Europe and Russia	73
South America	50
Africa	24
Middle East	15
Australia	6
Switzerland	5

Table 4.3. Stylized balance sheet and weights from Basel III

#	Assets	Wi	#	Liabilities & Equity	Wi
A-01)	Loans 100%	100%		Deposits & short term funding	
	Gross loans		P-02)	Total customer deposits	80%
	Less: reserves for impaired loans / NPLs		P-03)	Deposits from banks	0%
	Other Earning Assets		P-04)	Other deposits and short-term borrowings	0%
	Other Earning Assets			Other interest bearing liabilities th EUR	
A-05)	Loans and advances to banks	80%	P-06)	Derivatives	0%
A-06)	Derivatives	35%	P-07)	Trading liabilities	0%
A-07)	Other securities	35%	P-08)	Long term funding	100%
A-08)	Remaining earning assets	35%	P-09)	Other (non-interest bearing)	100%
			P-10)	Loan Loss Reserves	100%
A-10)	Fixed Assets	100%	P-11)	Other Reserves	100%
A-11)	Non-Earning Assets	100%			
			P-12)	Equity	100%
	TOTAL ASSETS			**TOTAL LIABILITIES & EQUITY**	

Table 4.4. Geographical analysis

	LMI		LMI_LN		NSFR		NSFR_LN	
	Mean	Std	Mean	Std	Mean	Std	Mean	Std
Europe	3,899,431	11,699,528	11.1399	5.1061	0.8523	0.1766	0.5323	0.2245
USA and Canada	982,896	4,439,873	8.6804	4.6067	0.9637	0.1635	0.5468	0.2702
Japan	1,413,856	1,364,232	13.7143	1.1403	0.9639	0.0559	0.6732	0.0414
South America	1,426,016	4,318,294	10.7647	4.9423	0.8212	0.1695	0.5029	0.2309
Africa	480,845	861,392	10.6363	5.4481	0.8905	0.1345	0.5915	0.1748
Asia	3,613,108	15,978,762	11.1933	5.2563	0.9128	0.1113	0.5556	0.2319
East Europe	852,589	2,174,785	10.4012	4.6932	0.7911	0.1305	0.5092	0.2027
Middle East	2,339,171	1,927,139	14.2280	1.0928	0.9245	0.0532	0.6543	0.0277
Australia	14,770,875	12,173,392	15.8209	1.4954	0.7777	0.0607	0.5748	0.0342
Switzerland	6,952,190	14,014,125	9.9670	6.5483	0.7895	0.1676	0.4177	0.2723
All	**2,447,895**	**10,018,895**	**11.0119**	**4.8809**	**0.8929**	**0.1500**	**0.5571**	**0.2211**

Table 4.5. Descriptive statistics for time analysis

	LMI		LMI_LN		NSFR		NSFR_LN	
	Mean	Std	Mean	Std	Mean	Std	Mean	Std
Pre-Crisis	1,206,774	4,536,078	9.7906	5.3107	0.9035	0.1688	0.5147	0.2664
Crisis	1,978,150	7,034,823	11.4347	4.2865	0.8739	0.1540	0.5789	0.1855
Post-Crisis	3,510,181	13,296,491	11.6148	4.7108	0.8930	0.1377	0.5745	0.1993
All	**2,447,895**	**10,018,895**	**11.0119**	**4.8809**	**0.8929**	**0.1500**	**0.5571**	**0.2211**

Table 4.6. Correlation matrix for LMI

	LMI_LN	TA_LN	LR_LN	TIER1_LN	CREDITGROWTH_LN	NPL_LN	MMARKETTOLIAB_LN	ROE_LN	CTI_LN	GDPGROWTH_LN	CPI_LN	MONETARYCONDITIONS_LN
LMI_LN	1											
TA_LN	0.9340 **	1										
LR_LN	0.3922 **	0.3188 **	1									
TIER1_LN	0.4218 **	0.4028 **	0.2760 **	1								
CREDITGROWTH_LN	0.2230 **	0.2151 **	0.2313 **	0.1201 **	1							
NPL_LN	0.1048 **	0.1793 **	0.1906 **	0.0219 *	0.0353 **	1						
MMARKETTOLIAB_LN	0.2901 **	0.3042 **	0.1518 **	0.0804 **	0.1038 **	0.1453 **	1					
ROE_LN	0.1835 **	0.1959 **	0.0808 **	0.0464 **	0.1301 **	-0.0335 **	0.0716 **	1				
CTI_LN	0.3995 **	0.4543 **	0.4371 **	0.2221 **	0.1767 **	0.1989 **	0.0313 **	-0.1411 **	1			
GDPGROWTH_LN	-0.0351 **	-0.0451 **	-0.0123	-0.0718 **	0.2040 **	-0.0293 **	0.0328 **	0.2101 **	-0.1460 **	1		
CPI_LN	-0.0835 **	-0.0910 **	0.1011 **	-0.0795 **	0.0948 **	0.1701 **	0.0606 **	0.1227 **	-0.0712 **	0.3579 **	1	
MONETARYCONDITIONS_LN	-0.0476 **	-0.0696 **	0.0793 **	-0.0190	0.0926 **	0.1428 **	0.1206 **	0.1359 **	-0.0837 **	0.2931 **	0.7404 **	1

**Correlation is significant at the 0.01 level (2-tailed). *Correlation is significant at the 0.05 level (2-tailed).
This table shows the results of the bivariate test, Pearson Product Moment.
Coefficient. Dependent variable is the Liquidity Mismatch Index (LMI)
The independent variables are: Total Assets (TA_LN), Leverage Ratio (LR), TIER 1 (TIER1_LN), Credit Growth (CG_LN), Non-Performing Loans Ratio (NPL_LN), Money Market Funding to Total Liabilities (MML_LN), Return on Equity (ROE_LN), Cost-to-Income Ratio (CTI_LN), Gross Domestic Product Growth (GDPG_LN), Consumer Price Index (CPI_LN), monetary conditions (MMR).

Table 4.7. Correlation matrix for NSFR

	NSFR_LN	TA_LN	LR_LN	TIER1_LN	CREDITGROWTH_LN	NPL_LN	MMARKETTOLIAB_LN	ROE_LN	CTI_LN	GDPGROWTH_LN	CPI_LN	MONETARYCONDITIONS_LN
NSFR_LN	1											
TA_LN	0.8505 **	1										
LR_LN	0.5238 **	0.3188 **	1									
TIER1_LN	0.4057 **	0.4028 **	0.2760 **	1								
CREDITGROWTH_LN	0.2335 **	0.2151 **	0.2313 **	0.1201 **	1							
NPL_LN	0.2087 **	0.1793 **	0.1906 **	0.0219 *	0.0353 **	1						
MMARKETTOLIAB_LN	0.0450 **	0.3042 **	0.1518 **	0.0804 **	0.1038 **	0.1453 **	1					
ROE_LN	0.1509 **	0.1959 **	0.0808 **	0.0464 **	0.1301 **	-0.0335 **	0.0716 **	1				
CTI_LN	0.5788 **	0.4543 **	0.4371 **	0.2221 **	0.1767 **	0.1989 **	0.0313 **	-0.1411 **	1			
GDPGROWTH_LN	-0.0710 **	-0.0451 **	-0.0123	-0.0718 **	0.2040 **	-0.0293 **	0.0328 **	0.2101 **	-0.1460 **	1		
CPI_LN	-0.0787 **	-0.0910 **	0.1011 **	-0.0795 **	0.0948 **	0.1701 **	0.0606 **	0.1227 **	-0.0712 **	0.3579 **	1	
MONETARYCONDITIONS_LN	-0.1059 **	-0.0696 **	0.0793 **	-0.0190	0.0926 **	0.1428 **	0.1206 **	0.1359 **	-0.0837 **	0.2931 **	0.7404 **	1

**Correlation is significant at the 0.01 level (2-tailed). *Correlation is significant at the 0.05 level (2-tailed).
This table shows the results of the bivariate test, Pearson Product Moment.
Coefficient. Dependent variable is Net Stable Funding Ratio (NSFR)
The independent variables are: Total Assets (TA_LN), Leverage Ratio (LR), TIER 1 (TIER1_LN), Credit Growth (CG_LN), Non-Performing Loans Ratio (NPL_LN), Money Market Funding to Total Liabilities (MML_LN), Return on Equity (ROE_LN), Cost-to-Income Ratio (CTI_LN), Gross Domestic Product Growth (GDPG_LN), Consumer Price Index (CPI_LN), monetary conditions (MMR).

Table 4.8. GMM estimation model for determinants of bank liquidity risk: LMI and NSFR

Variable	LMI_LN		NSFR_LN	
	Coefficient	Prob.	Coefficient	Prob.
LR_LN	35.4144	0.0000	1.4589	0.0000
TIER1_LN	0.0529	0.0000	0.0027	0.0000
CREDITGROWTH_LN	0.8268	0.0000	0.0183	0.0000
NPL_LN	5.5498	0.0000	0.6342	0.0000
MMARKETTOLIAB_LN	4.7314	0.0000	-0.1529	0.0000
ROE_LN	0.1308	0.3009	0.0478	0.0000
CTI_LN	1.3647	0.0000	0.1559	0.0000
GDPGROWTH_LN	-0.0209	0.8724	-0.0112	0.1540
CPI_LN	-1.4825	0.0000	-0.0425	0.0231
MONETARYCONDITION	-1.0579	0.0109	0.0057	0.8351
AR(1)	0.6472	0.0000	0.6265	0.0000
AR(2)	0.0056	0.5491	-0.0235	0.0109
C	7.6547	0.0000	0.3704	0.0000
R-squared	0.9904		0.9918	
Adjusted R-squared	0.9894		0.9910	
Prob.	0.0000		0.0000	
Durbin-Watson stat	1.9124		1.9769	

5. Conclusion

The main purpose of this conclusion is to summarize the theoretical and empirical findings of this research composed by three different but complementary studies. Additionally, we aim to provide a resume of the contribution of this work to the existing body of knowledge on banks liquidity through the usage of financial information from banks' financial statements and finally, as a third purpose, to provide paths for future research.

The collection and processing of data have been the major challenges of this work. From a universe of more than 18 thousand financial institutions, of different types, the final sample includes 645 commercial banks that are the result of several interactions. After all, the real representation of the banking sector affects commercial banks, which is why this study focus on them.

After the data collection and processing the second biggest challenge of this work was define the independent variables, his correct transformation and the definition of the most appropriate regression model.

Due to the long sample period, thirteen years, and the existence of perhaps only one credible data source (Bankscope) the data collection was made in two stages, the first one from 2003 to 2011 and the second from 2012 to 2015. Due to this many of the banks present different ID codes requiring the reconciliation of the data.

Over eight thousand observations were obtained for each of the 645 banks. This led to the third big challenge of this study, identifying a model that supported this volume of data in a two-entry structure, requiring a data panel mixed model.

5.1. Empirical framework

The empirical analysis began with the choice and definition of the appropriate measures for bank liquidity. Based upon the banks' financial statements data between 2003 to 2015 three liquidity measures were constructed: the net stable funding ratio, the short-term funding ratio and the liquidity mismatch index. Additionally, the leverage ratio was calculated to become the dependent variable for capital.

Net stable funding ratio, short-term funding ratio (as a proxy for the liquidity coverage ratio) and leverage ratio are all the three Basel III measures. According to Basel III, the leverage ratio is defined as the amount of assets and commitments that should not represent more than 33 times the regulatory capital. In this case we observe heterogeneity across countries motivated probably by diverse country-specific regulatory requirements. The net stable funding ratio assumes that long-term financial resources must exceed long-term commitments and, to verify the robustness of the output data we apply short term funding ratio which assumes that high-quality and highly-liquid available assets must exceed the net short time cash outflows. A higher net stable funding ratio and a higher leverage ratio will correspond to lower bank liquidity in line with extant studies. Finally, the liquidity mismatch index is a recent measure developed by researchers wishing to consider the liquidity of assets minus the liquidity promised through liabilities. This measure intends to capture relevant exposures and represents a useful diagnosis for systemic liquidity risk.

Two sets of independent variables were used. The first one includes bank and country specific variables: total assets, to measure banks' size, the leverage ratio as a measure of the proportion of shareholders equity to assets, the TIER 1 as regulatory measure, the credit growth, the non-performing loans ratio, the money market funding to total liabilities, the return on equity (ROE) as a performance measure, the cost-to-income ratio, the gross domestic product growth, the Consumer Price Index and the monetary conditions are the money market rates in each country. The second set of independent variables aims to analyze the banks' balance sheet patters and includes gross loans, interbank borrowing, wholesale debt, interbank lending, customer deposits, stable funding and trading exposure. To test all the data several estimation models were used, with preference to the generalized method of moments.

To obtain a good and appropriate understanding of banks liquidity effects this empirical work is composed by three studies. The first is "The structure of banks' balance sheet – A liquidity risk approach" and aims to analyze the evolution of banks' balance sheet structures along the thirteen years period, from 2003 to 2015. The second study is "Determinants of liquidity risk" and intends to shed light on the link between the structure of banks' balance sheets and business profiles and liquidity. The third one is "Liquidity mismatch as a systemic measure" and aims to provide insights into the measurement of systemic liquidity risk through banks balance sheet data and asset and liability management with the expectation of offer some additional ideas on the banks' systemic funding liquidity risk.

5.2. Summary of results

Despite all the studies and analyzes performed and all the findings, this work contributes to the compilation and systematization of a panel data related to worldwide commercial banks. The sample created for this work brings a better understanding and knowledge improvement of the banks' behavior during the period under analysis that includes the biggest financial crisis of the last century.

Regarding the bank patterns we found that only 10% of the banks have NSFRs above 1%, the minimal value recommended by regulators. In a broad overview, the commercial banks analyzed do not comply with the minimal values required to long-term liquidity. However, when we analyze the series using sub periods, we find that in the pre-crisis period the percentage of banks with NSFR lower than 1% was 80% and with a concentration of 90% for values between 0.70% and 1.15%, indicating that, in this period, short-term liquidity was the banks' main concern. The impact on bank liquidity is obvious and we can verify that in the crisis period the percentage of banks with NSFR lower than 1% increases to 90% of the analyzed institutions and that the concentration of NSFR between 0.69% and 1% representing 91% of the analyzed commercial banks. In the post-crisis period, we have seen a reduction of long-term liquidity in institutions with 93% of banks presenting an NSFR levels below 1% and concentration between 0.69% and 1% NSFR of 96% of commercial banks. The pattern for all these periods is the existence of a negative relation between the independent variables and the NSFR. One important remark is that interbank borrowing is presented in the model for the global period as the variable with most impact on the NSFR. For STFR the pattern for all these periods is that when the coefficients are significant there exists a positive relation between the independent variables and the dependent variable. Regarding the LMI the pattern for all the periods is the existence of negative relations between the independent variables and the dependent variable. The analysis also shows that liabilities have a greater impact on the LMI in the period of crisis and post-crisis, indicating an increase in funding sources. Banks' business models appear to have no impact on liquidity.

Regarding the liquidity risk determinants, the estimation model results highlight that bank size, capitalization, credit improvement, assets quality funding sources, profitability and efficiency can have a positive impact on long-term liquidity risk management. Regarding country variables we have found a negative impact on long-term liquidity of GDP growth. Overall, internal factors have a bigger impact on bank liquidity than macroeconomic factors. When we replace the liquidity measure with the short-term funding ratio the results are consistent and in accordance with the results obtained by the use of the NSFR, which also means the existence of a relationship between the two measures. Additionally, the well capitalized banks have a better long-term liquidity that translates into institutions and are more stable and better able to deal with crisis scenarios and bear crisis periods.

Regarding LMI as a liquidity systemic risk measure, we have found the existence of similarities between the statistical behavior of LMI and NSFR namely by exhibit the same behavior by region. Additionally, and in a time period analysis the LMI and the NSFR have the same evolution from pre-crises period to post crises period that is an increase of liquidity. This study confirms that LMI is a good approach to be used as a systemic liquidity risk measure.

5.3. Contributions

Liquidity risk remains one of the banks' most worrying challenges. However, previous studies often presented contradictory results and there is no consensus on how to measure the systematic liquidity risk.

Thus, and beyond all the analysis performed and all the findings, this work is different from other works because it contributes to the creation of long data series on worldwide commercial banks. The sample analyzed includes 645 commercial banks from 55 countries for 13 years and added the calculation of a set of indispensable ratios and indicators to the better understanding and knowledge improvement of the banks behavior during the period under analysis that include the biggest financial crisis of the last century.

Compared to other studies, this study covers a significant number of commercial banks over a broad period including three sub periods and they are pre crisis period, crisis period and post crisis period. This coverage allows us to assess the reaction and behavior of long-term liquidity of banks in three different scenarios and thus infer about the factors and variables that have impact on both liquidity and capital. This coverage allows us to assess the reaction and behavior of short and long term liquidity of banks with three different liquidity measures, in three different scenarios and in different geographies.

This work contributes to additional knowledge by empirically testing the new liquidity measures against a kind of effects represented by determinants of liquidity as bank specific determinants, country determinants and time determinants. Through this analysis, the empirical findings exhibit the determinants of liquidity and the importance of measuring bank liquidity and bank liquidity risk. Additionally, was tested the impact of the determinants of liquidity against the Basel III liquidity measures and the new proposed liquidity measure (LMI). This comparative analysis allowed to relate both measures and infer about is relation and extension. This work was already performed considering the interbank linkages and the interconnected financial markets as we compute a cross-border sample.

A useful liquidity measure must be convenient to apply in micro and macro prudential regulation and should be able to quantify the banks and the system liquidity. This both dimensions will be need it to rank the banks in the system and evaluate the banks risk level. Indeed, the liquidity buffers regulation is a very important issue, not only for micro-prudential, but also systemic perspective reason. The analysis performed in this work allowed to produce a varied set of data and relationships between liquidity variables and several determinants that allow the authorities not only to identify which specific determinants of banks have the greatest impact on banks' liquidity but also to know the impact of economic determinants such as GDP, inflation or market rates. This data will be a useful support to understand liquidity and liquidity risk behavior across the time as well as in a cross-border dimension and through this calibrate the actual tests and controls.

Also, banks liquidity management could take advantage of the information produced in this work. Due to the use of real data obtained directly from banks' financial statements, it was possible to identify patterns in banks behavior and trends in liquidity indicators. This work also made it possible to understand the impact of banks' balance sheet aggregates on liquidity indicators, which provides banks' assets and liabilities management with important information on the behavior of liquidity in function of the composition of banks' balance sheets.

This work also made it possible to identify and analyze relationships between banks' balance sheet items and liquidity indicators for which there are very few previous results.

Through this work we also introduce the LMI as systemic liquidity risk measure computed over a sample of 645 worldwide commercial banks from 55 countries which gives this analysis a dimension not yet addressed in other similar academic works, which normally focus on a specific geography. The statistical analysis performed over this new liquidity indicator made it possible to know its evolution from a temporal and cross-border perspective. Additionally, the determinants analysis performed over the LMI made not only with bank specific variables but also with macro-economic variables and also with balance sheet aggregates allowed to improve the knowledge about the behavior of this indicator. All this new knowledge about this new liquidity ratio will help regulators and managers to better understand the liquidity cycles and with this help him to make the best decisions for liquidity controls.

The findings stemming from these three studies provide broad support to academics, banks and authorities perform potential initiatives on structural liquidity and leverage and allow us to conclude about the complementary nature of these areas. Through this work the determinants of long-term liquidity risk were assessed and analyze which kind of variables impact on the new indicators proposed by Basel Committee.

5.4. Limitations of this work and recommendations for future research

This study is limited to commercial banks. However, we believe that this is minor issue as the commercial banks are one of the main institutions of a developed market system as well as the importance of his link with the economic system which directly impacts the level of production efficiency. This fact is already confirmed by the major presence of commercial banks in the global systemically important banks list produced by the Financial Stability Board.

Hoping to predict and prevent risk situations, new liquidity measures were proposed by academics and regulators. The LMI is a good example of simple measure that must be explored with real and effective data from banks financial statements and through a cross-border dimension of liquidity risk. In complement to the Basel III liquidity measures, new concepts like the eligible liquidity ratio and advances to stable funding ratio must be evaluated and analyzed.

Finally, the existent indicators were impacted by the lack of longer time series and data granularity. Improved qualitative background data must be used in order to bring quality to the indicator's interpretation.