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DISSERTATION

DIGITAL PAYMENTS AND LIQUIDITY RISK MANAGEMENT IN TRADITIONAL BANKS: A EURO AREA PERSPECTIVE

CAMILLA GUIMARÃES MARTINS

OCTOBER - 2024

Lisbon School of Economics & Management
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For Your endless grace, love, and blessings. Thank You for the strength and wisdom to accomplish this journey.

ABSTRACT

With the ongoing digital transformation in financial services, digital payments have gained prominence, affecting the operations of traditional commercial banks, particularly in managing liquidity risks. This dissertation explores how digital payments influence key liquidity indicators, including the Liquidity Coverage Ratio, Loan-to-Deposit Ratio, and Liquid Asset Ratio, using data from 2018 to 2022. Three estimation methods were applied: the Fixed Effects Model, Random Effects Model, and Ordinary Least Squares Method. The study tests the hypothesis that digital payments are significantly associated with the liquidity risk profiles of banks, considering both bank-level and country-level variables. In general, the results from the Ordinary Least Squares Method suggest a statistically significant relationship between digital payments and *liquidity* variables. However, the Fixed Effects and Random Effects models present mixed results, with limited significance for the digital variables, suggesting that they failed to consistently capture the effects of digital payments on liquidity risk. Overall, the study highlights the need for banks to adjust their liquidity management strategies to remain stable in an increasingly digitalized environment.

KEYWORDS: digital payments; electronic payment; liquidity risk management; liquidity requirements; commercial banks; euro area

JEL CODES: G21; G28; G32; G38; C23

Resumo

Com a transformação digital em curso nos serviços financeiros, os pagamentos digitais ganharam destaque, afetando as operações dos bancos comerciais tradicionais, especialmente na gestão dos riscos de liquidez. Esta dissertação explora a forma como os pagamentos digitais influenciam os principais indicadores de liquidez, incluindo o *Liquidity Coverage Ratio*, *Loan-to-Deposit Ratio*, e *Liquid Asset Ratio*, utilizando dados de 2018 a 2022. Foram aplicados três métodos de estimação: o Modelo de Efeitos Fixos, o Modelo de Efeitos Aleatórios e o Método dos Mínimos Quadrados Ordinários. O estudo testa a hipótese de que os pagamentos digitais estão significativamente associados com os perfis de risco de liquidez dos bancos, considerando tanto as variáveis ao nível do banco como ao nível do país. Em geral, os resultados do Método dos Mínimos Quadrados Ordinários sugerem uma relação estatisticamente significativa entre os pagamentos digitais e as variáveis de *liquidez*. No entanto, os modelos de Efeitos Fixos e Efeitos Aleatórios apresentam resultados mistos, com pouca significância para as variáveis digitais, sugerindo que não conseguiram capturar consistentemente os efeitos dos pagamentos digitais no risco de liquidez. No geral, o estudo destaca a necessidade de os bancos ajustarem suas estratégias de gestão de liquidez para manterem-se estáveis em um ambiente cada vez mais digitalizado.

Palavras-chave: pagamentos digitais; pagamentos eletrónicos; gestão do risco de liquidez; requisitos de liquidez; bancos comerciais; zona euro

Códigos de classificação JEL: G21; G28; G32; G38; C23

GLOSSARY

CAR – Capital Adequacy Ratio

D-payments – Digital Payments

FE – Fixed Effects Model

GDP – Gross Domestic Product

LA – Liquid Assets Ratio

LCR – Liquidity Coverage Ratio

LDR – Loan to Total Deposit Ratio

LRM – Liquidity Risk Management

NIM – Net Interest Margin

NFC – Near Field Communication

NPL – Non-performing Loan

OLS – Ordinary Least Squares

PSD2 – Payment Services Directive 2

RE – Random Effects Model

WGI – Worldwide Governance Indicator

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ACKNOWLEDGMENTS

Completing this dissertation, after overcoming numerous challenges, stands as one of my most significant personal accomplishments. I would therefore like to express my deepest gratitude to everyone who has contributed to this important stage in my life.

Firstly, I would like to thank Professor Florence Mendes Correia Carp Pinto Basto for her constant support, availability and valuable advice. Her contribution was essential to the completion of this work, and her guidance helped me overcome the challenges along the way.

I must also express my deepest gratitude to my family, who always supported me and gave me the opportunity to pursue my studies. Most of all, I would like to thank my mother for her unconditional support and for believing in my dreams. Without her, none of this would have been possible.

Finally, I would like to thank my friends for their companionship and encouragement throughout this journey. In particular, to the friendships I cultivated during my master's, with whom I shared moments of genuine connection, and that I will always hold close to my heart.

1. INTRODUCTION

During a time marked by fast technological growth and changing consumer desires, the financial sector has experienced a significant change. A major advancement in recent years has been the widespread use of digital payment (D-payments) systems, changing the way people and companies handle financial transactions. In the middle of this digital transformation, traditional Eurozone banks face a critical intersection, navigating the complexities of incorporating D-payments solutions into their operations while ensuring effective liquidity risk management (LRM).

The transition from cash to D-payments methods and the subsequent decline in cash usage have long been seen by economists as natural progressions in monetary and payment systems (Srouji, 2020). This transition has been accelerated by factors such as increased internet and smartphone usage, the rising adoption of digital commerce, and the growing demand for faster and more convenient payment options (Ramli & Hamzah, 2021). As a result, although cash is still widely used, payments are increasingly being conducted with digital instruments, which reflects consumer preferences for efficiency and simplicity.

Traditional banks are essential to preserving financial stability and promoting economic activity within the Eurozone - group of 20 member nations that use the Euro as their common currency. Nevertheless, the emergence of D-payments technologies - from cryptocurrency to mobile wallets - has created additional layers of liquidity risk and put traditional methods of managing liquidity in risk. Despite these insights, empirical research on the relationship between D-payments and LRM on commercial banks remains limited and warrants further investigation. This document aims to analyse this relationship comprehensively to understand its implications for the banking sector, exploring if D-payments are associated with the LRM of traditional banks in the Euro Area. In other words, it intends to uncover the implications of digitalization on liquidity risk dynamics, identifying challenges and opportunities, and proposing strategies to enhance banks' resilience in evolving payment landscapes. For this purpose, variables representing D-payments and bank liquidity were collected, alongside bank-level and country-level variables. This approach acknowledges the diverse characteristics of the banks in the sample, which originate from different countries. By gathering this data, the research question will be tested using different statistical approaches.

This dissertation is divided into five chapters. The second chapter presents the literature review, covering the following points: (1) introduction to the concept of D-payments, description of the types of D-payments and their position in the Euro Area context, (2) introduction to the concept of LRM, definition of Basel III requirements and dependent variables definitions, (3) analysis of the relationship between D-payments and LRM. The third chapter describes the sample, the methodology adopted, the empirical model used and a description of all the variables under study. The fourth chapter is dedicated to the analysis and discussion of the results obtained. Finally, the fifth chapter presents the conclusions, the limitations of the study and suggestions for future research.

2. LITERATURE REVIEW

2.1 Digital Payments

2.1.1 Definition of Digital Payments

D-payments has revolutionized the way transactions are conducted, offering a convenient and instant method for both payer and payee. Unlike traditional methods involving cash, D-payments rely solely on digital ways for sending and receiving money. This eliminates the need for physical currency notes, making transactions smoother and more efficient. Whether it's paying for purchases via a smartphone using wireless technology or conducting electronic transactions over the internet with credit or debit cards, D-payments encompasses a wide array of methods (Khando et al., 2023). Such as mobile payments, through apps or e-wallets, cryptocurrencies like bitcoin, which allow encrypted peer-to-peer transactions, online transfers, and other electronic systems. Later, some of these cashless instruments will be discussed.

Furthermore, point-of-sale transactions have been easier with the introduction of smartphone technology. Whether at a kiosk terminal or in a retail store, users can quickly and safely make contactless payments using applications that use Near Field Communication (NFC), QR codes, or Bluetooth-based transmission (Mützel, 2021).

The offerings of global internet giants such as Amazon, Apple, Facebook, Google, and Samsung demonstrate the widespread availability of D-payments solutions (Mützel, 2021). These companies provide unique D-payments solutions tailored to everyday retail transactions, contributing to the widespread adoption and integration of D-payments methods into our daily lives.

Following the Covid-19 pandemic, D-payments have become much more important. Consumers were forced to switch to online shopping due to social distancing policies and restricted mobility, which increased the volume of digital commerce (Acopiado et al., 2022). The use of contactless and other D-payments systems was accelerated by lockdowns and worries about the spread of viruses via physical money. This shift not only facilitated safer transactions but also propelled industries towards greater collaboration and innovation. As face-to-face activities diminished, transactions for goods and services migrated to online platforms, reinforcing the prominence of D-payments in our daily lives (Acopiado et al., 2022).

As consumers increasingly switch from physical to digital instruments and D-payments technologies gain popularity, they are promoting more efficient, faster, and more convenient forms of payment. Credit and debit cards are two of these technologies that stand out for their versatility in terms of payment methods. These cards are compatible with both online and offline transactions and, when used in person, they often have NFC chips that make it possible to make payments without any problems. NFC technology facilitates touch-free payments by connecting electronic devices over short distances (Khando et al., 2023). This technology is essential for contactless D-payments, which use both NFC and Magnetic Secure Transmission (MST) technology. NFC enables consumers to make payments with their mobile wallets using various devices like tablets, smartphones, or smartwatches, enhancing convenience, and minimizing physical contact during transactions (EMARKETER, 2023).

In summary, the widespread adoption of D-payments has been propelled by various factors, including advancements in technology, supportive regulatory frameworks such as the Payment Services Directive 2 (PSD2) in the Euro Area, policies aimed at reducing cash usage, and the COVID-19 pandemic. These combined forces have reshaped the landscape of financial transactions, paving the way for the rapid expansion of D-payments platforms worldwide (Panetta et al., 2023).

2.1.2 Card Payments

Payment cards, including credit cards, debit cards, and prepaid cards, are among the most common types of financial instruments used for transactions. Customers obtain them from banks and financial institutions, allowing them to access their bank accounts and make purchases in person at points-of-sale (POS) terminals or online. In this sense, a payment card is digitally associated with the cardholder's account or accounts. Furthermore, the card can be used to verify the identity of the cardholder in transactions, ensuring a safe way to make payments. Providing the Card Verification Value (CVV) number and expiry date of the card is necessary for users to utilise payment cards safely and efficiently, minimising the risk of fraud number and expiry date of the card (Franciska & Sahayaselvi, 2017). In general, these security measures improve the security and reliability of card-based transactions, providing guarantees for both cardholders and companies.

Debit cards allow customers to pay directly from their bank accounts, eliminating the need for cash or cheques. When a debit card transaction is made, the required amount of money is deducted from the cardholder's account immediately. Customers use debit cards to deposit funds in advance into their bank accounts, ensuring they have enough funds available for withdrawals at the moment of purchase (Rachna & Singh, 2013).

Credit cards provide flexibility by letting users utilise their money or withdraw cash from ATMs by borrowing from the issuer. Unlike debit cards, which deduct funds straight from the cardholder's bank account, credit cards have a credit limit set by the issuer. The maximum amount a cardholder may borrow is shown by this credit line, sometimes referred to as a credit limit. When making purchases, cardholders can choose to either pay off the entire outstanding balance by the deadline or make a smaller payment called the "minimum amount" (Franciska & Sahayaselvi, 2017). Cardholders can adjust their finances based on their preferences and needs with this flexibility in repayments.

In addition, prepaid cards are purchased with a certain amount of money already loaded, allowing users to use funds up to that specific limit. Like debit cards, prepaid cards can be obtained without the need for a bank account (Khando et al., 2023). This flexibility makes prepaid cards accessible to individuals who may not have traditional banking services.

2.1.3 Mobile Payments and Digital Wallets

Mobile payments refer to the process of conducting transactions for goods, services, and bills using a mobile device (Khando et al., 2023). This cashless method is facilitated by a mobile payment instrument, such as a mobile credit card or a mobile wallet. These transactions fall into two main categories: everyday purchases and bill payments. For daily purchases, mobile payments serve as a complement or competitor to traditional payment methods. As far as bill payments are concerned, mobile payments give access to account-based payment instruments such as money transfers, internet banking, direct debit assignments or electronic invoice acceptance (Dahlberg et al., 2008). The expansion of mobile commerce and online e-commerce has driven the growth of digital mobile payment products in the retail consumer market. Popular mobile payment options include well-known systems like PayPal, Apple Pay, Google Pay, and Samsung Pay (Jegerson & Hussain, 2023).

Digital wallets offer a convenient cashless mode of payment accessible through mobile phones or other devices. Users load money from their bank accounts using debit/credit cards or net banking, enabling transactions with people or merchants directly from the wallet. These wallets provide a range of services and operate mainly through apps, which have gained preference over websites, especially on smartphones (Bagla & Sancheti, 2018). While some digital wallets require an internet connection for transactions, others offer offline capabilities limited to online transactions. For retail transactions, NFC and QR-code-based technologies are prevalent, facilitating over-the-counter payments via smartphones. QR-code-based e-wallets enable contactless payments through QR image scans, both printed and displayed (Ramli & Hamzah, 2021).

2.1.4 Cryptocurrencies

The financial world has been completely transformed by cryptocurrency, which is a digital currency protected by cryptography. In order to meet the demands for decentralisation, money supply control, and inflation reduction, it evolved as a peer-to-peer payment system using modern cryptology and communications technologies (Khando et al., 2023). While cryptocurrency payments offer pseudonymous transactions and irreversible transactions through a global peer-to-peer network, they operate as a "push-based" payment system, allowing users to transfer specific amounts to merchants securely (Nuryyev et al., 2021).

At the core of cryptocurrency lies the theory of solving encryption algorithms to create finite, unique hashes. This innovative approach grants cryptocurrencies like Bitcoin unparalleled agility in being bought, sold, and used worldwide, making them a robust contender in today's financial realm (Devries, 2016). Facilitating fast, secure, and anonymous person-to-person payments over the internet, cryptocurrencies overcome traditional limitations of time and space (Nuryyev et al., 2021).

The majority of cryptocurrencies use encryption to provide security while operating on decentralised networks driven by blockchain technology. For example, fee-free transactions and worldwide accessibility are two ways that the blockchain-based cryptocurrency Bitcoin has the potential to revolutionise the digital financial market (Khando et al., 2023). Cryptocurrency stands out as a flexible and effective way to execute transactions globally in the current digital ecosystem.

2.1.5 Landscape of the Digital Payments in Euro Area

In the Euro Area, D-payments are growing significantly due to shifting consumer preferences and technological improvements. However, with expansion comes issues, and governments and regulatory agencies are being forced to modify regulations to deal with emerging technologies, consumer protection, money laundering prevention, and data privacy (Putrevu & Mertzanis, 2023).

Different countries have distinct payment habits which reflect cultural and economic differences. Although, cash continues to occupy a crucial place in the payment's ecosystem, even with the rapid growth of D-payments. Public demand for cash remains stable, serving both as a means of payment and as a store of value (Putrevu & Mertzanis, 2023).

In the Euro Area, the PSD2 stands as a supportive regulatory framework. The goal of PSD2 is to make electronic payments easier, including credit transfers, debit transfers, card payments, and payments made online and through mobile devices. It was first proposed in 2007 with the goal of promoting a single market for payments throughout the European Union. The directive, updated in 2015, prioritizes enhancing the ease and security of internet payment services, bolstering consumer protection, and promoting innovative payment solutions.

According to a report by Statista (2024), the total transaction value in the Euro Zone Digital Payments market reached approximately €957.225 billion in 2022, encompassing various segments such as Mobile POS Payments, Digital Commerce, and Digital Remittances. E-payments have evolved from a technological novelty to one of the leading payment options, with e-payment transactions in the European Union growing by over 21% in 2021. Moreover, there has been a drastic increase in the number of e-payments since 2017, reaching a total of around 7.4 billion transactions. However, card payments remain the most used digital instruments, with the number of card-based payments in the Euro Area increasing by 13.5% in the second half of 2022.

Digital payments increase the fluidity and speed of money flows, leading to more frequent and smaller transactions, requiring banks to maintain higher liquid assets (Charles M. Kahn et al., 2022). This requires agile liquidity management practices to meet obligations and ensure stability. Thus, the development of D-payments can be significantly linked to LRM, forcing banks to adapt their strategies to maintain liquidity in the face of rapid changes in transactions, underlining the need for comprehensive risk management in the digital age.

2.2 Liquidity Risk Management

2.2.1 Definition of LRM and its Importance in the Banking Sector

The paper of Mohammad, Asutay, Dixon and Platanova (2020) states that given to the short-term liability contracts' inherent characteristics, the holders of deposit accounts are entitled to a reimbursement at any moment. Therefore, the liquidity risk develops on the liability side when several account holders take simultaneous withdrawals of their deposits at a time when the bank is unable to meet such huge demands. To manage this risk, banks typically sell liquid assets or borrow from the money market. However, liquidating assets can be costly if sold at low prices, potentially leading to insolvency risk.

Liquidity risk not only impacts a bank's performance but also its reputation, risking loss of depositor confidence. It arises from the bank's inability to meet obligations without incurring unacceptable losses, affecting both earnings and capital (Arif & Nauman Anees, 2012). For example, if a bank cannot meet its short-term liabilities, it may have to borrow funds at higher costs or sell assets at a loss, directly impacting earnings due to increased costs and asset sale losses.

Timely recognition of liquidity risk sources is crucial to avoiding losses. Therefore, banks need to maintain a certain level of liquid assets to effectively manage and reduce this risk. This involves holding minimum cash balances as a buffer to ensure they can meet their short-term obligations promptly. By doing so, banks are better prepared to handle unexpected large withdrawals by depositors, mitigating potential liquidity crises. This method decreases the likelihood of defaults, decreases borrowing expenses, and boosts financial stability overall, promoting economic growth (Sidhu et al., 2022).

Market liquidity risk and funding liquidity risk are the two primary categories of liquidity risk. The first arises when banks struggle to sell illiquid assets promptly at market prices (Mohammad et al., 2020). Funding liquidity risk, on the other hand, involves the possibility that a bank may not be able to settle obligations immediately over a specific timeframe (Drehmann & Nikolaou, 2013). When a bank is unable to meet its obligations on time, it's considered illiquid, potentially leading to default. Funding risk, closely linked to liquidity risk, pertains to a bank's ability to secure funds continuously. While liquidity risk focuses on the asset side of the balance sheet, funding risk concerns the liability side (King, 2013).

Bank liquidity is crucial for meeting financial obligations as they come due, encompassing the capacity to fund lending, investments, and withdrawals while managing liabilities (Hacini et al., 2021). According to the theory of financial intermediation, banks fulfil their vital role in the economy by creating liquidity through the balance between long-term assets and short-term liabilities, but they are always exposed to risk (Alaoui Mdaghri & Oubdi, 2022). In practice, banks create liquidity by matching illiquid assets with liquid liabilities, offering depositors easily accessible funds while investing in longer-term projects. In addition, banks facilitate seamless payment and settlement systems, ensuring the efficient transfer of goods and services, which strengthens economic activity (Arif & Nauman Anees, 2012).

LRM is vital for banks, and they must ensure that they have sufficient liquidity to manage risks effectively. As stated in the paper of Hacini, Boulenfad and Dahou (2021), the primary aim is to align cash inflows with outflows, fostering stability across the banking sector. By keeping liquidity at adequate levels, banks can cope with fluctuations in demand and market conditions, boosting shareholder confidence. This equilibrium is crucial for successful banking intermediation, promoting confidence and trust among stakeholders (Hacini et al., 2021). Risk managers play a pivotal role in mitigating liquidity risk, vital for maintaining the stability and profitability of banks, bolstering customer confidence, and guiding strategic decisions (Mohammad et al., 2020).

2.2.2 Basel III Requirements

In response to vulnerabilities highlighted during the crisis, the Basel Committee on Banking Regulation and Supervision (BCBS) initiated negotiations for new international standards, aiming to bolster LRM and financial stability (Simion et al., 2024). This led to the development of an international framework for assessing liquidity in banking, complementing stricter capital adequacy rules. While national-level principles for LRM existed pre-crisis, in December 2010 Basel III introduced more comprehensive global standards, addressing both short-term and long-term liquidity mismatches (Dietrich et al., 2014). These accords encompassed the implementation of regulatory leverage ratios alongside risk-weighted capital ratios and liquidity ratios (Roulet, 2018). Compliance with Basel III necessitates banks to restructure their balance sheets to enhance liability stability and asset liquidity (Alaoui Mdaghri & Oubdi, 2022).

Furthermore, the revised Basel III capital requirement mandates banks to maintain a capital buffer to absorb losses during economic stress. Leverage requirements were also strengthened to prevent potential crises stemming from decreased leverage, which could impact asset prices and bank capital adversely (Obadire et al., 2022). In an effort to preserve liquidity buffers and reduce the likelihood of future financial crises, the liquidity requirement was also improved to incorporate new ratios including the Liquidity Coverage Ratio (LCR) and the Net Stable Funding Ratio (NSFR). Overall, the Basel III Accord has expanded the scope of risk coverage to include countercyclical and liquidity concerns, strengthening the financial resilience, efficiency, and reliability of banking institutions by addressing both macroeconomic and portfolio-specific risks (Obadire et al., 2022).

2.2.3 Liquidity Coverage Ratio

The Liquidity Coverage Ratio (LCR) serves as a critical measure for banks, determining the necessary amount of high-quality, unencumbered liquid assets to endure a month without access to wholesale funding while still managing cash outflows (King, 2013). It's essentially the ratio between these assets and total net cash outflows over a 30-day period, with a minimum requirement of 100% (Dietrich et al., 2014), ensuring that the stock of high-quality liquid assets equals or exceeds projected outflows. This standard aims to mitigate liquidity risk by enhancing a bank's ability to convert assets into cash during stressful periods (King, 2013).

To comply with LCR requirements, banks must hold more high-quality liquid assets (HQLAs), prioritizing short-term liquidity obligations like demand deposits (Alaoui Mdaghri & Oubdi, 2022). However, this restriction may limit the amount of liquidity that banks are able to produce as they allocate resources to creating liquidity buffers rather than to investing in illiquid assets that accelerate economic growth.

Oversight of LCR implementation is closely monitored by institutions like the Bank for International Settlements (BIS) and the European Banking Authority (EBA). Studies have shown that LCR implementation impacts interest rates and maturity volumes in the interbank market, underlining its significance in shaping financial market dynamics (Heuver & Berndsen, 2022). Ultimately, the LCR was designed to fortify banks against short-term liquidity shocks, safeguarding against significant liquidity outflows by mandating a minimum liquidity buffer (Simion et al., 2024).

2.2.4 Loan-Deposit Ratio

The Loans to Total Deposits Ratio (LDR) is a metric used to assess a bank's liquidity and credit risk, as well as showing what percentage of a bank's loans are funded by its deposits. This ratio is calculated by dividing the total amount of loans a bank has issued by the total amount of deposits it holds (Hacini et al., 2021). The LDR provides valuable information on the proportion of assets a bank can generate from its liabilities and is a useful tool for assessing banks' funding profiles (Adenuga et al., 2021).

A higher LDR suggests that a bank is heavily utilizing its deposits to issue loans, which can signal financial pressure and increased risk. This high ratio indicates that the bank may face liquidity issues, as it relies extensively on deposits as a stable funding source (Hacini et al., 2021). Therefore, the LDR is crucial for understanding a bank's liquidity level, risk exposure, fund utilization, and intermediation activities (Adenuga et al., 2021).

As a general expectation, larger deposits can lead to the creation of more amount of loans (Adenuga et al., 2021). However, an excessively high LDR can imply that the bank is over-leveraging its deposits, potentially leading to liquidity problems and financial instability (Hacini et al., 2021; Rengasamy, 2014).

2.2.5 Liquid Assets Ratio

Defining a bank's liquidity policy is essential since banks need a strong liquidity risk management framework to guarantee they have enough liquid assets to endure stress situations (Kumar, 2013). Regulators require banks to maintain these liquid assets, and must evaluate banks' liquidity strategies, intervening if necessary to protect depositors and the financial system from the liquidity risk (Davis, 2008; Kumar, 2013).

Banks enhance their liquidity by holding a significant portion of liquid assets, ensuring immediate cash availability and collateral options like government securities (Davis, 2008). Despite the necessity, banks often avoid holding liquid assets due to their impact on profitability and the infrequency of crises. Central banks' liquidity provisions can lead to weak liquidity risk management, resulting in low liquid assets and poor liability management (Davis, 2008).

The Liquid Assets Ratio (LA), defined as liquid assets to total assets, indicates that a higher amount of liquid assets or better matching of asset and liability flows reduces liquidity risk but also profitability (Iannotta et al., 2007). Conversely, loans in distress can negatively affect both profitability and liquidity by disrupting expected cash flows (Kumar, 2013). Additionally, banks might increase risk-taking, as more liquid loans can be easily sold during crises (Mohammad et al., 2020).

2.3 Understanding the Relationship: Digital Payment Innovations and Liquidity Risk in Traditional Banking

Modern technology is essential to the way commercial banks conduct business in a changing environment. Nowadays, banks must adapt to technological advances to stay efficient and competitive. In order to preserve financial stability, banks must keep more liquid assets and modify their liquidity management procedures due to the acceleration and rise in transactions caused by D-payments. This digital shift has led to a surge in banking transactions, impacting profitability and liquidity management positively (Shanti et al., 2023).

A considerable portion of banking transactions now occur through computers or mobile devices, providing customers with immediate access to financial services (Kitsios et al., 2021). The adoption of digital payment services not only helps banks retain existing customers but also attracts new ones, providing numerous advantages for both banks and their customers. These benefits include immediate access to financial services, the ability to monitor investments, track rewards, manage expenses, and enhance overall transaction efficiency. Additionally, banks leveraging digital technologies benefit from time savings, lower operating costs, and enhanced monitoring and risk management capabilities (Kitsios et al., 2021).

In summary, although digital transformation has the potential to enhance liquidity, it could simultaneously decrease consumer loyalty and cause unpredictable deposit patterns, thereby increasing the likelihood of liquidity risk (Gupta, 2023). Digital transactions can have a significant impact on deposit patterns, potentially destabilizing liquidity levels. Thus, the interaction between LRM and D-payments emphasises the necessity of a comprehensive approach to risk management in the digital era. To reduce the possible negative effects of D-payments on liquidity, financial institutions must improve their liquidity management strategies, stressing the importance of resilience and adaptability in the face of technological advances. In an increasingly digitalized financial environment, this comprehensive strategy ensures that banks can successfully manage risks while preserving financial stability.

Therefore, considering what has been written in the previous sections, the following hypothesis is formulated:

H1: Digital payments ***are associated*** *with the liquidity risk management of banks belonging to the Eurozone.*

3. DATA AND METHODOLOGY

3.1 Sample

This research aims to test the connection between digital payments and the liquidity risk management of European banks, specifically those from Eurozone member countries. For this study, a sample time horizon covering the last five years, from 2018 to 2022, was selected. This timeframe was chosen to ensure access to the most recent and relevant data for the variables under investigation. Additionally, a significant factor influencing this timeframe was the full implementation of the LCR, in the European Union, set at a minimum of 100%, which took effect in January 2018. The financial variables were retrieved from the Orbis and Bloomberg database, while variables related to D-payments were collected from management annual reports available on each bank's website and reports available in the European Commission website.

Regarding the selection of banks for the study, an initial sample of 52 banks was defined, considering the following criteria's: (i) active commercial banks, (ii) publicly listed companies, (iii) Euro Area region and (iv) consolidated accounts with C1 and C2 codes. Furthermore, it was necessary to reduce the initial sample and exclude certain banks due to inconsistency in presenting the proportion of D-payments over the years and the lack of available data in some cases.

In light of the above, a final sample consisting of 39 banks from 16 countries was defined. The table A presented in Appendices shows the composition of the sample by country, where it can be observed that Italy is the country with the highest representation in the sample. The table B presented in Appendices illustrates how the number of observations comprising the sample was determined.

3.2 Descriptive Analysis of Variables

3.2.1 Dependent Variables

With the aim of evaluating the effectiveness of the LRM of the banks under analysis, it was defined the following variables as *liquidity* measures: Liquidity Coverage Ratio (LCR), Loan-Deposit Ratio (LDR), and Liquid Assets Ratio (LA).

In evaluating bank liquidity, the selection of LCR variable is supported by literature on bank liquidity risk management, which frequently utilizes these measure (Alaoui Mdaghri & Oubdi, 2022; Dietrich et al., 2014; Sidhu et al., 2022). This is partly attributable to the liquidity standards outlined in the Basel III Accord. The LCR can be defined as the ratio between the high-quality liquid assets stock value and the total net outflows over the next 30 calendar days (Hartlage, 2012).

The LDR, a commonly used indicator for evaluating a bank's liquidity, is computed by dividing total loans by total deposits (Hacini et al., 2021; Klomp & Haan, 2012; Rengasamy, 2014). This ratio indicates how efficiently a bank can meet its short-term needs. A higher LDR suggests that the bank may lack adequate liquidity, thereby increasing risk and reducing profitability (Sidhu et al., 2022).

The LA was incorporated into the analysis as a third measure of the banks' *liquidity*. This variable assesses a company's ability to meet its short-term obligations and fund unexpected liquidity needs (Gatev & Strahan, 2006; Klomp & Haan, 2012; Mohammad et al., 2020). It's derived by dividing the liquid assets by the total assets. In this context, the formulas below demonstrate how the calculation of these dependent variables are carried out, with each observation being computed individually:

$$(1) \quad LCR_t = \frac{Value\ of\ HQLA_t}{\sum Net\ outflows\ over\ the\ next\ 30\ calendar\ days_t} \geq 100\%$$

$$(2) \quad LDR_t = \frac{Total\ Loans_t}{Total\ Deposits_t}$$

$$(3) \quad LA_t = \frac{Liquid\ Assets_t}{Total\ Assets_t}$$

Where the index *t* corresponds to the year.

3.2.2 Independent Variables

To assess how D-payments are linked to the LRM of the banks included in the sample, two independent variables were defined to represent the level of D-payments adoption by these institutions. Given that there is insufficient data on the adoption rates of D-payments by each bank or similar variables, it was decided to use Powergrep to investigate the importance attributed by each bank to D-payments, as expressed in their annual reports. Powergrep is a tool that allows analysing the frequency with which certain expressions are repeated in a specific document. Through this tool, the frequency of terms such as "*digital payment*", "*e-payment*", "*online payment*", "*card payment*", "*credit card*", "*debit card*", "*prepaid card*", "*mobile payment*", "*digital wallet*", "*cryptocurrency*", "*contactless payment*", “*digital channel*”, “*instant payment*”, “*automated payment*”, “*online channel*”, “*mobile banking*”, “*digital client*”, “*digital customer*”, “*online banking*”, “*electronic payment*”, “*digital transaction*”, “*cashless payment*”, “*internet banking*”, “*digital services*”, “*Apple Pay*”, “*Samsung Pay*”, and “*Google Pay*” in annual reports was examined. The percentage of occurrences of these terms compared to the total number of words in the reports was calculated. The natural logarithm of these values was then taken and used as an independent variable called DPay. These analyses provide insight into banks' involvement with D-payments and their strategic significance for the institution.

Regarding the other independent variable related to digitalization, this study uses the Digital Economy and Society Index (DESI), published by the European Commission, at a country-level variable. The DESI measures the progress of European Union Member States in the field of the digital economy and society. This index analyses four policy dimensions: human capital, connectivity, integration of digital technology, and digital public services, encompassing over 30 digital indicators (Apetri & Tîra, 2020). The DESI scores range from 0 to 100, with 0 representing the lowest level of digital performance and 100 indicating the highest level of digital achievement (European Commission, 2022). To minimize the impact of dimensions, the natural logarithm of the digitalization index is taken during the regression process (Xu & Yang, 2024).

3.3 Empirical Model

As mentioned before, this study aims to investigate how digital payment variables are correlated to banks' liquidity risk management. Ordinary Least Squares (OLS) method, Fixed Effects Model (FE) and Random Effects Model (RE) was employed for panel data analysis. To address heteroscedasticity and error autocorrelation, the cluster option was included in regressions, assuming banks as clusters. Furthermore, all regressions included a year dummy variable to capture fixed effects over the period from 2018 to 2022 (Petersen, 2006).

In order to test the hypothesis formulated above, the following model was constructed, where the dependent variable *liquidity* is measured by LCR, LDR and LA, alternatively. This model encompasses the independent variables described in section 3.2.2, the bank-level and country-level control variables, and the dummy variable for the year.

$$(4) \quad Liquidity_{it} = \beta_0 + \beta_1 DPay_{it} + \beta_2 DESI_{it} + \beta_3 SIZE_{it} + \beta_4 NPL_{it} + \beta_5 NIM_{it} + \beta_6 CAR_{it} + \beta_7 GDP_{it} + \beta_8 WGI_{it} + year\ dummy + \varepsilon_{it}$$

Where the index *t* corresponds to the year and the index *i* represents each of the banks in the sample.

In this model, the independent variables include two distinct representations of D-payments. DPay assesses the impact of specific terms related to D-payments in the banks' annual reports. On the other hand, DESI represents the index that measures the digital performance of European Union Member States and tracks their progress in digitalization, expressed in the natural logarithm (section 3.2.2). Regarding, the variable to be explained, the *liquidity* of the banks, is calculated according to the dependent variables described in section 3.2.1.

In order to broaden the analysis, several control variables at the bank and country levels are used in this study, since it is necessary to explain the effects arising from the different characteristics of banks and countries (Iannotta et al., 2007).

The SIZE variable is intended to measure the size of the bank, using the natural logarithm of total assets (Agoraki et al., 2011; Alaoui Mdaghri & Oubdi, 2022; Dietrich et al., 2014). According to Alaoui Mdaghri and Oubdi (2022, p.134), "Large banks tend to create more liquidity compared to small banks due to their ability to access funding more easily from financial markets and central banks".

The variable Non-Performing Loan ratio (NPL) serves as a crucial indicator of asset quality and the level of credit risk exposure within a bank's loan portfolio (Arif & Nauman Anees, 2012; Hou & Yang, 2024; Klomp & Haan, 2012; Roulet, 2018). This metric reflects the proportion of loans that are either in default or nearing default. Consequently, it holds significant implications for a bank's liquidity position.

The Net Interest Margin (NIM) variable is defined as the ratio of net interest income to average total assets (Pak, 2020; Sidhu et al., 2022). This indicator reflects the profitability of a bank's core activities, such as lending and deposit-taking. By computing the difference between the interest income generated from loans and the interest paid on deposits relative to the bank's average total assets.

Finally, regarding the last bank-level variables, a measure of Capital Adequacy Ratio (CAR) was introduced to give insight into the bank's overall financial robustness and resilience (Obadire et al., 2022; Roulet, 2018; Simion et al., 2024). This measure is delineated as the ratio of Tier 1 and Tier 2 capital to risk-weighted assets, where Tier 1 capital typically encompasses common equity and retained earnings, whereas Tier 2 capital includes subordinated debt and specific types of hybrid instruments (Committee on Banking Supervision, 2006).

In terms of the control variables at country-level, these are divided into two variables: Gross Domestic Product (GDP) and the Worldwide Governance Indicator (WGI). The data for each country was obtained from the World Bank database, World Bank Governance Indicators.

Regarding the GDP, the real growth rate of GDP measures economic growth by showing the economic output of each country in different years of study (Distinguin et al., 2013; Mohammad et al., 2020; Naceur & Omran, 2011).

The WGI is a score that aggregates six distinct dimensions of governance, enabling an evaluation of the quality of legal institutions in each country (Kaufmann et al., 1996; Mohammad et al., 2020). Once the values for the six governance dimensions had been collected, it was used a statistical technique called Principal Component Analysis in order to construct a single representative score for all governance dimensions (Kaufmann et al., 1996).

All the variables used in the regression analysis are clearly defined and summarized in Appendices - Table C.

4. EMPIRICAL RESULTS

4.1 Descriptive Statistics

The analysis in Table 1 below shows the descriptive statistics of the variables involved in the chosen study model.

In terms of *liquidity*, the banks have average values of 236.89%, 86.13%, 28.37% referring to the LCR, LDR and LA, respectively. The high LCR mean value suggests that, on average, these institutions hold more than double the required liquid assets to cover short-term obligations, indicating a conservative approach to liquidity management aimed at ensuring financial stability even in stressed conditions. The LDR mean shows that these institutions are generally cautious in their lending practices, utilizing only a portion of their deposits for loans, thereby preserving liquidity. Meanwhile, the mean of LA indicates that a significant proportion of total assets is kept in liquid form, further underscoring the priority placed on liquidity. Together, these mean values suggest that the institutions are prioritizing liquidity over aggressive lending or investment strategies, aiming to safeguard against potential liquidity crises.

The analysis of the independent variables, DPay and DESI, provides insights into how much emphasis the banks in the sample place on digitalization and D-payments. The mean value of DPay is 0.01378%, with a narrow range of values (from 0.000721% to 0.134683%), indicating that the discussion of digital payment terms relative to the total content of annual reports is consistent across institutions. The DESI index, which measures the digital performance of EU Member States on a scale from 0 to 100, has a mean score of 48.42, indicating a moderate level of digital development across the region.

The scores range from 32.46 to 72.24, reflecting that most countries perform within a similar range without extreme outliers. This narrow range suggests low variability, indicating that EU countries face comparable challenges and progress rates in digitalization.

With regard to the control variables, more specifically the SIZE variable, it has an average value of 18.45, which means average assets of around 103 million euros.

The NPL mean value suggests that, on average, around 5.9% of the total gross loans in the banks' portfolios are non-performing, which reflects a moderate level of credit risk. However, the relatively high standard deviation of 7.51 indicates significant variability across the banks in the sample, with some institutions managing to keep their NPLs quite low and performing well in terms of credit risk management, while others are facing much higher levels of loans at risk of default.

As for the NIM variable, it has an average value of 2.03%, which suggests that the banks in the sample are generating a modest profit margin from their main lending activities. The relatively low average indicates that interest spreads are not exceptionally high, which may reflect competitive pressures in the credit market or a conservative approach to risk, where banks may be prioritizing safer, lower-yielding loans. This variable has the lowest standard deviation (0.7232), which suggests that there is moderate variation in NIM between banks and greater uniformity in the profitability of interest-generating activities.

The mean CAR value of 18.30% suggests that, on average, the banks in the sample maintain capital levels well above the regulatory minimum, which is normally around 8%-12%, according to Basel III. This strong capital buffer indicates that these banks are well-capitalized, providing them with the ability to absorb potential losses and continue operating during periods of financial stress. The standard deviation of 4.00% shows moderate variability in CAR across the banks, indicating that while most institutions maintain a similar level of capital adequacy, some are significantly more capitalized than others.

The WGI, which measures governance quality across six dimensions with scores ranging from -2.5 to 2.5, has a negative average score of 0.73, indicating generally weak governance among the countries studied. On the other hand, the GDP growth rate has a positive average of 2.05%, suggesting that despite governance challenges, these countries maintain moderate economic growth.

Table I - Descriptive Statistics

Variable	Obs.	Mean	Median	Standard Deviation	Minimum	Maximum
LCR	195	236.8901	182.0000	170.2005	62.0000	1375.0000
LDR	195	86.1334	90.2300	26.7289	11.0500	183.8700
LA	195	28.3740	26.8500	11.2944	6.7000	64.2300
DPay	195	-8.8916	-8.8934	0.8841	-11.8442	-6.6146
DESI	195	3.8787	3.9000	0.1824	3.4800	4.2800
SIZE	195	18.4513	18.4100	1.9122	13.0100	21.7000
NPL	195	5.9017	3.5800	7.5116	0.3700	46.7000
NIM	195	2.0324	1.8700	0.7232	0.6700	4.2300
CAR	195	18.3084	17.7000	4.0049	10.6600	41.6800
GDP	195	2.0486	2.4400	5.6698	-11.1700	15.1300
WGI	195	-0.7372	-1.1200	2.0405	-3.9600	4.2300

Variables: *LCR* = Value of $HQLA_t$ / Total Net Outflows over the next 30 Calendar $Days_t$; *LDR* = Total $Loans_t$ / Total $Deposits_t$; *LA* = Liquid $Assets_t$ / Total $Assets_t$; *DPay* = Natural logarithm of the number of times that the terms related to *digital payment* are mentioned in the report divided by the total number of words in the annual report; *DESI* = Natural logarithm of the digitalization index; *SIZE* = Natural logarithm of total assets; *NPL* = Total Non-Performing $Loans_t$/Total Gross $Loans_t$; *NIM* = Net Interest $Income_t$/Average Total $Assets_t$; *CAR* = (Tier 1 Capital + Tier 2 $Capital)_t$ / (Risk-Weighted $Assets_t$); *GDP* = GDP real growth rate of each country; *WGI* = Unique score that aggregates six distinct dimensions of governance, which was obtained from the Principal Component Analysis; The variables LCR, LDR, LA, NPL, NIM and CAR are expressed in percentage.

4.2 Correlation Matrix

Table II shows the Pearson Correlation matrix of the different variables included in the model. To assess the degree of correlation between these variables, it was applied the methodology outlined by Obilor & Amadi (2018). According to their approach: (1) correlation coefficients below 0.40 indicate a low correlation, (2) coefficients between 0.40 and 0.60 reflect a moderate correlation, and (3) coefficients above 0.60 represent a high correlation.

The LCR has a moderate negative correlation with the LDR, suggesting that as banks increase their loans relative to deposits, their liquidity coverage decreases - a relationship that is statistically significant at the 5% level. Additionally, LCR shows a low positive correlation with LA, implying that other factors may influence LCR more significantly. Meanwhile, LDR and LA also have a moderate negative correlation, which is statistically significant, suggesting that banks with higher liquid assets tend to have lower loan-to-deposit ratios.

The correlation analysis between DESI and DPay reveals that their relationship is very weak and not statistically significant, suggesting that digitalization and digital payments, although important aspects of modern banking, may operate independently of each other in this context. DPay generally shows weak correlations with the dependent variables, but it has a negative and statistically significant correlation with LDR, indicating that higher levels of D-payments are associated with reduced *liquidity*. Conversely, DESI, while also exhibiting low and mostly insignificant correlations with the dependent variables, shows a positive and statistically significant correlation with LDR. This suggests that higher levels of digitalization can be associated with improved *liquidity* measures. The opposing signs of the correlations between DPay and LDR (negative) and DESI and LDR (positive) underscore distinct dynamics in how digital payments and broader digitalization are connected to bank liquidity. Overall, these findings indicate that although digitalization plays a crucial role in modern banking, its direct correlation to specific *liquidity* measures remains limited and complex.

Regarding the control variables, SIZE negatively correlates with LCR and positively with LDR, both moderately and significantly, indicating that larger banks tend to have lower liquidity coverage and higher loan-to-deposit ratios. Additionally, the moderate negative correlation between NPL and DESI, which is statistically significant, suggests that higher digitalization is linked to lower levels of bad loans. Furthermore, NIM shows moderate, positive, and significant correlations with DPay and NPL, indicating that higher NIM is associated with more digital payment activities and higher non-performing loans. In addition, CAR positively correlates with LCR and negatively with LDR, both moderately and significantly, indicating that banks with higher capital adequacy tend to have greater liquidity coverage and lower loan-to-deposit ratios. Finally, there is a strong, positive and statistically significant correlation between WGI and DESI, suggesting that better governance is closely linked to higher levels of digitalization in banks.

Overall, most of the other correlation coefficients not discussed exhibit a weak correlation, as they are below 0.40.

In addition to this analysis, Variance Inflation Factors (VIFs) were calculated for each of the estimated regressions using Stata (StataCorp, 2023) to check for the presence of multicollinearity. The possibility that the results are influenced by multicollinearity is dismissed, as the VIF values for all regressions are below 10 (Gujarati et al., 2003; Shrestha, 2020). This indicates that there is no strong correlation between the variables, and no exact linear relationships exist among them. Consequently, the variables can be included in the same regression model simultaneously.

Table II - Pearson Correlation Matrix

	LCR	LDR	LA	DPay	DESI	SIZE	NPL	NIM	CAR	GDP	WGI
LCR	1										
LDR	-0.521*	1									
LA	0.1140	-0.366*	1								
DPay	0.1060	-0.242*	0.0070	1							
DESI	-0.0200	0.225*	-0.0180	-0.0670	1						
SIZE	-0.486*	0.377*	0.191*	-0.1270	0.0250	1					
NPL	-0.0750	-0.0950	-0.144*	0.298*	-0.436*	-0.179*	1				
NIM	-0.158*	-0.0950	-0.178*	0.385*	0.1110	-0.162*	0.355*	1			
CAR	0.564*	-0.405*	0.318*	0.0270	0.249*	-0.210*	-0.234*	-0.176*	1		
GDP	0.0510	-0.1290	0.1250	0.0700	0.177*	-0.1240	-0.0740	0.1370	0.0680	1	
WGI	-0.171*	0.317*	0.1350	-0.161*	0.622*	0.276*	-0.333*	0.0260	0.1340	0.1000	1

** represents statistical significance at the 5% level*

Variables: *LCR* = Value of $HQLA_t$ / Total Net Outflows over the next 30 Calendar $Days_t$; *LDR* = Total $Loans_t$ / Total $Deposits_t$; *LA* = Liquid $Assets_t$ / Total $Assets_t$; *DPay* = Natural logarithm of the number of times that the terms related to *digital payment* are mentioned in the report divided by the total number of words in the annual report; *DESI* = Natural logarithm of the digitalization index; *SIZE* = Natural logarithm of total assets; *NPL* = Total Non-Performing $Loans_t$/Total Gross $Loans_t$; *NIM* = Net Interest $Income_t$/Average Total $Assets_t$; *CAR* = (Tier 1 Capital + Tier 2 $Capital)_t$ / (Risk-Weighted $Assets_t$); *GDP* = GDP real growth rate of each country; *WGI* = Unique score that aggregates six distinct dimensions of governance, which was obtained from the Principal Component Analysis.

4.3 Analysis and Discussion of the Results

4.3.1 General Analysis

As mentioned earlier, the primary objective of this study is to evaluate how D-payments are correlated with the LRM of banks within the Euro Area. To achieve this, the study initially estimated the model using pooled Ordinary Least Squares (OLS) and then proceeded to estimate Fixed Effects (FE) and Random Effects (RE) models due to the panel structure of the data. Following these analyses, the methods mentioned before were applied to each of the three models with different dependent variables - LCR, LDR, and LA - to identify the most appropriate and efficient statistical model for explaining the observed results.

Given that the sample was structured as panel data, it was crucial to assess for heteroscedasticity and autocorrelation, which could affect the reliability of the estimates. To address this, group heteroscedasticity was tested using a modified Wald statistic (Greene, 2003), and autocorrelation in panel data was found using the Wooldridge (2002) test. The results from these tests confirmed the presence of both heteroscedasticity and autocorrelation, which led to the decision to use the option cluster (bank) to enhance the reliability of the results.

Moreover, to evaluate the potential impact of multicollinearity on the results, the VIFs were calculated for each estimated regression using Stata (StataCorp, 2023). The analysis confirmed that all VIFs were indeed below 10, indicating no signs of multicollinearity (Gujarati et al., 2003; Shrestha, 2020). Consequently, all variables outlined in section 3.3 could be included simultaneously in the different regressions. Additionally, to account for fixed time effects, and ensure a comprehensive analysis, year dummy variables were incorporated into the econometric model. This approach allows for a robust assessment of the temporal variations that could influence liquidity risk management practices across the banks studied.

4.3.2 Ordinary Least Square

The results obtained from the estimation using the OLS method, as presented in Table III, offer valuable insights into the behaviour of the dependent variables, with each column representing the values for LCR, LDR, and LA. This table provide a comprehensive overview of the statistical relationships and significance of various factors influencing these liquidity measures in European banks.

Firstly, regarding the variable DPay, statistically significant coefficients were found only in the first two models. Specifically, in the LCR model, the coefficient is positive (19.60) and significant at the 1% level, indicating that an increase in D-payments is positively associated with an increase in the *liquidity*. Conversely, in the LDR model, the coefficient is negative (-3.49) and statistically significant at the 10% level. This suggests that an increase in D-payments leads to a reduction in the *liquidity*, although with a weaker influence compared to the LCR model.

When examining the impact of DESI, the results vary across the models. In the LCR model, the coefficient (7.51) is not statistically significant, implying that the level of digitalization, as measured by DESI, does not significantly affect the LCR. However, the LDR model presents a positive (71.69) and statistically significant coefficient at the 1% level, indicating that higher levels of digitalization are associated with a higher LDR. This suggests that as the digital economy and society evolve, European banks tend to have a higher proportion of loans relative to deposits. Additionally, the LA model reveals a significant relationship with DESI, but in this case, the coefficient is negative (-20.20), indicating that increased digitalization is linked to a decrease in the proportion of liquid assets held by banks.

The variable SIZE shows statistically significant coefficients across the different liquidity measures under study, all at the 1% significance level. In the LCR model, the negative coefficient (-33.93) suggests that larger banks tend to have lower LCRs. In contrast, the positive coefficients in the LDR and LA models (3.00 and 1.56, respectively) imply that larger banks are more engaged in lending relative to their deposits and tend to hold more liquid assets.

With regard to the bank-level control variables in the econometric model, the analysis revealed that not all variables were statistically significant across different levels of significance. For instance, the NPL variable did not show statistically significant coefficients for any of the *liquidity* measures under study (0.32, 0.26 and 0.37 for LCR, LDR and LA, respectively).

For the digital variable NIM, negative and statistically significant coefficients (0.02 and 0.02, respectively) were observed at the 5% level for the linear regression models with LCR and LDR as dependent variables. This finding indicates that as banks earn more from their interest-bearing assets relative to their interest expenses, there is a negative impact on the *liquidity* levels of European banks when measured in terms of LCR and LDR.

The last bank-level control variable to be analysed is CAR, which exhibited statistically significant coefficients across all three dependent variables-LCR, LDR, and LA-at a 1% significance level. In the LCR and LA models, the positive coefficients (21.09 and 0.98, respectively) suggest that higher capital ratios have a positive impact on banks' *liquidity*. Conversely, in the LDR model, the negative coefficient (-2.79) indicates an inverse relationship between CAR and LDR, suggesting that as banks increase their capital adequacy, they tend to reduce their loan-to-deposit ratios.

The analysis of the country-level control variables underscores the complex relationships between macroeconomic conditions, governance, and bank liquidity. The GDP variable displayed negative and statistically significant coefficients (-1.38 and 0.91, respectively) in two regressions—specifically, the LDR regression at the 5% level and the LA regression at the 1% level - indicating that higher GDP per capita is associated with a reduction in bank *liquidity*. Similarly, the WGI variable showed statistical significance at the 10% level in the regressions for LCR and LA. In the LA model, the positive coefficient (0.93) suggests that better governance is linked to improved *liquidity* for banks in European countries, while the LCR model (-11.02) presents an inverse relationship , implying that better governance may reduce *liquidity* in this specific context.

In summary, the LCR and LDR models demonstrate stronger explanatory power and significance compared to the LA model. Although the LA model is statistically significant, it explains less of the variance in liquid assets, suggesting that other factors may influence banks' liquid asset levels.

Table III – OLS Regression Results

Variable	LCR	LDR	LA
DPay	19.603***	-3.486*	0.602
	(0.008)	(0.058)	(0.492)
DESI	7.505	71.687***	-20.201***
	(0.880)	0.000	(0.008)
SIZE	-33.934***	3.004***	1.555***
	(0.002)	(0.000)	(0.000)
NPL	0.315	0.263	0.367
	(-1.841)	(0.352)	(-0.089)
NIM	0.016**	0.020**	0.249
	(-30.501)	(-5.789)	(-1.448)
CAR	21.087***	-2.789***	0.976***
	(0.000)	(0.000)	(0.000)
GDP	-4.289	-1.381**	0.914***
	(0.166)	(0.011)	(0.000)
WGI	-11.017*	0.663	0.928*
	(0.051)	(0.488)	(0.058)
Constant	744.073**	-204.157***	-66.480**
	(0.012)	(0.001)	(0.033)
Number of Observations	195	195	195
Adjusted R^2	49.34%	44.10%	21.10%
F-test	10.384	13.199	4.820
p-value	0.000	0.000	0.000

*** *$p<0.01$*, ** *$p<0.05$*, * *$p<0.1$*

Variables: *LCR* = Value of $HQLA_t$ / Total Net Outflows over the next 30 Calendar $Days_t$; *LDR* = Total $Loans_t$ / Total $Deposits_t$; *LA* = Liquid $Assets_t$ / Total $Assets_t$; *DPay* = Natural logarithm of the number of times that the terms related to *digital payment* are mentioned in the report divided by the total number of words in the annual report; *DESI* = Natural logarithm of the digitalization index; *SIZE* = Natural logarithm of total assets; *NPL* = Total Non-Performing $Loans_t$/Total Gross $Loans_t$; *NIM* = Net Interest $Income_t$/Average Total $Assets_t$; *CAR* = (Tier 1 Capital + Tier 2 $Capital)_t$ / (Risk-Weighted $Assets_t$); *GDP* = GDP real growth rate of each country; *WGI* = Unique score that aggregates six distinct dimensions of governance, which was obtained from the Principal Component Analysis. A year dummy variable was included in this model. It’s also included in the model the coefficients values. The robust standard errors are in brackets.

4.3.3 Fixed Effects Model and Random Effects Model

The FE and RE models were selected for this study because of the panel structure of the data. The outcomes derived from the estimation using these models, as shown in Tables IV and V provide robust frameworks for examining relationships within the dataset, making them an integral part of the study.

Selecting the best estimation technique for the data was essential before beginning the analysis of the findings. To do this, a test proposed by Hausman (1978) was used (Wooldridge, 2002). The goal of this test was to help guide the decision between the FE and RE models for the three different dependent variables under consideration, each with its own dependent variable.

The analysis involved testing the null hypothesis that the RE model is the more efficient choice, against the alternative hypothesis favouring the FE model. The outcomes of these tests provided clear insights, enabling informed decisions about which model is more efficient for this statistical study.

For both the LCR and LDR models, p-values below 0.05 (0.0000 and 0.0025, respectively) were obtained, indicating that the null hypothesis can be rejected in both cases, suggesting that the FE model is more suitable than the RE model for these datasets. In contrast, for the model with the dependent variable LA, the p-value greater than 0.05 (0.2085) indicates that the RE model is more appropriate, as the null hypothesis cannot be rejected. This suggests that the RE model is a suitable choice for this dataset, although the FE model was favoured in the previous cases.

The analysis of FE Models (Table IV) reveals that, about the D-payment variables DPay (-1.57 for LCR and 1.40 for LDR) and DESI (130.94 for LCR and -0.48 for LDR), there were no statistically significant coefficients, as the p-values were well above any conventional significance thresholds. This suggests that neither D-payments nor the broader digital economy are significantly linked to the *liquidity* of European banks within these models.

Regarding the control variables present across all models, most of these variables did not demonstrate statistical significance, with p-values exceeding conventional thresholds. As such, there is insufficient evidence to establish a causal relationship between these variables and the dependent variables. However, a few exceptions stand out, indicating some level of significance in certain contexts.

Regarding the model where liquidity is measured by LCR, the only statistically significant coefficient is the SIZE variable, which is negative (-347.01) and significant at the 10% level. This indicates an inverse relationship between bank size and *liquidity*, suggesting that larger banks tend to maintain lower LCRs, potentially relying less on liquid asset buffers as they grow. The other variables in this model did not show significant effects on bank *liquidity*.

Turning to the LDR model, the only control variable that demonstrated a statistically significant coefficient was NPL, which showed strong significance at the 1% level. The positive coefficient (0.60) for NPL suggests that higher levels of non-performing loans are associated with better *liquidity* among the banks in the sample. However, SIZE, which was significant in the LCR model, does not show statistical significance in the LDR model (0.17), and other variables similarly lack significant effects on LDR.

Concerning to the RE Model, the independent digital variables didn't display statistically significant coefficients at any level of significance. Among the control variables, only the CAR variable emerged as particularly positive (0.57) and statistically significant at 1% level. This result suggests that higher capital adequacy ratios contribute to better *liquidity* in banks, implying that institutions with stronger capital positions tend to adopt a more conservative approach to liquidity management by maintaining higher levels of liquid reserves.

Finally, across all models, the hypothesis of joint nullity of the independent variables can be rejected, as the F-test shows values of less than 0.05, confirming that these models are appropriate and reliable for analysing the performance of European banks.

Table IV - FE Model Results with LCR and LDR as Dependent Variable

Variable	LCR	LDR
DPay	-1.569	1.401
	(0.864)	(0.515)
DESI	130.935	-0.480
	(0.313)	(0.970)
SIZE	-347.011*	0.173
	(0.098)	(0.982)
NPL	-2.924	0.595***
	(0.159)	(0.000)
NIM	103.395	-2.780
	(0.122)	(0.523)
CAR	4.027	0.125
	(0.117)	(0.765)
GDP	-0.485	-0.084
	(0.881)	(0.708)
WGI	-6.271	1.342
	(0.817)	(0.794)
Constant	5832.102*	100.895
	(0.091)	(0.586)
Number of Observations	195	195
Adjusted R^2	27.26%	21.35%
F-test	4.101	6.967
p-value	0.001	0.000

**** $p<0.01$, ** $p<0.05$, * $p<0.1$*

Variables: *LCR* = Value of $HQLA_t$ / Total Net Outflows over the next 30 Calendar $Days_t$; *LDR* = Total $Loans_t$ / Total $Deposits_t$; *LA* = Liquid $Assets_t$ / Total $Assets_t$; *DPay* = Natural logarithm of the number of times that the terms related to *digital payment* are mentioned in the report divided by the total number of words in the annual report; *DESI* = Natural logarithm of the digitalization index; *SIZE* = Natural logarithm of total assets; *NPL* = Total Non-Performing $Loans_t$/Total Gross $Loans_t$; *NIM* = Net Interest $Income_t$/Average Total $Assets_t$; *CAR* = (Tier 1 Capital + Tier 2 $Capital)_t$ / (Risk-Weighted $Assets_t$); *GDP* = GDP real growth rate of each country; *WGI* = Unique score that aggregates six distinct dimensions of governance, which was obtained from the Principal Component Analysis. A year dummy variable was included in this model. It's also included in the model the coefficients values. The robust standard errors are in brackets.

Table V - RE Model Results with LA as Dependent Variable

Variable	Coefficient	p-value	Significance Level
DPay	0.348	0.517	
DESI	-8.117	0.244	
SIZE	0.948	0.292	
NPL	-0.149	0.124	
NIM	-0.309	0.890	
CAR	0.567	0.002	***
GDP	0.057	0.704	
WGI	0.379	0.625	
Constant	36.776	0.254	
Number of Observations		195	
χ^2		60.63	
p-value		0.000	

**** p<0.01, ** p<0.05, * p<0.1*

Variables: *LCR* = Value of $HQLA_t$ / Total Net Outflows over the next 30 Calendar $Days_t$; *LDR* = Total $Loans_t$ / Total $Deposits_t$; *LA* = Liquid $Assets_t$ / Total $Assets_t$; *DPay* = Natural logarithm of the number of times that the terms related to *digital payment* are mentioned in the report divided by the total number of words in the annual report; *DESI* = Natural logarithm of the digitalization index; *SIZE* = Natural logarithm of total assets; *NPL* = Total Non-Performing $Loans_t$/Total Gross $Loans_t$; *NIM* = Net Interest $Income_t$/Average Total $Assets_t$; *CAR* = (Tier 1 Capital + Tier 2 $Capital)_t$ / (Risk-Weighted $Assets_t$); *GDP* = GDP real growth rate of each country; *WGI* = Unique score that aggregates six distinct dimensions of governance, which was obtained from the Principal Component Analysis. A year dummy variable was included in this model. It's also included in the model robust standard errors.

4.3.4 Comparing Fixed/Random Effects and OLS Regression Models

After verifying the OLS regressions and FE/RE model's effectiveness, the next step involves two separate comparisons: one between the OLS model and the FE model, and another between the OLS model and the RE model. These comparisons aim to identify the most efficient method for evaluating the association of digital variables with the different *liquidity* measures. The Hausman test is applied in both comparisons to determine which model is most appropriate, given the panel structure of the data.

The Hausman test is first used to compare the FE model with the pooled OLS model. In this case, the null hypothesis states that the FE model is more efficient, as it accounts for unobserved heterogeneity correlated with the explanatory variables. The alternative hypothesis, however, suggests that the pooled OLS model is preferable, assuming that unobserved effects are uncorrelated with the regressors, and thereby ignoring any time-invariant differences between units.

If the Hausman test reveals a p-value smaller than the selected significance level, the null hypothesis can be rejected, suggesting that the pooled OLS model is more appropriate due to its efficiency when significant unobserved effects are not present. However, if the p-value higher than the significance level, the null hypothesis cannot be rejected, implying that the FE model should be used. Regardless of this outcome, the results from the FE model are not invalidated, and the FE model remains appropriate when cross-sectional or time-specific effects are significant, as it provides unbiased estimates in the presence of unobserved heterogeneity correlated with the explanatory variables.

For example, in the analysis of the LCR and LDR models, p-values of 0.0001 and 0.0011, respectively, allowed us to reject the null hypothesis in both cases. This suggests that the pooled OLS model is a more efficient option than the FE model for these *liquidity* measures, as it offers better efficiency in these cases.

Next, the Hausman test is also applied to compare the RE model with the pooled OLS model. Here, the null hypothesis asserts that the RE model is more efficient, as it addresses unobserved heterogeneity that is uncorrelated with the explanatory variables. The alternative hypothesis, as in the FE comparison, proposes that the pooled OLS model is better suited for the data, assuming that unobserved effects are irrelevant or do not correlate with the regressors.

For the model with the dependent variable LA, a p-value of 0.0487, slightly below the 0.05 significance level, points to the pooled OLS model being the better choice over the RE model. When the p-value is lower than the significance threshold, the pooled OLS model tends to be more suitable. On the other hand, if the p-value is higher, the RE model becomes the preferred option. In this case, the pooled OLS model offers a more efficient estimation for this *liquidity* measure.

In summary, the p-values in all cases fall below the 0.05 significance level, indicating that the null hypothesis is consistently rejected. This suggests that the pooled OLS model is more appropriate than both the FE and RE models for analysing the relationship between D-payments variables and *liquidity* measures, according to the Hausman test results. This highlights the need to select the most efficient model by considering the data structure and the significance of unobserved effects.

5. CONCLUSION, LIMITATIONS AND FUTURE RESEARCH

The goal of this research is to clarify how digital payments influence liquidity risk management in Eurozone banks, including the liquidity coverage ratio, loan-to-deposit ratio and liquid assets ratio. For this purpose, the digital variables analysed include the percentage importance of specific digital terms in total annual reports, as well as the natural logarithm of the digitalization index. A sample of 39 Eurozone banks was chosen for a 5-year period (between 2018 and 2022) in order to get conclusions from this study.

Analysing the Ordinary Least Squares results reveals a statistically significant relationship between digital payments and liquidity risk. Specifically, the DPay variable shows a positive and significant effect on liquidity levels in the LCR model, while in the LDR model, the coefficient is statistically negative, suggesting that an increase in digital payments improves liquidity in one case but reduces it in another. For the DESI variable, digitalization does not significantly affect liquidity levels in the LCR model, but it has a positive and significant influence in the LDR model, indicating that as digitalization increases, banks tend to have better liquidity. However, the Random Effects and Fixed Effects models revealed few statistically significant coefficients for the digital variables, indicating that these models did not consistently capture the effects of digital payments on liquidity risk. The Hausman test confirmed that the Ordinary Least Squares model is more appropriate, providing a more efficient framework for assessing the relationship of digital variables with banks' liquidity risk.

This study presented several limitations that significantly impacted the final research results. One of the main limitations was the relatively small number of years for which data were available for both dependent and independent variables. Furthermore, not all banks included in the study provided consistent data for all the years analysed, both in terms of digital variables and liquidity variables, which led to the need to reduce the sample period.

Another relevant factor was the lack of consistent and sufficient disclosure by most European banks of essential digital metrics in their annual reports. The scarcity of public data made it difficult to study the connection between digital payments and liquidity risk management and limited the study to only two types of digital variables. Additionally, the lack of information from some banks on dependent variables also proved to be a significant limitation. Lastly, the regression models could be improved by including new variables that would better capture the complexity of the relationship between digital payments and liquidity risk management.

For future research, it would be interesting to further explore the correlation of different variables related to digital payments with bank liquidity. To this end, we recommend collecting additional data on variables that are beginning to be publicised, broadening the scope of the analysis. These variables could include the percentage of transactions carried out by digital means in each bank, the number of customers using these means to make payments, and the amounts invested in digital infrastructure, among other relevant indicators. This data would allow for a more complete analysis of how digital payments are associated with bank liquidity.

In addition, it would be interesting to consider including other dependent variables in the study, allowing for a more comprehensive approach. Expanding the sample of banks would also be an important step and could include institutions from different geographical regions to increase the representativeness of the results and identify possible regional variations in how digital payments are linked with liquidity.

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APPENDICES

Table A - Sample Distribution by Country

Country	Number of observations	Percentage (%)	Cumulative (%)
Austria	10	5.13	5.13
Croatia	5	2.56	7.69
Cyprus	5	2.56	10.26
Estonia	5	2.56	12.82
Finland	5	2.56	15.38
France	15	7.69	23.08
Germany	10	5.13	28.21
Greece	10	5.13	33.33
Ireland	15	7.69	41.03
Italy	60	30.77	71.79
Lithuania	5	2.56	74.36
Malta	10	5.13	79.49
Netherlands	5	2.56	82.05
Portugal	5	2.56	84.62
Slovenia	5	2.56	87.18
Spain	25	12.82	100.00
Total number of banks	195	100	

Table B – Composition of the Sample

		Step Result	Search Result
Status	Active Companies	337 270 533	337 270 533
World Region	Euro Area - EU20	67 384 140	42 768 834
Specialisation	Commercial Bank	103 684	567
Accounting Practice	IFRS	5 367 418	295
Consolidation Code	C1, C2	2 705 345	182
Listed / Unlisted Companies	Publicly Listed Companies	84 998	52
Initial Sample			52
Final Sample			39
Potential number of observations		260	
Observations dropped due to missing values		65	
Final Observations		195	

Table C – Description of the Variables

Variable	Definition	References
Dependent Variable		
LCR	LCR_t = Value of $HQLA_t$ / Total Net Outflows over the next 30 Calendar $Days_t$	(Alaoui Mdaghri & Oubdi, 2022; Dietrich et al., 2014; Hartlage, 2012; Heuver & Berndsen, 2022; King, 2013; Sidhu et al., 2022; Simion et al., 2024)
LDR	LDR_t = Total $Loans_t$ / Total $Deposits_t$	(Hacini et al., 2021; Klomp & Haan, 2012; Rengasamy, 2014; Sidhu et al., 2022)
LA	LA_t = Liquid $Assets_t$ / Total $Assets_t$	(Gatev & Strahan, 2006; Klomp & Haan, 2012; Mohammad et al., 2020)
Independent Variables		
DPay	Natural logarithm of the number of times that the terms "digital payment", "e-payment", "online payment", "card payment", "credit card", "debit card", "prepaid card", "mobile payment", "digital wallet", "cryptocurrency", "contactless payment", “digital channel”, “instant payment”, “automated payment”, “online channel”, “mobile banking”, “digital client”, “digital customer”, “online banking”, “electronic payment”, “digital transaction”, “cashless payment”, “internet banking”, “digital services”, “Apple Pay”, “Samsung Pay”, and “Google Pay” are mentioned in the report divided by the total number of words in the annual report.	Annual management reports of banks.
DESI	Natural logarithm of the digitalization index. Index developed by the European Commission to measure the progress of EU member states in digital performance and competitiveness. It assesses four main dimensions: (i) human capital, (ii) connectivity, (iii) integration of digital technology, (iv) digital public services. Values range from 0 to 100, with higher scores reflecting stronger digital performance.	(Apetri & Tîra, 2020; Xu & Yang, 2024)

Control Variables		
Bank-level Control Variables		
SIZE	Natural logarithm of total assets.	(Agoraki et al., 2011; Alaoui Mdaghri & Oubdi, 2022; Dietrich et al., 2014)
NPL	NPL_t = Total Non-Performing $Loans_t$ / Total Gross $Loans_t$	(Arif & Nauman Anees, 2012; Hou & Yang, 2024; Klomp & Haan, 2012; Roulet, 2018)
NIM	NIM_t = Net Interest $Income_t$ / Average Total $Assets_t$	(Pak, 2020; Sidhu et al., 2022)
CAR	CAR_t = (Tier 1 Capital + Tier 2 Capital) $_t$ / (Risk-Weighted $Assets_t$)	(Committee on Banking Supervision, 2006; Obadire et al., 2022; Roulet, 2018; Simion et al., 2024)
Country-level Control Variables		
GDP	GDP real growth rate of each country.	(Distinguin et al., 2013; Mohammad et al., 2020; Naceur & Omran, 2011) World Bank database, World Bank Governance Indicators.
WGI	Score that aggregates six distinct dimensions of governance: (i) Voice and Accountability, (ii) Political Stability and Absence of Violence/Terrorism, (iii) Government Effectiveness, (iv) Regulatory Quality, (v) Rule of Law, and (vi) Control of Corruption. This score was obtained from a statistical technique called Principal Component Analysis. Values range from -2.5 to 2.5, with higher values indicating stronger levels of governance in the country.	(Kaufmann et al., 1996; Mohammad et al., 2020) World Bank database, World Bank Governance Indicators.
Year Dummy	Dummy variable for each year; takes the value 1 if the data is for the respective year and zero otherwise.	

DISCLAIMER

This master thesis was developed with strict adherence to the academic integrity policies and guidelines set forth by ISEG, Universidade de Lisboa. The work presented herein is the result of my own research, analysis, and writing, unless otherwise cited. In the interest of transparency, I provide the following disclosure regarding the use of artificial intelligence (AI) tools in the creation of this thesis:

> I disclose that AI tools were employed during the development of this thesis as follows:
>
> - AI-based research tools were used to assist in literature review and data collection.
> - AI-powered software was utilized for data analysis and visualization.
> - Generative AI tools were consulted for brainstorming and outlining purposes. However, all final writing, synthesis, and critical analysis are my own work. Instances where AI contributions were significant are clearly cited and acknowledged.

Nonetheless, I have ensured that the use of AI tools did not compromise the originality and integrity of my work. All sources of information, whether traditional or AI-assisted, have been appropriately cited in accordance with academic standards. The ethical use of AI in research and writing has been a guiding principle throughout the preparation of this thesis.

I understand the importance of maintaining academic integrity and take full responsibility for the content and originality of this work.

Camilla Guimarães Martins – 26/09/2024