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Paulick, Jan

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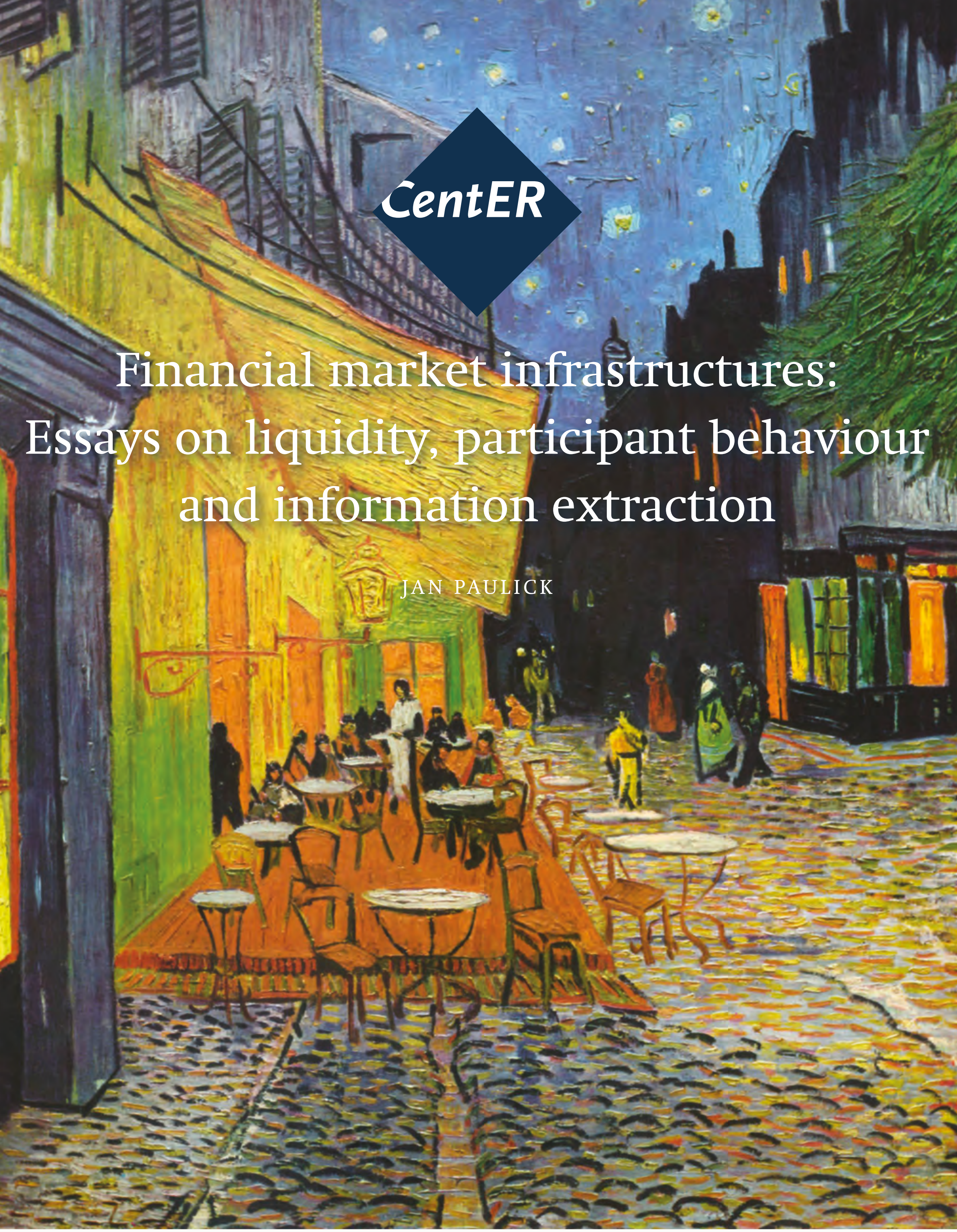

CentER

Financial market infrastructures: Essays on liquidity, participant behaviour and information extraction

JAN PAULICK

Tilburg University

Financial market infrastructures:
Essays on liquidity, participant behaviour and information extraction

Proefschrift ter verkrijging van de graad van doctor aan Tilburg University

op gezag van de rector magnificus, prof. dr. W.B.H.J. van de Donk, in het

openbaar te verdedigen ten overstaan van een door het college voor

promoties aangewezen commissie in de Aula van de Universiteit op vrijdag

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door

Jan Rene Paulick,

geboren te Würzburg, Duitsland

Promotores:	prof. dr. R.J. Berndsen (Tilburg University) prof. dr. L.T.M. Baele (Tilburg University)
Copromotor:	dr. R. Heijmans (De Nederlandsche Bank)
leden promotiecommissie:	prof. dr. F.C.J.M. de Jong (Tilburg University) dr. R. Wandhöfer LLM (The London Institute of Banking & Finance) prof. dr. J.M. Groeneveld (Tilburg University) prof. dr. W. Bolt (Vrije Universiteit Amsterdam)

Economics is not an exact science. It's a combination of an art and elements of science. And that's almost the first and last lesson to be learned about economics: that in my judgment, we are not converging toward exactitude, but we're improving our data bases and our ways of reasoning about them.

— *Paul Samuelson (1915-2009)*

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Jan Paulick, March 2022

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Chapter 1

Introduction

The economic analysis of financial market infrastructures (FMIs) has gained increasing interest staring around the turn of the millennium, partly due to the rising importance of settlement systems that is driven by globalization and technological developments (Bech et al., 2008). In particular, the economic analysis of payments has gained traction. Kahn and Roberds (2009) provide an overview of the evolving literature on payment economics and how it relates to various policy issues and other fields within economics. Increasing interest also manifests itself in a growing number of conferences being devoted to payment economics[1] and textbooks on the subject (see Berndsen, 2018).

FMIs, such as payment systems, are often seen as the "plumbing" or "backbone" (Diehl, 2016) of the financial system. FMIs provide the underlying network of the financial system and are critical for the smooth functioning of financial markets. FMIs clear and settle debt obligations and transfers of assets between market actors stemming from various underlying business reasons and differ in their design and functioning. Besides payment systems, which are the focus of the thesis, FMIs include securities settlement systems, central securities depositories, trade repositories and central counterparties (CPSS-IOSCO, 2012).

The identification of risks is the overarching goal of the analysis of FMIs. Given their economic importance, accumulating risks or failures of FMIs can impact financial stability. Therefore, standards and principles for risk mitigation are implemented. In 2001, the Committee on Payment and Settlement Systems published core principles for systemically important payment systems. The now-in-place principles for financial market infrastructures (PFMIs) lay out standards for risk identification and mitigation as well as responsibilities for regulators, supervisors and overseers of FMIs (CPSS-IOSCO, 2012). The PFMI are also part of the key standards for sound financial systems identified by the Financial Stability Board.[2]

The focus of the thesis lies on large-value payment systems (LVPS) that typically settle transfers with a high value or high priority. Many LVPS settle transactions immediately on a gross basis and are also referred to as Real-Time Gross Settlement (RTGS) systems. This stands in contrast to net settlement systems in which accumulated payment obligations are settled on a net basis between participants at a specified time. Hence, RTGS systems require higher amounts of liquidity for settling payments while risks are minimized. In

[1] Examples are the annual Bank of Finland Simulator seminar series that started in 2003 and the Economics of Payments conference in its tenth iteration in 2021.

[2] See `www.fsb.org/work-of-the-fsb/about-the-compendium-of-standards/key_standards/`.

net systems, the credit and liquidity risks are higher as settlement is deferred to a later point in time, thus introducing risks of settlement lags or defaults of counterparties. As the use of liquidity in RTGS systems is typically higher, central banks often extend free intraday credit against collateral to banks. This allows banks to smooth some of their peak positions within RTGS systems. RTGS systems have been increasingly adopted across the world due to risk considerations (World Bank, 2011). Nowadays, RTGS systems are most often the standard mode for large-value interbank settlement. In the euro area, the main RTGS system is TARGET2.[3] However, large-value payments in euro may also be settled via the privately owned EURO1 system that operates on a deferred net settlement basis.

With advances in data processing and computing power, the analysis of large amounts of payments data on a transaction-level has become feasible for researchers. The analysis of granular data is preferable to employing aggregate indicators because no information is lost and the researcher enjoys more flexibility. This concerns for example the construction of tailor-made indicators employing different aggregation methods and indicators based on data that includes only specific payment types. Pre-aggregated data does not allow tweaking measures according to specific research questions. Transaction-level data permit studying system characteristics and participant behavior within the system in detail and can offer important insights for system operators and overseers.

The economic analysis of FMIs also relates to monetary policy and the stability of the financial system. Central banks typically settle monetary policy operations in their wholesale systems, thus requiring commercial banks to participate in the system. The implementation of monetary policy affects the flows of liquidity within the payment system and alters incentives for banks, for example regarding liquidity management. The payment system thus often mirrors the conduct of monetary policy measures and its transmission, for example via money market transactions settled in central bank money. Wholesale systems form an integral part of the financial system. Effective risk management thus affects financial stability. Studying the behavior of banks within the payment system can reflect their financial and operational resilience.

This thesis includes separate projects unified by the notion that data from FMIs can be highly useful to gain a better understanding of system dynamics, but also offer valuable insights on financial market developments in general. The chapters rely heavily on data from TARGET2, which was introduced in May 2008 replacing its predecessor TARGET. The examined time period, starting in 2008, was characterized by the global financial crisis 2007/2008, expansionary monetary policy in the wake of the crisis, the sovereign debt crisis in Europe peaking between 2010 and 2012, negative interest rates introduced in 2014, unprecedented asset purchases by the Eurosystem since 2015 and most recently by the effects of the global Covid-19 pandemic staring in early 2020. The time period analyzed here is far from what may be called "normal" times in terms of financial market development and monetary policy environment. While this may weaken the applicability of some of the policy implications to different settings, crisis periods offer particularly interesting insights into FMIs' functioning and participant behavior in unprecedented circumstances. At the same time, given the continuous development of markets, FMIs themselves, regulation and technology, "normal" times are not easy to define.

[3]TARGET2 refers to the second generation Trans-European Automated Real-time Gross Settlement Express Transfer System which is operated by the Eurosystem.

The common focus of the chapters on FMIs leads to a better understanding of the workings and interplay of markets, the monetary policy environment and infrastructures. The thesis contributes to the literature by applying novel approaches to FMI data and employing transaction-level data to tackle new research questions. The heavy reliance on transaction data allows for the identification of patterns on a micro level and developing tailor-made aggregate indicators for inference of dynamics over time.

To give context to the contribution of the individual chapters, overall literature strands can be classified systematically. Building on Müller (2016), the literature on payment economics can be divided into three types, shown in Figure 1.1. Below each type, applications are listed. It should be noted that the themes and applications are not intended to be exhaustive.

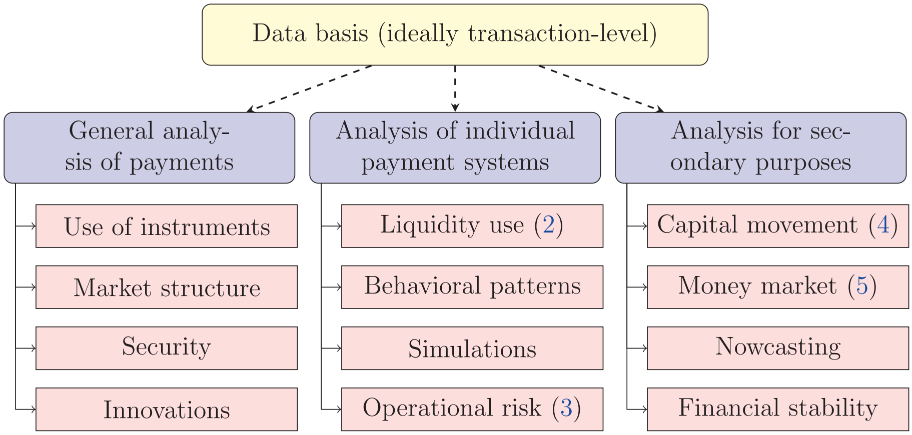
The first type is the general analysis of payments. Analysis that falls into this category is the use of payment instruments, such as regularly conducted surveys by central banks (see for example, Bagnall et al., 2016), the analysis of security in payments, e.g. in the context of cyber resilience, and literature on the market structure that ultimately determines the safety and efficiency of the overall payment system that is formed by different systems and instruments (see for example, Calomiris and Kahn, 1996). The role of innovation in the payment sphere includes the evolving market of new instruments and systems. In this context, current discussions often focus on the role of central banks against the background of innovation in fiancial markets and the potential introduction of central bank digital currency (CBDC). For motivations across jurisdictions and evolving discussions around CBDC, see for example Auer et al. (2020).

The second line of research analyzes individual payment systems. This includes studies on liquidity use, exemplified in Chapter 2 in the context of tiering (indirect settlement) and participant behavior. In the context of system design features, Martin and McAndrews (2008) describe liquidity saving mechanisms and their effect on participant incentives. Simulations allow studying outcomes under different scenarios and evaluate system mechanisms by replicating the functioning of payment systems. As described, among others, by Diehl (2012), simulation studies can overcome some of the weaknesses in applying models and represent virtual experiments. Other applications focus on different types of risks within a system with Chapter 3 providing an example related to operational risks posed by system participants.

The third type of analysis constitutes deriving information from payments data for secondary purposes, i.e. other purposes than the subject of payments itself. One better known example in the euro area is the interpretation of the movement of capital between countries via TARGET2 (called TARGET2 balances), which is intensely debated in academia and the public (see for example, Sinn and Wollmershäuser, 2012; Whelan, 2014).[4] Another application is the use of an algorithm to identify money market loans from payments data, as proposed by Furfine (1999) which lays the foundation for analysis in Chapter 5. The timely availability of payments data is an important advantage compared to other economic data. Payments data is often available on the next day or even in real-time, while supervisory data or economic indicators are mostly available only weeks or months after the observation period. Promptly available data offers the benefit of establishing trends or detecting risks in financial markets. As described for example by

[4]The subject is briefly picked up in Chapter 6, dynamics are discussed against the background of collateral submission in Chapter 4.

Figure 1.1: Typology of literature in payment economics



Note: The figure illustrates a modified typology of literature in payment economics following Müller (2016) (own depiction). The top level is the underlying data basis that forms the foundation for empirical work. Below are the three types of literature classification and examples of applications for each type. Numbers in brackets refer to chapters in the thesis as examples of the applications within the categories. The example themes and applications are not intended to be exhaustive.

Galbraith and Tkacz (2018), payments data can be used as proxy to forecast or "nowcast" macroeconomic spending and GDP. Chapman and Desai (2021) apply machine learning models to retail payments data to study various macroeconomic indicators at the beginning of the Covid-19 pandemic. As a last example of analysis for secondary purposes, payments data can offer insights for financial stability considerations. In this area, one example is Rainone (2021) studying banks' deposit outflows via payments data.
To be explicit, the research questions and their importance may be stated along these lines:

- What is the effect of tiered payments on liquidity usage (Chapter 2)? Is a purely risk-based view of tiering in oversight warranted?

  The results show that tiered payments give banks more leeway in liquidity management. Benefits and risks should be weighed more carefully by system designers and overseers.

- Can an algorithm identify (unreported) participant outages from payments data (Chapter 3)? How frequent are such outages?

  The developed algorithm provides a hitherto absent data set on outages that is useful for evaluating compliance with reporting requirements. Furthermore, the data can provide the basis for assessing risks from participant outages in payment systems.

- What drives collateral mobilization in Germany and the euro area (Chapter 4)? How does the development relate to financial market dynamics, monetary policy implementation and technical drivers?

The results show that changes in the collateral framework and technical aspects of collateral mobilization drive dynamics during the observation period. A shift towards domestic channels reflects a home bias, especially during the sovereign debt crisis.

- How does money market data extracted from payments data compare to reported data (Chapter 5)? What drives the differences and how does this affect certain loan types and loans by certain banking groups?

  The systematic approach highlights that the different data captures cross-border loans, loans of different banking groups and recurring daily loans unevenly. The analysis is useful for developing reporting frameworks and extracting money market loans from payments data. For researchers and practitioners, the results help guide the choice of data.

The thesis proceeds as follows:

In Chapter 2 we study the impact of payments that banks settle on behalf of client banks (tiered settlement) on the relative liquidity use of settlement banks (direct participants) in TARGET2. Using bank fixed effects and various controls, we estimate a panel data model employing transaction-level data which shows that a higher share of tiered payments from client banks reduces relative liquidity use by settlement banks. The different channels that drive this effect are investigated further. Metrics on timing, delay, and payment priorities suggest that settlement banks can make use of more leeway in settling tiered payments from client banks compared to their own payments. We conclude that to some degree settlement banks employ tiered arrangements to manage intraday liquidity more efficiently. This could hint to "free riding" or higher recycling of liquidity from client banks' payments. However, the results are also consistent with settlement banks' monitoring role or tiered payments potentially exhibiting different characteristics which may be attributable to contractual arrangements.

Chapter 3 identifies operational outages of participants using an improved algorithmic approach relative to Klee (2010). Operational risks are a major source of risk for financial market infrastructures. System outages of TARGET2 are immediately observed by the operator and contingency measures as well as back-up solutions are in place. However, participant outages could also cause systemic damage, but are not immediately known to the operator. In TARGET2, critical participants are required to report outages. However, an easy to use algorithm to detect outages – be they reported or not – might be a useful tool for the operator to support analysis and to encourage more reliable reporting of outages by participants. The employed algorithm identifies intervals where payment activity is deemed so low that an operational outage may be assumed. As contingency measures allow participants to initiate a limited number of transactions the approach sets different thresholds and conditions, rather than merely identifying intervals without transactions. The strategy is best suited for larger banks that exhibit stable payment patterns. We address the identification of false positives (wrongly identified outages) by focusing on consecutive intervals, unlikely to occur due to chance, while we mitigate the identification of false negatives (undetected outages) by employing a relatively broad approach. However, due to the lack of comprehensive reported data, the algorithmic approach does not offer conclusive evidence on outages. Since publication, the Eurosystem employs the approach for cross-checks with reported outages of system participants and the approach has been applied to the Canadian large value transfer system by Arjani and Heijmans (2020).

Chapter 4 relates to financial markets and monetary policy implementation with a focus on collateral posted for participation in monetary policy operations. Participation in Eurosystem credit operations requires that credit institutions post collateral. The chapter describes and analyzes – for the period February 2008 to March 2016 – developments in the market value of marketable assets submitted as collateral in Germany and the Eurosystem against the backdrop of the financial market crisis. The development is characterized by an initial strong increase at the onset of the crisis and a decrease after 2010 because of lower funding requirements. The posted collateral followed the course of the funding requirements, which initially rose sharply in the wake of the financial crisis. Due to high liquidity inflows, which were reflected in the increasing TARGET2 claims of the Bundesbank, the refinancing needs and posted collateral decreased after 2010. However, the posted collateral relative to refinancing operations remained remarkably high. For the relationship between refinancing operations and the posting of collateral, Granger causality tests provide evidence that refinancing operations have predictive power for submitted collateral in the next period, but not vice versa. This implies that the decline in posted collateral is largely the result of the decrease in liquidity requirements. The increase in the overall stock of collateral held by the Deutsche Bundesbank reflects the changes taking place in financial markets. Due to high liquidity inflows culminating in the Bundesbank's escalating TARGET2 claims, funding requirements and collateral stocks fell. Shifts between different submission channels are partly due to more technical aspects, but may also stem from a "home bias" and portfolio reallocations. More broadly speaking, this may be seen in the context of the collateral framework by the Eurosystem depending on the composition of counterparties and their refinancing needs (Bindseil et al., 2017). Policymakers should view the evolution of collateral stocks against the background of changes in the framework and liquidity needs based on the market environment.

Chapter 5 investigates why and how data sets on the unsecured interbank money market differ. Considerable resources have been devoted to gathering data for the measurement of money market activity due to its importance for monetary policy transmission. Seemingly, data on the unsecured money market measures activity in the same segment and one may assume very similar results in comparison. However, little is known about the differences between available data and the structural effects of methodological choices. We use the novel data set from the Money Market Statistical Reporting and compare it to survey data and data derived from Furfine-type algorithms in the Eurosystem based on work by Arciero et al. (2016) and Frutos et al. (2016). The marked differences in volumes and interest rates are driven by the asymmetric measurement of transactions, in particular affecting individual classes of banks, cross-border loans and specific types of loans. These deviations are significant in terms of magnitude and affect overall rates and volumes. Even fundamental questions like the share of cross-border transactions depend on which data is used.

Chapter 6 discusses overarching themes of the preceding chapters, highlights areas for future research and concludes the thesis.

Author contribution and publications

I am the lead author of Chapter 2, and one of the two lead authors for Chapter 3, Chapter 4 and Chapter 5.

Chapter 2 is published as Tilburg University, CentER Discussion Paper, Chapter 3 is published in the Journal of Financial Market Infrastructures, Chapter 4 is published in in the Journal of Financial Market Infrastructures, Chapter 5 is published as Deutsche Bundesbank Discussion Paper, an enhanced and expanded deep-dive into differences between the algorithms was published in the Journal of Financial Market Infrastructures.

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Chapter 2

No more Tears without Tiers? The Impact of Indirect Settlement on liquidity use in TARGET2

Joint work with Ron Berndsen (Tilburg University and LCH), Martin Diehl (Deutsche Bundesbank) and Ronald Heijmans (De Nederlandsche Bank).
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Diehl, Heijmans and Paulick are members/alternates of one of the user groups with access to TARGET2 data in accordance with Article 1(2) of Decision ECB/2010/9 of 29 July 2010 on access to and use of certain TARGET2 data, as amended on 22 September 2017 by Decision (EU) 2017/2080. he Deutsche Bundesbank, De Nederlandsche Bank, the MIB and the MIPC have checked the paper against the rules for guaranteeing the confidentiality of transaction-level data imposed by the MIB pursuant to Article 1(4) of the above-mentioned issue. The views expressed in the paper are solely those of the author and do not necessarily represent the views of the Deutsche Bundesbank, De Nederlandsche Bank or Eurosystem.

Short summary

We study the impact of tiered settlement on relative intraday liquidity use (liquidity consumption) for settlement banks in TARGET2. We estimate a panel data model employing transaction-level data from 2010 to 2019 which shows that a higher share of tiered payments from client banks reduces relative liquidity consumption by settlement banks. Metrics on timing, delay, and payment priorities suggest that settlement banks can make use of more leeway in settling tiered payments from client banks compared to their own payments. Payment timing as a proxy for external delay suggests that tiered payments are used to smooth settlement banks' liquidity positions. Results on payment delay within the system show no clear dynamic over time, whereas payment priorities are consistently lower for tiered payments. We conclude that to some degree settlement banks employ tiered arrangements to manage intraday liquidity more efficiently. To a certain extent this hints to "free riding" or higher recycling of liquidity from client banks' payments. However, the results are also consistent with settlement banks' monitoring role or tiered payments potentially exhibiting different characteristics which may be attributable to contractual arrangements.

Keywords: RTGS systems, banks, payments, tiering, liquidity, TARGET2

JEL classification: E42, E58, G21.

2.1 Introduction

Internal and external risk mitigation is the foundation for the smooth functioning of financial market infrastructures (FMIs). Payment systems form the underlying infrastructure for the settlement of debt obligations in an economy. The Principles for Financial Market Infrastructures (PFMIs), developed by CPSS-IOSCO (2012), formulate high international standards for these FMIs and offer guidance on potential sources of risk and risk mitigation.

The settlement of payments on behalf of clients by direct system participants, called tiering, is a universal feature of payments systems. Principle 19.4 of the PFMIs state that "An FMI should regularly review risks arising from tiered participation". Risk exposures operators and overseers look at include credit, liquidity and operational risk. According to the PFMI these risks may be especially large for highly tiered systems.

Instead of directly sending payments to a payment system, some banks[1] choose to delegate settlement. The arrangement of an indirect participant (client bank) processing payments through a direct participant (settlement bank) forms a tiered arrangement. The underlying economic reasons that influence banks' decision on how to access a payment system are manifold. For smaller banks it might be more cost-efficient to chose tiered settlement arrangements, avoiding costs related to operational setup and liquidity management.

Tiered participation not only entails risks, but can increase the efficiency of payment systems. Costs of payment settlement decrease with tiered participation as direct participants can profit from economies of scale (see for example Adams et al., 2010; Chapman et al., 2013). Pooling liquidity leads to lower cost of capital as settlement banks can use higher traffic volumes to offset payments in the system or settle payments internally on their own books without entering them into the payment system and drawing on liquidity.

From a settlement bank's perspective, tiered payments feed into the overall liquidity disposition of payments that are settled in a way to minimize liquidity use. Monitoring intraday liquidity is part of the Basel framework in order to ensure banks are able to meet payment obligations. Central bank reserves and the participation in wholesale payment systems are only one part of banks' liquidity management, but arguably one of the most important parts. Correspondent banking arrangements, secured and unsecured credit lines and unencumbered assets also factor into banks' intraday liquidity management and should be monitored in accordance with Basel Committee on Banking Supervision (2019).

In this study, we investigate the effect of tiering on the relative intraday liquidity use (liquidity consumption) of settlement banks in TARGET2.[2] empirically. Liquidity consumption is defined as the maximum amount of liquidity needed intraday to settle the payments of a direct participant relative to all payments sent by that participant. The measure indicates how efficient a bank uses liquidity sources to make payments. Assuming liquidity is costly, settlement banks exhibiting lower values of liquidity consumption settle

[1] With regard to terminology, we use credit institution interchangeably with the term bank throughout the paper. Direct participants in a payment system are referred to as settlement banks, indirect participants are referred to as client banks. For brevity, we at times refer to settlement banks as banks and direct participants as participants.

[2] TARGET2 refers to the second generation Trans-European Automated Real-time Gross Settlement Express Transfer System operated by the Eurosystem.

payments in a more cost-efficient manner. Liquidity in the form of central bank reserves can be assumed to be costly as it is acquired from the central bank or the interbank market. In addition, there is an opportunity cost to dedicating liquidity for the purposes of settling payments. Liquidity is more costly to acquire when interest rates are high. In addition, liquidity is usually scarce. When liquidity is scarce and interest rates are high, the cost of acquiring liquidity is thus expected to be larger. Tiering generally decreases liquidity needs as payments offset when concentrated among fewer direct participants. However, little is known about the effect of tiering at the participant level and how tiering factors into banks' liquidity management. To shed some light on this question, we employ a panel data model and identify channels via which tiering affects liquidity consumption.

Using transaction-level data from TARGET2, we find that higher shares of tiered payments reduce relative liquidity needs for settlement banks. The results are robust controlling for pooling effects via bank fixed effects, payment activity and other factors. The main driver appears to be that banks have more discretion in settling tiered payments. Payment timing suggests that tiered payments help settlement banks to smooth their liquidity positions by assigning lower priorities to them compared to banks' own or in-house payments. To some degree this indicates discriminatory practices, as settlement banks treat their own payments with higher urgency, thus using more liquidity for settling own payments relative to tiered payments.

However, settlement banks reducing their cost of liquidity is also consistent with their role in monitoring client banks and offering cost-efficient settlement services based on private information on creditworthiness (see for example Chapman et al., 2013). Smoothing liquidity positions from this perspective may be a way to mitigate settlement banks' risk from tiered arrangements. The findings are also consistent with tiered payments exhibiting different characteristics. Tiered payments may arrive later in the day and by nature be less urgent, so settlement banks can use these payments to optimize their liquidity positions. Treating tiered payments with less urgency may also result from contractual bilateral arrangements between client banks and their settlement banks. As no information is available on payments before they enter the system, such reasoning cannot be ruled out here. The findings show that once payments enter the system, tiered payments are different to in-house payments.

We conclude that tiered arrangements help settlement banks in managing liquidity more efficiently. However, this gain in efficiency comes at the potential cost of concentration and hence operational bulk risks. In addition, there could be a higher credit risk for client banks in tiered arrangements resulting from settlement banks' active liquidity management. However, the trade-offs and settlement banks' risk mitigation vis-à-vis client banks is outside the scope of this study. TARGET2 makes up only one (though important) part of banks' overall liquidity position. Other systems, bilateral relationships and exposures may play a significant role for some banks' liquidity disposal.

2.2 Tiering in large-value payment systems

In contrast to securities transactions, payments do not require agreement between counterparties before a transaction is settled. Payments are rather the result of underlying business transactions. However, the tiered structure in payments can be seen in the broader context of financial markets. Markets with a tiered structure include foreign exchange, government and corporate bond markets. Starting in the 1980s, the study of the microstructure of financial markets in terms of the impact of organization and design on trading cost and prices became increasingly relevant (see for example, de Jong and Rindi, 2009). In the literature, different types of participants are often distinguished based on their information and motive for trading, but also their roles in the market. Grossman and Miller (1988) study the role of market makers as intermediaries. Market makers provide immediacy to clients as described already by Demsetz (1968) highlighting the importance of transaction cost. Dealers in bond and foreign exchange markets provide immediacy, meaning the opportunity to trade without delay. This requires traders to hold inventory. Intermediaries assume price risks stemming from having to wait for buyers or sellers of securities. Bid-ask spreads are a compensation for the risk on the inventory and for the cost of searching for counterparties to process the trades.

As another reason for tiered structures in financial markets, setting up internal infrastructures is costly. Access to financial infrastructures, such as payment systems or exchanges, may require additional investments and fees. Smaller market actors, such as investors or banks, may save cost by using intermediaries.

In analogy to securities markets, direct participants offering payment services may be seen as broker-dealers that buy and sell securities on clients' behalf and assume risk by extending intraday credit. In contrast to securities, central bank reserves are the only asset in wholesale payment systems. Direct participants hence only manage the overall stock (inventory), but not individual types of assets. Though there are no price risks in payments, tiered structures fundamentally arise from similar considerations. Direct participants assume risks, for example operational risks, whereas indirect participants do not need to setup a constant presence in the payment system. Similar to securities markets, costs for clients would include setting up trading operations, fees from participation in financial exchanges and holding sufficient liquidity as outlined by Vayanos and Wang (2012).

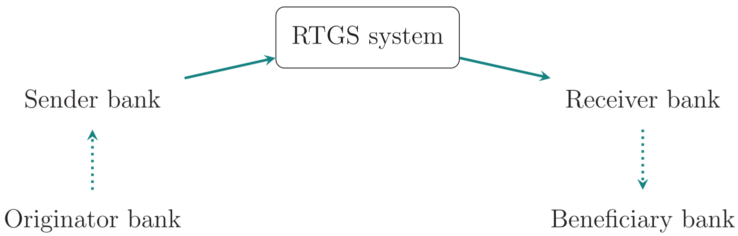
The relationship between direct and indirect participants and the cost of service is not investigated here, but has been studied in other markets. Among others, Stoll (1978) studies the cost of dealers in equity markets and the efficiency of different market structures. Inventory cost is somewhat related to the cost of holding liquidity for payments. Liquidity in the form of central bank reserves can be assumed to be costly as it is acquired from the central bank or the interbank market. Liquidity is more costly to acquire when interest rates are high. In addition, liquidity is usually scarce. When liquidity is scarce and interest rates are high, the cost of acquiring liquidity is thus assumed to be larger.

Direct participants facilitate payments from their account and ensure sufficient liquidity is available for settlement. Similar to primary dealers in bond markets, direct participants usually interact with the central bank (analogous to the issuer) and often engage in secondary trading in the money market (analogous to secondary markets). Over the counter (OTC) money market transactions serve as one source for funding payments for immediate settlement. Banks borrow from banks with a surplus of liquidity. As highlighted by Duffie et al. (2005), prices in OTC markets are determined by liquidity considerations in the context of immediate trading, outside options and the market power of intermediaries. Interest rates in the unsecured money market typically reflect riskiness of borrowers and bargaining power (Rochet and Tirole, 1996; Abbassi et al., 2021). Similarly, direct participants in payment systems may earn profits by charging higher fees to client banks as a compensation for assuming risks.

Large-value payment systems (LVPSs) typically settle transfers with a high value or high priority. Many LVPSs, such as TARGET2, settle transactions immediately on a gross basis and are also referred to as Real-Time Gross Settlement (RTGS) systems. This stands in contrast to net settlement systems in which payments are settled at a specified time on a net basis. Hence, RTGS systems typically require higher amounts of liquidity for settling payments.

Aside from central banks and government entities, direct access to an LVPS is mostly restricted to credit institutions. Credit institutions can access payment systems directly or indirectly through a correspondent bank, though there are regulatory restrictions and access criteria that may apply.[3] Importantly, participation in monetary policy operations may require direct access to an LVPS. Indirect participants do not hold an account in the LVPS and thus settle payment obligations via direct participants subject to bilateral agreements as illustrated in Figure 2.1.

Figure 2.1: Tiered settlement



The level of tiering differs widely across systems. While there are over 1,000 direct participants in TARGET2, there are only around 30 direct participants in the UK's payment system CHAPS.[4] As indirect participants, almost 700 credit institutions from the European Economic Area (EEA) and more than 4,000 correspondents worldwide can settle payments via TARGET2.[5] For CHAPS the number is quite similar, as roughly 5,000 financial institutions settle payment via CHAPS. The ratio of direct to indirect participants is roughly 1:5 for TARGET2 and 1:160 for CHAPS, meaning CHAPS is a much higher tiered system than TARGET2.

The numbers of direct and indirect participants gives an indication of how broadly banks access a system. In addition, the number of direct participants hints to the number of options potentially available to client banks. However, not all direct participants offer settlement on behalf of client banks. In TARGET2, out of 1,209 participants in the sample, 438 do not send any tiered payments, only 266 settle tiered payments greater than 1 percent of their traffic, and only 128 participants settle tiered payments greater

[3]For an overview of RTGS system features and institutional design see CPSS (2005).

[4]See `ecb.europa.eu/paym/target/target2` and `bankofengland.co.uk/payment-and-settlement/chaps` for information and recent numbers.

[5]In TARGET2 there are so-called indirect participants and addressable BICs (Bank Identifier Codes). In both cases, banks use a direct participant to connect to TARGET2, but only supervised credit institutions established within the EEA can become indirect participants. In the context of this study the difference is not relevant and we refer broadly to indirect participants.

than 5 percent of their traffic. As smaller participants are much less likely to engage in settlement on behalf of client banks, we restrict the sample to larger participants for robustness. The concept of tiering employed here refers to volumes and values of payments rather than the number of participants.

Levels of tiered participation depend on institutional design and the system's pricing policy. Depending on what outcome a regulator desires, legal requirements and rules of access may be designed in a way to encourage direct participation. The risks of tiered settlement are often emphasized by policymakers and regulators. As described by Finan et al. (2013), the Bank of England persuaded large indirect participants to become direct participants in the UK's highly tiered CHAPS system on account of financial stability considerations. CHAPS can be considered as an extreme example, with historically few direct participants. However, even in this setting Benos et al. (2017) find, using transaction-level data, that the effects of the largest indirect participants becoming direct participants (de-tiering) have small effects on risk measures.

For other systems, such as the US RTGS system Fedwire, information on tiered payments is not available from transaction data. Thus, the analysis of risk relies on information gathered from other sources. Overall, risks for Fedwire from tiered arrangements are believed to be small and manageable through regular reviews and by the mitigation of risks posed by direct participants (see Fedwire Funds Service, 2019).

Tiered participation partly reflects the banking system structure and historical developments. In the case of the Australian RTGS system, for example, restrictions were previously applied to tiered arrangements. These were lifted in 2003, allowing participants with 0.25 per cent of overall payment value to process payments via settlement banks. Potentially due to setup costs, there has been inertia in changing access, with few banks making adjustments (see Arculus et al., 2012).

For banks, a variety of factors influence the decision on how to access a payment system. Table 2.1 summarizes benefits and risks of tiering from a client bank's risk perspective. Cost-effectiveness and exposure to risks have to be balanced. Direct participation may entail operational setup costs and investments in liquidity management. Indirect participation may give rise to credit risk, as exposures accumulate during the day against settlement banks. In addition, payment services to client banks may be bundled together with other services, thus making direct participation less attractive for some banks. Typically smaller domestic banks and foreign banks are more likely to become indirect participants.

For banks that directly participate in a payment system, tiered settlement is offered when profits outweigh the cost of providing settlement services. Direct participants may profit from economies of scale and tiering may help recoup some of the investment cost for operational setup. Importantly, the banking structure may also affect the degree of tiering. For example, head institutions of savings banks and credit cooperatives often provide services including payment settlement to member banks. This not only includes settlement in RTGS systems but also payments settled in internal giro systems.

Tiering often leads to uncollateralized, credit positions between banks. Rochet and Tirole (1996) study tiered arrangements in the context of interbank monitoring and systemic risk. Kahn and Roberds (2009) discuss the trade-off between widespread access to an LVPS versus the efficiency gains achieved by private monitoring in tiered relationships. Chapman et al. (2013) show that tiered arrangements can arise via two channels. The

Table 2.1: Benefits and risks of tiered participation from a client bank's perspective

	Positive effects of tiering	Negative effects of tiering
Credit risk	Risk exposures against other banks may be more efficiently managed by settlement bank.	Credit risk against settlement bank. Risk exposures against other banks may accumulate if inefficiently managed by settlement bank.
Liquidity risk	Liquidity may be more efficiently managed by settlement bank. Client bank is charged cost of liquidity and profits.	Settlement bank may draw on liquidity provided by client banks. Costs of liquidity and operations may be lower than settlement bank fees.
Operational risk	No operational setup costs and fewer own resources dedicated to operations. High operational proficiency via outsourcing to larger players.	Operational proficiency dependent on settlement bank. Dependency on settlement banks may lead to lock-in effects.

first is through settlement banks monitoring client banks. In a setting with imperfect information, settlement banks leverage private information on creditworthiness by offering different settlement modes. The modes of settlement are similar to system-level differences between deferred net settlement systems and RTGS systems. Tiering represents a balance between deferred settlement, with lower liquidity costs but higher credit risk, and immediate settlement, with high liquidity costs but low or absent credit risk. The second channel is through settlement banks benefiting from economies of scale that reduce overall cost in the system. Given their roles, failures of settlement banks would lead to substantial welfare losses in terms of operational risks and loss of information.

From a central bank perspective, monitoring payment system activity is crucial for risk mitigation. A variety of approaches are available to identify different risks. Berndsen and Heijmans (2020) develop a traffic light approach, based on different indicators to identify credit, liquidity and operational risk in TARGET2. Triepels et al. (2018) apply an unsupervised learning method to detect anomalies in RTGS systems. Sabetti and Heijmans (2021) apply a similar approach to Canadian LVPS data and discuss how deep-learning methods could be implemented by operators. Rubio et al. (2020) built on their work to asses deep networks to detect anomalies in the largest systemically important payment system in Ecuador. Aside from anomalies that can relate to different sources of risk, liquidity risk is of particular interest for the smooth functioning of payment systems and financial stability. Heuver and Triepels (2019) apply supervised machine learning in an experimental setting to identify banks encountering liquidity stress.

From a settlement bank's perspective, liquidity needed to fund payments in RTGS systems needs to be obtained from the central bank or the interbank market at a cost. The central bank may also offer overdraft facilities for banks to fund payments. Additionally, received payments allow banks to recycle liquidity from other participants to fund outgoing payments. McAndrews and Rajan (2000) develop a measure to decompose different sources of payment funding and find incoming payments account for 25 to 40 percent of liquidity sources during the day in Fedwire.

Intraday behavior in RTGS systems is also studied by Bech and Garratt (2003) using a game theory approach. Typically, banks have an incentive to postpone payments when liquidity is costly and they thus delay payments and recycle incoming payments. To account for banks changing behavior during disruption events, rather than assuming a given behavior Arciero et al. (2009) employ agent-based modelling to simulate payment activity. Liquidity saving mechanisms in RTGS systems can affect banks' behavior as shown by Martin and McAndrews (2008). One example is the use of limits in TARGET2 which allow maximum bilateral or multilateral exposures to be set (see Diehl and Müller, 2014).

Banks relying heavily on incoming payments as a liquidity source can be labelled free-riders. Diehl (2013) provides an overview of different measures and interpretations in the context of free-riding in TARGET2. Heijmans and Heuver (2014) show that banks react dynamically to stress events and some banks delay payment. They find that indicators on timing can help detecting liquidity problems. Abbink et al. (2017) study the effect of disruptions on banks' reactions in an experimental setting. Path dependency of disruptions may lead to inefficient coordination outcomes at the system level. Concerning market structure, a homogeneous market could relate to a highly tiered system with few active banks. The study finds that a heterogeneous market structure achieves efficient coordination more easily due to a leadership effect.

Depending on banks' use of liquidity, costs incurred by direct participants are passed on to indirect participants. Adams et al. (2010) simulate the emergence of tiered arrangements in a network structure where banks balance the liquidity costs incurred through direct participation and the service fees they pay as indirect participants. The service fee consists of direct participants' liquidity costs and profits. Cost of liquidity as determined by central banks is found to influence choices on system participation. Liquidity pricing is modeled proportionally to liquidity usage or up to a certain amount as free when banks have to post collateral to the central bank for prudential reasons. In such regimes, banks can draw on liquidity provided against collateral without incurring additional cost.

Arango and Cepeda (2017) study the trade-off between increased liquidity savings and larger credit risk with a higher degree of tiering in the context of the Colombian RTGS. Liquidity savings are found to increase non-monotonically. At the same time, credit risk changes little when smaller participants become indirect members, while substantial increases are found if large participants become tiered. This points to the fact that finding an optimal balance between credit and liquidity risks depends on the banking structure and type of banks. Lasaosa and Tudela (2008) use a simulation approach to study tiering in CHAPS. Results indicate that increasing tiering would lead to significant liquidity savings stemming from pooling. At the same time, concentration risk would increase substantially, while effects on credit risk appear to be small.

Operational disruptions due to technical outages in a payment system can affect the whole system or its individual participants. In the context of tiering, participant disruptions are of interest. Tiering has at least two opposite effects which are hard to quantify (see for example Arculus et al., 2012). Since tiering contributes to a higher concentration of settlement banks, the impact of any operational failure of a settlement bank becomes larger. However, a bank transmitting significantly more payments than others may be better at fulfilling its operational duties. Client banks are in general smaller in terms of transaction volume and value and may lack the funds to invest in state-of-the-art operational systems and to dedicate more payment specialists to the tasks of liquidity management. This aspect is reinforced by the sizable complexity of modern RTGS-systems, which offer a large range of options and mechanisms and require some degree of specialization among the bank's liquidity managers. Moreover, only a limited share of banks offer tiering and can be considered to have specialized. Therefore, it stands to reason that the probability of a failure of a large settlement bank is lower than the probability of an operational failure of a client bank. However, as comprehensive data on operational outages for direct and indirect participants is not available.[6], this assumption is difficult to verify. We are inclined to assume that the operational risks are at least not significantly changed by tiering and that it is more likely that tiering leads to higher operational proficiency.

The effect of tiering on operational and credit risks is not considered here. Contractual arrangements between direct and indirect participants on prefunding of payments, collateral and limits are not taken into account as these factors are unobserved. In addition, internal payments that give rise to credit risk are unknown from TARGET2 data.

2.3 TARGET2 data

2.3.1 Overview and sample

TARGET2 is the largest LVPS in Europe and one of the largest RTGS systems in the world. The system is owned and operated by the Eurosystem. In 2019 around 340,000 transactions were settled on average per business day, amounting to roughly 1.7 trillion euro.[7] Annual payments settled in TARGET2 amounted to 37 times the annual GDP in the euro area. Even though TARGET2 relies on a single technical platform, from a legal perspective, individual central banks in the Eurosystem own separate (national) components. In addition, some EU central banks that are not members of the Eurosystem are connected to TARGET2. In the system, domestic and cross-border payments in euro are settled in real time, including interbank and customer payments, monetary policy operations and transfers with ancillary systems and other financial market infrastructures. Underlying business reasons for large-value or urgent transfers are manifold, including for example payments for goods and services, the purchase or sale of securities, loan payments or transactions based in the real economy.

The measures in section 2.4 are constructed using TARGET2 transaction data from 2010 to the end of 2019. We focus on transactions of commercial banks as participants of TARGET2. Transaction-level data is filtered for central bank operations, participants' liquidity transfers between their own accounts and technical transfers in order to focus on business-related payments that affect settlement banks' liquidity position during the day and to exclude payments that serve the purpose of liquidity management. In addition, we disregard start-of-day balances that banks hold, in part, for fulfilling minimum reserve

[6]On the availability and identification of operational outage data in different jurisdictions, see for example Klee (2010), Glowka et al. (2018) and Arjani and Heijmans (2020) Note that the constructed data in these studies is not representative, as data for smaller banks is usually less reliable.

[7]See `https://www.ecb.europa.eu/pub/targetar/html/ecb.targetar2019.en.html`.

requirements. The filtering allows us to study payment behavior and intraday liquidity, irrespective of how liquidity used for payments is provided.

Besides customer and interbank transactions, we include transactions to ancillary systems and other market infrastructures, such as the securities settlement system T2S. For some ancillary systems, such as continuous linked settlement (CLS) for foreign exchange related transactions, there are fixed time windows for settlement. Thus, participants may not be able to time such payments according to their own preferences. Nevertheless, these payments affect participants' liquidity constraints during the day. Central banks and ancillary systems themselves are not included as participants as they typically do not engage in active liquidity management and exhibit different characteristics than commercial banks.

The sample spans over 2,500 business days with a total of more than 1,200 direct participants. Note that the term participant relates to BICs (Bank Identifier Codes), i.e. accounts in TARGET2. Banks may use multiple BICs to settle their payments. Different accounts of the same participant are not grouped together, but results are similar when sub-accounts are consolidated.[8]

Due to changes in the banking system structure, settlement banks drop in and out of the sample. In addition, some banks do not interact with TARGET2 everyday creating an unbalanced panel. We drop observations where direct participants only send or receive payments and when payments sent are below a threshold of 1,000 euro. In these cases, active liquidity management on the part of settlement banks is deemed irrelevant and payment activity too low to generate meaningful results. More than 1.7 million daily observations remain in total after the adjustments.

2.3.2 Tiering concept applied to TARGET2

Credit institutions established in the European Economic Area (EEA) are eligible as direct participants, while credit institutions from outside the EEA may use direct participants as access points to TARGET2 which is also referred to as correspondent banking. TARGET2 data includes transaction details that make it possible to identify payments sent and received on behalf of client banks. While these fields in payment messages are optional, they are typically filled by banks in TARGET2 in order to enable a quick routing of the payments. Arguably, the provided transaction details allow to identify the vast majority of tiered payments sent and received.

Banks settling payments on behalf of client banks are referred to as senders and receivers, the client banks using the service of settlement banks are called originators and beneficiaries (for illustration see Figure 2.1). In the transaction data there are multiple message fields, in some instances forming a chain of on-behalf information. Only the first and last BIC in a chain of payment information are used in the analysis to identify the ultimate client banks.

Tiered payments may be settled internally in the accounts of a settlement bank. These payments do not provide a source of intraday liquidity for the settlement bank or act as a drain on its intraday liquidity as they do not link to the payment system. However, these *internalized payments* do have implications for exposures and liquidity positions between settlement and customer banks and thus for potential risks. Surveys of correspondent

[8] This stems from the fact that many banks use one or few main accounts for payments.

banks in the UK have shown that internalized payments make up around one third of interbank payment values (see Adams et al. (2010)). In the case of TARGET2, it might be assumed the share is lower as the system is less tiered. Internalized payments are out of scope here, as no information on internal transactions is available from payment system data. Importantly, such information is also not available to system operators and overseers.

Tiering is defined here in a narrow sense as the settlement on behalf of client banks which do not belong to the same banking group, similar to, the definition employed by Benos et al. (2017) among others. In a wider sense, tiering can be seen as settlement on behalf of any client bank, irrespective of affiliations. The reasoning for choosing the narrow definition here, stems from the fact that intragroup settlement arrangements may differ in economic terms from arrangements with outside banks. Intragroup payments may exhibit other properties due to broader interconnections between banks that entail more than payment operations stretching across other areas of banking. Therefore, extra-group relations provide a less biased measure of tiered settlement arrangements for investigating the effects of indirect settlement on participants' behavior. Henceforth, we refer to tiering as tiering in the narrow sense and intragroup transactions as a separate category.

Initially, transactions on behalf of clients include intragroup transfers as well as transfers on behalf of clients outside the banking group. To distinguish extra-group transfers as tiered settlement, we use data from the SWIFT Bank Directory Plus[9] to classify payments according to banking group structures. The directory data includes information on individual BICs and their affiliated banking groups, which is mapped to data from TARGET2. Data from the directory is available from 2012 onward. Data before might not reflect banking group structures accurately, as mergers and other changes to the group structures are not accounted for. The further back in time one looks prior to the available data, the greater the inaccuracies even though group structures typically remain relatively stable. In order to avoid too much potential distortion in the data, we include only two previous years, starting in 2010. Therefore, the data should exhibit only a few inaccuracies and is the most reliable information available.

The SWIFT data on legal heads of banks is combined with transaction data. When originator and sender (or respectively the receiver and beneficiary) of a payment have the same legal head institution, these payments are labelled as intragroup transfers. Tiering henceforth refers only to payments that are respectively sent or received by settlement banks on behalf of an originator or beneficiary outside the banking group of the acting bank. Own payments are those transactions where no originator or beneficiary is involved in the transaction.[10]

2.4 Measures

This section describes the indicators employed to measure the impact of tiering. In order to analyze the effects of tiered settlement, we construct measures related to liquidity consumption, timing and delay. The measures are calculated using only the aforementioned

[9]See `swift.com/SWIFTRef` for further information on the dataset.

[10]In addition, cases where the originator or the respective beneficiary coincide with the sender or receiver are treated as own payments.

subset of TARGET2 transactions.

2.4.1 Liquidity use and consumption

Importantly, measures on liquidity use do not entail sources of liquidity such as participants' account balances, liquidity transfers and monetary policy operations. In the setting relevant here, the actual liquidity needed by direct participants to settle payments intraday is of interest.
The payments sent by a participant i on a business day b are given by:

$$S_i^b = \sum_{t=0}^{T} s_i^b(t) \tag{2.1}$$

With individual payment values in a time interval t (ranging from 0 to T) given by s. Respectively, payments received R are given by:

$$R_i^b = \sum_{t=0}^{T} r_i^b(t) \tag{2.2}$$

Total payments sent on a given business day in TARGET2 are given by the sum of payments sent by participants i (with i ranging from 1 to N) on day b:

$$S^b = \sum_{i=1}^{N} S_i^b \tag{2.3}$$

Liquidity needed to settle payments during the day is given by the debit position of participants which has a positive value here, while received payments factor in negatively.[11] The debit position D (running balance) of each participant at a time interval t is given by the difference between sent (s) and received (r) payments:

$$D_i^b(t) = s_i^b(t) - r_i^b(t) \tag{2.4}$$

As described in Leinonen and Soramäki (1999), the liquidity needed to settle all payments during the day given their order is expressed by LN which is calculated as the maximum of the running balance for the payment categories included in the study. This gives us the daily maximum debit position of each participant. The measure corresponds to the daily maximum intraday liquidity usage in the Basel framework Basel Committee on Banking Supervision (2019) applied to TARGET2. The minimum is set at zero. The minimum is set at zero.[12] Consequently, negative debit positions, i.e. arising intraday credit positions, are not considered:

$$LN_i^b = \max_{t \in [0,T]} (D_i^b(t), 0) \tag{2.5}$$

[11] This is contrary to typical account statements.

[12] Zero is the supposed start-of-day balance of the participant and serves as the starting pint for calculation.

An LN above zero occurs when the value of the sent payments exceeds the value of payments received at some point during the day. A positive LN can also be referred to as maximum exposure, largest net debit position, or liquidity provision to the system. for a participant i on a business day b.
And on the system-level, with S_b from Equation 2.3 as:

$$LC^b = \frac{\sum_{i=1}^{n} LN_i^b}{S^b} \tag{2.6}$$

We call LC liquidity consumption, which is bounded by 0 and 1. As LN can never be larger than the sum of sent payments, a value of 1 means all payments are sent by a participant before any payments are received. A value of 0 means a participant does not draw on liquidity for settling payments, with incoming payments being recycled to fully fund outgoing payments.
In line with Denbee et al. (2014) we also use the cost-based measure of relative liquidity need for robustness, which is defined as:

$$cLN_i^b = \frac{LN_i^b}{\sum_{i=1}^{n} LN_i^b} - \frac{s_i^b}{\sum_{i=1}^{n} S_i^b} \tag{2.7}$$

Negative values signify that a bank provides less liquidity to the system relative to its share of payments, and vice versa for positive values.

2.4.2 Timing

One channel via which banks may manage liquidity is by postponing payments before they enter the system. Internal queue management is one tool that banks may employ to shuffle payments and manage liquidity positions more efficiently.

Timing indicators show when payments are settled on average in the system. We follow Massarenti et al. (2012) who apply timing indicators to TARGET2 data as described by Kaliontzoglou and Müller (2015). However, for tiered payments no information is available to observe when client banks send instructions to the direct participants. Therefore, the lag between receiving instructions from client banks and sending them to the system is unknown. However, we could assume that there is no reason why there may be significant and consistent differences for indirect participants relative to direct participants. Reasons why there may be consistent difference are banks' business models with regard to client banks. For example, in terms of European time, indirect participants located in the US are late payers and indirect participants located in Asia are early payers. Abstracting from such reasoning, the settlement time and time differences of own payments and tiered payments can provide indications of how settlement banks time different types of payments and how they may differ structurally.

The average timing of sent payments TS of bank i on day b is given by:

$$TS_i^b = \frac{\sum_{i=1}^{n}(s_i^b(t) * t)}{\sum_{i=1}^{n}(s_i^b)} \tag{2.8}$$

The respective average receiving time of payments TR is given by:

$$TR_i^b = \frac{\sum_{i=1}^{n}(r_i^b(t) * t)}{\sum_{i=1}^{n}(r_i^b)} \tag{2.9}$$

The difference between received and sent payments TD indicates whether payments are recycled or whether banks, on average, send out payments before incoming payments arrive. The measure can therefore be interpreted as a proxy for the external delay of payments:

$$TD_b = TR_b - TS_b \tag{2.10}$$

Assuming there are no structural reasons for timing differences between direct and indirect participants, differences in TD for non-tiered and tiered payments would result from direct participants treating tiered payments differently in terms of timing, for example via internal queue management. Contractual arrangements between direct and indirect participants are unknown. Therefore, postponing settlement of payments on behalf of indirect participants may be in line with contractual provisions.

A negative value of TD indicates that banks send payments later than they receive them, while a positive value shows that banks send payments earlier than they receive them. Abstracting from structural differences, a negative value implies that banks recycle liquidity rather than providing it. If it is assumed that all payment instructions arrive at banks independently, meaning without structural differences in the timing of sent and received payments across categories, the difference in timing would measure external delay. Differences in timing would occur if banks rearranged payments and thus delayed payments outside of (external to) the system.[13] The actual transmission and obligation to pay is unobserved, as payments show up in the data only upon entering the system. Assuming that payments do not differ structurally in terms of when direct participants receive payment instructions, payment timing can be regarded as a proxy for how participants manage their payments outside the system. Payment timing across different categories of payments can serve as an approximation for the treatment of payments in internal queues. Arguably, for a definitive interpretation of results, the unobserved given conditions outside the system are critical.

2.4.3 Delay indicator

Through delaying payments, direct participants may hold back liquidity and rely on incoming funds for making payments. Delays occur in two ways. First, as described above, participants can externally delay sending payments for settlement in TARGET2. Second, within the system, delay can occur between when payments are sent to the system and when they are actually settled in the system. Delay between when direct participants receive payment instructions and when payments are sent to the system can only be observed indirectly. By contrast, delay within the system can be observed directly. Delay within the system occurs when liquidity is not sufficient for settlement and payments get queued. Banks may also use different liquidity saving mechanisms available in TARGET2. These include reserving liquidity for highly urgent payment, which means this liquidity is not available for lower priority payments. Participants may also set bilateral and multilateral limits, thus limiting their net positions vis-à-vis other participants.

[13] It could be the case that tiered payments are sent to settlement banks later in the day. Note that on a system level, the timing of all sent and received payments is equal if all participants are observed. This is not the case for different categories of payments, such as tiered payments. The sending leg and receiving leg of payments may fall into different categories.

Following Kaliontzoglou and Müller (2015), we measure the delay in payments by comparing the introduction[14] and settlement time in the system relative to the latest possible settlement time. The latest possible settlement time considered here is the close of business. The indicator of delay is stated as:

$$DI_i^b = \frac{\sum_{i=1}^{n}(s_i^b(t) * (t_{2,i} - t_{1,i})}{\sum_{i=1}^{n}(s_i^b(t) * (T - t_{1,i})} \tag{2.11}$$

Where $t_{1,i}$ is the time during the business day when the payment is available to be settled, $t_{2,i}$ is the actual settlement time of the payment and T is the end of day, i.e. the latest possible settlement time.[15]

2.5 Results

The results are organized starting with the overall levels of tiering and liquidity consumption. To formally test the effect of tiering on liquidity consumption, we then estimate a panel data model on the settlement bank-level. Timing and delay indicators then identify channels via which tiering reduces relative liquidity use.

For the interpretation of results, the following is implicitly or explicitly assumed:

- Tiered and non-tiered payments do not differ structurally in terms of when payment obligations arise and when incoming payments are received by other participants. Without active liquidity management, similar arrival and sending times are expected. This assumption holds if the payment categories do not differ structurally due to their underlying business cases, emergence from activity in different time zones or other considerations by client banks. Testing the assumption would require banks' internal data and business logic.

- Banks actively manage liquidity to limit intraday peaks. They are able to shuffle payments to some degree in order to limit their overall liquidity position across payments from different client banks as well as intragroup and their own payments. Given regulatory frameworks and incentives for banks, this assumption should hold. However, the degree of active liquidity management likely differs across banks.

- Direct participants have some leeway in when they settle payments. Given internal queuing mechanisms for payment settlement, this assumption holds. However, contractual arrangement may limit leeway.

- Resulting from the previous points, payment timing in the system differs largely due to liquidity management rather than different average instruction times across tiered and non-tiered payments.

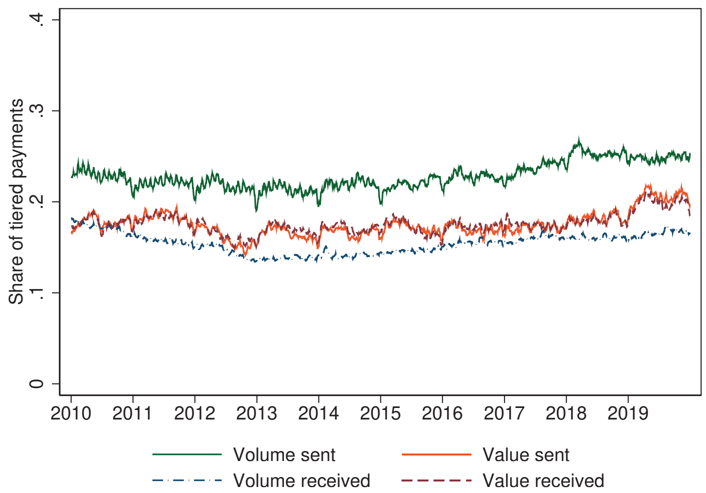
[14]Participants can specify the date and time when a payment should be executed. The first attempt for settlement by the system will be made at that point in time. In those cases we use the time for payment execution rather than when the instruction for later settlement reached the system.

[15]Cut-off times differ for different types of payment. For simplicity, we assume the latest cut-off for all payments to be the end of the day.

2.5.1 Tiering and liquidity consumption

The share of tiered payments, calculated as share based on Equation 2.1, lies roughly between 15 to 25 percent over the observation period (see Figure 2.2). The number of tiered payments is higher on the sending side. However, in terms of values, the share of tiered payments is similar on the sending and receiving side. This means the average size of payments on the receiving side is larger for tiered payments. At the same time, indirect participants send higher volumes of payments than they receive, which can either indicate that client banks have a greater number of lower denominated payment obligations or that they break up payment obligations into smaller tranches compared to received payments. Overall, the level of tiering is relatively low in TARGET2.[16].

Figure 2.2: Share of tiered payments on system level

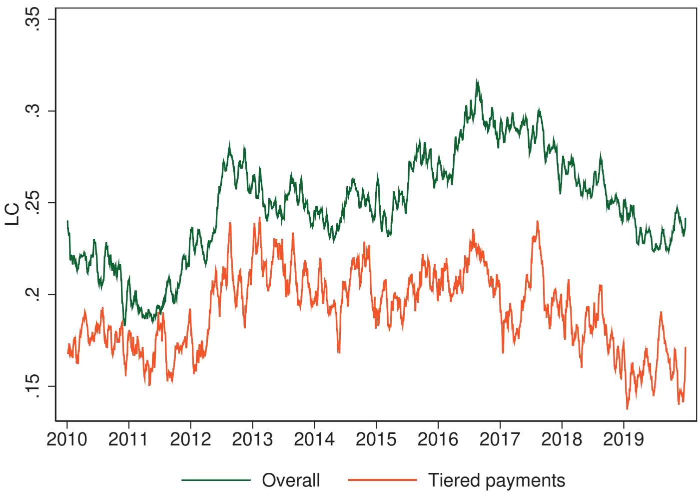


Note: The share of tiering is calculated using the number and value of tiered payments divided by all included payments in the sample.

Figure 2.3 shows liquidity consumption based on Equation 2.6 calculated for tiered and non-tiered payments. Directly comparing outcomes in terms of the relative use of liquidity shows that participants use less liquidity relative to payments for tiered transactions. However, isolating different categories of payments here does not take into account the overall liquidity position of participants. There might be a bias, as liquidity management may change during the day, depending on a participant's net overall position. It cannot be ruled out that banks' own payments are by nature (and not by choice) of higher priority and need to be settled earlier in the day, thereby increasing banks' liquidity use for their own payments. Aside from such caution, the consistently lower levels of liquidity consumption for tiered payments indicate that tiered payments leave settlement banks more discretion, enabling them to use less liquidity.

[16]For our subset of the data, tiering levels are higher compared to values on the overall system level. On yearly levels of tiering in TARGET2, see the respective Annual reports on TARGET2.

Figure 2.3: Liquidity consumption on system level



Note: Moving averages over 30 calendar days. Liquidity consumption is calculated on the system level including all payments in the scope of the study and for outgoing and incoming tiered payments. For the indicator on tiered payments, all non-tiered payments are ignored. Intraday balances do not reflect actual liquidity positions, but a hypothetical scenario where only the payments of interest here would be processed.

2.5.2 Model of liquidity consumption

To test the effect of tiering and explain the outcomes in terms of liquidity consumption on the direct participant level, we estimate a panel data model using bank and time fixed-effects. We prefer fixed effects over random effects as the latter assume the unobserved bank-level effects are uncorrelated with the independent variables. As the level of tiering and size of settlement banks probably factor into the unobserved effects, we prefer fixed effects here. However, the results are robust to employing random effects. Liquidity consumption is calculated daily across direct participants. As the independent variable of interest, the share of tiered payments is included. Table 2.2 reports summary statistics for the variables in the model.

We use the log of overall payments sent by direct participants as controls to account for size. Direct participants with more payments should be better able to manage liquidity, as they can smooth their liquidity usage by pooling payments (see Adams et al., 2010)). Accounting for size allows to abstract from such pooling effects. The average priority of the direct participant's sent payments controls for the urgency of payments, while the difference in the average timing of sent and received payments accounts for the degree of active liquidity management. In addition, we include the concentration of sent and received payments respectively, calculated as the Gini coefficient of payment values. The concentration of payments determines to some extent how granular participants can manage liquidity. Higher concentration of payments inhibits participants from shuffling payments as only a few large payments can be rearranged compared to a situation with smaller payments that can allow for more granular liquidity management. As controls for the cost of liquidity and the overall levels of liquidity, the overnight interbank money market rate and overall liquidity[17] are included. The money market rate is calculated using an algorithm proposed by Furfine (1999), applied to TARGET2 data following Arciero et al. (2016) and Frutos et al. (2016). We use a modified version of the latter to calculate the euro money market rate.[18] The algorithm identifies interbank loans by matching payments with plausible repayments the next business day.

We estimate the model with data from 2010 to 2019 using fixed effects for direct participants and time effects on a yearly basis to account for changes over time. Changes over time can occur as a result of shifts in banking structures or payment processing. Events such as Brexit may trigger changes in how banks access TARGET2, for example by consolidating liquidity management or client banks using a different direct participant to route payments.[19]

The effect of tiered arrangements may partly be picked up in bank fixed effects. Specifications without fixed effects exhibit higher coefficients and significance levels for tiering and other control variables.[20] The estimated model may therefore be regraded as a conservative estimate of the effects of tiered arrangements.

[17] Calculated as the sum of current account holdings and the use of the deposit facility, minus the use of the marginal lending facility.

[18] For a discussion on measurement of money market rates, see Müller and Paulick (2020).

[19] The model is robust to employing time fixed effects on a monthly basis. However, including monthly fixed effects leads to multicollinearity with the prevailing money market rate and overall liquidity. We therefore prefer the yearly fixed effects to allow for the interpretation of the effects of the money market rate and liquidity conditions.

[20] Results are available upon request.

Table 2.2: Summary statistics

Variables	N	mean	sd	min	max
Tiering share	1,726,472	0.03	0.11	0.00	1.00
Liquidity consumption	1,726,472	0.43	0.33	0.00	1.00
Cost-based liquidity use	1,726,472	0.00	0.01	-0.12	0.13
Concentration out	1,726,472	0.79	0.22	0.00	1.00
Concentration in	1,726,472	0.83	0.20	0.00	1.00
Priority of payments	1,726,472	1.63	0.69	1.00	3.00
Log value sent	1,726,472	17.69	3.05	6.91	25.90
Time difference	1,726,472	-0.15	3.14	-10.85	10.96
Money market rate	2,555	-0.02	0.42	-0.54	1.63
Log liquidity	2,555	13.43	0.81	11.64	14.54

Note: The share of tiered payments is calculated as the value of tiered payments sent relative to all payments sent by a participant, the log value sent is the log-transformed value of overall payments sent, the time difference is the difference in average timing between all received and sent payments, the concentration is measured by the Gini coefficient for outgoing and incoming payments, the priority of payments is the average priority of payments (values between 1 and 3), the money market rate is expressed as a percentage (calculated via loans identified from TARGET2 data), and log-transformed overall liquidity measured in millions of euro (ECB data).

The model for liquidity consumption is stated with the share of tiered payments by settlement bank i on business day b as the independent variable of interest and different control variables in vector X'_{it}. Bank-level effects are denoted α and yearly time effects as π.

$$LC_i^b = \alpha_i + \beta_1 tiering_{ib} + \beta_2 X_{ib} + \pi_y + \epsilon_{it} \tag{2.12}$$

We estimate the model for the full sample between 2010 and 2019 using fixed effects for direct participants and yearly fixed effects. One issue in the case of TARGET2 is that direct participants with very low payment activity may distort results using relative measures. Small participants may only access TARGET2 for certain types of payments or are simply very small and do not actively engage with the system or play any significant role within the system.

We estimate the model for all direct participants, and sub-samples of direct participants with at least 0.1 percent (128 direct participants) of overall traffic value and a threshold of 0.5 percent (50 direct participants). Results are presented in Table 2.3. In terms of significance and magnitude, the effect of tiering is quite stable within different sub-samples. The results for the sub-samples of participants are more meaningful, as larger settlement banks are more relevant in the context of tiered arrangements and of higher interest due to their importance in the payment system. Including only the largest 50 settlement banks seems most useful to investigate differences for those participants that are most critical to the system and most active in offering tiered arrangements.

In all specifications, the share of tiered payments has a negative impact on liquidity consumption, meaning a higher share of tiered payments leads to participants using less liquidity relative to their payment obligations. The effect is statistically significant at least on the 10 percent level and significance increases when only including larger participants. In terms of economic significance, the effect increases as smaller participants are dropped. While the change in one unit of tiering has an effect of roughly 0.05 on liquidity consumption, the effect increases to around 0.21 for large participants. The effect of tiering does not constitute a mere pooling effect, given the control variables and estimation using fixed effects.

Concerning liquidity risk, the results indicate that settlement banks' liquidity risk is lower the higher the share of tiering. This result holds controlling for other factors relevant to liquidity management and to settlement banks' business models. Therefore, tiering allows settlement banks to save on liquidity input beyond mere pooling effects.

The size of direct participants measured by log value sent leads to increases in liquidity consumption. Larger participants thus appear to provide more liquidity relative to payments to the system, but the effect is not significant when smaller direct participants are dropped. This is counter-intuitive to the hypothesized direction. The fixed effects specification of the model may partly capture the effect of the size of participants as larger participants take advantage of pooling effects, which could explain this result.

Unsurprisingly, the average difference in the timing of payments leads to increases in liquidity consumption and is significant at the 1 percent level in all specifications. Participants sending payments earlier than they receive them, on average, use more liquidity. As expected, a higher concentration of outgoing payments increases liquidity usage, while the opposite is true for the concentration of incoming payments. Highly concentrated sent payments gives direct participants less leeway for liquidity management as few large payments affect intraday balances. For incoming payments, the same reasoning applies, as receiving banks have less leeway in liquidity management when payments arrive in larger bulks. The coefficients are not significant for larger participants. This may result from the fact that larger participants here refers to those settling higher payment values. Even when those are higher concentrated, there might still be leeway to rearrange payments, while a higher concentration among few payments of smaller participants make liquidity management difficult. A higher average priority increases liquidity consumption, although the effects are not significant for larger participants. While higher average priorities lead to payments being settled in a more timely manner and thus act as a drain on liquidity, larger participants may predominately use internal queuing mechanisms rather than priorities within the system.

It is expected that the cost of liquidity measured by the overnight money market rate will have a negative effect and overall liquidity will have a positive effect. Higher money market rates imply that liquidity is more expensive and thus banks put more effort into managing liquidity more conservatively. High levels of overall liquidity arguably loosen the liquidity constraints on banks and provide less incentive for active liquidity management. The effects are substantial and significant in all specifications for the money market rate. The effect of overall liquidity is positive and significant in most specifications.

For robustness, we estimate the model with an alternative outcome variable, the cost-based measure of liquidity need cLN:

$$cLN_i^b = \alpha_i + \beta_1 tiering_{ib} + \beta_2 X_{ib} + \pi_y + \epsilon_{it} \tag{2.13}$$

Results in Table 2.4 show a similar picture. The R squared for specifications including smaller direct participants is low. A likely explanation is the heterogeneity of direct participants in those specifications. Direct participants with little payment activity and probably little liquidity management likely lead to the low levels of explained variance. The effect of tiering is slightly less consistent and the significance of some control variables changes. The effect of payment concentration becomes less significant and changes direction for payments sent. Meanwhile, the effect of timing differences stays highly significant. The effect of liquidity cost mostly remains negative and that of overall liquidity is positive. However, for the cost-based liquidity need they are not statistically significant. Liquidity conditions and cost may be picked up to some degree by the yearly fixed effects. Notably, the explained variance is lower for the cost based measure compared to liquidity consumption.

2.5.3 Timing

As one route of explanation for the results on liquidity consumption, timing differences are observed for tiered and non-tiered payments. The timing indicators from Equation 2.10 are calculated for larger participants (0.1 percent threshold) and all other participants. For simplicity, these are called large and small participants, respectively. Types of payments are all payments sent and received, payments on banks' own behalf, intragroup payments and tiered payments. Figure 2.4a shows timing differences are positive for large participants for their own payments, but not for tiered payments. In terms of value-weighted timing, large participants receive tiered payments before they send them out. For non-tiered payments the opposite is the case. Non-tiered payments are on average sent earlier than incoming payments arrive. Intragroup payments do not show a clear pattern over time. In earlier years, timing differences of intragroup payments were in fact positive and only turned negative in recent years. At the same time, time differences for tiered payments lie in lower negative territory for the full time period. Banks' own payment hover above zero for most of the period before turning more positive in recent years, creating a wedge with intragroup payments. Given that results are value-weighted, figures for large participants are almost identical to the overall system level.

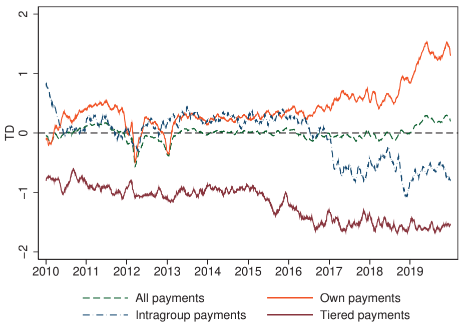
Comparing results with those of smaller participants, Figure 2.4b shows a highly uneven picture. Dynamics change over time and time differences for tiered payments move from negative to positive values. The volatile observations may be attributed to changes in group structures and payment routing. The dynamic probably also reflects that smaller banks less frequently settle payments on behalf of other clients and engage less actively in liquidity management.

Reasons for the observed differences between tiered and non-tiered payments could be that participants wait for incoming liquidity before sending payments on behalf of their client banks. This could be done by giving tiered payments a lower priority in internal or system queues. At the same time, client banks receiving payments earlier than sending their instructions to direct participants would also explain the observed differences. Importantly, the observed difference in treatment of tiered payments may result from settlement banks limiting exposures to their client banks. Chapman et al. (2013) argue that settlement banks monitor client banks and offer settlement modes based on credit risk. Thus, settlement bank may limit exposures to their client banks by deprioritizing client payments.

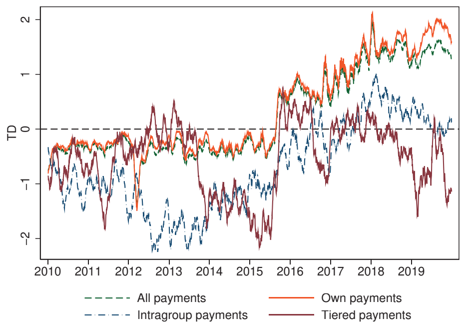
Importantly, timing differences can serve as a proxy for internal payment queuing of direct participants. This assumes for different categories of payments that there is no difference between the sending and the receiving side in when direct participants become aware of them. Whether this assumption is realistic or not can hardly be validated, as bank internal data is not available.

Figure 2.4: Timing differences

(a) Large participants



(b) Small participants



Note: Moving averages over 30 calendar days. Results for large participants depicted on the left-hand side are almost identical to the overall system level. Large participants are those with at least 0.1 percent of overall sent payments over the observation period, accounting for 91 percent of traffic.

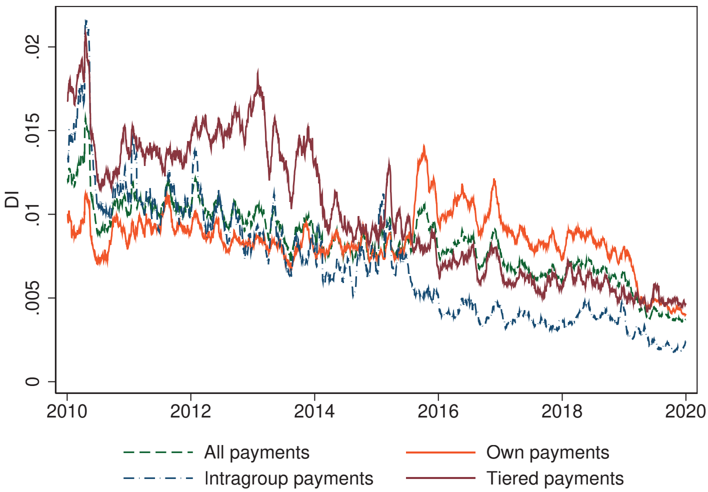
2.5.4 Delay

Delay indicators from Equation 2.11 depicted in Figure 2.5 show an uneven development over time. While tiered payments tended to exhibit higher levels of delay in earlier years, in recent years the levels have fallen below the delay of banks' own payments. One reason could be that the expansion of monetary policy and the asset purchases of the Eurosystem have decreased active liquidity management incentives at the system level, as liquidity has become less sparse. As delay occurs mainly due to a lack of liquidity within the system, ample liquidity probably contributed to fewer delays. In conjunction with timing differences, some banks may have shifted liquidity management outside the system, while system-internal delay was further minimized. Over time, participants may also have become more efficient with liquidity management at system-level. For recent years, we find no evidence of significant differences across tiered and non-tiered payments, meaning tiered payments are not delayed once sent to the system for settlement.

Interestingly, delay in TARGET2 has been accompanied by an overall decrease in the use of priorities. We categorize priorities from normal (1) to highly urgent (3).[21] Value-weighted priorities are lower for intragroup and tiered payments, while banks' own payments are prioritized higher.

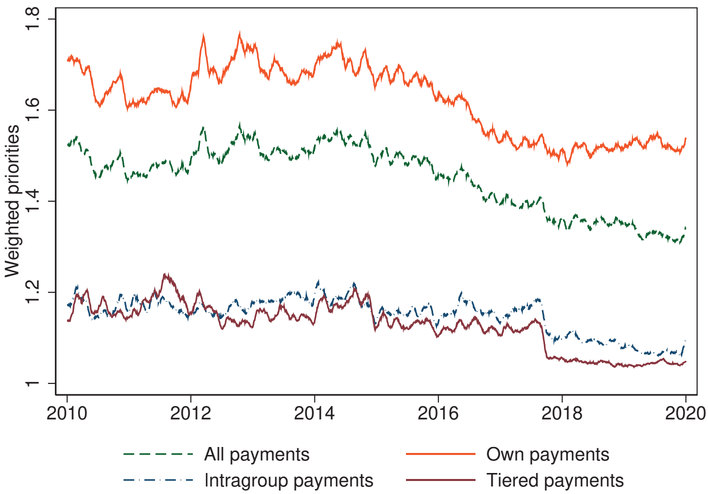
[21] We deviate from the values in the original data, which range from 2 (normal, 4 (urgent) to 7 (highly

Figure 2.5: Delay indicator for different payment types



Note: Moving averages over 30 calendar days.

Figure 2.6: Value-weighted priorities for different payment types



Note: Moving averages over 30 calendar days. Priority categories constructed with range from 1 (normal) to 3 (highly urgent).

urgent.

2.6 Discussion

The analysis is limited to information from systems data focusing on payments once they enter TARGET2. Information on settlement banks' internal procedures and contractual arrangements with client banks is obtained only implicitly. Importantly, TARGET2 is only one part of banks' overall liquidity position. Other systems, bilateral relationships and exposures may play a significant role for some banks' liquidity disposal. These limitations of the study point to the need to shift the focus of policy to participants, rather than focusing solely on systems as a whole. Importantly, agreements between direct and indirect participants cannot be observed. Taking a more holistic, participant-centric view could be highly beneficial. Gathering more data on participants and their internal procedures for settlement, could shed more light on questions of potential free-riding, postponement of payments and exposures.

In terms of operational proficiency, tiering may have benefits, that are not directly observable in the system. The results on a participant-level in this study have highlighted differences between large and small participants and areas where closer investigation from a regulatory perspective would be useful. Tiering may pose additional risks, such as banks' giving preference to own payments over tiered ones. This could put indirect participants at a disadvantage if direct participants face financial stress or experience outages. At the same time, tiering should not only be regarded as a source of risk.

Liquidity needs for settling payments are lower when tiering is more prevalent and may lead to an operationally more stable system. Heterogeneity between participants at a system level should be taken into account. Therefore, policies on tiering at a system-level should consider cases of individual participants and their behavior, with special attention given to large and interconnected participants. The introduction of RTGS systems around the world lead to instant rather than delayed settlement at the cost of higher liquidity needs. Tiering reintroduces netting at a participant level, thus delaying settlement while reducing liquidity needs. Similar to RTGS systems introducing liquidity saving mechanisms, this offers benefits but also comes with risks. Higher degrees of tiering can thus be seen as tipping the scale in favor of liquidity savings.

Intraday positions are not necessarily risky on a system level, as banks supplying liquidity to other participants, by sending payments on a net basis for at least a limited time, exhibit high intraday exposures. However, effective liquidity management and its monitoring is aligned with risk considerations at a bank level.

Direct participants managing tiered payments in a way that allows them to save on liquidity could be beneficial for indirect participants, as the cost of liquidity is lower compared to a situation in which more participants join the system as direct participants. The more efficient direct participants manage liquidity needs, the lower the fees paid by indirect participants should be.

2.7 Conclusion

This paper investigated the impact of tiered settlement on liquidity consumption using TARGET2 transaction data. Our results show that tiering has beneficial effects on liquidity risk. Tiered payments enable settlement banks to smooth their liquidity positions intraday beyond a mere pooling effect which results from aggregating payments at a participant level. The results are robust, including several controls and bank fixed-effects. Lower liquidity needs due to tiering are therefore unlikely to occur because of pooling effects or heterogeneous liquidity management across banks. Timing and priorities of payments appear as channels via which tiered payments are incorporated into settlement banks' active liquidity management. Payment timing as a proxy for external delay suggests tiered payments are treated with less urgency than settlement banks' own or in-house payments. Payment priorities also point in this direction as they are consistently lower for tiered payments. Results on payment delay within the system show no clear dynamic over time. This is in line with findings from the literature that the use of liquidity saving mechanisms in payment systems can be low, as banks use in-house tools to manage payment queues before entering the system.

While in line with contractual arrangements, some degree of "free-riding" or higher recycling of liquidity from client banks' could pose risks for indirect participants, as their payments are treated with less urgency. However, the results are also consistent with settlement banks' monitoring of indirect participants and their differing terms of settlement for their clients. While seemingly less likely, sent and received tiered payments could inherently exhibit different characteristics due to geographical and other factors.

Policy makers need to balance efficiency gains and potentially emerging risks. Future research could build on findings here and in the literature to derive welfare effects of tiered settlement. Arguably, internal processes of banks would need to be better understood to evaluate risks posed by tiered arrangements. As system overseers and operators typically have no access to bank internal contracts and data, our analysis relies on inference and system-internal dynamics.

Table 2.3: Liquidity consumption model

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Liquidity consumption											
Tiering share	-0.054**	-0.046**	-0.054**	-0.046**	-0.165***	-0.154***	-0.165***	-0.154***	-0.213***	-0.209***	-0.213***	-0.209***
	(0.024)	(0.023)	(0.024)	(0.023)	(0.048)	(0.050)	(0.048)	(0.050)	(0.057)	(0.057)	(0.058)	(0.057)
Log value sent	0.008***	0.018***	0.008***	0.018***	0.014	0.011	0.015*	0.012	0.003	0.002	0.003	0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.009)	(0.008)	(0.009)	(0.008)	(0.012)	(0.011)	(0.012)	(0.011)
Time difference	0.053***	0.055***	0.053***	0.055***	0.057***	0.058***	0.057***	0.058***	0.051***	0.051***	0.051***	0.051***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)	(0.005)	(0.006)	(0.005)
Concentration out		0.041***		0.041***		0.225***		0.224***		0.179		0.180
		(0.013)		(0.013)		(0.083)		(0.083)		(0.112)		(0.112)
Concentration in		-0.464***		-0.464***		-0.192**		-0.192**		-0.192		-0.191
		(0.018)		(0.018)		(0.090)		(0.090)		(0.124)		(0.125)
Priority		0.014**		0.014**		0.036**		0.036**		0.031		0.031
		(0.005)		(0.005)		(0.014)		(0.014)		(0.031)		(0.031)
Money market rate			-0.024***	-0.023***			-0.030***	-0.028***			-0.023**	-0.021**
			(0.003)	(0.003)			(0.006)	(0.006)			(0.009)	(0.009)
Log liquidity			0.009***	0.010***			0.014***	0.015***			0.015**	0.016**
			(0.002)	(0.002)			(0.005)	(0.004)			(0.007)	(0.007)
Constant	0.278***	0.424***	0.176***	0.310***	-0.047	-0.066	-0.216	-0.243	0.181	0.156	-0.003	-0.038
	(0.047)	(0.045)	(0.056)	(0.053)	(0.195)	(0.195)	(0.204)	(0.203)	(0.269)	(0.286)	(0.285)	(0.309)
Observations	1,726,472	1,726,472	1,726,472	1,726,472	268,496	268,496	268,496	268,496	110,830	110,830	110,830	110,830
R-squared	0.231	0.265	0.232	0.265	0.339	0.348	0.340	0.349	0.298	0.304	0.299	0.305
Direct participants	1,216	1,216	1,216	1,216	128	128	128	128	50	50	50	50

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

Note: All the specifications include settlement bank and year fixed effects. Heteroskedasticity robust clustered standard errors (for serial correlation) in parentheses. The main variable of interest is the share of tiered payments, calculated as the value of tiered payments sent relative to all payments sent by a participant. Additional controls include log-transformed overall payments sent, the difference in average timing between all received and sent payments in hours, concentration measured by the Gini coefficient for outgoing and incoming payments, the average priority of payments (values between 1 and 3), the money market rate in percent (calculated via loans identified from TARGET2 data), and log-transformed overall liquidity measured in millions of euro (ECB data).

Table 4: Cost-based model

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Cost-based liquidity use											
Tiering share	-0.001***	-0.001***	-0.001***	-0.001***	-0.165***	-0.007**	-0.007***	-0.007**	-0.213***	-0.016***	-0.016***	-0.016***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.048)	(0.003)	(0.003)	(0.003)	(0.057)	(0.005)	(0.005)	(0.005)
Log value sent	0.000***	0.000***	0.000***	0.000***	0.014	0.002***	0.001***	0.002***	0.003	0.002**	0.001*	0.002**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.009)	(0.000)	(0.000)	(0.000)	(0.012)	(0.001)	(0.001)	(0.001)
Time difference	0.000***	0.000***	0.000***	0.000***	0.057***	0.001***	0.001***	0.001***	0.051***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.004)	(0.000)	(0.000)	(0.000)	(0.006)	(0.000)	(0.000)	(0.000)
Concentration out		-0.001**		-0.001**		-0.009		-0.009		-0.018*		-0.018*
		(0.000)		(0.000)		(0.006)		(0.006)		(0.010)		(0.010)
Concentration in		-0.001***		-0.001***		-0.007*		-0.007*		-0.008		-0.008
		(0.000)		(0.000)		(0.004)		(0.004)		(0.010)		(0.010)
Priority		-0.000		-0.000		0.000		0.000		0.000		0.000
		(0.000)		(0.000)		(0.001)		(0.001)		(0.002)		(0.002)
Money market rate			-0.000	-0.000			-0.000	-0.000			0.000	-0.000
			(0.000)	(0.000)			(0.000)	(0.000)			(0.001)	(0.001)
Log liquidity			0.000	0.000			0.000	0.000			0.001	0.000
			(0.000)	(0.000)			(0.000)	(0.000)			(0.001)	(0.001)
Constant	-0.003***	-0.003***	-0.003**	-0.003**	-0.047	-0.020**	-0.030**	-0.021**	0.181	-0.021	-0.041*	-0.026
	(0.001)	(0.001)	(0.001)	(0.001)	(0.195)	(0.008)	(0.012)	(0.010)	(0.269)	(0.015)	(0.023)	(0.021)
Observations	1,726,472	1,726,472	1,726,472	1,726,472	268,496	268,496	268,496	268,496	110,830	110,830	110,830	110,830
R-squared	0.018	0.020	0.018	0.020	0.339	0.123	0.111	0.124	0.298	0.158	0.139	0.158
Direct participants	1,216	1,216	1,216	1,216	128	128	128	128	50	50	50	50

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

Note: All the specifications include settlement bank and year fixed effects. Heteroskedasticity robust clustered standard errors (for serial correlation) in parentheses. The main variable of interest is the share of tiered payments, calculated as the value of tiered payments sent relative to all payments sent by a participant. Additional controls include log-transformed overall payments sent, the difference in average timing between all received and sent payments in hours, concentration measured by the Gini coefficient for outgoing and incoming payments, the average priority of payments (values between 1 and 3), the money market rate in percent (calculated via loans identified from TARGET2 data), and log-transformed overall liquidity measured in millions of euro (ECB data). Numbers are rounded to three decimal digits and may therefore exhibit values of zero, more detailed results are available upon request.

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Chapter 3

The absence of evidence and the evidence of absence: an algorithmic approach for identifying operational outages in TARGET2

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Short summary

We develop an algorithm to identify potential operational outages in TARGET2. As stated in the Principles of Financial Market Infrastructures (PFMI), plausible sources of operational risk should be identified in FMIs. For TARGET2 and other financial market infrastructures, little is known about operational outages of participants. This contrasts with system outages, which are generally well understood and documented. This paper attempts to close this gap by implementing an algorithmic approach to identify participants' operational outages based on transaction data. Using a series of criteria, time periods are identified during which activity was so low that it indicates that banks' ability to send payments was partly or fully hindered. The strategy is best suited for larger banks that exhibit stable payment patterns. The identification of false positives (wrongly identified outages) is addressed by focusing on consecutive intervals, unlikely to occur due to chance, while the identification of false negatives (undetected outages) is mitigated by employing a relatively broad approach. The data set we construct provides evidence on the potential absence of participants in the absence of other evidence. The results are useful for operators, overseers, and researchers, and could also be of interest for supervisors.

Keywords: Operational risk, payment systems, outages, TARGET2, financial market infrastructures, payment behavior

JEL classification: E42, G21

3.1 Introduction

Financial market infrastructures (FMIs) are often seen as the “plumbing network” of financial markets. Just as growing cities need resilient water and sanitation infrastructures to ensure their smooth functioning, market infrastructures are of vital importance for financial markets, which grow with globalization and digitalization. Expanding digitized markets make it possible to exploit economies of scale, but they can also make infrastructures more vulnerable to operational risk, especially technical failures.

For payment systems – specifically real-time gross settlement (RTGS) systems in which large and/or urgent transactions are settled – the monitoring of potential sources of operational risk is essential to ensure sound operations. According to the World Bank (2011), out of 139 survey countries, 116 reported using at least one RTGS system. Operational failures in RTGS systems can thus have a large impact on the financial system as a whole. Although RTGS systems are designed to withstand technical outages of various kinds, operational participant outages may still pose a major source of risk. Participant outages caused by an operational failure, such as the temporary breakdown of internal systems responsible for sending payment instructions to an RTGS, can induce liquidity accumulation in the affected account or payment stops on the part of other RTGS participants. In such cases a gridlock situation may occur in which no participant is willing to initiate a payment due to a shortage of liquidity. As a consequence, systemic risk in the payment system would increase and heighten the probability of financial failure among smaller or more liquidity-dependent participants. Contagion effects might amplify financial distress and potentially lead to more profound disruptions in the financial system. Therefore, operational risk is of high importance for operators and overseers of payment systems alike.

In line with the Principles for Financial Market Infrastructures (CPSS-IOSCO, 2012) a financial market infrastructure (FMI) should “identify the plausible sources of operational risk, both internal and external ...”, as, “... [f]or example, participants can generate operational risk for FMIs and other participants, which could result in liquidity or operational problems within the broader financial system.” In the case of TARGET2, which is owned and operated by the Eurosystem, the TARGET2 information guide requires participants deemed critical to report incidents that last longer than 30 minutes. That facilitates the early detection of participant-induced operational outages and enhances the capability to take countermeasures. However, for shorter time periods and non-critical participants there is no mandatory reporting. Reputational risk considerations might thus give critical participants an incentive to underreport. Longer-lasting operational outages might be broken up into smaller ones using manual workarounds. Additionally, outages of smaller participants might go unreported even though they could also have a high impact on the system. Hence, operational risk can arise due to an underestimation of the actual outage duration or due to outages induced by smaller participants.

To the best of our knowledge, no structured data set of operational outages has been available hitherto for TARGET2 countries which would facilitate an investigation of questions such as how often, for how long, and at what times participant outages occur. Our paper attempts to close this gap by employing a series of conditions to identify participant outages and looking for anomalies in payment behavior. As contingency measures such as the manual entry of transactions might reduce regular payment activity but not completely deter a participant from sending payments, we choose an algorithmic identification approach which accounts for differences in individual payment behavior. With the chosen approach we attempt to provide a more comprehensive basis for the quantification of operational risks in FMIs originating from participant outages. Essentially, we try to find evidence of absent participants where structured evidence was absent hitherto.

3.2 Related Literature

Our work relates to a number of studies which examine the effects of operational outages in RTGS systems and a large body of literature which exploits large-value payment system (LVPS) transaction-level data to analyze participant behavior in order to derive and improve policy decisions regarding FMIs.

Operational risk in payment systems has been examined from various angles in the past years.[1] Rochet and Tirole (1996) describe operational risks as risks related to computer and telecommunication system breakdowns that can have an impact on liquidity and credit risks due to settlement lags and potentially resulting payment failures. Several studies investigate the impact of a participant's failure to meet its payment obligations by using simulation techniques. Bedford et al. (2005) find that system resilience in the UK's RTGS system CHAPS in the event of an operational participant outage is high, although liquidity shortages for single participants may arise. Ledrut (2007) conducts a similar exercise for the Dutch RTGS system. She finds that even those banks that respond quickly to the failure of another participant may incur considerable losses. Clarke and Hancock (2013)) and Diehl and Müller (2014) show that system-inherent liquidity-saving features have the potential to significantly reduce liquidity shortages caused by participant failure.

Empirical analyses largely support these findings. Lacker (2004) examines the effectiveness of contingency measures implemented by the US payment system Fedwire. He provides evidence that these provisions were sufficiently stable to withstand an operational outage even in the event of severe operational disruptions as experienced on 9/11. Klee (2010) identifies operational outages at depository institutions in Fedwire of at least 30 minutes to evaluate aggregate uncertainty in the federal funds market at the end of the day. Her findings suggest that the aggregate effect of operational outages on the federal funds market is rather modest. A similar study by Merrouche and Schanz (2010) investigates the impact of operational shocks on aggregate liquidity in the payment system. Employing a data set which contains reported outages of individual institutions that are direct CHAPS participants, they analyze eight outages that lasted at least 15 minutes. Their comparison of the outages with a game-theoretic approach shows that "healthy" banks seem to withhold liquidity from credit institutions experiencing a payment failure,

[1] Operational outages can occur on the side of both the operator and the participant. From the operator's perspective, a variety of technical arrangements are usually in place to secure the business continuity of the system at any given point in time. In the case of TARGET2, such arrangements include separate operation and backup sites, contingency modules, and individual backup payment solutions (for more detailed information, see the TARGET2 Information Guide, Version 10.0). Beyond that, operational risk can also arise from technical infrastructure providers and interdependencies with other financial market infrastructures. Owing to the specific nature of the individual setup of each system, our analysis concentrates on operational and (more specifically) on participants' operational risk.

especially for the first half of the business day. They suggest that this effect stabilizes the system by preserving the exchange of liquidity between non-failed participants.

Risk indicators from payment transactions, as calculated by Heijmans and Heuver (2014), can be employed as early-warning signals for liquidity shortages and financial problems at payment system participants. Their indicators of the average time of incoming and outgoing payments, in particular, can give first hints for the identification of anomalies in transaction patterns potentially caused by operational outages. Benos et al. (2012) develop a set of risk indicators that measure the impact of liquidity risk due to operational outages. Their calculations indicate that the impact of operational outages on system liquidity has increased since the collapse of Lehman Brothers compared to the observation period before. Berndsen and Heijmans (2017) provide further empirical evidence on the use of risk indicators for operational risk in payment systems. Calculating indicators for the relative use of the system and throughput risk, they contribute especially to the monitoring of system performance.

Another way to identify potential operational outages is by analyzing outliers or anomalies in the intraday payment behavior of RTGS participants. Participants in payment systems usually follow some sort of payment pattern throughout the day, as shown, for example, by Massarenti et al. (2012). They describe intraday patterns for interbank payments in TARGET2. Their results indicate that the first and last hours of system operations are the most influential factors for processed value and volume. In contrast, payment instructions during the day exhibit a relatively stable pattern. Over a four-year observation period, they find that individual payment patterns are mostly constant over time. Similarly stable payment patterns in payment systems are observed for Fedwire by Armantier, Olivier and Arnold, Jeffrey and McAndrews, James (2008) and for CHAPS by Becher et al. (2008).

Intraday patterns can be caused by timing incentives, as laid out in the game-theoretical study by Bech and Garratt (2003). Diehl (2013) further explains that free-riding incentives may be a strong force behind the timing of payment transactions throughout the day. Van Ark and Heijmans (2016) find additional evidence for seasonal patterns on a daily, weekly, monthly, and annual basis. Triepels et al. (2017) exploit intraday patterns for the detection of anomalies via an autoencoder. Their findings suggest that anomalies in liquidity flows can be identified quite well by artificial neural networks. Another algorithmic approach to identifying certain flows of payments in transaction data has been introduced by Gavilan-Rubio and Alexandrova-Kabadjova (2018), who find structural changes in payment flows in the Mexican RTGS system SPEI.

Our study builds on the empirical analyses of operational risk in payment systems as well as on the analysis of participant payment behavior. Using a relatively generic algorithmic approach, we aim to combine the two strands of literature to identify potential operational outages by comparing each participant's payment behavior throughout the day with the participant's average payment behavior in the respective year. Our study thus contributes to the literature by introducing a novel identification approach which filters intervals with anomalously low payment activity from transaction data that can be employed as an indicator for operational outages at the level of the participant. With regard to algorithmic approaches applied to transaction data, as established by Furfine (1999), Armantier and Copeland (2012) and Arciero et al. (2016)), we also extend the application of algorithms into a different field of analysis.

3.3 Data and method

3.3.1 Data basis

Our analysis and the development of the identification algorithm are based on transaction-level data from TARGET2,[2] the Eurosystem's real-time gross settlement (RTGS) system for settlement in euro. TARGET2 was developed by the Eurosystem, which is simultaneously the system owner and operator. In contrast to other LVPS, TARGET2 settles not only interbank and customer payments,but also transactions related to monetary policy operations and operations of other financial market infrastructures. All transactions are settled in central bank money with immediate finality.

TARGET2 is operated on a single shared platform, but business relationships are still established between the TARGET2 users and the respective central bank. Currently, 20 euro central banks (including the ECB) and five central banks from non-euro-area countries (Bulgaria, Croatia, Denmark, Poland and Romania) are connected to TARGET2.

With a daily turnover averaging 1.7 trillion euro and about 342,000 transactions in 2016, TARGET2 is one of the largest RTGS systems in the world. Furthermore, it settled 90% of the total value settled via large-value payment systems in euro.[3] The amount settled in approximately six days of operations corresponds to the euro area's GDP in a whole year. This underlines the important role which TARGET2 plays in Europe's financial markets.

3.3.2 Building a participant payment pattern (PPP) data set

The specific research question of our paper, identifying participants' operational outages, requires the construction of a dedicated data set, which we refer to as participant payment pattern data set (PPP data set). In order to successfully identify participants' operational outages, the data set must fulfil certain conditions: (i) the data set must be large enough; (ii) the data set should only include transactions that are submitted by participants; (iii) the data set should only include transactions on regular business days; and (iv) the data set must be suitable for fast analytical processing. The following two sections will describe in detail why the data set must meet these conditions and how we develop the data set from TARGET2 transaction data.

Data selection

Our data basis includes transactions from the years 2009 to 2016. In order to avoid needlessly inflating the data set with redundant data, we only include participants that seem large enough to exhibit regular daily payment behavior. We set a relatively low threshold so that every participant that has at least a 0.05% share of the overall transaction volume from 2009 to 2016 is included in the data set.

To avoid a bias towards earlier years we only include participants that were active in 2016. That way, participants dropping out of the sample due to mergers, bankruptcies

[2]TARGET2 stands for Trans-European Automated Real-time Gross settlement Express Transfer system.

[3]The other 10% was settled via EURO1, a LVPS operated by EBA CLEARING. More information on EURO1 can be found at https://www.ebaclearing.eu/services/euro1/overview.

and other reasons before 2016 are excluded. However, this means there might be a bias towards earlier years, as participants only join the sample later. We chose this approach in order to account for banking consolidation while maintaining an accurate picture in the most recent period.

In our study we attempt to identify operational outages, i.e. instances where participants are unable or constrained in their ability to enter transactions in TARGET2. Thus, we focus our analysis on transactions sent by participants. Unfortunately, the TARGET2 database has no strict attribute to identify transactions that are entered by participants. Therefore, we need to derive participant-entered transactions using different attributes which exclude transactions that are entered without being initiated by participants.

The transaction classifications (as detailed in the Apendix in Table A2) give an indication of whether a transaction is entered by participants or not. Apart from interbank and customer transactions, payments to CLS are also initiated by participants. All other transactions, for instance transactions with central banks as well as ancillary systems, can be initiated without participant intervention. Therefore, we only include interbank and customer payments as well as transactions to CLS in the PPP data set.

Connected payments, a feature that is used to synchronize two or more transactions, help us to further narrow the data set down to participant-entered transactions. Connected payments are mapped using a specific link code stored in the TARGET2 database. Primarily, a link code is provided in cases where a transaction is submitted via an ancillary system and is thus not entered by a participant. As connected payments occur in both interbank and customer transactions and in payments to CLS, they have to be dropped, too. By excluding all transactions with a link code, we try to assure that only participant-entered transactions are included in our PPP data set. Nevertheless, this identification of participant-entered transactions is only an approximation.

In general, the business day in TARGET2 consists of a daytime and a night-time settlement cycle. Our participant payment pattern data disregard transactions during the night-time settlement cycle (between 6 pm and 7 am), as only a small number of transactions are entered then. Therefore, this period is not conducive to estimating regular payment behavior. Furthermore, participants' operational outages during night-time settlement will not lead to system disruptions – for instance, in the context of liquidity or unsettled transactions – and are therefore not relevant for our approach. In consequence, we only include transactions during the settlement cycle from 7 am to 6 pm, including the last hour of the day when interbank transactions can be settled, but customer payments cannot.

By focusing on transactions between 7 am and 6 pm, we ignore delayed closing hours. This seems accurate to us because a single participant's drop in activity is highly unlikely to lead to delayed closing. Generally, only TARGET2 system outages will lead to delayed closing for participants. Moreover, the PPP data set should include only business days where regular payment behavior can be assumed. In the case of a TARGET2 system outage, we expect an irregular daily payment pattern. Thus, we exclude all business days where an operational outage of TARGET2 has occurred.[4]

Apart from days with a TARGET2 system outage,payment activity is typically very low or non-existent altogether on national holidays or holiday-type days,[5] in comparison

[4]This information is taken from the respective TARGET2 Annual Reports.

[5]Holiday-type days are days that are not national holidays, but where business activity is typically

to normal business days. Furthermore, we assume that this effect is not confined to holidays in the country where the account is kept; national holidays in the country where the parent institution is located also matter. Thus, we exclude all holidays in both the country where the account is kept and the country where the parent institution is located. For this purpose, we use the data of the parent institution and its location from the SWIFT Bank Directory Plus. The parent institution is identified using data from December 2016. This should not affect results, as the parent institution country is unlikely to change over shorter periods of time. In cases where the parent institution country changes over the period, this would affect only the excluded holidays and would therefore only have a minor impact on the identification of outages. For the identification of national holidays, we also use holiday data from the SWIFT Bank Directory Plus. As the holiday data set does not cover all years of our observation period, we complete the data set with publicly available information on holidays.

In a final step, we flag our data set with backup and mandated payments[6] as separate categories for robustness checks of our results, because they can be useful for identifying contingency measures. However, the data alone are insufficient for identifying operational outages. The reasons for this are that backup and mandated payments may be used for other purposes, such as testing, and are employed only as and when necessary.

Data preparation

The data selection specifications outlined above produce an extensive data set. For more effective analytical processing, we aggregate the relevant information at the transaction level (volume and value) for each participant to ten-minute intervals. Compared to transaction-level data, aggregated transaction volumes are more suitable for identifying periods of very low payment activity that differ strongly from normal activity. [7]

For allocation to the respective times, we use the introduction time, meaning the time a transaction is entered in the system, rather than the settlement time. This is necessary as we want to identify a potential operational outage of a participant, i.e. a situation where a participant is unable or constrained in its ability to enter transactions in TARGET2. In contrast, the settlement time would be better suited to identify outages of the whole system.

Aggregation results in 66 ten-minute intervals over the business day and reduces the data set from more than 480 million transactions down to roughly 24 million observations.

low, such as Christmas Eve. In the remainder of this paper, national holidays and holiday-type days are referred to as holidays.

[6]Backup payments are payments that a participant can enter via the Information and Control Module (ICM) only in the event of an operational or technical outage and are only allowed to be used for CLS, EURO1 and liquidity redistribution transactions. According to the Information Guide for TARGET2 Users, mandated payments are payments initiated by an entity that is not party to the transaction (typically by an NCB or an ancillary system in connection with ancillary system settlement) on behalf of another entity. In particular, for example, an NCB sends a credit transfer (with a specific message structure) on behalf of a failed direct participant (only in contingency situations). Mandated payments to technical accounts are not possible.

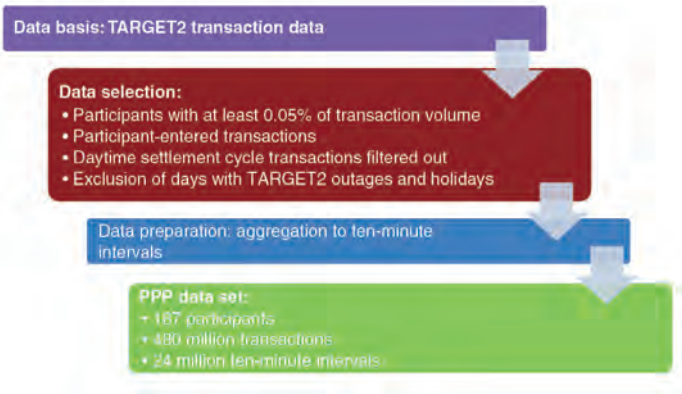
[7]Further details and an explanation of how this approach differs from other identification approaches can be found in the section on the identification approach.

Summary of the data selection process

The previous two sections described the selection and preparation of the TARGET2 data to build a participant payment pattern data set. Figure 3.1 summarizes the development process.

The participant payment pattern data set ends up with data from 187 participants that submitted more than 480 million transactions, which were aggregated to more than 24 million ten-minute intervals. On the one hand,this high number of participants and transactions creates a large data set; on the other, it condenses the data. In addition, the data selection process gives the best-possible assurance that only transactions that are submitted by participants and initiated on normal business days are included in the data set. Thus, the four requirements we initially defined in section 3.2 for a data set suited to identifying potential operational outages have been fulfilled.

Figure 3.1: Development process of the PPP data set



3.3.3 Identification approach

General principle: the identification of low payment activity

The identification approach used for operational outages of TARGET2 participants is mainly based on the idea that, in the event of an operational outage, a participant will be unable to initiate payments. In theory, this will automatically lead to a period where no transactions take place for the duration of the operational outage, as has been used by Klee (2010). The approach used by Klee (2010) calculates the time between two transactions of a participant and assumes that an operational outage has occurred whenever no transactions take place over a period of at least 15 minutes, also taking into account institutions' typical payment patterns for that time of day. A potential operational outage is identified whenever the inactive interval deviates from the typical payment pattern.

However, a number of contingency measures, installed by both participants and TARGET2, complicate the assumption that, during an operational outage, participants will not be able to enter any transactions. According to the Information Guide for TARGET2 Users, at least critical participants have to implement contingency measures. It appears likely that other participants will have implemented such business continuity measures as well. As their implementation lies in the responsibility of the participants, their details are unknown. Nevertheless, it is likely, in the event of an operational outage, that at least manual or alternative interfaces will be available to ensure the processing of important payment transactions. Additionally, TARGET2 employs tools in the event of operational failure by a participant. For instance, the national service desks could grant access to the backup payment functionality via the Information and Control Module (ICM), which permits the initiation of critical transactions[8] upon request. Furthermore, the national service desks could enter a limited number of transactions on behalf of the participant affected. Taking all this into account, a participant is not necessarily unable to initiate any transactions in the event of an operational outage. Instead, the participant may be able to initiate a limited number of transactions in TARGET2. Therefore, we develop an identification approach that reflects these institutional setups.

In general, our approach identifies intervals where payment activity is deemed to be so low that it can be assumed that an operational outage has occurred. This also includes intervals without any transactions. The challenge is to find criteria for the quantitative definition of intervals with low payment activity. Owing to a lack of existing thresholds, we tested different calibrations, also taking into account anecdotal evidence.

Our approach follows the idea that an interval with low payment activity occurs when the transaction volume of an interval in a single business day is low in comparison with the distribution of the annual transaction volume for the respective interval. As the payment structure does not follow a normal distribution but is usually characterized by an unequal distribution and outliers, we use the median for comparison purposes. After using different calibrations, we flag intervals that lie in the first percentile as intervals with low activity.

More precisely, low payment activity (LPA) of a participant (p) on a given business day (d) in a ten-minute interval (i) is identified when the volume of transactions ($tvol$) of a participant (p) during a ten-minute interval (i) on a business day (d) lies in the first percentile of observations of the participant (p) in the respective ten-minute interval (i) over a year (y).

Low payment activity ($LPA_{p,i,d}$) is observed if:

$$tvol_{p,i,d} \leq v_{p,i,0.01}, \tag{3.1}$$

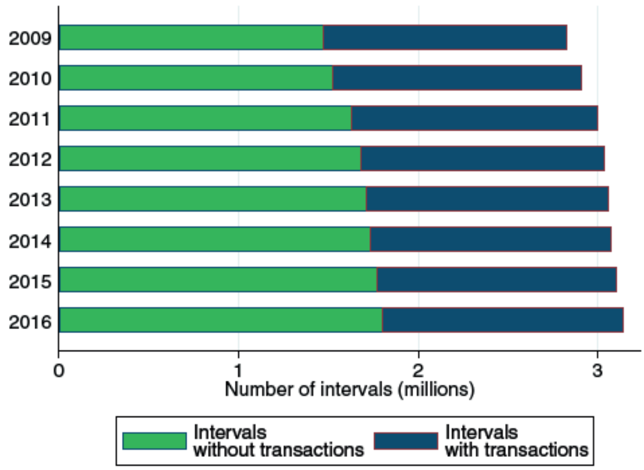
where $v_{p,i,0.01}$ is given by:

$$v_{p,i,0.01} := max\{x \in \mathbb{R} | Pr_{p,i}[X \leq x] \leq 0.01\}, \tag{3.2}$$

As a consequence, low payment activity is assumed to occur below the one-percent threshold which represents an upper bound for the likelihood of identification, but also assumes that outages occur in the lowest one percent of respective intervals. As explained later in this paper, we therefore focus on consecutive intervals for which the occurrence of low payment activity, and thus an operational outage "by chance", is unlikely.

[8]Principally, critical transaction payments to the CLS account, to the EURO1 collateral account or the EURO1 prefunding account, and payments for redistributing liquidity.

Figure 3.2: Share of intervals without transactions before adjustments



Regular payment patterns: introduction of adjustments

We found that intervals with low payment activity are related not only to potential operational outages but also to general and individual payment behavior. Figure 3.2 shows the share of intervals without any transactions. It becomes clear that, for the identification of operational outages, intervals with low payment activity or none whatsoever as a result of general or individual payment behavior also have to be taken into account.

By excluding holidays from our data set, we have already taken generally low payment activity into account. Furthermore, for intervals with less than ten transactions on average per year, low payment activity is harder to measure. As a second adjustment for generally low payment activity, we therefore only consider intervals that have at least ten transactions on average per year in the analysis.

In addition, we observed, much like Klee (2010), different individual types of payment behavior across participants, which vary by day of month, by time of day, by country, and, of course, from one participant to the next. In the Appendix, Figure A1 shows examples of differences in payment behavior for individual banks.

Therefore, we include two adjustments for intervals with normally low payment activity. The first adjustment compares payment activity of a participant in ten-minute intervals over the year with payment activity of a whole day (i.e. the sum of all transactions during the day) over the year. If the ratio of both medians is under 5%, meaning that less than 5% of a regular day's payments over the year are initiated in the respective ten-minute interval, the low level of transactions is more likely to be due to generally low payment activity during this interval than to an operational outage.

Use adjustment (1) if

$$\frac{\widetilde{tvol}_{p,i,y}}{\widetilde{tvol}_{p,y}} \leq 0.05, \tag{3.3}$$

After the first adjustment, some intervals remain that might identify typically low payment activity other than an operational outage. This is mainly due to peaks of transactions on some days, for instance, at the end of month, which artificially exaggerate the median. In addition, some participants irregularly submit payments at certain times, meaning that, at times, no or very few payments are sent routinely. To allow for these intervals of low payment activity, we implement a second adjustment. Ten-minute intervals (i) of one participant (p) are excluded from recognition as low payment activity whenever more than 10% of the intervals over a full year (y) have fewer than ten transactions.

Use adjustment (2) if

$$\frac{n(low)_{p,i,y}}{n_{p,i,y}} \geq 0.1, \tag{3.4}$$

where $n(low)$ is the number of intervals with fewer than ten transactions and n is the number of all intervals in a year:

$$n(low)_{p,i,y} := \#(i \in \{1, n\} : tvol_{p,i,d} < 10) = \sum_{i=1}^{n} \mathbb{1}_{tvol_{p,i,d}<10} \tag{3.5}$$

Where a ten-minute interval satisfies these adjustments, it is unlikely that the low payment activity in this interval will be related to an operational outage, and we therefore do not include it in our further analysis.

Measuring duration of low payment activity

Another important factor for identification – and, at a later stage, analysis – is the duration of a potential operational outage. Klee (2010) states that an operational outage might be identified as a period of fifteen minutes in which no payments are settled. Our approach also takes periods with a small number of transactions into account. Thus, we use a different identification method than Klee (2010) and develop a new measurement for the duration of low payment activity. To determine the duration of low payment activity, we use the PPP data set. By linking and counting consecutive ten-minute intervals identified as having low payment activity, we are able to derive the approximate duration of low payment activity, even as contingency measures are put in place.

We start by linking intervals with one, two, three and four (or more) successive ten-minute intervals for which low payment activity was identified. We refer to these intervals as outage intervals. Two consecutive ten-minute intervals in which low payment activity is identified are called a double outage interval. Logically, we distinguish between single, double, triple and four-times outage intervals.

The linking process requires just a minimum of consecutive intervals with low payment activity. Every sequence of ten-minute intervals with low payment activity that fulfills the minimum requirement is included in the outage interval. For example, a four-times outage interval includes sequences of four or more consecutive intervals. As a consequence, this means that single, double and triple outage intervals are not included in four-times outage intervals.

In the interest of greater clarity, Table 3.1 shows what the linking process for consecutive intervals with low payment activity might look like. A "Yes" indicates that low

Table 3.1: Example of linking consecutive outages intervals

Ten-minute intervals	Single outage interval	Double outage interval	Triple outage iinterval	Four-times outage interval
09:00	No	No	No	No
09:10	Yes	Yes	Yes	Yes
09:20	Yes	Yes	Yes	Yes
09:30	No	No	No	No
09:40	No	No	No	No
09:50	Yes	Yes	Yes	Yes
10:00	No	No	No	No
10:10	Yes	Yes	Yes	Yes
10:20	Yes	Yes	Yes	Yes
10:30	Yes	Yes	Yes	Yes
10:40	No	No	No	No
10:50	No	No	No	No
11:00	Yes	Yes	Yes	Yes
11:10	Yes	Yes	Yes	Yes
11:20	Yes	Yes	Yes	Yes
11:30	Yes	Yes	Yes	Yes
11:40	Yes	Yes	Yes	Yes

Legend:

Potential outage
No potential outage

payment activity was identified in that ten-minute interval. In addition, bold text shows that a sequence of consecutive intervals suffices for classification as an outage interval.

Figure 3.3 shows the number of intervals for the use of the different types of outage intervals. The number of intervals decreases from shorter to longer outage intervals, as larger outage intervals do not include smaller ones.

Generally speaking, the longer the outage interval, the greater the likelihood that low payment activity will indeed be due to an operational outage. In addition, longer periods of low payment activity can be assumed to lead to more significant disruptions in TARGET2. In the remainder, we define the potential outage of a participant as a sequence of at least four consecutive ten-minute intervals in which a low payment activity is identified. This duration also reflects the reporting requirements of critical participants in TARGET2.

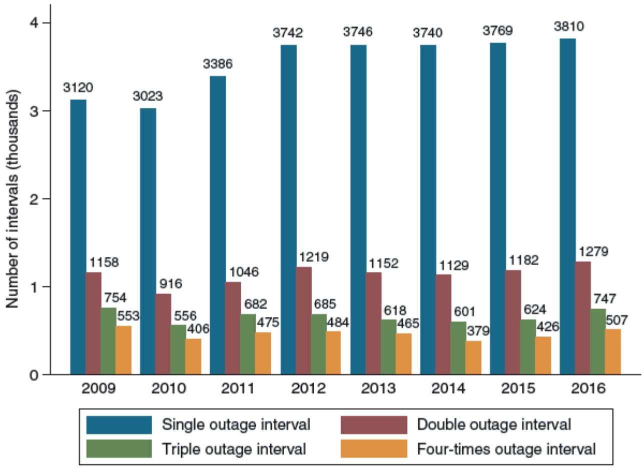
In consequence, we define a potential participants' operational outage as a sequence of at least four consecutive ten-minute intervals in which a low payment activity is identified.

Identification under uncertainty

As in any identification approach, there is the danger of wrongly identifying outages that are not really outages – incidents known as false positives (or type I errors). At the same time, false negatives (type II errors) are real outages that are not identified by the approach. Between false positives and false negatives, there is an inherent trade-off in identification under uncertainty.[9] Therefore, we adjust our approach to address this issue to some degree. The identification of false positives is potentially mitigated by focusing on consecutive intervals, which are unlikely to occur by chance. Assuming there is no

[9]For a discussion of type I and type II errors in the context of money market measurement in TARGET2, see Arciero et al. (2016).

Figure 3.3: Duration of low payment activity: different outage intervals



correlation between time intervals, low payment activity occurring in one time interval should be independent from payment activity in the next interval. Implicitly, we assume time intervals to be uncorrelated and independent, except in the presence of a holiday or outage. If that is the case, a false positive is very unlikely to occur as at least four consecutive intervals need to be affected. The identification of false negatives is addressed by employing a relatively large sample and using relatively cautious assumptions.As the chosen specifications can be considered relatively broad, the loss of observations due to filtering is minimized. Nevertheless, outages on holidays and outages of banks with unstable payment behavior will cause false negatives in our approach.

Absent a structured data set for validating the results, we are unable to quantify type I and type II errors. Only a very limited number of known outages were employed to verify the approach.

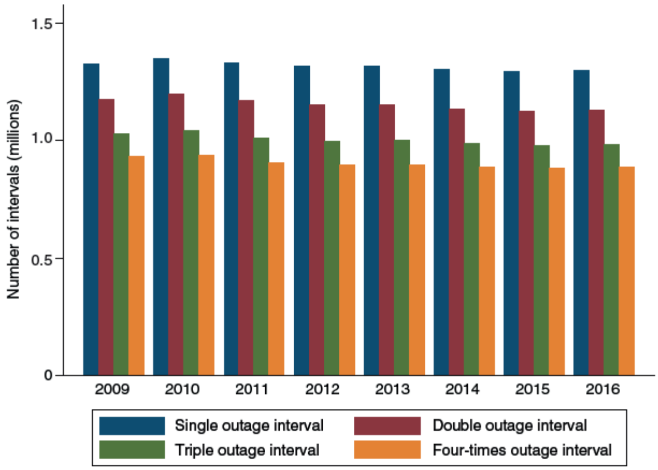
Summary

The previous sections reveal the need to develop an approach that identifies operational outages not just as times without a single transaction but as times with anomalously few transactions. The theoretical considerations are confirmed by Figure 3.4. Compared with Figure 3.3, this shows the number of consecutive intervals without any transactions. The adjustments to take general and individual payment behavior into account are not applied. However, even in cases of four or more consecutive intervals without any transactions, nearly one million intervals are identified as potential outages. Given the assumption that operational outages are rather rare, this high number is not considered realistic.

In general, our approach identifies longer consecutive intervals where payment activity is deemed to be so low that an operational outage can be assumed and is not due to general or individual payment behavior. The elements of our identification approach are summarized in Figure 3.3.

However, as we pointed out in Section 3.3.3, the identification approach is only an estimation of potential operational outages. Owing to a lack of reliable data on operational outages, we are unable to validate our results. However, we attempt to strike a balance between false positive and false negative identifications.

Figure 3.4: Number of intervals for different consecutive intervals without any transactions

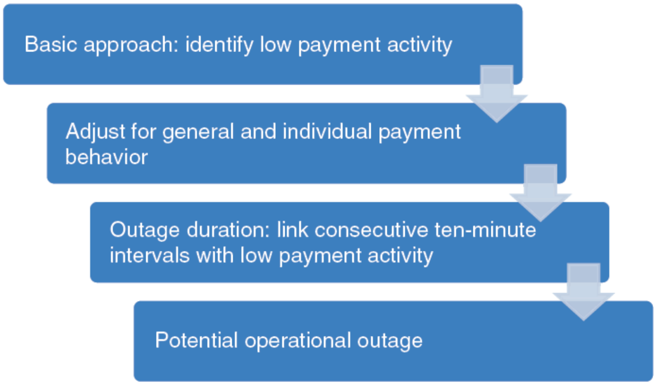


3.4 Results

Here we provide aggregate and mean identified outages over time as well as their distribution by length, by country and by when they occur. Results referring to intervals provide the number of ten-minute intervals that are flagged as potential outages.When the number of outages is referred to, this indicates the number of potential outages that last for at least four consecutive intervals. One outage with consecutive intervals is counted once, regardless of how many consecutive intervals are identified.

In total, the potential operational outages are spread over more than forty participants, meaning that, for a number of banks, no outages were detected by our approach. This is partly because the approach is less likely to identify outages of smaller banks, whose transaction volumes are lower. Outages are more likely to be identified for larger banks, as they process higher volumes of payments. Since our approach accounts for payment volumes, this bias predominantly exists for banks with higher and more stable payment volumes. Outages of banks with unstable payment behavior are less likely to be identified and, thus, will be detected less frequently. This bias in results leads to the conclusion that the approach taken here is better suited for banks with higher and more stable payment volumes, but not for all banks participating in TARGET2. At the same time, the approach has the advantage that only meaningful disruptions, and disruptions that diverge from typical payment activity by participants, are identified.

Figure 3.5: Elements of identification approach



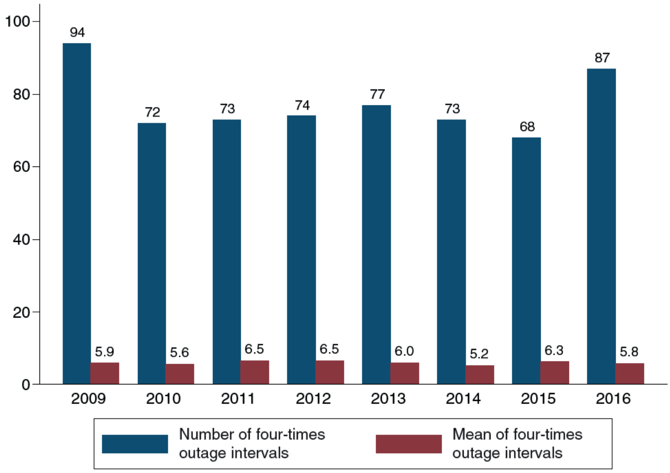
3.4.1 Potential outages over time

The occurrence and mean duration of potential four-times outage intervals are shown in Figure 3.6. Overall, the number of outages is relatively constant over time. The number of occurrences appears to decrease slightly as time progresses, with the exception of 2016, when a marked rise occurs. While not particularly pronounced, the number of outages could have decreased as participants' operations became more stable as they gathered more experience of TARGET2, which was launched in 2008. Results may be affected by the fact that we include only credit institutions that were still active in 2016. This means that for earlier years, there may be a downward bias, as banks that ceased operations before 2016 are not included in our sample. This bias could understate the downward trend we observe over time. The length of outages does not follow a discernible trend over time; the mean reaches a maximum value of six-and-a-half consecutive ten-minute intervals in 2011 and 2012.

Figure 3.7 depicts the number of presumed outages, divided into identified outages without any transactions and those where some transactions were sent. The share of potential outages with zero transactions accounts – with the exception of 2013 and 2015 – for more than 20% of the total identified outages. Thus, while the approach includes cases where participants were able to process some payments, a significant part is made up of instances where participants did not send any payments for prolonged periods of time. This suggests that different types of outages take place. Partial outages may leave the door open for manual processing or for participants to resort to contingency measures provided either by internal interfaces or by the system operator. The type of outage also depends on the reaction of the affected entity. In some cases, contingency measures may be put to use, while in others the participant may wait for the main problem to be fixed.

Potential outages per participant, as depicted in Figure 3.8, show a similar evolution to aggregate numbers. The long-term decline in potential outages ends with a small jump in 2016, but the peak is still in 2009. On average, participants had 0.47 four-times outage intervals in 2016. Presumably not included in this number are the outages that occur during times of low traffic and in spells in which participants typically do not send

Figure 3.6: Number and mean of outages



substantial numbers of payments. In absolute terms, there is no comparative data to determine whether this level of outage events is high or low. According to anecdotal evidence, the number does appear to be broadly in line with actual experience.

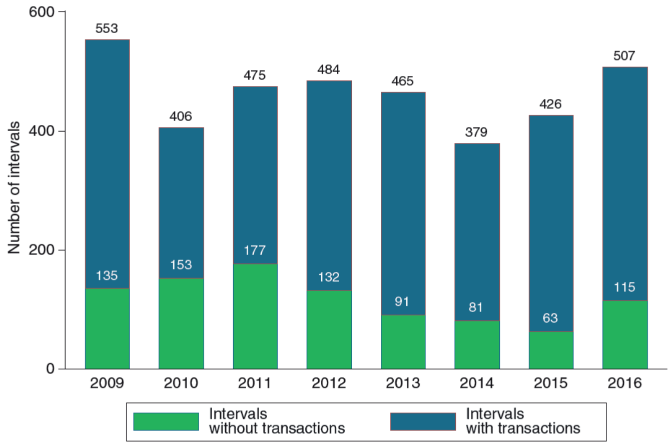
The number of outages per participant does not account for the fact that several potential outage intervals might occur on the same day and might be related to each other. However, the picture changes slightly when the number of days on which there has been at least one identified outage is considered. Figure 3.8 confirms the overall downward trend also for days affected by at least one potential outage. With roughly 250 opening days a year, a participant outage occurs on approximately one-third to one-quarter of business days.

3.4.2 Length of identified outages

The duration of outages was chosen to reflect reporting requirements for critical participants. The interpretation by length of outage is dependent on two factors. One factor is that, as they increase in length, the likelihood of actual outages increases, as the chance of false positives becomes ever more unlikely. While it is possible for gaps in the submission of payments not to originate from outages, prolonged gaps over time periods that usually exhibit higher traffic will presumably be caused by outages. The second factor is that longer outages are less likely to occur. Therefore, identified outages in four consecutive intervals are more likely to occur, as they are also a subset of longer outages.

Figure 3.10 shows the distribution of the length of identified outages across years, starting with outages occurring in at least four consecutive intervals. The majority of potential outages lasts no longer than six intervals. Considering that longer operational outages involve a higher risk to the smooth functioning of TARGET2 and to the participant itself, longer periods with potential outages are more severe. Although the absolute number is relatively low, the length of potential operational outages peaks at twenty-two

Figure 3.7: Potential outages with and without transactions



ten-minute intervals, which equates to an outage lasting more than three-and-a-half hours.

3.4.3 Timing of identified outages

In terms of days of the week and the days on which more outages occur, there appears to be a pronounced effect for Mondays (Figure 3.11). While this could be attributed to participants suffering from "Monday blues", software testing and update processes running at weekends are more likely culprits. More surprising is the increase in outages on Thursdays. Anecdotal evidence suggests this could be due to mid-week update processes that are run not at weekends but on Wednesday evenings to avoid weekend system updates.

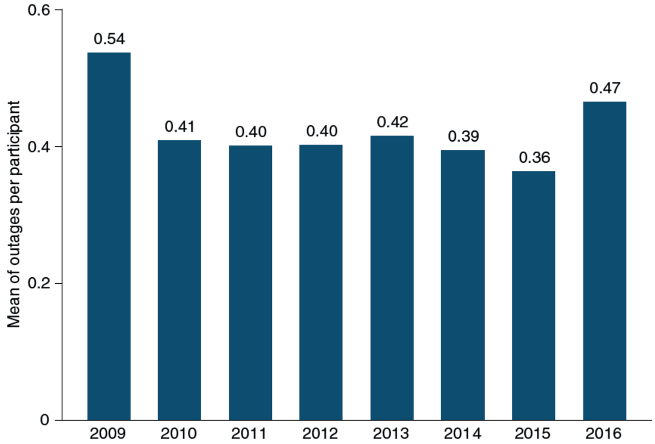
Concerning the time of day when outages occur, no particularly strong pattern is evident (Figure 3.12). Spikes appear in the morning hours, around noon and in the late afternoon. No outages are identified after 17:00, as customer payments, which make up a large share of payment volumes, can only be submitted before 17:00.

3.4.4 Country distribution of identified outages

What is perhaps unsurprising is that the distribution of outages across countries broadly follows the distribution of participants in the sample, although smaller countries in the sample tend to drop out when looking at potential outages (see Figure 3.13 and Figure 3.14). This holds true both for the country where the TARGET2 account is kept and for the country where the group parent is located.

The main reason for this most probably relates to bank size. For smaller countries, banks present in the sample might be filtered out by the algorithm due to lower payment activity. This means that countries with smaller banks may be underrepresented when looking at potential outages. This explains the tendency of outages to concentrate in some countries as opposed to covering a more diverse sample.

Figure 3.8: Mean of outages per participant



3.4.5 Robustness

As a robustness check, we investigate in which of the potential outage intervals backup and mandated payments were submitted, which indicate the adoption of business contingency measures (Figure 3.15. The approach identified a number of intervals in which business contingency measures were applied. However, in comparison with the total number of outage intervals, the number is relatively small. Contingency measures can only be employed for critical payments and should thus be expected only for a limited number of outages.

Figure 3.9: Days with at least one potential outage

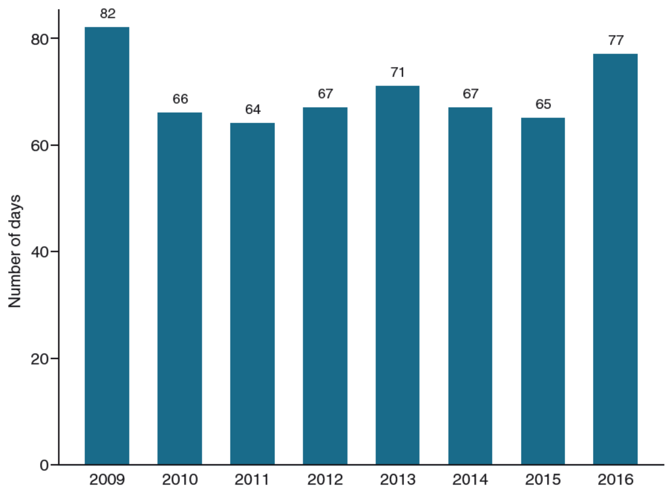


Figure 3.10: Distribution of the length of outage intervals

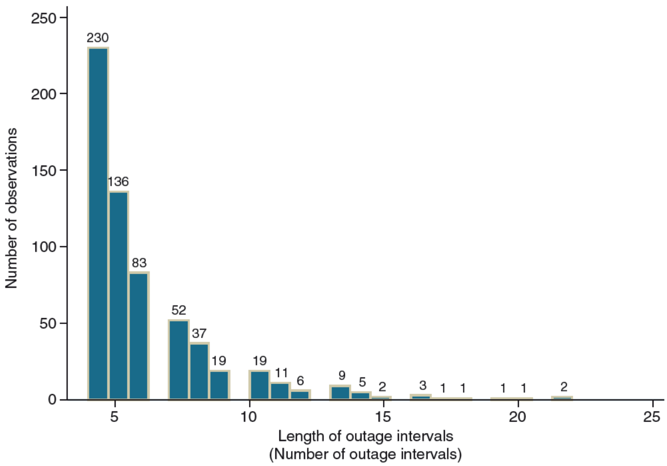


Figure 3.11: Potential outages by day of the week

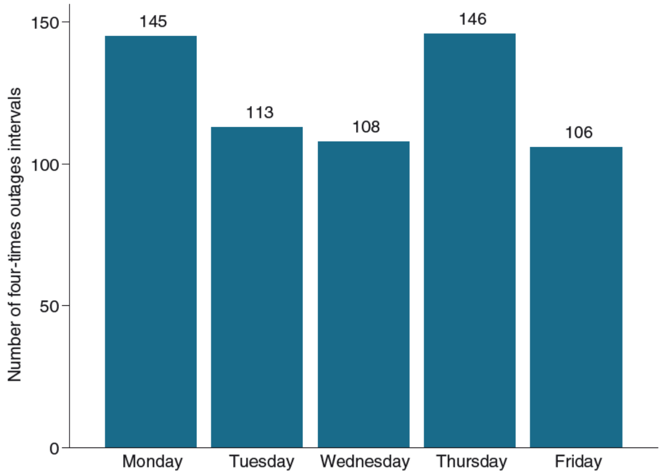


Figure 3.12: Timing of potential outages

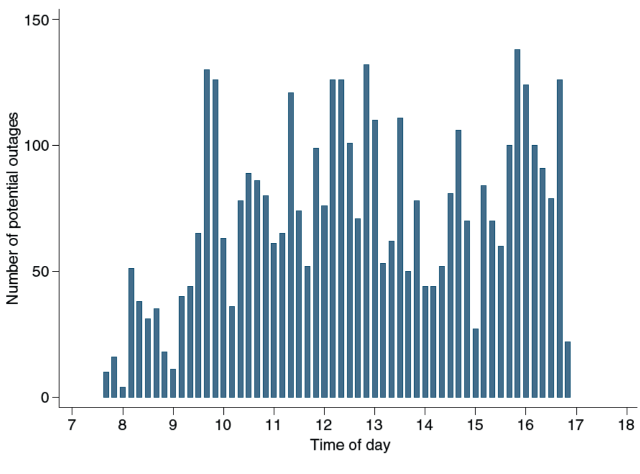
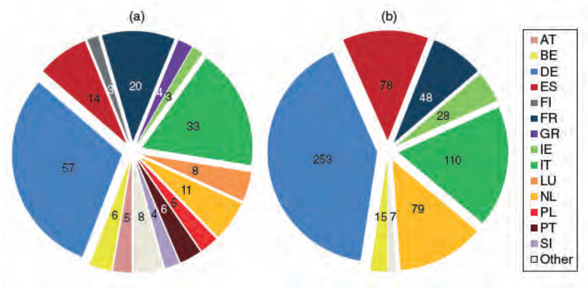
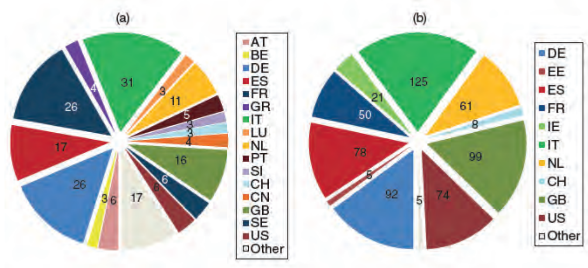


Figure 3.13: Sample and potential outages by TARGET2 country



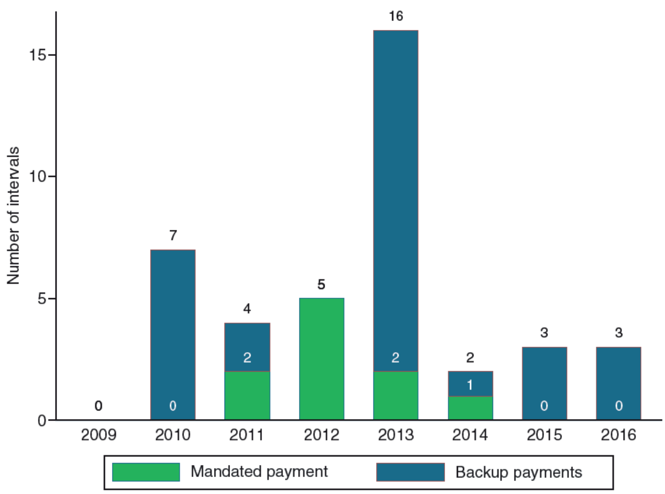
(a) Participants included by country of TARGET2 account. (b) Number of outage intervals by country of TARGET2 account.

Figure 3.14: Sample and potential outages by country of parent



(a) Participants included by country of parent institution. (b) Number of outage intervals by country of parent institution.

Figure 3.15: Number of intervals with mandated and backup payments



3.5 Conclusion

The algorithm applied can identify cases in which outages are likely; however, an element of uncertainty remains, since there are other reasons for what is essentially lower-than-usual payment activity. Factors such as seasonal effects, structural differences in payment submissions, diverse business models and other factors influence participants' payment behavior and pose challenges for identifying operational outage incidents. This creates uncertainty in the data, which is partly addressed by the way the algorithm is calibrated, but, naturally, that uncertainty cannot be fully eliminated.

As for the further development of approaches, there are alternatives that could be tested. One possibility would be to employ machine-learning techniques to identify periods exhibiting lower-than-usual payment activity. Such an approach could be used to compare results with the algorithm employed here to test and validate results.

The algorithmic approach requires a number of assumptions and a focus on key participants and time periods. In the context of this study, we are unable to make observations about banks with little traffic. Therefore, the outage picture is incomplete. At the same time, this ensures that only outages occurring during times above a certain threshold of activity are identified. In this way, only outages that cause meaningful disruptions in payment traffic are included in the constructed data set.

One major benefit of this approach is that it identifies not only full shutdowns but (potentially) also outages that are partial or to some degree contaminated through contingency measures. Thus, by using payment transaction data, potential outages can be identified and provide a data set that can be used to quantify sources of operational risk for FMIs originating from participant outages. While technically induced system outages on the operator's side are well documented for TARGET2, and presumably most other payment systems, our contribution improves the visibility of operational risk and at least partly closes a gap in our knowledge about participant outages in TARGET2.

The generated data set permits an analysis of outage incidents in terms of time, duration and frequency. This can serve as a basis for quantifying operational risk in TARGET2 originating from participants and the potential effects of outages. The approach and constructed data set is useful for operators, overseers and researchers in assessing and addressing operational risks stemming from participants in TARGET2. This approach could also be employed in the context of other FMIs. For future research, data on outages could support analysis of the potential effects of participant outages on the functionality of payment systems, distortions in the market and indicators of risk.

Appendix

Figure A1: Differences in payment behavior for randomly chosen banks

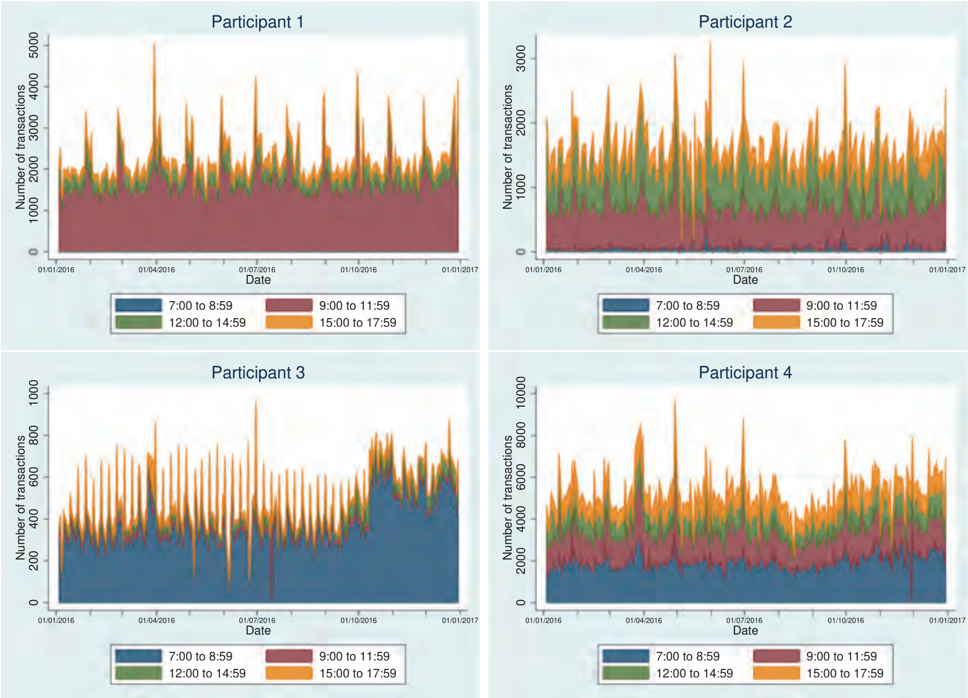


Table A2: Transaction types in TARGET2

Main transactions
Customer payments
Interbank payments
Transactions with central bank
Cash operations
Intraday repo and similar transactions
Payments sent and/or received on behalf of customers
Inter-NCB payments
Other transactions
Transactions with ancillary systems
Trade-by-trade settlement of SSS
Other settlement operations
EBA EURO1
CLS
EBA STEP2
Liquidity transfers
Intraday transfers by LVPS
Intraday transfers by retail systems
Intraday transfers by SSS
Internal transfers between different accounts of the same participant
Commercial transfers between different accounts of the same participant
Transfers to T2S
Transfers back to TARGET2 from T2S

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Chapter 4

Mobilization of collateral in Germany as a reflection of monetary policy and financial market developments

Joint work with Alexander Müller, Jan Fichtner and Hubert Wittenmayer.
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Short summary

Participation in Eurosystem credit operations requires that credit institutions post collateral. Therefore, the development of deposited collateral reflects changes in financial markets and monetary policy. This paper describes and analyzes – for the period February 2008 to March 2016 – developments in the market value of marketable assets submitted as collateral in Germany and the Eurosystem against the backdrop of the financial market crisis. The development is characterized by an initial strong increase at the onset of the crisis and a decrease after 2010 because of lower funding requirements. The posted collateral followed the course of the funding requirements, which initially rose sharply in the wake of the financial crisis. Due to high liquidity inflows, which were reflected in the increasing TARGET2 claims of the Bundesbank, the refinancing needs and posted collateral decreased after 2010. However, the posted collateral relative to refinancing operations remained remarkably high. Credit institutions can use different submission channels for collateral. We identify significant shifts among these channels. While these shifts are partly due to more technical aspects, they may also stem from a "home bias" and portfolio reallocations.

Keywords: Collateral, mobilization channels, Eurosystem, monetary policy, financial system

JEL classification: E42, E51, E58, G21

4.1 Introduction

In order to participate in Eurosystem credit operations, credit institutions must provide the Eurosystem with collateral. This paper describes and analyzes developments in the market values of marketable assets posted as collateral in Germany and the Eurosystem against the backdrop of the financial market crisis for the period from early 2008 to 2016. These developments initially saw refinancing requirements rise sharply before falling again after 2010, and they had a considerable impact on collateral holdings. We identify shifts between mobilization channels, at least some of which may be due to an increase in home bias and portfolio shifts alongside technical aspects.

In times of very low interest rates, the characteristics of collateral frameworks, the channels of collateral mobilization and the modes of collateral utilization all increase in importance significantly (see Belke, 2015; Nyborg, 2015). This paper is a contribution to a growing body of research on aspects of collateral. In particular, we focus on the question of how monetary policy is transmitted by and reflected in the mobilization of collateral over time, both concerning the market value of pledged collateral and the utilization of different submission channels. This paper proceeds as follows. Section 2 analyzes the development of pledged collateral regarding the market value of deposited securities. In Section 3, we present findings on how the utilization of different mobilization channels has changed from 2008 to 2016. Finally, Section 4 concludes.

4.2 Developments in the market values of submitted collateral since 2008

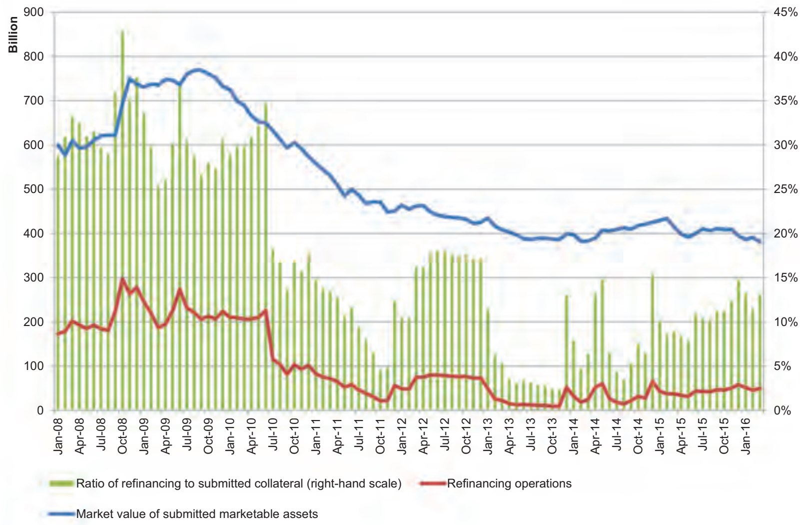
Counterparties' collateral holdings at the Bundesbank were increased at the outbreak of the financial crisis, which in turn increased their potential for acquiring liquidity through Eurosystem monetary policy operations.When Lehman Brothers collapsed in September 2008, the total volume of assets held for refinancing purposes rose sharply. The total volume of marketable assets deposited with the Bundesbank climbed from €600 billion in January 2008 to €770 billion in September 2009, a high level at which it remained until the start of 2010.

Immediately after the collapse of Lehman Brothers, conditions on the money market deteriorated dramatically. Liquidity and solvency problems at individual credit institutions led to a major loss of trust between banks. General levels of uncertainty in the financial sector escalated, as did market participants' concerns regarding sufficient liquidity. This resulted in the segmentation of the interbank money market into financial institutions with liquidity surpluses and financial institutions with liquidity deficits, which could no longer be offset against each other.[1]

At the end of 2008, the Eurosystem took various measures to stabilize financial markets, which had an impact on the submission of collateral. First of all, the Eurosystem's main refinancing operations were changed from variable rate tenders to fixed rate tenders with full allotment. This increased the refinancing volume, which, in turn, raised the amount of collateral required. Moreover, the list of eligible assets was expanded by

[1]For an overview of the effects of the collapse of Lehman Brothers on the interbank market, see Deutsche Bundesbank (2009, 2010) and European Central Bank (2009).

Figure 4.1: Developments in refinancing operations and the market value of marketable assets submitted to the Bundesbank as collateral.



Note: The refinancing operations presented here include main refinancing operations and longer-term refinancing operations. Data shows monthly averages.

lowering the minimum credit threshold for marketable and nonmarketable assets from A to BBB (except for asset-backed securities), effective from October 22, 2008 (European Central Bank, 2008a,b) This measure counteracted a potential shortage of high-quality assets. Figure 4.1 clearly shows an increase in the mobilization of collateral in connection with the higher refinancing volume at the end of 2008 and in 2009, after which the further posting of collateral mirrors the rise in funding requirements. This is particularly apparent from the brief rise in the ratio of refinancing to submitted collateral in October 2008. Since the middle of 2010, there has been an overall decline in the ratio of refinancing operations to submitted collateral, which currently stands at around 10%. The market value of the mobilized collateral in relation to the volume of refinancing operations is therefore fairly high, which may be due in part to a lagged adjustment of the submission of collateral to the refinancing requirements.

In addition, it should be noted that banks generally pledge collateral with a higher market value to central banks than is really needed. This excess collateral can then be used for intraday TARGET2 operations or for potential margin calls. This is likely one important reason why the market value of pledged collateral is always considerably higher than bank borrowing in the Eurosystem. Further, private banks frequently post comparably illiquid and low-quality collateral to the domestic central bank. This is rational for banks, because such risky securities may either not be accepted by other private banks at all or, if they are accepted, they may only be used under unfavorable conditions (see Belke, 2015; Nyborg, 2015).

The increase in marketable assets in 2008 shown here was accompanied by an increase in the mobilization of nonmarketable assets, whose value almost doubled from around €40 billion in mid-2008 to €78 billion in mid-2009. Since then, this figure has remained roughly stable. As a result, only changes in the submission of marketable assets are analyzed here. For simplicity, the value of collateral provided is calculated based on its market value and not on its (lower) lending value. This does not significantly distort the trends, as in the period under observation it only resulted in changes in the haircuts to be applied to the market values in the case of specific subsections of asset classes in the eligible collateral pool.

In the second quarter of 2010, the international financial and economic crisis turned into a combined and mutually reinforcing sovereign debt and banking crisis in Europe. There was a sharp decline in longer-term refinancing operations in mid-2010, owing to the expiry of the first one-year tender. In December 2011 and February 2012, for the first time, the Eurosystem provided commercial banks with liquidity through longer-term refinancing operations (LTROs), with maturities of up to thirty-six months (European Central Bank, 2011). However, this measure was not accompanied by a rise in the collateral deposited by the Bundesbank's counterparties. On the contrary, the collateral stock almost halved between September 2009 and the beginning of 2014.

Since 2012, however, the value of assets posted as collateral has been becoming more stable, which reflects the overall decline in the ratio of refinancing operations to posted collateral. Testing for a structural break in the development of refinancing operations and collateral using a supremum Wald test, we found a statistically significant break in December 2011.

Figure 4.2 shows the strong correlation (0.93) between refinancing operations and collateral submitted. The results of Granger tests suggest that there is a time lag in the adjustment of the collateral holdings to the more volatile refinancing requirements, but not the other way around (see Box 1).

Box 1: The relationship between refinancing operations and posting of collateral

The Granger causality test determines for two stationary time series whether, after a time lag, one time series is useful in forecasting the other. However, in contrast with what its name suggests, the test cannot determine causality (see Granger, 1969; Lütkepohl, 2005).

For the relationship between refinancing operations and the posting of collateral, Granger causality tests provide evidence that the collateral stock can be (partly) forecast using the refinancing volume, but not vice versa. This implies that collateral submission is adjusted according to refinancing needs. The alternative hypothesis would imply that collateral is adjusted in anticipation of refinancing operations; however, this hypothesis of forwardlooking collateral submission is rejected.

Table 4.1: Tests of hypotheses for Granger-causality (one lag).

Null hypotheses	***F*-statistic**	**Probability**	**Result**
H0: refinancing operations (RO) do not Granger-cause submitted marketable assets	12.70	0.001	Reject H0
H0: submitted marketable assets (SMAs) do not Granger-cause refinancing operations	0.82	0.367	Accept H0

Table 4.2: VAR results (first difference on monthly averages).

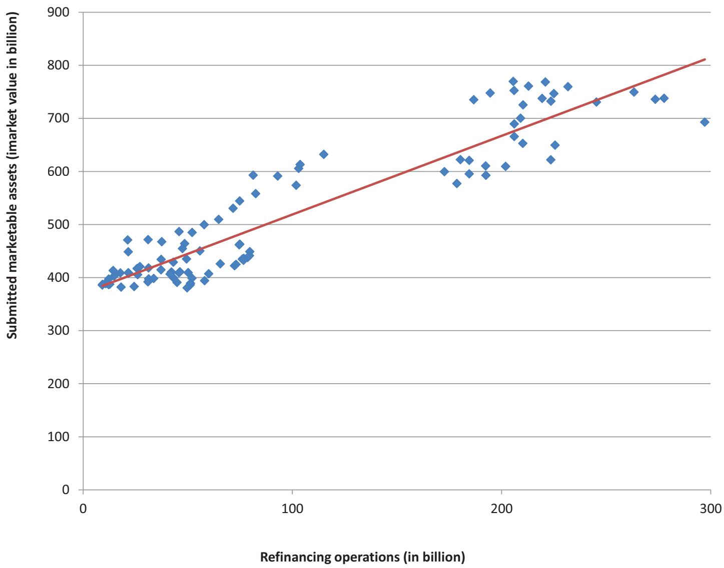
VARIABLES	(1) Δ RO	(2) Δ SMA	(3) Δ RO	(4) Δ SMA
Δ RO $_{t-1}$	0.00106	0.241***		0.271***
	(0.00994)	(3.564)		(4.100)
Δ SMA $_{t-1}$	-0.137	0.163*	-0.136	
	(-0.907)	(1.698)	(-0.941)	
Constant	-1.623e+09	-1.356e+09	-1.623e+09	-1.669e+09
	(-0.741)	(-0.972)	(-0.746)	(-1.194)
Observations	97	97	97	97
R-squared	0.009	0.176	0.009	0.150
Adjusted R-squared	-0.0118	0.158	-0.00119	0.141
Prob > F	0.647	0.000114	0.349	8.73e-05

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Results of vector autoregressive (VAR) regressions with one lag are presented in Table 4.2. In terms of the selection of the number of lags, we get conflicting results when using different information criteria. We focus on the results for one time lag, but the results are similar when including more lags. To achieve a stationary time series, we use first differences. As a robustness check, we find the results for levels to be similar. The residuals are not normally distributed, due to an outlier in October 2008. This stems from the fact that in October 2008 eligible securities were expanded, and there was a switch from rate tenders to full allotment.The date can therefore be regarded as an external shock or a structural break in the data. As further robustness checks, we test for Granger causality excluding October 2008, for the periods before and after October 2008 and for the periods before and after December 2011, for which a structural break was identified from the data (see Table 4.3). We find the dynamics to be unaffected, with significance slightly decreasing with more limited sample sizes. The results always remain significant at a 5% level and are never significant at conventional levels for the alternative null hypothesis.

The results show that refinancing operations have predictive power for submitted collateral in the next period, with a positive coefficient. Arguably, the reason for this is that collateral is adjusted upward following periods with higher refinancing and downward following periods with less refinancing operations. This indicates that the decline in posted collateral is largely the result of the decrease in liquidity requirements over time, but not vice versa. Therefore, the potential forward-looking collateral submission for future refinancing needs is discarded.

Figure 4.2: Scatter plot of refinancing operations and posted marketable assets (monthly averages).



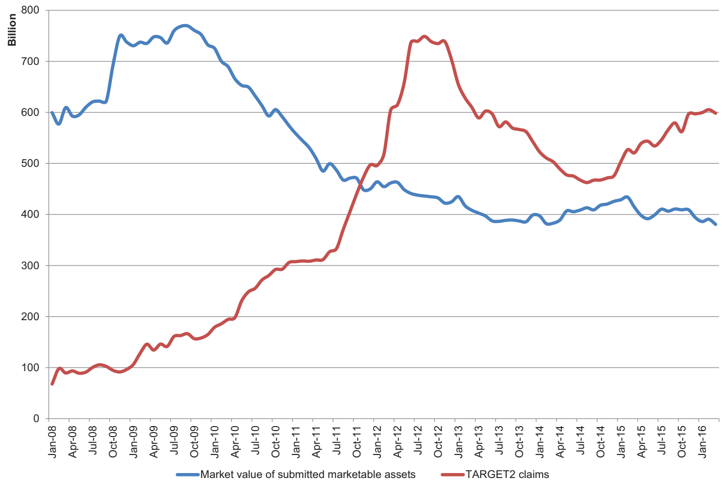
German banks' ample liquidity is in part the result of liquidity inflows, most notably from the peripheral countries, which are reflected in the Bundesbank's elevated TARGET2 claims (European Central Bank, 2015b). This means that German commercial banks needed to rely less strongly on refinancing loans to obtain central bank money because they received central bank money through transfers from the euro area (Deutsche Bundesbank, 2011). The resulting improvement in the banks' liquidity positions means a reduction in the amount of collateral they need to hold for refinancing operations.We can thus identify a contrasting development in the volume of pledged collateral and the Bundesbank's positive TARGET2 balance between 2012 and 2014 (see Figure 4.3)

The covered bond purchase program (CBPP), the asset-backed securities purchase program (ABSPP) and the secondary markets public sector purchase program (PSPP) adopted by the European Central Bank Governing Council are also likely to have contributed to lower funding requirements among counterparties (European Central Bank, 2015a).

Table 4.3: Robustness checks for different time periods.

Null hypotheses	**Robustness check**	**Observations**	***F*-statistic**	**Probability**
H0: RO does not Granger-cause SMA	October 2008 excluded	96	7.77	0.007
H0: SMA does not Granger-cause RO	October 2008 excluded	96	0.64	0.424
H0: RO does not Granger-cause SMA	Up to October 2008	8	11.15	0.021
H0: SMA does not Granger-cause RO	Up to October 2008	8	2.42	0.181
H0: RO does not Granger-cause SMA	After October 2008	89	8.60	0.004
H0: SMA does not Granger-cause RO	After October 2008	89	0.45	0.502
H0: RO does not Granger-cause SMA	Up to December 2011	46	6.17	0.017
H0: SMA does not Granger-cause RO	Up to December 2011	46	0.22	0.642
H0: RO does not Granger-cause SMA	After December 2011	51	5.79	0.020
H0: SMA does not Granger-cause RO	After December 2011	51	2.23	0.142

Figure 4.3: Market value of marketable assets deposited with the Bundesbank and TARGET2 balance.



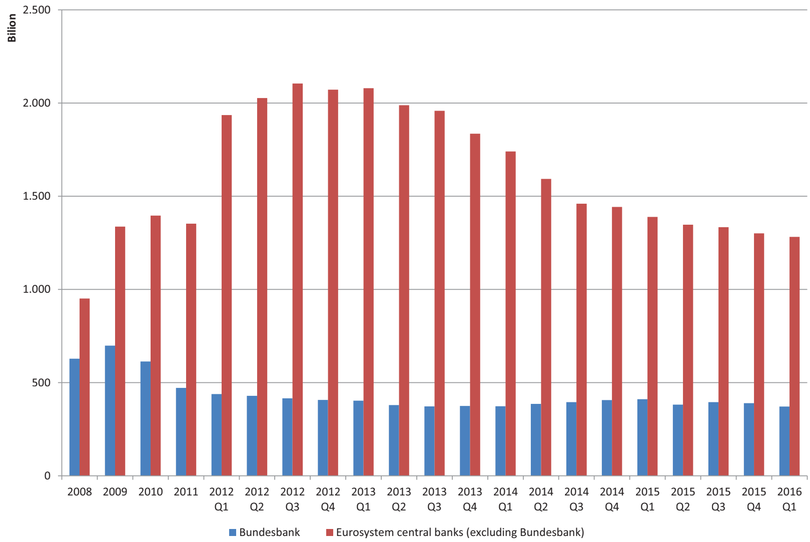
With regard to the scale of the PSPP, ABSPP and CBPP3, a monthly purchase volume of €60 billion was originally foreseen; in April 2016 this was increased to €80 billion per month. In addition, in June 2016, the Eurosystem central banks have begun the corporate sector purchase program (CSPP), buying bonds issued by nonbank corporations established in the euro area that have a sufficient credit rating (investment grade) (European Central Bank, 2016b). The CSPP – amounting to €6.4 billion for June 2016 – will contribute to the asset purchase program's average monthly purchase volume of €80 billion (European Central Bank, 2016a). The initially adopted purchasing window from March 2015 (or from October and November 2014 for CBPP3 and ABSPP) until 2016 has been extended to at least March 2017 (European Central Bank, 2016c).

The extensive provision of liquidity via these securities programs could mean that counterparties avail themselves of an even smaller refinancing volume at the Bundesbank, and thus pledge less eligible collateral (Deutsche Bundesbank, 2015). At the moment, however, there are no signs of a decline, which could potentially be attributable to the lagged adjustment in the submission of collateral. An important development to observe will be the future availability of high-quality collateral, such as German government bonds, whose yields have turned negative even for the ten-year bonds in mid-June 2016.

A comparison of the eligible collateral submitted to the central bank in Germany over time with that submitted in the rest of the Eurosystem (excluding Germany) reveals that after the onset of financial market turmoil in August 2007 and the Lehman Brothers insolvency in September 2008, the volume of collateral held initially increased sharply in both cases (see Figure 4.4).

However, in the ensuing period, a countervailing trend set in. The fall that can

Figure 4.4: Comparison over time of eligible collateral deposited with the Bundesbank and the Eurosystem central banks (excluding the Bundesbank).



be observed in Germany as of 2009 reflects already improved liquidity conditions for German institutions. In the rest of the Eurosystem, on the other hand, the mobilization of collateral continued to rise after 2009 until it reached an initial peak in 2010, before falling slightly in 2011. Following this, there was again a strong rise in the value of pledged collateral, above all to enable participation in the two three-year LTROs in December 2011 and February 2012. Demand amounted to approximately €500 billion on both of these allotment dates.

In absolute figures, the total amount of collateral deposited by the counterparties in the rest of the Eurosystem climbed from €950 billion in 2008 to around €2.1 trillion in the third quarter of 2012. As of the first quarter of 2013, holdings of collateral fell continuously until the start of 2015, at which time they stood at €1.4 trillion.

4.3 Changes over time in mobilization channels

At present at the Bundesbank, 38% of pledged marketable collateral is submitted via Xemac, 27% is submitted via the domestic channel, 31% is submitted via the correspondent central banking model (CCBM) and 4% is submitted via third-party custody (for more information on these mobilization channels, see Box 2 and Figure 4.5).

Box 2: Mobilization channels of marketable assets

There are four channels via which marketable assets may be submitted in the form of a pledge to the Bundesbank (see also Table 3).

1. Domestic securities pledge (domestic): eligible assets held at Clearstream Banking Frankfurt (CBF) are individually transferred to the Deutsche Bundesbank's safe custody account held at CBF, or transferred via eligible links to the Deutsche Bundesbank's safe custody account at CBF or Clearstream Banking Luxembourg (CBL).

2. Securities deposited at a domestic custodian bank may be transferred individually to the Deutsche Bundesbank within the framework of third-party custody.

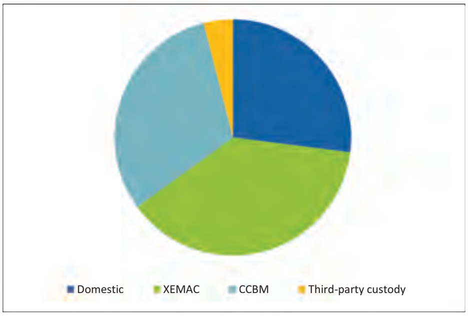
3. The eligible securities deposited at CBF or CBL may also be made available in favor of the Deutsche Bundesbank as a global amount via Xemac (triparty system), CBF's collateral management system. The cross-border mobilization of collateral is also possible via other triparty services (CmaX from Clearstream Banking Luxembourg and AutoSelect from Euroclear).

4. Eligible securities deposited in other Eurosystem member states may be used on a cross-border basis under the CCBM. The national central banks maintain safe custody accounts with each other for this purpose.

Table 4.4: Mobilization channels of eligible assets to the Deutsche Bundesbank.

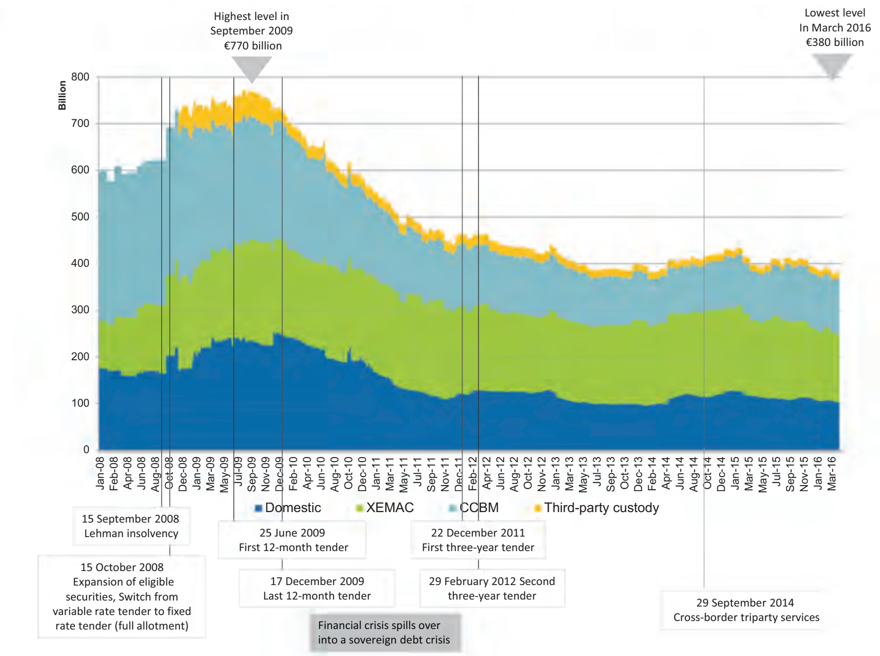
Method	**Custodian Bank**	**Transmission**
Domestic	CBF	Individually to the Deutsche Bundesbank's safe custody account at CBF or CBL
Third-party safe custody	Domestic custodian bank	Individually to the Deutsche Bundesbank's safe custody account
Triparty systems	CBF, CBL, Euroclear France S.A./Euro-clear Bank S.A. (ECL)	Provision of global amounts (securities claim amounts) via Xemac, CmaX or Autoselect
CCBM	Foreign central bank	Individually to the foreign central bank's safe custody account in favor of the Deutsche Bundesbank

Figure 4.5: Distribution of the volume of marketable assets among the various mobilization channels (as at end-March 2016).



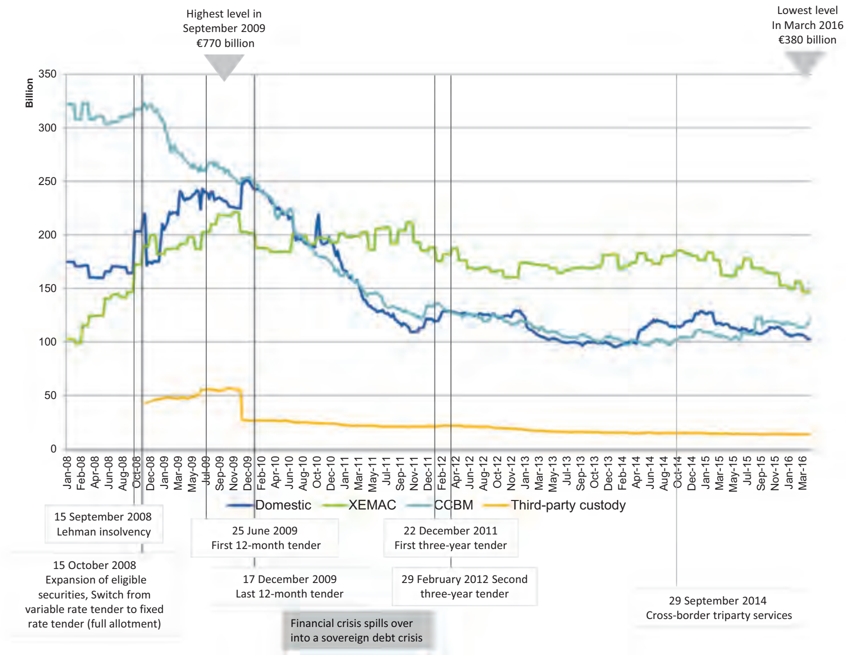
All submission routes recorded increased directly following the outbreak of the financial crisis and the introduction of monetary policy measures and reached their peak – a total of €770 billion – in September 2009. Subsequently, structural shifts occurred to the mobilization channels used for pledging collateral (see Figure 4.6).

Figure 4.6: Volume of marketable assets by mobilization channel (aggregated).



In particular, holdings with Xemac rose gradually, while a decline in domestic and CCBM submissions was observed. The volumes of marketable assets via each mobilization channel are shown individually in Figure 4.7. A shift between the individual channels is clearly identifiable.

Figure 4.7: Volume of marketable assets by mobilization channel (aggregated).



Particularly noteworthy is the growing importance of the Xemac system, which has evolved from a relatively insignificant submission channel in 2008 to the largest one in 2016. With respect to the increasing use of the Xemac mobilization channel over time, technical features, such as the ease of use of securities holdings for several purposes beyond monetary policy operations, might play a role.

In September 2008, around half of all securities submitted were posted via the CCBM submission channel, which clearly dominated until 2009 before subsequently recording the lowest growth in both relative and absolute terms. The submission of collateral via the CCBM channel had dropped even shortly after the crisis began, before the total amount of deposited collateral had reached its peak. The lower use of this mobilization channel by counterparties of the Bundesbank could be due to a preference for domestic securities (home bias) and a redistribution of collateral stock. It is possible that the Deutsche Bundesbank's counterparties reduced their securities holdings due to the credit ratings of the government debt instruments of affected euro area periphery countries being downgraded and their prices falling. The use of CCBM reached its lowest point to date in summer 2014, when it slumped to €98 billion, less than one-third of the value recorded in spring 2008.

In November 2009, third-party custody plummeted from around €55 billion to €25 billion. This abrupt drop is attributable to the discontinuation of third-party custody services by one third-party custodian. By March 2016, the value of securities held in third-party custody had been reduced once again by almost half and stood at €13 billion.

4.4 Conclusion

The increase in the overall stock of collateral held by the Deutsche Bundesbank is clearly indicative of the changes taking place in financial markets. Collateral stock developments mirror funding requirements to a certain extent, with the latter initially rising sharply on account of the financial crisis. Using Granger causality tests, we find that refinancing operations have predictive power for future collateral mobilization, but not vice versa. Due to high liquidity inflows, which were reflected in the Bundesbank's escalating TARGET2 claims, funding requirements – and hence collateral stock – fell. The extensive provision of liquidity via the securities purchase programs could lead to a further reduction in overall collateral holdings in the coming months. Shifts between mobilization channels were largely caused by technical aspects. However, the decline in CCBM could also be attributable to counterparties shifting their portfolios.

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Chapter 5

”The devil is in the details, but so is salvation” – Different approaches in money market measurement

Joint work with Alexander Müller.
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The authors of this paper are each member of one of the user groups with access to TARGET2 data in accordance with Article 1(2) of Decision ECB/2010/9 of 29 July 2010 on access to and use of certain TARGET2 data, as amended on 22 September 2017 by Decision (EU) 2017/2080. The Deutsche Bundesbank, the MIB and the MIPC have checked the paper against the rules for guaranteeing the confidentiality of transaction-level data imposed by the MIB pursuant to Article 1(4) of the above-mentioned issue. Access to MMSR data (DOI 10.12757/Bbk.mmsr.0716 0419.01.01) was granted by the Bundesbank (Research project 2017/0047). Confidentiality of the transaction-level data was checked by the authors. The views expressed in the paper are solely those of the author and do not necessarily represent the views of the Eurosystem.

Short summary

Considerable resources have been devoted to gathering data for the measurement of money market activity which forms the basis for the calculation of benchmark rates. However, little is known about the differences between available data and the structural effects of methodological choices. We use the novel dataset MMSR and compare it to data derived from a Furfine-type algorithm as well as aggregate survey data. The deviations in volumes and interest rates are driven by the asymmetric measurement of transactions, in particular affecting individual classes of banks, cross-border loans and specific types of loans. These differences are significant in terms of magnitude and affect overall rates and volumes. Even fundamental questions like the share of cross-border transactions depend on which data is used. We show structurally that belonging to different classes of banks affects loan rates. Based on the results, there are specific considerations for policymakers and researchers why one dataset may be preferable to the others.

Keywords: Money Market, Overnight interest rates, Measurement methodology

JEL classification: C80, E42, E50, G10, G21

5.1 Introduction

Money markets constitute a key element of monetary policy implementation. For central banks, the money market is of high importance as it signals the monetary policy stance and allows to evaluate the transmission of monetary policy. As stated by Minsky (1957), "[t]he ability of a central bank to achieve its objectives depends upon how its operations affect the various elements that make up the money market." Consequently, accurate measures of market activity and rates in different money market segments form the basis of policymakers' decision-making. Measuring money markets also motivates and shapes regulatory requirements and has provided impetus for ample research.

From a commercial bank's perspective, interbank money markets are a vital tool to cover short-term financial needs. Interbank benchmark rates also serve as the underlying of financial instruments and thus affect the pricing of derivative contracts.

Considerable resources have been devoted to gathering data that allow money market activity to be measured over time and across countries in order to assess the transmission of conventional and unconventional monetary policy measures. The data are used in a variety of studies on the money market itself and financial conditions in the economy. Newly available data from the Money Market Statistical Reporting (MMSR) has stirred a policy debate on how money market reference rates are calculated and how various methodological options should be incorporated.[1]

In spite of their widespread use and importance for policy, less attention is paid to how the data are generated and how the methodology used to produce different data sources affects outcomes on the micro and macro levels. We attempt to bridge this gap by studying different data sources on the unsecured interbank money market for Europe and Germany in particular. To our knowledge, no studies have yet been undertaken that compare different data sources and methods of data elicitation in interbank markets in-depth. In particular, we match data generated by Furfine-type algorithms to a transaction-level dataset of reported unsecured transactions.

Our paper contributes to the literature on general measurement methodology by comparing different datasets on macro and micro levels, namely: survey data (EONIA), identified loans from TARGET2 payments data using a Furfine-type algorithm (T2)[2], and reported data (MMSR). We argue that although the devil is in the details, deviations are structurally explainable, and that an environment with methodological plurality can reduce overall uncertainty ("salvation").[3]

We identify methodological differences that may appear rather technical at first sight, but which determine how broadly the market is captured and what aspects or practices are in scope of measurement. We find that it is not only straightforward choices such as the selection of panel banks that affect outcomes. Loans not settled in central bank money but

[1]The ECB launched two public consultations on developing a Euro unsecured overnight interest rate in November 2017 and March 2018 (see Euro short-term rate at `www.ecb.europa.eu`, and European Central Bank, 2017, 2018).

[2]The data is constructed by matching payments settled in TARGET2. In TARGET2, euro payments are settled in real time, including interbank and customer payments, monetary policy operations and cash positions from ancillary systems. Henceforth we refer to money market loans identified by Furfine-type implementations as T2 data and to the payment system as a whole as TARGET2.

[3]The title of the paper was inspired by a quote by Navy Admiral Hyman G. Rickover (1900 - 1986), mentioned in *Rickover and the Nuclear Navy* by Francis Duncan.

in internal systems of banking communities and therefore being closer to loans within a banking group in economic terms are not captured by Furfine-type algorithms. Loans with foreign counterparties are represented unevenly across as well as within datasets because reporting requirements of MMSR do not cover them in the same way as a Furfine-type algorithm is able to identify them. Different elicitation methods therefore have blind spots with respect to certain banks, cross-border transactions and loans with interest rates below the deposit facility rate.

Such differences may lead to different conclusions, with potential implications for policy. Even basic observations on the money market, like the share of cross-border transactions or whether domestic banks engage in net lending or net borrowing, depend on which data are employed. Additionally, the methodological choices and their influence on the calculation of rates depend on the prevailing monetary policy environment. In any event, awareness of the underlying features of data sources is relevant for all researchers and policymakers using money market data to assess financial market activity and monetary policy transmission. One source of data may be preferred over another to avoid certain blind spots and to chose the optimal measurement methodology depending on the research question. However, given the discretionary nature of policy choices it is not possible to structurally evaluate how different data would affect policy outcomes.

5.2 Measuring the money market

5.2.1 Overview and importance

Central banks aim to steer short-term interest rates via monetary policy operations and signal the monetary policy stance (for example, see Gaspar et al., 2001).[4] The policy rates transmit to the short-term interbank money market (see Nautz and Scheithauer, 2011). From there, interest rates transmit to other short-term market rates, deposit and credit interest rates, yields of other derivatives and asset classes and the exchange rate (for instance, see Kuttner and Mosser, 2002). The short-term money market thus plays a pivotal role for monetary policy implementation and the communication of policy decisions. Measures for the short term money market such as benchmark rates are crucial for operationalizing and monitoring monetary policy implementation. In the euro area, the Euro Overnight Index Average (EONIA) used to be the main operational target of the Eurosystem's monetary policy operations before the introduction of unconventional monetary policy instruments, and remained an important indicator thereafter. Moreover, Benchmark rates constitute the underlying of financial contracts. EONIA served as an underlying for an estimated 22 trillion euro of outstanding financial contracts in 2018.[5] Benchmark rates have recently undergone a paradigm shift internationally, with both the regulatory environment and the calculation basis coming under scrutiny (for an extensive discussion of recent developments, see Schrimpf and Sushko, 2019). In the euro area, EONIA was replaced by a new reference rate based on MMSR data, called €STR. [6]

[4] See also Monetary policy instruments, at `www.ecb.europa.eu`.

[5] See European Central Bank (2018) and Working Group on Euro Risk-Free Rates, Update on quantitative mapping exercise, May 2018, at `www.ecb.europa.eu.`

[6] The official name was changed from ESTER to €STR. The ECB had earlier announced the launch of a trademark protection process for the name ESTER. See the press release, ECB changes the acronym

When defining a benchmark, the choice of market segments and reporting entities is crucial for regulators and has been discussed extensively in various jurisdictions.[7] This paper focuses on one specific market – the unsecured interbank overnight market – to investigate how different forms of data elicitation affect aggregate indicators in this market.

The unsecured money market constitutes an over the counter (OTC) market. As highlighted by Duffie et al. (2005), prices are determined by liquidity considerations, outside options and the market powers of intermediaries (market makers). Concerning market segments, credit risk is reflected in the unsecured market, whereas the secured market mitigates counterparty risk. As pointed out by Rochet and Tirole (1996), the unsecured money market reflects monitoring between banks. Furfine (2001) supports this notion with data for the Federal funds market and finds that money market rates reflect, to a certain degree, the credit risk of banks. Blasques et al. (2018) identify uncertainty and monitoring as significant factors for the structure of money markets using a dynamic network model. Both EONIA and €STR are reference rates for the unsecured overnight market. However, €STR is not limited to the interbank market, but also contains banks' borrowing from other financial institutions. As central banks mainly focus on banks as the counterparties of monetary policy operations, the interbank market is still the most relevant.

The majority of unsecured interbank loans occur within a short time horizon. Similarly to previous studies, we find that the majority of interbank loans occur in the overnight segment (more than 80 percent for MMSR data). Admittedly, though, as Upper and Worms (2004) point out, longer-term maturities can be important for studying contagion in interbank markets. In the absence of transaction-level data, they use balance sheet data on exposures for this purpose, but are unable to identify individual counterparties. As has been demonstrated by Nautz and Offermanns (2008), amongst others, the volatility of short-term rates is transmitted to longer term interest rates. Nevertheless, despite the relevance of long-term maturities for specific research questions, we henceforth constrain the analysis to the overnight unsecured interbank market due to its much larger significance and for comparability.

5.2.2 Measurement

We identify three general data collection categories for the measurement of money market activity. Survey data, identified loans from payments data using a Furfine-type algorithm, and reported data.

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for its euro short-term rate and the previously available document, ESTER methodology and policies - European Central Bank, at `ecb.europa.eu`. A principle driving force behind this change was the newly established Benchmark Regulation (EU) 2016/1011, on the basis of which EONIA was defined as a critical benchmark (in conjunction with Implementing Regulation (EU) 2017/1147). At the same time, EONIA was considered non-compliant with the new benchmark requirements due to a high concentration within both the panel banks' activity and the geographical location of panel banks, in combination with a decreased importance of the underlying market segment.See ECB, Why are benchmark rates so important?, at `www.ecb.europa.eu`. See also `www.emmi-benchmarks.eu/euribor-eonia-org/eonia-review.html`.

[7] Besides the euro area, these include Japan, Switzerland, the United Kingdom and the United States (Schrimpf and Sushko, 2019). Switzerland and the United States chose a secured rather than an unsecured rate.

Survey data

As a first method, surveys among banks elicit measures of money market activity and interest rates. For the Eurosystem, the biennial Euro money market survey and reference rates based on surveys like EONIA or EURIBOR (Euro Interbank Offered Rate) are the most prominent examples. However, survey data suffers from significant shortcomings. It is often costly to elicit survey data, meaning that it is only available at low frequencies. In most cases, survey data are not available as granular, transaction-level data, but are reported as aggregate figures. Transaction-level data are important as the microstructure of interbank markets should be taken into account when designing policy measures, as shown for example by Georg (2011). This is especially true in times of stress.

Survey data rely on voluntary contributions from market participants, raising questions about their degree of representativeness. Another important reason of the gradual decline of their importance as data source are the concerns about their notorious unreliability. Incorrect survey data can be the consequence of involuntary errors and even of outright manipulation. This is particularly the case when surveys are not backed by actual transactions as it was the case for manipulations that came to light for the LIBOR and EURIBOR benchmark rates (see, amongst others, Mollenkamp and Whitehouse, 2008; Duffie and Stein, 2015; Wheatley, 2012; Eisl et al., 2017). The use of actual transactions rather than quotes obtained via surveys can improve the data quality. EONIA data are, in contrast to EURIBOR data, supposed to be based on actual transactions rather than expert judgements. They should therefore be less prone to tampering. However, as underlying transactions are not reported at granular level, there is still scope for misreporting. Futhermore, one-sided (lender only) reporting is a source of uncertainty and increases the risk misreporting, as the data cannot be cross checked.

Furfine-type algorithm

As a second measurement method, Furfine (1999, 2001) has contributed seminal work on extracting loan-level data for analyzing the microstructure of the interbank market. Furfine (1999) proposed an algorithm to identify individual money market loans in large value payment systems data. The basic logic of this method is rather simple: the payout and payback of a money market loan are identified in the transactions of payment systems. They are matched based on the assumption that a money market loan leads to a round value payment from the creditor to the debtor and a payment of the same value, plus interest, from the debtor to the creditor upon maturity. Generally speaking the algorithm identifies eligible payments from one *bank A* to another *bank B* on day t in the amount of x, and searches for an offsetting transaction from *bank B* to *bank A* on the next business day $t+1$ that equals the original amount x plus a viable interest rate i.

Despite some critical assessments, such as by Armantier and Copeland (2012), Furfine-type algorithms have been further developed and applied by researchers and central banks across the world. In many cases, these have produced encouraging partial validations. The implementation of such algorithms has generated new and comprehensive microdata for many countries where data were previously absent.[8]

[8] Kovner and Skeie (2013) use balance sheet data and conclude that the algorithm delivers a meaningful measure of overnight Fed funds activity; however, they stress various caveats. Rempel (2016) proposes an estimation of the vulnerability of the algorithm to false identifications and suggests methodological

The paper builds on the two implementations of Furfine-type algorithms for the euro area by Arciero et al. (2016) and Frutos et al. (2016). Both have been partially validated and further developed, in particular to allow for zero and negative interest rates when the Eurosystem set a negative overnight deposit rate and money market rates also became negative, as described in Rainone and Vacirca (2020). Müller and Paulick (2021) provide a comparison of the two implementations. The resulting datasets have been used as the basis for a variety of literature and to support policymakers; see, for example, Heijmans et al. (2016); Abbassi et al. (2014); Gabrieli and Georg (2014); Garcia-de Andoain et al. (2016). Gabrieli and Labonne (2018) provide an overview of studies employing T2 data. The possibility of complementing aggregate survey-based information and reference rates with granular data on individual transactions is often cited as the main benefit of using this data, inter alia in European Central Bank (2013, 2015).

Reported data

As a third elicitation method, regulators require banks to report actual transactions. In contrast to survey data, reporting is obligatory for panel banks, often on a transaction level. These are potentially the most reliable data. Transactions can be cross-checked with the counterparty's data, making potential manipulation harder. This form of data elicitation is, just like survey data, costly, for banks and regulators both. Such reporting frameworks were therefore often not put in place until recently. As for survey data, the sample size is often restricted to the major players. Precise criteria and detailed instructions for reporting as well as the various verification options are determining factors for the quality of the data.

In the Eurosystem, data on various segments of the money market have been reported under the MMSR since mid-2016. This was clearly motivated by a perceived need for highly granular and readily available data on the money market. Compared with the already available data based on Furfine-type algorithms, the MMSR data covers a broader scope, extending beyond the unsecured interbank money market. Banks that fulfill certain conditions are required to report their money market transactions on a daily basis. Transactions have to be reported both by borrowers and lenders, allowing transactions to be cross-checked within the data.[9]

The fact that the newly established reference rate €STR - replacing the survey-based EONIA - is based on MMSR data shows that as well as having the advantage of providing granular high-frequency data, the regulatory reporting is also perceived as a more reliable

improvements using Canadian payment systems data. Demiralp et al. (2004, 2006) suggest additional conditions and refinements and Kuo et al. (2013) include additional maturity bands. Millard and Polenghi (2004) apply a similar algorithm for the UK, Hendry and Kamhi (2009) for Canada, Guggenheim et al. (2011) for Switzerland, Akram and Christophersen (2013) for Norway, and Abildgren et al. (2018) for Denmark. Data based on Furfine-type algorithms have also been used to assess the representativeness of main reference rates after doubts of their reliability have been raised publicly; see, for example, Guggenheim et al. (2011)

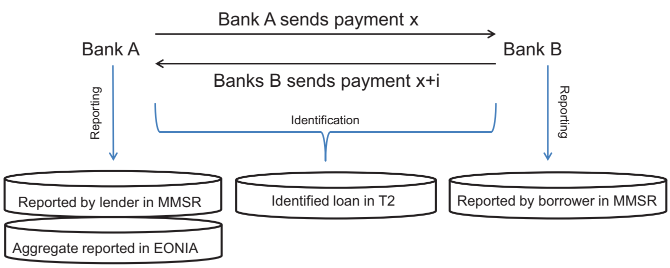
[9]The legal basis is set out in Regulation (EU) No 1333/2014 of the European Central Bank of 26 November 2014 concerning statistics on the money markets (ECB/2014/48). The importance of practical implementation aspects for this type of data is highlighted by two amending regulations, Regulation (EU) 2015/1599 (ECB/2015/30) and Regulation (EU) 2019/113 (ECB/2018/33), which clarify and simplify reporting instructions and provide detailed parameters for the reporting in order to improve the quality of the data.

source for the calculation of reference rates. In the first public consultation for developing a euro unsecured overnight interest rate by the European Central Bank (2017), MMSR data was assessed with regard to data sufficiency and representativeness and deemed appropriate .

The relevance of methodological differences between T2 and MMSR data is highlighted by the extensive use of T2 data to define and assess the calculation method of the MMSR-based €STR. T2 data are used because their availability dates back further. Eisenschmidt et al. (2018) calculate measures of fragmentation in the euro area unsecured interbank money market. In their study, the developed fragmentation indicator is calculated using T2 and MMSR data, highlighting the importance of a deep understanding of the differences between the data sources.

Figure 5.1 summarizes how interbank money market loans are captured by the three different data sources.

Figure 5.1: Stylized example of loan coverage in data sources



5.3 Data overview

We first generally compare the three different elicitation methods: survey data, data generated by a Furfine-type algorithm and reported data. The data differ in terms of methodology, scope, sample size and other attributes. Table 5.1 summarizes the data properties. Due to methodological differences among the available data, deviations between the datasets are to be expected, but the extent is unclear. It is not possible to evaluate or validate one in relation to another. Rather, we then focus on comparing the datasets and identifying structural differences empirically for transaction-level reported MMSR and identified T2 data. Which data are preferred for specific research questions depends on various factors, such as the concerned banking system structure, the current policy environment and the segments of the market that are being investigated. Based on our results, we outline concrete considerations on which dataset fits specific areas of interest.

First, EONIA comprises survey data. All overnight lending transactions of panel banks are included in its calculation. Data are reported by each bank and aggregate values and value-weighted interest rates are publicly available. We use EONIA data for comparing aggregates but not in the main part comparing T2 data and MMSR data on a transaction level. EONIA was permanently discontinued as a benchmark in January 2022. Since October 2019 the rate was calculated tracking €STR,

Second, we use loan-level data identified from TARGET2 with a Furfine-type algorithm. Despite the differences between the implementations by Arciero et al. (2016) and Frutos et al. (2016) as described in Müller and Paulick (2021), those differences are more subtle than those with different forms of data elicitation. We therefore focus on the data from the implementation by Frutos et al. (2016) when we refer to T2 data).[10] The dataset differs in some aspects from the versions described in the original literature as we use, similar to other studies, the most recent version of the continuously improved data. We use the full T2 dataset for aggregate comparison and restrict it to a German sample for the comparison on a transaction-level with German MMSR data.

Third, reported data under MMSR include publicly available aggregate values and rates. Official €STR data are published starting since October 2019, but daily data using the same methodology were previously available. The calculation of the reference rate is trimmed, with the top and bottom 25 percent of transactions in terms of value being removed. In addition, €STR also contains banks' borrowing from other financial institutions. For comparability, we use the untrimmed rates and interbank data only. Importantly, our paper also draws on confidential transaction-level data for Germany. The German sample consists of over one hundred reporting agents with reported unsecured money market loans, compared with 52 reporting agents on the European level, as the Bundesbank collects additional reporting agents' data.[11]

As only MMSR covers other market segments, we restrict the analysis to the unsecured interbank segment and specifically to overnight loans available in all three datasets.[12] The sample varies quite widely, ranging from 28 panel banks for EONIA to 52 reporting agents for MMSR on a European level, and 1209 participants (total BICs over the considered time period since 2016) active in the money market, as identified from TARGET2 data. Note that T2 data potentially covers all participants in TARGET2.[13] In addition, in

[10] We use T2 data in this context only for the identified money market loans. By contrast, TARGET2 data refers to all payments settled in TARGET2, of which money market loans are a subset.

[11] Regulation (EU) No 1333/2014 on the MMSR defines MFIs with balance sheet assets larger than 0.35 percent of total balance sheet assets in the euro area as reporting agents. In addition, national central banks may collect data from additional reporting agents based on individual requirements. For Germany, all banks holding a TARGET2 account and with a balance sheet larger than 1 billion euro are defined as reporting agents. See Deutsche Bundesbank (2017).

[12] Overnight loans refer to loans that are agreed upon and settled on the same day. In addition, T2 data might also include tomorrow/next (tom/next) and spot/next transactions that are not reported in EONIA and are listed as a separate maturity in MMSR. Tom/next refers to loans where settlement occurs the business day after the loan has been agreed upon, whereas spot/next refers to loans settled two business days after the loan has been arranged. However, the number of transactions with this maturity is negligible in the MMSR dataset. We therefore also retain tom/next and spot/next transactions in MMSR data for consistency with T2 data.

[13] Credit institutions or branches of credit institutions established in the EEA are eligible for direct participation in TARGET2. These direct participants may also settle transactions on their account on behalf of indirect participants and/or addressable BICs. As the Furfine-type algorithms take into account the originator and beneficiary institution of the transaction, the sample may potentially contain institutions from around the world. Including the branches of direct and indirect participants, a total of 44,165 credit institutions around the world (80 percent of which are located in the EEA) were accessible

Table 5.1: Data sources overview

	EONIA	T2	MMSR
Measurment Method	Survey	Furfine-type algorithm	Reporting requirement
Scope	Unsecured money market transactions	Unsecured money market transactions	Secured, unsecured, foreign exchange swap and euro overnight index swap money market transactions
Sample	Panel of 28 banks	Potentially all reachable participants in TARGET2, Active 1,209 participants (total BICs), 116 participants (German BICs) since July 2016	Panel of 52 reporting agents (EU panel) and 118 reporting agents (German panel)
Coverage of transactions	Undertaken by panel banks in EU/EFTA (location of entity)	Settled in TARGET2 (independent of booking location)	Booked in EU/EFTA (independent of origination and execution location)
Level of granularity	Aggregate across banks	Transaction	Transaction
Side of market	Lending only	Lending and borrowing	Lending and borrowing
Data availability	January 1999 to January 2022 (permanent discontinuation, since October 2019 tracking methodology based on MMSR)	May 2008 onwards	July 2016 onwards
Frequency	TARGET2 business day	TARGET2 business day	TARGET2 business day
Uncertainty and main reason for uncertainty	High Only aggregated data is provided on voluntary basis	Medium Identified transfers may not reflect actual money market transactions	Medium Misreporting may occur, matching of borrowing and lending not always possible
Data transmission	Day of trade	Day after maturity	Day of trade

Note: T2 data only becomes available after the repayment of the loan has occurred (day after maturity). By definition, this creates a time-lag compared to EONIA and MMSR. While this difference might be relevant when used for monitoring or benchmark rates, it does not affect the results of our analysis.

TARGET2, banks may use multiple BICs to settle transactions.

A seemingly rather technical issue is the coverage of loans in the different datasets. As will be shown in the next section, loan coverage is one of the main reasons for observed

via TARGET2 at the end of 2020; see TARGET Annual Report 2020, at www.ecb.europa.eu.

deviations among datasets, even more so in combination with which side of the market is captured. EONIA covers all transactions undertaken in the EU and EFTA, meaning that the location of the party into whose ledger the transaction is entered is relevant.[14] For MMSR, the reporting agents are required to report transactions that are booked in EU and EFTA, irrespective of the country of residence and where the transaction is settled. T2 data is naturally restricted to transactions settled in TARGET2, irrespective of where parties are located or where the transaction is booked.

Depending on whether the lending or borrowing side of the market is being considered, the differences in coverage can exacerbate structural measurement gaps. If, for example, parties engaging in lending are located outside EU and EFTA, but loans are booked by borrowers in EU and EFTA and settled in TARGET2, this will lead to discrepancies in the loans captured between as well as within the different datasets. Transactions that are booked by a foreign branch might go unreported in MMSR, while settlement still occurs in TARGET2.

All data sources are based on completed transactions, in contrast to other reference rates such as EURIBOR, which reflect offered rates. Nevertheless, the data sources differ in terms of the settlement of the transactions. Transactions in T2 data reflect only those transactions that have been settled in central bank money with actual fund transfers taking place, while the other two data sources can also include transactions settled outside of TARGET2, in particular on accounts of commercial banks (correspondent banking) or in other payment systems not using central bank money, such as EURO1 and internal networks (giro systems).

A related aspect is the consolidation of banking groups. All datasets exclude intragroup transaction, but the consolidation of banking groups used as the basis to exclude them differs. For EONIA and MMSR the panel banks are instructed to exclude intragroup loans from their reporting. Loans identified from TARGET2 are consolidated with information from the SWIFT Bank Directory Plus on banking group structures.[15] However, transactions settled outside TARGET2 in internal giro systems, are not necessarily classified as intragroup transactions in MMSR and EONIA. Giro systems in Germany are employed by the Landesbanken and savings banks as well as credit cooperatives. In economic terms, such transactions can be considered to be somewhere in between intra and extra-group. Whilst it can be argued that the relationship among banks operating an internal giro system is different to that between competitor banks, they are legally separate entities. One might also argue that more generally, loans not settled in central bank money are of a different quality than those settled in commercial bank money and internal systems.

Rolled-over loans are another important source of deviations. In EONIA, they are not reported unless both parties are actively involved in the issuance of a new contract (Arciero et al., 2016). In TARGET2, they can only be identified if the amounts are settled back and forth, which seems unlikely. MMSR, on the other hand, contains call account/call money (CACM) transactions. Instead of individual trades, they reflect the

[14] See www.emmi-benchmarks.eu, EONIA FAQs.

[15] T2 data may feature additional deviations as transactions settled on behalf of clients might wrongly be attributed to the bank settling the transaction. This is mitigated by the fact that the Bank Identifier Codes (BICs) of the originator and the beneficiary are used instead of settlement agents. However, it cannot be fully ruled out that these fields have not been filled in correctly by banks.

outstanding amount on cash and savings accounts with a notice.[16] These accounts are routinely rolled over unless notice is given or there are changes in the amount without full redemption. Therefore, these transactions should not be reflected in EONIA or in T2 data. Even though the CACM transactions were excluded for the calculation of the €STR reference rate under MMSR after the first public consultation, we retain these transactions for the transaction level analysis as they are actively used in the German market and in order to investigate the degree to which they are reflected in T2 data.

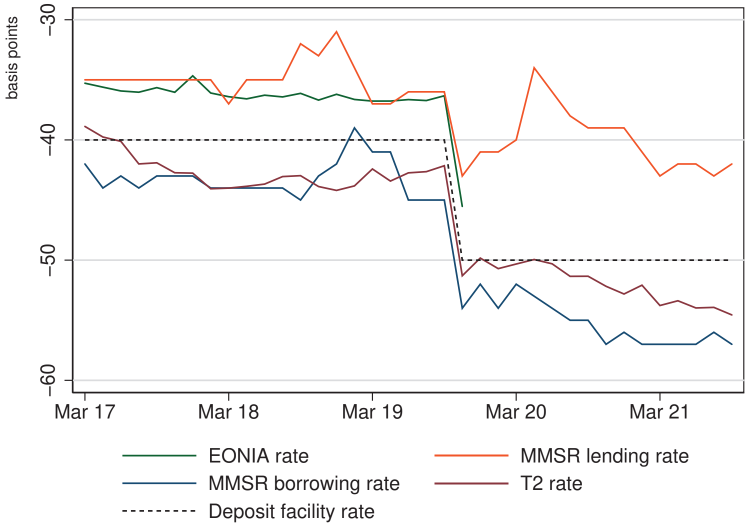
Comparing aggregate rates from the different data sources across reserve maintainance periods shows that there are marked differences in trends as well as absolute levels (Figure 5.2). Note that the trimming of 25 percent applied to the calculated benchmark rates under MMSR is not considered here, and that we use data at the euro area level. The differences are in the order of up to 20 basis points. Given the size of the market, we consider them to be substantial. Furthermore, the dynamic over time differs between data sources. Besides the expected differences occurring due to different sample sizes and the market side that is being captured, there are unexpected differences that stem from data elicitation methods.

EONIA and the lending side of MMSR should capture a similar market segment, as only lending transactions are reported under EONIA. Figure 5.2 shows that the EONIA and MMSR lending levels are fairly similar, though they do display differences in dynamics due to the methodological differences and differing samples. Notably, the MMSR lending rate increased in 2018 while EONIA remained stable. The MMSR borrowing rate lies markedly below the lending rate and below the deposit facility rate. For an interim period, EONIA was calculated as the borrowing rate based on MMSR data plus a spread of 8.5 basis points until its discontinuation at the beginning of 2022 when the transition to €STR was finalized. Concerning the calculation of benchmark rates, this illustrates that the reporting side of transactions affects the level of interest rates as well as their dynamics. Interestingly, the spread between borrowing and lending rates has widened considerably after the lowering of the deposit facility rate in 2019. Rates from T2 data roughly follow the MMSR borrowing rate and lie between the borrowing and lending rates after the decrease in interest rates in September 2019. The MMSR borrowing rate dropped further from the deposit facility at -50 basis points thereafter.

The comparison of interbank borrowing and lending rates illustrates that on average, euro area reporting agents borrow at lower rates in the money market than they lend. The same observation can be made for the German reporting agents and the German extended sample. The main reason for this is that the MMSR borrowing side captures more loans with very low interest rates.The reasoning for rates below the deposit facility may be the expansive monetary policy stance. Banks with access to standing facilities can profit by borrowing money below the deposit facility rate. At the same time, few banks suffer from liquidity shortages in times of ample reserves and thus will only borrow liquidity at rates

[16] See Reporting instructions for the electronic transmission of money market statistical reporting, December 2018. The inclusion of CACM transactions was also subject of the first public consultation (European Central Bank, 2017). While some respondents indicated a preference for including CACM transactions due to the importance of such transactions in their jurisdiction and for their own money market activity, it was decided to exclude them from the calculation of rates. Compared with deposit transactions, it was argued, CACM practices and pricing differ across jurisdictions and are only used by a small number of reporting agents. Notwithstanding these arguments, we find high usage in the overnight interbank market for the broader German panel.

Figure 5.2: Aggregate rates



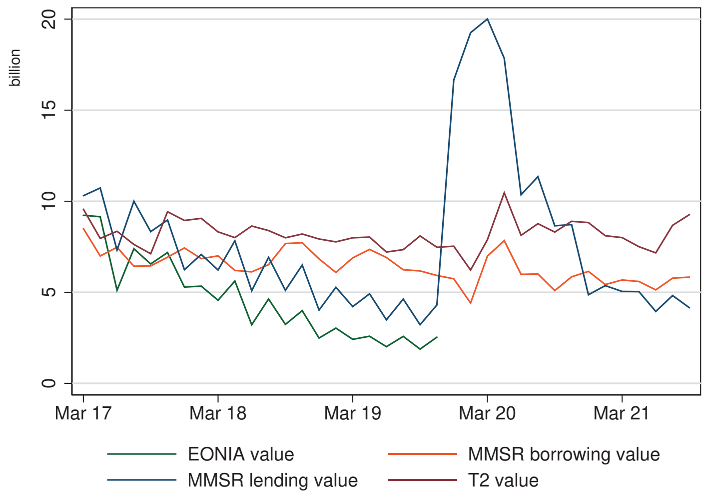
Note: Data points per reserve maintainance period. Source: ECB and authors' calculations.

below the renumeration rate of reserves. The difference stems mainly from transactions with counterparties outside Germany and the euro area that are not reporting agents. We observe from the data that counterparties outside the euro area are much more likely to lend at rates below the deposit facility rate. As shown by Bech and Klee (2011) and Abbassi et al. (2021), banks without access to the standing facilities engage in this type of lending. Transactions below the deposit facility rate occur almost exclusively in the borrowing transactions (32 percent of loans) and are virtually non-existent in the lending transactions (0.3 percent of loans). As transactions from counterparties outside the euro area are more likely to be booked abroad, the reporting requirement only applies to the reporting agent on the borrowing side of the transaction. The rate calculated from T2 data is closer to the borrowing rate than to the lending rate as T2 data are not subject to this reporting bias. Both legs of a transaction are settled in TARGET2 irrespective of where the transaction is booked.

In terms of value, EONIA and MMSR lending data exhibit similar dynamics, but with a constantly higher value of MMSR loans until the out-phasing of EONIA (Figure 5.3). This is likely due to the larger sample employed by MMSR compared to EONIA panel banks. T2 data and MMSR borrowing data show differences in levels as well as in their evolution, but broadly follow a similar path. T2 overall values lie higher than MMSR borrowing values. This is likely because there is no sample restriction on the banks captured in T2 data.

Following the introduction of the two-tier system in the euro area in October 2019, MMSR lending values increase sharply, while borrowing and T2 values show no increase. The two-tier system exempts a part of banks' excess liquidity holdings from negative remuneration. This led to a redistribution of liquidity from banks with liquidity holdings beyond their exemption allowance to banks with liquidity holding below their allowance. Particularly, savings banks and cooperatives held liquidity well below their allowances. The jump in lending reflects to a large degree flows from central institutions and Landesbanken to credit cooperatives and savings banks (see Deutsche Bundesbank, 2021). At the same time, those savings banks and credit cooperatives are largely not part of the reporting sample. Hence, transaction are reported on the lending side, but not on the borrowing side. As many of the loans settle in giro systems, they are not reflected in T2 data either.

Figure 5.3: Aggregate values



Note: Data points per reserve maintainance period. Source: ECB and authors' calculations.

In terms of policy implications, aggregate results show that market dynamics do depend on which side of the market is captured and which data source is employed. Market dynamics and absolute values show marked differences at times. Some of the differences appear counterintuitive at first, as the effects of seemingly nuanced differences in data generation strongly affect results. Importantly, limiting analysis to one dataset or side of the market would obscure the effect of monetary policy measures in the market.

5.4 Transaction level comparison of T2 and MMSR data

In order to investigate the underlying reasons for the observed differences at aggregate level, we directly compare the German sample of MMSR and T2 data on a loan level. In the comparison, we control for known deviations in order to identify remaining sources of differences.

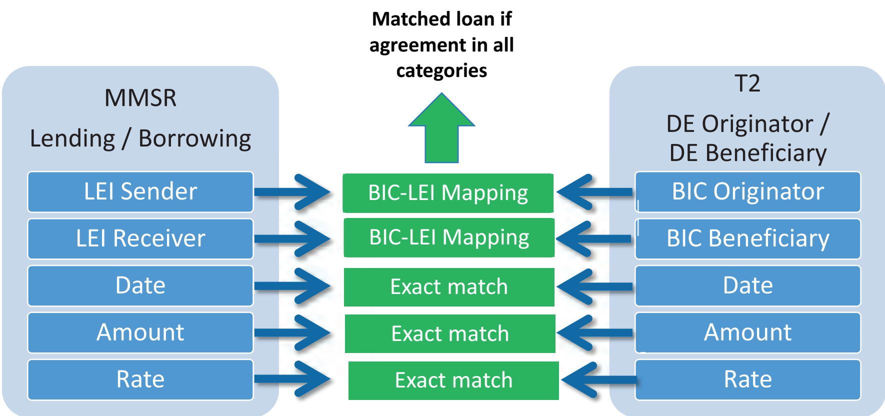
5.4.1 Matching results

Since the data do not share common identifiers, we use five loan characteristics and match loans only if all five characteristics match. Besides the payout and repayment date, the amount and interest rate also have to match exactly. The lender and borrower of transactions have to correspond for matched loans as well.

As the identifiers of entities differ in both datasets, we map Legal Entity Identifiers (LEIs) and BICs (BIC-LEI Mapping) based on data from the SWIFT Bank Directory Plus with manually added information on settlement agents and group structures. Available mapping data mostly infer a mapping where one LEI refers to one BIC. However, one entity commonly employs multiple BICs for settling payments. This may be due to mergers and acquisitions, different branches, subsidiaries or business areas. A mere one-to-one mapping would therefore not capture all payments of a legal entity. For this reason, we map LEIs to all BICs known to belong to a given institution in TARGET2. In some cases, multiple LEIs settle payments via the same BIC, which is also captured by our extended mapping. The BICs mapped to the LEI in the MMSR data are matched with the BIC of the originator and beneficiary of the transactions in T2 data.

We split MMSR data into two datasets, one for lending and one for borrowing transactions. Both are matched to T2 data in two independent matching processes. Each loan is only matched once, thus eliminating multiple matches.

Figure 5.4: Matching of German MMSR and T2 data



The transaction-level datasets differ in terms of geographic scope: T2 data potentially cover all participants accessing TARGET2, while MMSR transaction-level data are available only for a specified sample of German reporting agents. We therefore apply a filter for German transactions in T2 data ex ante to the matching process. The filter is based on the country code included in the BIC of the originator (lending dataset) and the beneficiary (borrowing dataset).[17]

In addition to the ex ante filter necessary to align the data scope, we control for explainable unmatched transactions. We apply an additional ex post filter, taking into account CACM transactions reported under MMSR.[18]

Rolled-over CACM transactions will most likely not be identified by a Furfine-type algorithm as it is highly unlikely that the same full amount plus interest rate is settled back-to-back every day. At the same time, there are good arguments to treat rolled-over CACM transactions differently to other money market loans. Kovner and Skeie (2013) point out that in market usage, at times only immediately available balances are referred to as "pure fed funds", as opposed to continuing contracts. For similar reasoning, CACM transactions are excluded as instruments for the calculation of €STR (see European Central Bank, 2018).

However, instead of simply dropping all CACM transactions, we identify and filter only those with an unchanged amount from one day to another in each lender-borrower pair. In other words, we only keep those CACM transactions when there is a change in the amount, i.e. an active change in the underlying economic parameters by the two parties. Using this adjusted filter, the likelihood of a match for a non-rolled-over CACM transaction with a transaction in T2 data should still be reduced compared to other money market loans, given that potentially only the delta amount is transferred.[19] However, excluding CACM transactions across the board leads to a significant reduction in the number of matched transactions. CACM transactions with changes to the terms are in some instances settled in TARGET2, while this is almost never the case for rolled-over CACM transactions.

Additional explanations can be found for remaining unmatched transactions, both for MMSR data and for T2 datas. On the T2 side, these consist of money market loans involving banks that are not reporting agents in MMSR. On the MMSR side, these are loans reported for counterparties that are not active in TARGET2. As an additional technical aspect, the Furfine-implementation is restricted to the identification of "round" amounts (minimum amount and constant increments) in order to reduce false positive identifications. Odd amounts reported under MMSR are therefore not matched with T2 data by definition. Figure 5.5 and Figure 5.6 summarize the matching results for the borrowing and lending sides respectively in treemaps.

The following main observations can be made: First, the explainable differences between the two datasets are significant. On the T2 side, a significant number of transactions originate from institutions not being a reporting agent in MMSR, even taking into account the larger German sample. Against this background, T2 data should be considered as an important complement to MMSR data with restricted sampling. On the MMSR side, a very substantial share of transactions is made up of rolled-over CACM transactions which are not identified in T2 data.

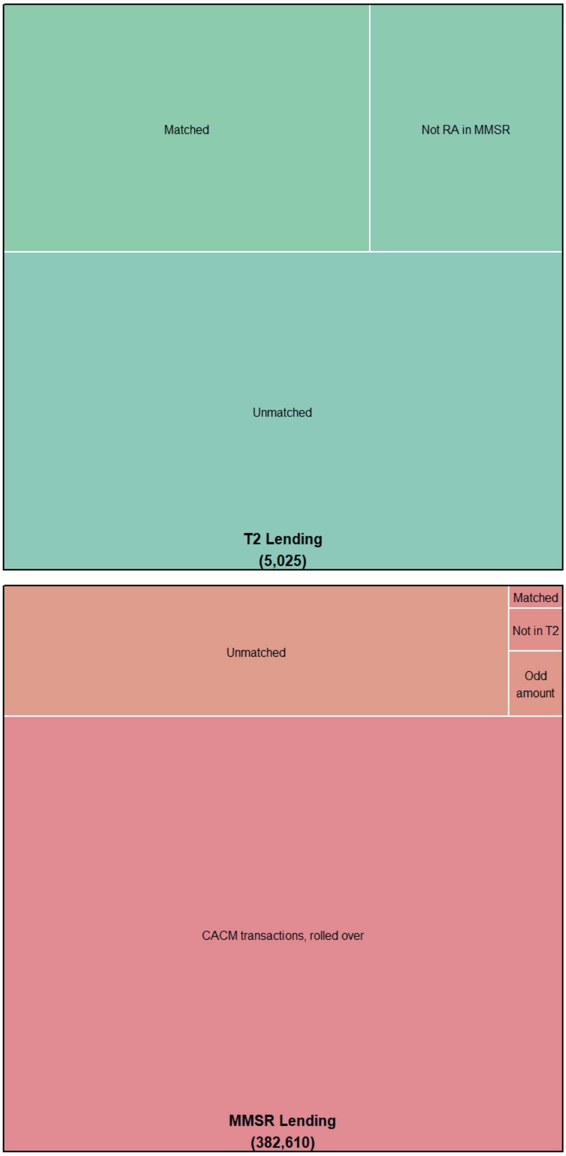
Second, the results for T2 and MMSR data still differ significantly after taking into

[17]Broader filters which also include payment transactions where the BIC of the sending or receiving settlement agents' account or the head institution of the banking group contains the country code "DE", have only limited effect on the number of matched transactions. This is in line with the MMSR reporting requirements, as these loans should not be reported by the settlement agent or the banking group head.

[18]As there might be multiple matches for one T2 transaction with both a CACM and a non-CACM transaction, matching non-CACM transactions take priority in the matching.

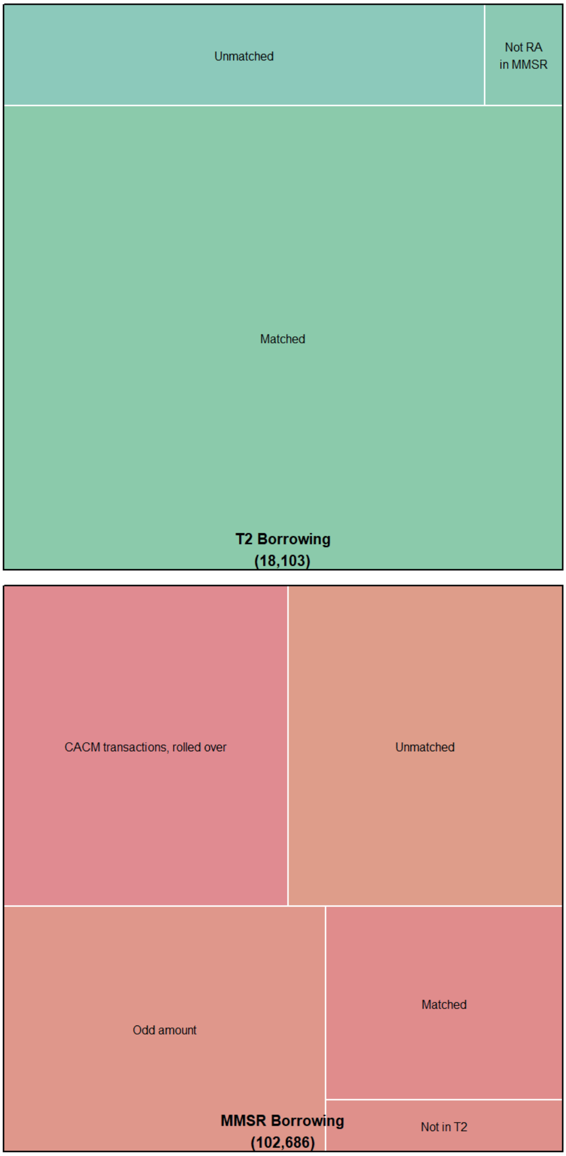
[19]We also accounted for the possibility of the settlement of delta amounts in the matching, but found only a negligible number of cases where this led to a match of loans with T2 data.

Figure 5.5: Overview of matches and deviations MMSR-T2, lending



Note: *Not RA in MMSR* is a TARGET2 participant that is not a reporting agent under the MMSR. *CACM, rolled-over* are Call account/call money transactions that are rolled-over transactions, meaning that there is no change in the underlying amount. *Odd amounts* are not taken into account in T2 data. *Not in T2* means no account for at least one of the involved parties could be identified in T2 data. *Matched* are transactions for which all details match in MMSR and T2. *Unmatched* transaction are those where none of the above apply. The size of rectangles corresponds to the share of concerned loans.

Figure 5.6: Overview of matches and deviations MMSR-T2, borrowing



Note: *Not RA in MMSR* is a TARGET2 participant that is not a reporting agent under the MMSR. *CACM, rolled-over* are Call account/call money transactions that are rolled-over transactions, meaning that there is no change in the underlying amount. *Odd amounts* are not taken into account in T2 data. *Not in T2* means no account for at least one of the involved parties could be identified in T2 data. *Matched* are transactions for which all details match in MMSR and T2. *Unmatched* transaction are those where none of the above apply. The size of rectangles corresponds to the share of concerned loans.

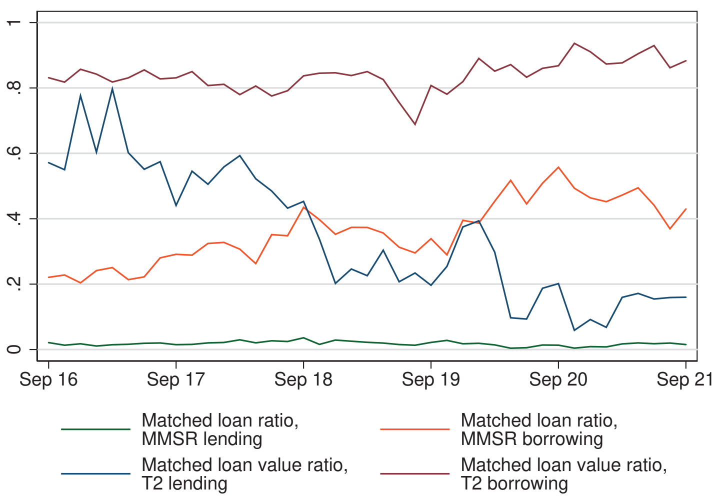
account the explanations for unmatched transactions. The ratio of matched transactions is higher in T2 data than in the MMSR data respectively. In other words, a larger share of loans in T2 data can also be found in the MMSR data than vice versa. In this respect, the coverage of MMSR data is broader than that of T2 data.

Third, the results for the borrowing and lending sides differ as well. In general, the share of matched loans is higher on the borrowing side both for T2 and for MMSR data. We attribute this to the location of counterparties, which leads to some of the loans not being reported on the lending side.

5.4.2 Explaining unmatched transactions

For the remainder of this paper, we consider only matched and remaining unexplained unmatched transactions. On this basis, Figure 5.7 shows the match ratios for T2 and MMSR data. These are calculated as the ratio of matched loans to overall loans in the respective datasets. On average, 35 percent of T2 loans are matched with MMSR loans on the lending side and 84 percent on the borrowing side. On the lending side, the ratio has been continuously declining. Part of the reason is the relatively low number of loans. Continuously unmatched loans between pairs of banks thus affect the ratio, especially if such loans increase over time. Looking at matches from the perspective of MMSR data, the ratios are markedly lower, ranging from about 20 percent to just above 60 percent (average 34 percent) for the borrowing side. On the lending side, an even smaller share of roughly 2 percent is matched with T2 loans, which stems from the fact that MMSR data includes a substantially larger number of loans than T2 data.

Figure 5.7: Matched loan ratios



Note: Data points per reserve maintainance period.

To explain differences in a structural way, we employ a probit model for individual transactions, using the outcome *unmatched* (equals 0) or *matched* (equals 1) as the dependent variable (see Table 5.2 and Table 5.4). The model is applied to the MMSR datasets of matched and unexplained unmatched transactions for both borrowing and lending. The coefficients indicate the change in the probability that an MMSR transaction is matched with a respective transaction in the T2 data. In addition, we calculate the average marginal effects of the explanatory variables (Table 5.3 and Table 5.5). The marginal effects can be interpreted as the average change in probability for being matched given an increases by one unit of the independent variables. As independent variables, several loan characteristics are included as controls. Importantly, the classes of banking groups the reporting agent belongs to are considered as dummy variables. The reference group is *big banks*. As a further explanatory variable, the dummy *giro system* captures whether the two banks involved in the money market loan belong to banking groups that operate a common settlement system, as pointed out for example by Upper and Worms (2004). These giro systems are employed by savings banks and Landesbanken as well as credit cooperatives in Germany, including the respective head institutions.[20] Such loans are often not be settled in TARGET2, but rather in the internal giro system, thus decreasing chances of being matched.

We run several specifications of the model for robustness. As a main result, the banking system structure appears as an important determinant of the matching outcome. From the marginal effects in Table 5.3 and Table 5.5, we conclude that differences are economically meaningful, as the effect on matching probabilities is quite substantial for some banking classes as well as for loan characteristics. More so, this is especially true for the borrowing side where matching ratios are higher. Within banking classes, loans by foreign banks are significantly more likely to be matched whereas loans by mortgage banks and savings banks are less or equally likely to be matched compared to the reference group of big banks. Economically significant effects are also observed for CACM transactions, loans with a rate at zero and below the deposit facility.

As expected, the giro system dummy is substantive and negative in all specifications. This is in line with the assumption that MMSR data contain loans not settled in TARGET2. This confirms the banking group structure as one of the main reasons for the observed deviations. It can also explain that the banking group specific effect is not statistically significant for savings banks in the models with additional controls. This may be due to the fact that savings banks typically engage in transactions with Landesbanken which is picked up in the giro system variable. The same is true for the group of credit cooperatives which includes the central institutions.

Regarding the impact of overall monetary policy conditions, the rate of the individual loan and the amount have opposing effects on the borrowing and lending side. This could relate to the measurement asymmetry of the two sides. The probability of matching is substantially lower for zero rate loans. This is in line with the argument that zero rate loans are a particular challenge for Furfine-type algorithms, while negative rates do not pose a general problem. Rates below the deposit facility rate are matched with a higher probability on the borrowing side. On the lending side, the effect is negative in the specifications excluding banking groups, but the absolute number of loans below the deposit facility rate is very low (1 percent of loans versus 43 percent in the borrowing data) Aslending below the deposit facility rate is reasonable for, often foreign, banks or branches that do not have access to standing facilities and which are typically not reporting agents,

[20]The respective head institutions are included in the classes of Landesbanken and credit cooperatives.

Table 5.2: Probit model, lending side

	(1)	(2)	(3)	(4)	(5)
	Match result MMSR lending				
Reporting agent banking class					
Regional and commercial banks	0.182*	0.211**	-0.104		
	(0.094)	(0.095)	(0.079)		
Landesbanken	1.109***	1.079***	0.644***		
	(0.092)	(0.093)	(0.074)		
Savings banks	-0.073	-0.138	-0.259**		
	(0.121)	(0.122)	(0.108)		
Credit cooperatives	0.597***	0.608***	-0.114		
	(0.116)	(0.117)	(0.096)		
Mortgage banks	0.081	0.009	-0.074		
	(0.157)	(0.158)	(0.147)		
Banks with special tasks	0.152	0.098	0.061		
	(0.122)	(0.121)	(0.110)		
Foreign banks and others	3.017***	2.965***	2.582***		
	(0.172)	(0.173)	(0.141)		
Big banks (reference group)					
Loan characteristics					
Loan amount (mio)	0.001***			0.000	
	(0.000)			(0.000)	
Rate of loan (bp)	0.009***			0.007***	
	(0.001)			(0.001)	
Rate below deposit facility	0.402***	0.159		-0.099	-0.331***
	(0.109)	(0.102)		(0.089)	(0.079)
Zero rate loan	-2.687***	-2.429***		-1.770***	-1.543***
	(0.424)	(0.423)		(0.337)	(0.335)
Instrument type CACM	-0.884***	-0.901***		-0.809***	-0.790***
	(0.036)	(0.036)		(0.032)	(0.032)
Within giro system	-1.521***	-1.557***	-1.332***	-1.169***	-1.188***
	(0.032)	(0.032)	(0.029)	(0.026)	(0.025)
Constant	-1.546***	-1.751***	-1.725***	-0.893***	-1.119***
	(0.095)	(0.089)	(0.071)	(0.044)	(0.019)
Observations	81,341	81,341	81,341	81,341	81,341
Pseudo R2	0.312	0.308	0.247	0.232	0.230

Table reports coefficients and standard errors in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 5.3: Average marginal effects, lending side

	Match result MMSR lending				
Reporting agent banking class					
Regional and commercial banks	0.002**	0.002**	-0.002		
	(0.001)	(0.001)	(0.001)		
Landesbanken	0.028***	0.028***	0.021***		
	(0.001)	(0.001)	(0.002)		
Savings banks	-0.001	-0.001	-0.004**		
	(0.001)	(0.001)	(0.002)		
Credit cooperatives	0.009***	0.010***	-0.002		
	(0.002)	(0.002)	(0.002)		
Mortgage banks	0.001	0.000	-0.001		
	(0.002)	(0.001)	(0.002)		
Banks with special tasks	0.002	0.001	0.001		
	(0.001)	(0.001)	(0.002)		
Foreign banks and others	0.325***	0.315***	0.387***		
	(0.043)	(0.043)	(0.043)		
Loan characteristics					
Loan amount (mio)	0.000***			0.000	
	(0.000)			(0.000)	
Rate of loan (bp)	0.000***			0.000***	
	(0.000)			(0.000)	
Rate below deposit facility	0.018***	0.006		-0.003	-0.009***
	(0.006)	(0.004)		(0.003)	(0.002)
Zero rate loan	-0.018***	-0.018***		-0.018***	-0.018***
	(0.000)	(0.000)		(0.001)	(0.001)
Instrument type CACM	-0.024***	-0.024***		-0.025***	-0.024***
	(0.001)	(0.001)		(0.001)	(0.001)
Within giro system	-0.112***	-0.117***	-0.094***	-0.072***	-0.074***
	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)

Standard errors in parentheses are calculated using delta-method.
*** p<0.01, ** p<0.05, * p<0.1

Table 5.4: Probit model, borrowing side

	(1)	(2)	(3)	(4)	(5)
	Match result MMSR borrowing				
Reporting agent banking class					
Regional and commercial banks	0.744***	0.873***	-0.701***		
	(0.059)	(0.058)	(0.043)		
Landesbanken	0.919***	0.925***	0.930***		
	(0.023)	(0.022)	(0.022)		
Savings banks	-0.061	0.063	-0.505***		
	(0.054)	(0.053)	(0.050)		
Credit cooperatives	0.811***	0.950***	0.878***		
	(0.037)	(0.036)	(0.034)		
Mortgage banks	-0.340***	-0.211***	-0.947***		
	(0.070)	(0.069)	(0.065)		
Banks with special tasks	1.677***	1.725***	1.187***		
	(0.033)	(0.033)	(0.029)		
Foreign banks and others	1.755***	1.876***	1.426***		
	(0.113)	(0.113)	(0.110)		
Big banks (reference group)					
Loan characteristics					
Loan amount (mio)	-0.003***			-0.003***	
	(0.000)			(0.000)	
Rate of loan (bp)	-0.007***			-0.008***	
	(0.001)			(0.001)	
Rate below deposit facility	0.645***	0.821***		0.844***	1.007***
	(0.029)	(0.025)		(0.023)	(0.019)
Zero rate loan	-2.111***	-2.244***		-1.917***	-1.991***
	(0.241)	(0.239)		(0.235)	(0.233)
Instrument type CACM	-1.866***	-1.730***		-1.542***	-1.393***
	(0.036)	(0.036)		(0.033)	(0.033)
Within giro system	-1.770***	-1.711***	-2.240***	-1.701***	-1.635***
	(0.041)	(0.042)	(0.037)	(0.040)	(0.040)
Constant	-1.348***	-1.370***	-0.766***	-0.788***	-0.739***
	(0.047)	(0.028)	(0.019)	(0.033)	(0.017)
Observations	43,485	43,485	43,485	43,485	43,485
Pseudo R2	0.409	0.388	0.284	0.338	0.316

Table reports coefficients and standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5.5: Average marginal effects, borrowing side

	(1)	(2)	(3)	(4)	(5)
	Match result MMSR borrowing				
Reporting agent banking class					
Regional and commercial banks	0.169***	0.204***	-0.115***		
	(0.014)	(0.014)	(0.006)		
Landesbanken	0.212***	0.217***	0.265***		
	(0.005)	(0.005)	(0.005)		
Savings banks	-0.012	0.013	-0.091***		
	(0.010)	(0.011)	(0.008)		
Credit cooperatives	0.185***	0.223***	0.249***		
	(0.009)	(0.008)	(0.010)		
Mortgage banks	-0.059***	-0.038***	-0.136***		
	(0.011)	(0.012)	(0.006)		
Banks with special tasks	0.385***	0.404***	0.343***		
	(0.007)	(0.007)	(0.008)		
Foreign banks and others	0.401***	0.434***	0.411***		
	(0.023)	(0.022)	(0.030)		
Loan characteristics					
Loan amount (mio)	-0.001***			-0.001***	
	(0.000)			(0.000)	
Rate of loan (bp)	-0.002***			-0.002***	
	(0.000)			(0.000)	
Rate below deposit facility	0.150***	0.198***		0.219***	0.266***
	(0.007)	(0.006)		(0.006)	(0.005)
Zero rate loan	-0.321***	-0.329***		-0.317***	-0.324***
	(0.012)	(0.010)		(0.013)	(0.011)
Instrument type CACM	-0.349***	-0.334***		-0.322***	-0.304***
	(0.004)	(0.004)		(0.004)	(0.005)
Within giro system	-0.351***	-0.344***	-0.428***	-0.353***	-0.345***
	(0.005)	(0.005)	(0.003)	(0.004)	(0.004)

Standard errors in parentheses are calculated using delta-method.
*** p<0.01, ** p<0.05, * p<0.1

they are unlikely to be reported on the lending side. Remaining reported transactions can be considered special cases or even falsely reported data and are therefore likely not present in T2 data. As expected, in terms of market practices, non-rolled-over CACM transactions have a lower probability of being matched.

The model shows that the structure of the banking system, market practices and the monetary policy environment affect the matches of individual loans between MMSR and T2 data. The segment of the market that is captured by the data differs depending on these factors. Based on the pseudo R-squared, these factors explain a substantial share of deviations.

Given the impact of the giro systems and banking classes, it can be argued on the one hand that the coverage of panel banks' activity in MMSR data is wider, but that on the other hand, this increased coverage includes loans not settled in central bank money. Loans that are settled internally could be considered of a different nature reflecting banking sector-specific practices.

5.5 Impact

Given the differences in matching likelihoods, the impact on aggregate rates and values of these deviations is of interest. For a comprehensive overview of differences in rates, matching outcomes, frequencies and values Table 5.6 provides summary statistics for the different categories of loans in the probit models and T2. Note that loans can belong to more than one category. Big banks stand out as their lending and borrowing rates are relatively far apart from each other. Marked rate differences can be observed for credit cooperatives on the lending side and regional and commercial banks on the borrowing side. Matching outcomes are uneven, but especially striking is a high matching ratio for foreign banks and others, though there are relatively few loans. On the borrowing side, high matching ratios are also observed for big banks, banks with special tasks and Landesbanken.

Keeping in mind uneven measurement, studies on the market structure may be heavily influenced by the inclusion or exclusion of loan categories and bank classes. For example, network topologies may differ significantly in terms of number of links and the importance of nodes in the network.

Within MMSR data, different interest rates may prevail among different bank classes which in turn are unevenly captured in T2 data. To structurally test differing interest rates among bank classes, we estimate a model of interest rate spreads using OLS. Spreads are the difference between the loan interest rate and the applicable deposit facility rate. As independent variables we employ bank classes as well as loan characteristics, similar to the model above. For a loan i, we estimate the spread dependent on the the reporting agent banking class c and different control variables in vector X_i.

$$Spread_i = \beta_0 + \beta_c Bank\,class_i + \beta' X_i + \epsilon_i \tag{5.1}$$

We remove outliers that lie well above observed rates which seem the result of special arrangements and heavily influence overall rates. These outliers play a very minor role for matching, but distort the estimation. The reference groups are again big banks with

Table 5.6: German sample by banking and loan categories

	Rate (bp)	**Rate diff.**	**Number of loans**	**Amount (in mio)**	**Matched, percent**
Lending side. MMSR					
Big banks	-57.9	-19.5	994	72,085	4.2
Foreign banks and others	-34.1	4.3	138	2,469	80.4
Banks with special tasks	-40.7	-2.2	645	27,565	4.8
Mortgage banks	-39.0	-0.5	333	15,297	3.6
Credit cooperatives	-30.1	8.3	21,375	243,100	0.2
Savings banks	-36.8	1.7	3,588	97,082	0.6
Landesbanken	-38.8	-0.3	49,728	2,027,161	2.1
Regional and commercial banks	-38.8	-0.3	4,540	350,573	3.4
Within giro system	-38.0	0.5	68,355	2,175,110	0.5
Instrument type CACM	-35.6	2.9	39,990	704,824	0.4
Zero rate loan	0.0	38.5	375	9,198	0.3
Rate below deposit facility	-66.5	-28.0	800	74,451	4.5
Overall	-38.5	0.0	81,341	2,835,330	1.8
Borrowing side. MMSR					
Big banks	-24.6	18.9	5,208	407,101	22.2
Foreign banks and others	-33.1	10.4	157	6,233	74.5
Banks with special tasks	-46.1	-2.7	3,682	222,664	66.3
Mortgage banks	-39.1	4.3	1,292	62,336	4.3
Credit cooperatives	-46.1	-2.6	5,463	323,619	19.3
Savings banks	-38.0	5.4	4,169	278,869	1.8
Landesbanken	-49.7	-6.3	21,082	1,357,830	46.5
Regional and commercial banks	-33.7	9.7	2,432	40,559	7.1
Within giro system	-41.4	2.1	10,429	608,074	1.0
Instrument type CACM	-41.1	2.4	6,783	166,641	3.6
Zero rate loan	0.0	43.5	742	12,032	0.3
Rate below deposit facility	-50.9	-7.4	24,705	1,639,738	54.4
Overall	-43.5	0.0	43,485	2,699,210	34.2
T2					
Lending	-47.6		4,265	771,328	33.8
Borrowing	-49.3		17,654	923,075	84.2

the average lending rate per loan at -50 basis points on the borrowing side and -49 basis points on the lending side.

The results in Table 5.7 and Table 5.8 show credit cooperatives are able to lend at relatively favorable terms. Lending money, the rate is roughly 27 basis points higher compared to big banks. The same is true to a lesser degree for foreign banks and savings banks, with significantly higher lending rates controlling for loan characteristics. Within giro systems loans, lie roughly 3 basis points lower, controlling for banking classes. At the same time, loan spreads are roughly 6 basis points higher on the borrowing side for loans in giro systems. This could point to the fact that within giro systems, there is less room for arbitrage, as counterparties have access to standing facilities. Compared to the other bank classes, Landesbanken, credit cooperatives and banks with special tasks borrow at relatively lower spreads on the borrowing side, with negative or slightly positive coefficients. Regional and commercial banks borrow at relatively high spreads, meaning rates are more favorable than the deposit facility rate. In times of ample central bank reserves some banks could engage in money market lending and borrowing for arbitrage, while some banks accept less favorable rates to finance liquidity needs. This is in line with a concentration of excess liquidity across countries as well as on a bank level, as observed by Aberg et al. (2021) and Baldo et al. (2017).

The loan type has little impact on loan spreads. Coefficients are significant on the lending side, but economically small. On the borrowing side, the effect is yet smaller and less significant statistically. Interestingly, higher loan amounts are associated with lower spreads on the lending side and higher spreads on the borrowing side.

Related to bank classes is the prevalence of cross-border loans. A particularly interesting observation concerns the importance of the geographical attribution of a loan, comparing the settlement location, relevant for T2 data, and the booking location, relevant for MMSR data. By definition, all transactions in TARGET2 are settled in the respective countries connected to TARGET2. However, the transacting banks may be located and book transactions anywhere in the world. A significant number of loans that were identified in T2 data as having both a German originator and beneficiary were matched in the borrowing dataset but not in the lending dataset of MMSR. The different geographical attribution causes deviations between lending and borrowing side in the MMSR data.

The following example illustrates this observation. Assume a German reporting bank borrows funds from a foreign branch of a German bank. On the borrowing side, the transaction is reported by the German reporting agent. On the lending side, the loan goes unreported as the foreign branch books the transaction abroad. At the same time, the transaction is still captured in T2 data, as settlement takes place via the German head institution in TARGET2.

In line with this reasoning, we find that the geographic distribution of counterparties in MMSR and T2 data differs significantly for Germany (Figure 5.8). The share of German counterparties is significantly higher for MMSR data, especially on the lending side. MMSR lending data largely include German counterparties (96 percent of the number of loans and 92 percent of loan values), while the discrepancy in T2 data is less pronounced or rather absent for transaction values. The observed differences in the datasets stem from the fact that domestic transactions are more likely to be settled in internal systems and are therefore not captured in the T2 data. Therefore, MMSR data include more trans-

Table 5.7: Loan rate spreads, lending side

	(1)	(2)	(3)	(4)
	Spread to deposit facility			
Reporting agent banking class				
Regional and commercial banks	14.080***	13.695***	14.361***	
	(1.159)	(1.169)	(1.169)	
Landesbanken	14.105***	14.534***	12.366***	
	(1.158)	(1.166)	(1.158)	
Savings banks	16.416***	17.283***	15.274***	
	(1.165)	(1.172)	(1.167)	
Credit cooperatives	27.447***	28.171***	26.430***	
	(1.163)	(1.170)	(1.158)	
Mortgage banks	8.826***	9.272***	9.456***	
	(1.166)	(1.173)	(1.172)	
Banks with special tasks	11.213***	11.777***	11.837***	
	(1.162)	(1.170)	(1.170)	
Foreign banks and others	16.005***	17.088***	17.088***	
	(1.545)	(1.555)	(1.555)	
Big banks (reference group)				
Loan characteristics				
Loan amount (mio)	-0.020***			-0.035***
	(0.001)			(0.001)
Instrument type CACM	0.744***	1.326***		5.661***
	(0.059)	(0.052)		(0.070)
Within giro system	-2.937***	-2.957***		1.399***
	(0.133)	(0.136)		(0.126)
Constant	-5.781***	-7.218***	-7.218***	6.201***
	(1.154)	(1.157)	(1.157)	(0.153)
Observations	81,341	81,341	81,341	81,341
R-squared	0.453	0.445	0.434	0.162

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

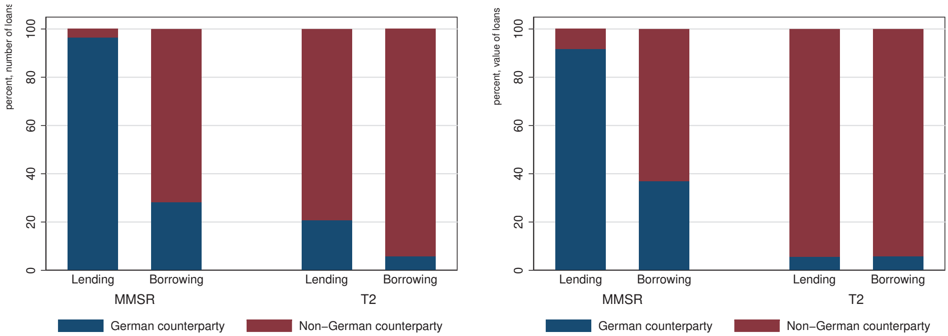
Table 5.8: Loan rate spreads, borrowing side

	(1)	(2)	(3)	(4)
	Spread to deposit facility			
Reporting agent banking class				
Regional and commercial banks	20.214***	19.955***	19.757***	
	(0.400)	(0.400)	(0.372)	
Landesbanken	-1.211***	-1.261***	-0.200*	
	(0.110)	(0.114)	(0.113)	
Savings banks	5.812***	5.789***	9.783***	
	(0.188)	(0.189)	(0.149)	
Credit cooperatives	0.572***	0.506***	4.514***	
	(0.166)	(0.169)	(0.163)	
Mortgage banks	8.582***	8.461***	8.354***	
	(0.121)	(0.124)	(0.116)	
Banks with special tasks	4.598***	4.528***	4.461***	
	(0.138)	(0.140)	(0.140)	
Foreign banks and others	12.010***	11.765***	11.770***	
	(1.251)	(1.253)	(1.253)	
Big banks (reference group)				
Loan characteristics				
Loan amount (mio)	0.006***			0.001***
	(0.000)			(0.000)
Instrument type CACM	-0.131	-0.362**		3.318***
	(0.145)	(0.143)		(0.125)
Within giro system	6.016***	5.976***		5.172***
	(0.092)	(0.091)		(0.072)
Constant	-6.371***	-5.880***	-5.884***	-4.531***
	(0.104)	(0.106)	(0.106)	(0.076)
Observations	42,935	42,935	42,935	42,935
R-squared	0.391	0.387	0.335	0.077

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

actions with both parties located in Germany. Additionally, cross-border transactions of German banks are not reported for MMSR when they are booked outside EU and EFTA, but such transactions are often captured in T2 data. The two datasets thus capture domestic and international money market activity to varying degrees. The composition of counterparties shows that cross-border transactions are predominately reported on the borrowing side for MMSR, as German banks borrow from counterparties abroad that do not report these loans. Therefore, MMSR data arguably suffers from a reporting bias for loaned and borrowed funds, which is exacerbated depending on a country's market structure. On the other hand, T2 data lacks a portion of domestic loans reported in MSMR. Even though this difference appears rather technical, substantial deviations arise from the different concepts of settlement location versus booking location of money market loans.

Figure 5.8: Counterparty locations for loans by German reporting agents



Lastly, we compare dispersion of interest rates in T2 and MMSR. Amongst others, Altavilla et al. (2019) calculate the dispersion of interest rates applied to the money market using T2 data as a proxy for interest rate uncertainty. The cross-sectional dispersion for a business day is given by the value-weighted standard deviation of interest rates. The rate of a loan i is denoted r:

$$Dispersion = \sqrt{\sum_{i=1}^{N} w_i (r_i - \bar{r})^2} \tag{5.2}$$

where weights are calculated for loan values v:

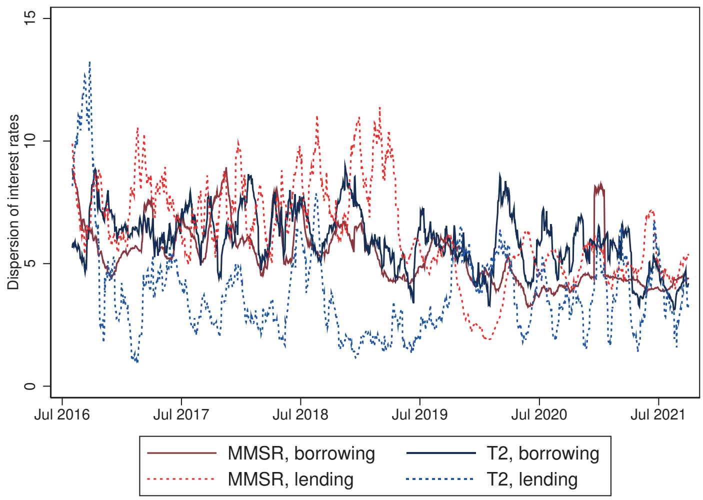
$$w_i = \frac{v_i}{\sum_{i=1}^{N} v_i} \tag{5.3}$$

and where:

$$\sum_{i=1}^{N} w_i = 1 \qquad \text{and} \qquad \bar{r_b} = \sum_{i=1}^{N} w_i r_i \tag{5.4}$$

Dispersion is more volatile for the lending side, both for MMSR as well as T2 data (Figure 5.9. At the same time, the dynamic differs on the lending side whereas MMSR and T2 data show very similar developments on the borrowing side. Interestingly, dispersion increases in all measures at the onset of the global pandemic in early 2020. Dispersion in T2 data increases slightly more steeply and earlier compared to MMSR data. However, the levels are not pronounced compared to spikes throughout the period, indicating uncertainty did not increase substantially.

Figure 5.9: Interest rate dispersion



Note: Calculated as moving average over 30 calendar days. Exclusion of outliers in MMSR data. Data starting in August 2016.

5.6 Policy implications

The analysis has highlighted some inherent differences in measurement when applying different methodologies and scope. Concerning benchmark rates, the switch from EONIA and the focus on the lending side to €STR with a focus on the borrowing rate, lead to a significantly lower level of the benchmark. Whereas EONIA typically lies above the deposit facility rate, €STR mostly lies below.

Blind spots and structural differences affect the calculation of benchmark rates. Even basic observations on the money market, like the share of cross-border transactions or whether domestic banks engage in net lending or net borrowing, depend on which data are employed.

The latter deviations are driven by banking group structures and the settlement infrastructure landscape. Loans among savings banks and cooperatives are frequently not settled in central bank money and are thus not captured by Furfine-type algorithms.

Loans with foreign counterparties are represented unevenly across and within datasets. This especially affects loans with an interest rate below the deposit facility rate. Such transactions may be of particular interest to policymakers as they are largely driven by banks without access to the standing facilities in the euro area. Due to reporting requirements these loans are captured only on the borrowing side in MMSR, but on both sides in T2 data.

Policymakers should be aware of these blind spots of the datasets in the context of monetary policy implementation. Looking at different measures and exploring deviations in results may give a first indication of the root causes of these trends. Comparing measures helps to confirm and deepen the insights gained by analyzing a single data source. Importantly, focusing on one measure may lead to policymakers being unaware of developments driven by specific banking classes. This could affect studies on fragmentation, for example. Not using the full variety of available data sources may lead to different policy implications. However, given the fact that policy choices are discretionary rather than strictly rule-based, it is hardly possible to structurally evaluate the effect of different measurement on policy outcomes.

Decisions on monetary policy are influenced by a variety of factors and the mandate of the central bank. Notwithstanding, the importance of the money market may be weighed differently by various central banks, and a thorough understanding of how indicators are calculated and information on market structures which is as complete as possible unifies all central banks.

Different methods of measurement are associated with their own benefits and disadvantages. Creating new surveys or putting new regulation in place can entail considerable costs. Furfine-type algorithms reveal themselves to be a useful addition to other sources at the least, and potentially even a satisfactory alternative, whilst also being relatively cheap to implement. Central banks looking to elicit or complement granular data may find the case of the euro area, and Germany in particular, useful as a reference for cost-benefit analysis and comparative studies.

The use of different identifiers (LEIs and BICs) across data sets required a tailor-made mapping, given that identifiers are not fully comparable and consequently there is no comprehensive mapping table. The use of an identifier like the LEI in payment messages could address such shortcomings. Ensuring data linkage capacities should be a high priority when designing new regulation on data reporting as well as in determining requirements for payment transaction data. For the identification of money market loans from payments data, the use of the LEI could improve the performance and comparability of data. At the same time, the fundamental working of the algorithms would not be altered as payment transactions would not include the business reason of the transaction.

Policymakers and researchers may find considerations in Table 5.9 useful when deciding what data source to use for specific market studies. The broader coverage regarding market segments, maturities and loan types is clearly speaking in favor of the MMSR data. In addition, the reliability of the data source is, despite the general shortcomings of reporting, not to be considered as lower than with a Furfine-type algorithm that also suffers from general uncertainty in identification accuracy, which is particularly high in low interest rate environments with occurrence of zero rate loans. The main argument in favor of T2 data is the longer period they cover and the broader geographical coverage. For the Eurosystem, if there is no specific research question that explicitly favors T2 data, MMSR data could be the default data source and T2 data could serve for robustness checks.

5.7 Conclusion

Given the importance of short-term interest rates for steering monetary policy, it is somewhat surprising that little work has focused on measurement issues and comparisons of data sources. Reasons for this may include data availability and the complexity of the data, as well as the fact that only one benchmark rate is usually employed by policymakers.

When measuring the money market, granular information is necessary for studying the microstructure of the market. We show that the banking system structure, market practices and monetary policy implementation affect which loans are captured in different datasets. The results are not only relevant for the unsecured interbank market in Germany and the euro area, but also for other countries and market segments.

We find that differences in aggregates stem from rather technical specifications. For example, delimiting the market in geographical terms highly depends on the concept employed. Where a transaction is booked or settled is the root cause for deviations in measurement in highly international markets. The resulting differences in aggregates are subtle in some cases, but can substantially affect outcomes guiding policy measures in other instances, especially in times of turmoil. Future research could draw on the results for answering research questions using different data sources. This could help evaluate policy questions from different angles and cross-checking results.

Policymakers should be aware of the differences and mindful of the structural issues in measurement. This is not to say that one dataset is always preferable to others. We find that instead of being competitors or substitutes, it is sensible to regard different data sources as being complementary to each other. An environment with methodological plurality can reduce overall uncertainty. Depending on an individual research question, however, the conceptual framework of a specific dataset may be preferable to others. Researchers should therefore carefully assess the choice of employed dataset. When setting up data frameworks, the pros and cons of the different elicitation methods and the benefits of methodological plurality should be weighed against the cost of data sources.

Table 5.9: Considerations for preferred data source

Research interests that favor the use of MMSR data	
Are segments beyond the unsecured money market of interest?	MMSR data includes further market segments; the secured money market, foreign exchange swaps and EONIA swaps. T2 data only includes the unsecured money market.
Are market participants beyond banks the area of interest?	MMSR data partly includes a broader scope of financial corporations beyond banks.
Are maturities beyond overnight of interest?	Overnight data is captured in both data sources. Longer maturities are included in MMSR data and can be identified from TARGET2 data. However, matching longer maturities presents a challenge for Furfine-type algorithms and there is a time lag as matching can only take place upon repayment at maturity.
Are loans between savings banks and cooperatives (including their respective head institutions) of particular interest?	Such loans potentially settle in giro systems and are hence imperfectly measured in T2. Given the special characteristics of these banking groups, researchers may choose to largely ignore them by using T2 data, including loans between them by using MMSR data, or cleaning the MMSR data for such loans.
Are loan types, such as Call Account/Call Money transactions of interest?	T2 data includes only loans that lead to involved parties exchanging payments. MMSR data captures other types of loans as well.
Are zero-rate loans of particular interest?	Furfine-type algorithms only imperfectly identify zero rates. This is not an issue on its own for reported data.
Are extreme loan rates of particular interest?	Due to special arrangements, market characteristics or access, some loans exhibit rates well above the marginal lending facility or below the deposit facility rate. Loans below the deposit facility are reported predominately on the borrowing side in MMSR and are well-identified in T2 data. Furfine-type algorithms may include a broad range of interest rates, but there is a potential trade-off with reliable identification. Extreme values do not present a challenge in principle in reported data, even though potential reporting errors increase uncertainty in such instances.
Research interests that favor the use of T2 data	
Is a broader panel of banks of interest?	T2 data potentially captures loans in euro by all banks if TARGET2 is used to settle the transactions. MMSR data covers the majority of the market, but only the larger players. The German MMSR sample is broader than on the European level. Counterparties typically settling loans in internal payment systems are underrepresented in T2 data.
Are entities outside the euro area of particular interest?	MMSR reporting requirements limit loans to those where the reporting agent books the loan on their books. MMSR data can thus lead to different conclusions on cross-border activity. T2 data includes all loans settled in euro, also involving parties from outside the euro area.
Is a longer time period, e.g. including the global financial crisis, of particular interest?	Data from payment systems can be obtained in hindsight if transaction level data is available. T2 data covers a longer time period (from 2008 onwards) whereas MMSR data begins in 2016.
Are loans settled in central bank money of interest?	T2 data naturally includes only loans settled in central bank money. MMSR data offers a wider scope, but does not allow to restrict the sample to settlement in central bank money.
Are intragroup loans of interest?	MMSR data does not contain intragroup transactions. T2 data usually exclude intragroup transactions but intragroup loans can be identified and kept in a separate dataset.
is there a need to adjust the identification procedure?	Researchers may adjust the parameters of the algorithm identifying money market loans. The setup costs for changes in reported data are typically higher.

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Chapter 6

Conclusion

6.1 Summary

In the chapters 2 through 5, we made an effort to translate the findings into concrete implications for (central bank) policymakers and researchers. Concluding the thesis, I shortly summarize the individual chapters, identify some of the overarching ideas and broaden the specific motifs into more general themes. From the, in some ways narrow, topic of wholesale payment systems, the content of its data and a view that focuses not only on the system but the participants, the chapter sheds some light on the interconnection of payments, financial markets and monetary policy developments. From this larger context, I elaborate on how research can support policymakers by providing concrete and actionable tools originating from in-depth analysis, before closing with some thoughts on future trends in payment economics research.

Chapter 2 shows that there are beneficial effects of indirect payment settlement (tiering) on the liquidity use of settlement banks in TARGET2. The effect is significant and beyond what one would expect from a mere pooling of payments. Payment timing as a proxy for external delay suggests tiered payments are treated with less urgency than settlement banks' own or in-house payments. While in line with contractual arrangements, some degree of "free-riding" or higher recycling of liquidity from client banks' could pose risks for indirect participants, as their payments are treated with less urgency. This could put indirect participants at a disadvantage if direct participants face financial stress or experience operational outages. However, the results are also consistent with settlement banks' monitoring of indirect participants and differing terms of settlement for their clients. Policymakers and operators of financial market infrastructures (FMIs) need to balance efficiency gains and potentially emerging risks. Overall, putting too strong of an emphasis on risks from tiered arrangement neglects positive effects observed in the study and the literature.

In Chapter 3, payment transaction data serves to identify potential outages and provide a data set that can be used to quantify sources of operational risk for FMIs originating from participant outages. While technically induced system outages on the operator's side are well documented for TARGET2, our contribution improves the visibility of operational risk and at least partly closes a gap in our knowledge about participant outages. We apply an algorithm to identify operational outages of individual TARGET2 participants in order to understand the occurrence of such operational risks. However, an element of uncertainty remains, since there are other reasons for what is essentially lower-than-usual payment activity. The algorithmic approach focuses on key participants and time periodsn with the result that only outages occurring during times above a certain threshold of activity are identified. Consequently, only outages that cause meaningful disruptions in payment traffic are included in the constructed data set. One major benefit of this approach is that it identifies not only full shutdowns but also outages that are partial or to some degree contaminated by contingency measures.

Chapter 4 looks at the increase in the overall stock of collateral held at central banks as indicative of the changes taking place in financial markets. Collateral stock developments mirror funding requirements to a certain extent, with the latter initially rising sharply on account of the global financial crisis. We find that refinancing operations have predictive power for future collateral submissions, but not vice versa. This suggests that there is inertia in the adjustment of the collateral holdings to the more volatile refinancing requirements. Due to high liquidity inflows to Germany, which are reflected in the Bundesbank's escalating TARGET2 claims, funding requirements – and hence collateral stock – fell. The observed shifts between different mobilization channels are largely caused by technical aspects, but may in part reflect a "home bias" and portfolio reallocations of banks.

Chapter 5 finds that the banking system structure, market practices and the monetary policy environment affect what types of loans the different data sets on interbank money market activity capture. Money market rates serve as benchmarks and are a key indicator for monetary policy decisions. Granular information is necessary for studying the microstructure of the market. The results are not only relevant for the unsecured interbank market in Germany and the euro area, but also for other countries and market segments. We find that differences in aggregates stem from rather technical specifications, but also depend on policy decisions concerning access to standing facilities. For example, delimiting the market in geographical terms foots on different concepts. Basing geography either on the location where a transaction is booked or where it is settled, turns out to be one of the root causes for measurement differences. Different definitions of geographical assignment notably affect cross-border loans. The resulting differences in aggregates are subtle in some cases, but can substantially affect outcomes guiding policy measures in other instances, especially in times of turmoil. Methodological plurality can reduce overall uncertainty. Future research could draw on the results to answer research questions using different data sources. This could help evaluate policy questions from different angles and cross-check results. Depending on an individual research question, however, the conceptual framework of a specific data set may be preferable to others.

6.2 Wholesale payment systems and the hidden content of payments data

Within the general field of economics, the study of payments has grown substantially, with an increasing number of theoretical and empirical studies. Kahn and Roberds (2009) already point this out and provide a discussion of the link to other areas of economics, such as monetary theory and industrial organization. Since the global financial crisis and the increased utilization of vast amounts of micro data, interest in payments studies has grown even further.

In one way or another, all studies here have relied on data from the Eurosystem's wholesale payment system TARGET2. In TARGET2, transactions are settled in central bank money, as compared to commercial bank money which always bears some credit risk. This is true even though risk mitigation may be effective via deposit insurance or collateralization. Ultimately, banks settle credit obligations stemming from a variety of sources, including net positions from other payment systems or FMIs, in central bank money. This fact highlights the importance of wholesale payment systems, as they reflect capital flows from financial market transactions and the real economy.

Wholesale payment systems thus offer a plethora of research opportunities, ranging from studies on the stability of the financial system to forecasting GDP using payments data, to studies on monetary policy implementation. Data is valuable as it reflects economic developments and might even be employed to develop early warning indicators for stress in financial markets. One example in this vein is the use of machine learning to identify banks that encounter liquidity stress by Heuver and Triepels (2019).

While the data contains a potentially huge amount of information, the interpretation and derivation of policy implications is often challenging and not straightforward. Foremost, the data contains information on when a payment was made from one system participant to another. The underlying economic reason for the transaction is nowhere to be found in the data itself, except for general categories of payment types.[1] Banks do not have to give a purpose for the payment and if they do, this information is typically not available to researchers for confidentiality reasons. Researchers must rely on secondary data to make sense of payment transactions or find a methodological approach to identify the purpose of individual payments to answer different research questions. Chapter 3 and Chapter 5 exemplify such endeavors in the context of TARGET2. While building on previous work, the studies required adaptations and refinements due to the institutional setup of TARGET2. Taking Chapter 3 as an example, contingency measures allow operators to instruct payments on behalf of banks. Such contingency payments do not differ from normal payment activity in the data. This makes it necessary to set low thresholds rather than identifying intervals with no payment activity at all. The identification of outages required fine-tuning the approach without being able to validate results beyond a handful of known outages. Slicing the data into ten minute intervals was based on a limited number of known outages as well as trial and error in determining what interval length provided sufficient payment numbers to identify low payment activity. In Chapter 5, the identification of money market loans requires inference based on payment characteristics, as the payment purpose is not evident in TARGET2 data itself.

Technical transfers, legacy technical arrangements in the system and banks' historically grown transaction management, to name a few, complicate a researcher's quest to interpret data. Thus, a deep knowledge of the system and participants' use of it is necessary to avoid false interpretations. While the data and documentation of system features offer some remedy, knowledge on standard practices, de facto operational procedures and participant reasoning are mainly or even solely known to practitioners. Therefore, an active exchange with day-to-day operators and overseers is not only a helpful tool for researchers, but often essential for appropriate data cleaning, designing effective research strategies and ultimately interpreting findings correctly. The studies here have profited from active exchanges with colleagues within and outside the Bundesbank's payments department, colleagues in the Eurosystem and beyond as well as industry practitioners.

Direct communication between researchers and practitioners may prove insufficient because of dispersion across different departments. This can aggravate researchers' sentiment that practical issues are negligible or benign and operators' sentiment that research is of little relevance to daily operations. Creating organizational overlap can encourage a more active exchange. More concretely, an organizational setup with researchers and analysts embedded in specialized departments, such as payments, offers one way of ensuring institutional knowledge pairs with analytical rigor. In addition, facilitating collaboration in project teams and dialogues between analysts and practitioners foster a better mutual understanding and creates synergies. Research may thus translate into actionable policy and monitoring tools. At the same time, practical issues may inspire relevant research

[1] Such categories include, for example, interbank and customer transfers, intragroup liquidity transfers or transfers to ancillary systems.

questions. Chapter 3 illustrates how research output can serve as a complementary tool for operators alongside reported data, while the practical usefulness of answering the research question hinges on the understanding of available and desired tools supporting operators.

Even with sound data and methodologies, the content of payments data and its meaning in economic terms can remain unclear. Perhaps the most prominent example of intense discussions around payment system data are the claims and liabilities between central banks arising from cross-border transactions, known as TARGET2 balances. The discussion does not revolve around TARGET2 as a payment system, but rather around the information that payment flows reveal. Essentially, claims and liabilities arise because the euro area shares a common currency but monetary policy implementation is decentralized. Legally speaking, separate TARGET2 components exist on a single technical platform. These components, with the exception of the ECB and so-called connected central banks, equate to countries in the euro area. A transfer between components gives rise to claims and liabilities reflected in the central banks' balance sheets. These balances have become a hot topic, particularly in Germany – which accumulated claims that passed the mark of one trillion euro in 2020 – and have fueled discussion on their drivers, riskiness, the role of monetary policy and, more broadly, the composition of the euro area.[2]

The analysis of payments data paired with secondary data sources can help put such developments in perspective and identify drivers of capital accumulations. Understanding the drivers is key for policy decisions and the assessment of risks. Whereas TARGET2 balances represented financial market stress during the sovereign debt crisis in 2011/2012, the increase since 2015 stemmed from the implementation of asset purchases by the Eurosystem (see for example, Deutsche Bundesbank, 2016; Eisenschmidt et al., 2017). The interpretation of broad dynamics is fundamental for more specific research questions. In Chapter 5, crisis episodes affect the occurrence of more extreme interest rates, while safe-haven flows affect refinancing behavior of German banks in Chapter 4. In Chapter 2, the overall level of available liquidity proves to affect liquidity disposition of banks. Understanding the interrelations of financial market stress, monetary policy measures and payment dynamics will persist as a highly relevant avenue for future research.

Payments data can be seen as a treasure that is almost worthless by itself, but becomes valuable for policy when meaning and reasoning is given to it. The achievement of researchers is thus to apply meaning to the data under uncertainty. This is a continuous endeavor and has led to an active research community on wholesale payment systems across the world. Ultimately, this informs discussions on emerging trends and developments. Given different customs and institutional designs across jurisdictions, some new methodologies can readily be applied to other jurisdictions, whereas in other instances, the methodology requires adaptations.

International cooperation in payments facilitates the establishment of best-practices. The flow of money is a universal concept. However, just like cultures differ, payment systems are subject to local customs and institutional characteristics. Collaboration in payment system analysis requires translating between local data. Comparable data even allows applying a common methodology for comparisons across jurisdictions.[3]

[2] On the discussions around TARGET2 balances, see for example Moro (2019) and references therein.

[3] One research project in this vein, employing data from multiple jurisdictions, was recently undertaken under the auspices of the Bank for International Settlements.

6.3 A more participant-centric view in payments

Traditionally, financial stability and oversight in payments have a strong focus on system-level developments. Overseers rely on a variety of indicators for their assessments of systemic resilience. While risks stemming from participants are well recognized and reflected in policy guidelines, they are often less stringently surveilled. To some degree, this stands in contrast to banking supervision, where the individual bank is of interest.

Risks arising at a participant-level appear to be studied less in payments. This might also stem partly from the fact that heterogeneity makes conclusions less straightforward. Chapter 2 and Chapter 3 have deviated from a system-level approach, as participants become the center of attention. The two chapters provide an indication that more attention should be directed towards participants as the parts that form the system. The behavior of few participants drives overall trends and could pose risks to the system. The risks stemming from participants are often less understood and deserve more attention, in particular due to interdependencies. The Basel Committee on Banking Supervision (2021) highlights principles for operational resilience for banks, with one principle focusing on interdependencies and interconnections. In the context of incident management, the principles recommend establishing communication plans to report outages, including to regulatory authorities. Chapter 2 highlights that banks' treatment of client payments saves liquidity beyond what would be expected from merely pooling payments. Individual business models of larger participants thus affect considerations on system access policy and the trade-off between risk considerations and efficiency gains. For a comprehensive assessment, a view of participant roles across payment systems and their client relations would be necessary. In this vein, CPSS (2008) distinguishes system-based interdependencies, institution-based interdependencies and environmental interdependencies and calls for taking a broad risk perspective. The report discusses, among other interdependencies, the role of financial institutions and the importance of their risk management. Disruptions or stress at a bank-level may affect multiple systems and counterparties.

A pointer to the importance of focusing attention on participants can be drawn from the analysis of tiered arrangements in Chapter 2. While overall tiering levels are relatively low for TARGET2, indirect participants' payments play a significant role in the liquidity management of direct participants. The negative effect on liquidity use is beneficial, but a holistic analysis would require further investigating the risks of individual participants employing additional data. The analysis is limited to information from system data focusing on payments once they enter TARGET2. Information on settlement banks' internal procedures and contractual arrangements with client banks is obtained only implicitly. Importantly, TARGET2 is only one part of banks' overall liquidity position. Other systems, bilateral relationships and exposures may play a significant role for some banks' liquidity disposal. However, due to data confidentiality, behavior of banks across jurisdictions is difficult to observe. Take for example a Dutch bank that participates in TARGET2 and Fedwire. Likely, the bank manages intraday liquidity in euros and dollars holistically. Since European and U.S. overseers and operators will either have access to TARGET2 or Fedwire transaction data, the interconnections of liquidity and risk positions in each system remain unclear. To study such interconnections, comprehensive bank-level data or a cooperative approach across jurisdictions is necessary.

Putting emphasis on participants could provide insights into risks and benefits of participant behavior in individual and across different systems, thereby strengthening financial system resilience. An avenue for future work may focus on liquidity use of banks across systems and potential interconnections. Thus, liquidity risks transferring across systems may be understood more comprehensively. Therefore, policies on tiering at a system-level should consider cases of individual participants and their behavior, with particular attention to large and interconnected participants.

In terms of operational risk, Chapter 3 highlights a gap in knowledge stemming from the lack of comprehensive information on participant outages. While operators understand the operational risks on a system-level quite well, this is not the case for risks from participants. While this may not affect day-to-day operations, assessing overall risks and costs imposed on other participants seems warranted. Understanding operational risks and their occurrence can contribute to the assessment of banks' resilience.

A deep understanding of bank behavior could help validate or refute assumptions that form the basis for analysis. In Chapter 3, it is assumed banks i) instruct a relatively constant stream of payment flows, at least during some business hours, ii) exhibit a somewhat stable payment profile with consistency across business days and iii) do not abruptly pause payment instruction for prolonged periods unrelated to outages. The assumptions are consistent with the clustering of banks' payment profiles by Glowka (2019). For the majority of banks, a predominant payment profile is identified.

The cause of outages was not investigated here, but future work could focus on quantifying occurrences by the root causes of outages. Different drivers of participant outages could conversely be observed over time, enabling the identification of main vulnerabilities for FMIs. Studying the vulnerabilities of system participants and interconnections with other infrastructures could inform the design of contingency measures.

6.4 Relation to the monetary policy environment and financial markets

Since the global financial crisis in 2007/2008, monetary policy has become an increasingly important tool and has affected financial markets in a major way. In the individual chapters, the monetary policy environment turns out to have a major impact on outcomes and the development of indicators over time.

In Chapter 5, monetary policy decisions affect measurement and specifically loans that result from "the new normal". For example, this is true for loans with an interest rate of zero and loans with (deeply) negative interest rates. Notwithstanding the shifting focus of monetary policy away from the money market, the general decline of the overall market volume has made the topic of measurement arguably even more interesting, as niches of the market weigh more heavily on aggregate indicators. Resulting from past scandals of outright rate manipulation of LIBOR and EURIBOR, new data for calculating benchmark rates has become a priority in various jurisdictions. A deep understanding on how the newly reported data is set up, what loans are within its scope, and how it differs from other money market data could be explored using the study here as a role model. Importantly, the effect of employing different data sources on empirical findings should be investigated in future work.

In Chapter 4, the effect of monetary policy is clearest. Collateral submission relates to liquidity needs and participation in monetary policy operations. Liquidity flows towards German banks, measured by the Bundesbank's TARGET2 balance, affect liquidity needs of German banks. After all, TARGET2 balances have been described as a barometer for stress during the sovereign debt crisis. The same can be said for the monetary policy response during crisis episodes. Therefore, researchers and policymakers employing data onwards from 2008 have to account for evolving conditions. Disentangling different effects is difficult and warrants caution when interpreting results.

In studies with a focus on payments and a system's perspective, monetary policy conditions need to be taken into account due to their influence on the behavior of participants and the framework in which the system operates. Sparse liquidity matters to banks as payments in RTGS systems significantly affect their liquidity positions. This creates incentives to use as little liquidity as possible. Intraday liquidity needs have to be anticipated beforehand, otherwise banks will have to rely on incoming payments, or in the case of TARGET2, on intraday credit which requires posting collateral. On the flip side, the availability of ample liquidity removes some previously existing constraints for banks regarding intraday liquidity management. If liquidity constraints are relaxed, banks have less incentives to postpone payments or coordinate payment schedules with other banks to minimize liquidity use. Thus, an expansionary monetary policy stance affects participant behavior in RTGS systems, as shown in Chapter 2.

In a nutshell, the effects of monetary policy affect wholesale payment systems, an area that - per se - usually does not factor much into considerations of monetary policy decisions. However, there is clear overlap between payments and monetary policy. The analysis of payments needs to factor in the monetary policy environment and reversely, studying payment flows and institutional design can contribute to monetary policy implementation. This can entail developing timely available indicators on economic and financial activity from payments data. Money market developments can be put into a broader perspective by adding data derived from payment systems capturing loans beyond available samples. Payment flows and information on liquidity disposition intraday can contribute to a more comprehensive understanding of liquidity conditions of banks. Vice versa, decision-makers should take repercussions of monetary policy decisions on capital flows into account. For example, ample liquidity disincentives active liquidity management in payment systems which in turn could create liquidity shortages if excess liquidity is absorbed abruptly. Measures should be evaluated with a more explicit focus on incentives and resulting cross-border effects.

The implementation of asset purchases has led to large liquidity accumulations in countries like Germany which serves as a financial hub. In contrast, the introduction of tiered remuneration in the euro area has in some instances lead to opposing capital flows, which albeit are very small in comparison.[4] To what extent such considerations factor into policy decisions is hard to quantify. At any rate, payments data can serve as a complement to available data sources as well as a tool for evaluating policy measures in respect to incentives and risk management of banks reacting to different monetary policy environments. Recent work, for example by Chapman and Desai (2021), Galbraith and Tkacz (2018) and Verbaan et al. (2017) highlights that there is still huge potential in using payments data for macroeconomic forecasting and monetary policy purposes.

As exemplified in Chapter 2, connections to financial markets can arise in the form of

[4]For a discussion of effects of tiered remuneration, see Deutsche Bundesbank (2021b).

market rates driving incentives to manage liquidity more efficiently. The cost of liquidity thus affects participant behavior in payment systems. At the same time, liquidity positions of banks in payment systems can affect financial markets. A recent study by Copeland et al. (2021) finds that intraday payment delay is associated with spikes in the repo market. To study such interconnections, the availability of (transaction-level) data of payments and financial market transactions is key for future research. This requires not only making multiple data sources available to analysts and researchers, but also ensuring data can be merged and made comparable. Ideally, common identifiers are employed, as identifiers differ in how entity groups and legal structures are mapped. In Chapter 5, the use of different identifiers (LEIs ans BICs) across data sets required a tailor-made mapping, given that identifiers are not fully comparable and consequently there is no comprehensive mapping table. The use of an identifier like the LEI in payment messages could address such shortcomings, while the inclusion of settlement information in financial market data is likely not feasible. Ensuring data linkage capacities should be a high priority when designing new regulation on data reporting as well as in determining requirements for payment transaction data.

6.5 From research to monitoring

The studies presented here should not only provide new insights and contribute to the relevant literature, but could also lead to the development of methodologies for implementable tools. Eurosystem central banks not only oversee, but also operate financial market infrastructures. Fulfilling regulatory requirements and proactively monitoring systems is a core task. The goal of the research presented is not primarily to develop monitoring tools. However, given its practical relevance, aspects of the work can inspire new tools for operators and overseers.

A good role model for applied research that turns out to be useful for monitoring, is work by Berndsen and Heijmans (2020). The authors develop indicators on risks in TARGET2 and translate threshold levels into a traffic light output that gives warnings for risk levels. The approach developed in the paper has since been used in the Eurosystem to monitor system performance and potentially arising risks. Breaking down research results is important for decision-makers who are not aware of the technicalities, but desire warning indicators at a quick glance if risks arise.

The idea in Chapter 3 is to provide a starting point for monitoring participant outages. Overseers and operators should monitor participant outages, as is also set out in CPSS-IOSCO (2012). Since its publication, the approach has been presented within the Eurosystem and in dialogues with commercial banks. Data on identified outages by the algorithm is now being used for cross-checks with reported outages and thus can be useful for evaluating the adherence to reporting requirements of system participants. Importantly, monitoring operational outages could identify data gaps. Building on this, regulatory requirements could be evaluated. Future research could employ the data to study effects of participant outages on the system as a whole and potentially arising risks in the form of gridlocks. In addition, the approach is employed in other jurisdictions. Arjani and Heijmans (2020) apply a slightly modified version to Canadian large value transfer system data and find encouraging results.

As for the further development of approaches, there are alternatives that could be tested. One possibility would be to employ machine-learning techniques to identify periods exhibiting lower-than-usual payment activity rather than the simpler algorithmic approach. A machine-learning approach could be used to compare results with the algorithm employed here to test and validate results.

In the context of monetary policy implementation, Chapter 5 may prove useful to investigate developments of the unsecured interbank money market. Available data sources yield different results at times, even for aggregate indicators. Therefore, policymakers should be aware of the variability and differences of the data, which can form a firmer foundation for policy decisions. Ideally, different data sources serve as the foundation for monitoring and the robustness of analysis.

Looking ahead, new technologies will be a game changer for policymakers. Today template-based reporting takes days or even months to collect, verify and ultimately translate into findings for policy. In the future, large amounts of granular data can be automatically collected and stored, translated into indicators using big data analytics such as text mining, and interpreted using artificial intelligence. Across a variety of areas, developments can be tracked in real time highlighting anomalies as they arise. Sound research, careful calibration and a deep understanding of the data has to lay the foundation for such a brave new world in monitoring.

6.6 Payments in the digital age and CBDC

An important strand of future work will evolve around innovation and the role of central banks.[5] Well-functioning payment systems rely on two pillars: a stable medium of payment (money) and efficient transfer systems. Maintaining price stability is a statutory task of central banks. At the same time, ensuring the smooth functioning of payments falls into the remit of central banks.

With digitization, the demands on the payment system and at the same time on central banks might change. One reason is that new forms of means of payments have been developed or are planned to be released. Examples include Bitcoin and the Diem (formerly Libra) project initiated by Facebook. Bitcoin is used for payments only in a niche and is unlikely to fulfill the function as a stable and efficient settlement medium. Diem has undergone multiple changes in its concept and ambitions due to concerns from regulators. However, they could pose challenges to central banks in fulfilling their mandates if they were to become widely used. As the studies here have focused on existing important infrastructures and established forms of money, new payment mediums have not been the subject of analysis. A second reason for changing demands are new technologies for transferring value in digital networks. Blockchain technology or more generally distributed ledger technology has been refined and adapted to the needs of the financial sector. Central banks actively consider implementing new technologies to increase efficiency in settlement processes.

Implementing new technologies can entail creating a new form of central bank digital currency (CBDC). Importantly, availability of CBDC could be restricted to the same participants as current RTGS participants, called *wholesale CBDC*, or issued to the general

[5]To some degree this section builds on the article Balz and Paulick (2019) which discusses the implications of private digital forms of money for central banks.

public, i.e. *retail CBDC*. Retail CBDC would be a new form of digital money that, like cash, is available to the general public and in contrast to cash is provided in digital form (for illustration, see Bech and Garratt, 2017).

The implications for the financial sector differ markedly. With the introduction of retail CBDC central banks not only extend their role in payments. From a balance sheet perspective, a shift from commercial bank deposits to CBDC is equivalent to withdrawal of physical cash. Retail CBDC as a form of electronic cash is thus associated with structural disintermediation of the banking sector and could affect the credit supply in the economy, unless limits or other measures are implemented (see for example, Bindseil, 2020). The most convincing arguments for a retail CBDC are the functioning as a backup system, fostering financial inclusion and preserving a public role in payments in the digital age via a secure and privacy-preserving instrument as an alternative to private initiatives driven by commercial interests.

Arguably, a digital central bank money is already available today in the form of central bank reserves. Balances with the central bank may thus be labeled as wholesale CBDC in a broader sense. However, typically wholesale CBDC refers to a variant of central bank money that is based on new technologies. Wholesale CBDC as a tokenized form of money, run for example on a DLT network, could offer benefits compared to today's RTGS systems by making settlement more efficient and integrated. For instance, so-called atomic transactions enable conditional delivery versus payment in securities transactions. Wholesale CBDC can foster interoperability across public and private systems making settlement more efficient. Wholesale CBDC could also enable new use cases, such as tokenized exchanges with automated settlement upon trade confirmation. That is not to say wholesale CBDC is the only possible solution for efficiency gains. Improved RTGS systems offering additional functionality or so-called trigger solutions linking different financial infrastructures could achieve similar policy goals, as discussed in Deutsche Bundesbank (2021a).

Depending on the design of potential CBDCs, concretely a wholesale or retail digital euro, some of the themes of research might be relevant. CBDC could be based on accounts or be issued in the form of tokens. The issuance as a value-based token is widely discussed in the context of the application of distributed ledger technology. As no decision on the introduction or general design has been made in most jurisdictions, the implications of the technical design are hard to evaluate at this point. However, it seems that the economic implications for financial sector risk are largely dependent on the design features from a policy perspective. The technical implementation is more of a factor for efficient and instant settlement. The underlying technology likely does not alter incentives and operations of wholesale system participants. As form typically follows function, the business decisions of central banks for retail CBDC, for example concerning remuneration, holding limits, or the treatment of tokens for reserve requirement, will drive developments.

In the context of wholesale CBDC, operational risk and participant behavior described in Chapter 3 and Chapter 2 seem useful for anticipating system dynamics and importantly, considering system access. Determining fee structures and access criteria will affect the setup of tiered arrangements, which could come with efficiency gains, but also emerging risks. Conceivably, fragmentation of liquidity due to the introduction of a new wholesale CBDC system alongside an RTGS system requires further analysis. The implications of fragmentation could benefit from a deeper analysis of interconnections between direct and indirect participants in existing and future wholesale systems. Concerning interbank lending, Chapter 5 shows that bank location and access to standing facilities affects interest rates. Future research could determine whether access to a wholesale CBDC alters dynamics in the money market. By granting access to financial institutions unable to hold central bank reserves hitherto, changes in incentives could occur and affect interest rates in the money market.

The potential introduction of retail CBDC warrants careful considerations. Depending on its design, retail CBDC could have wider implications for monetary policy implementation and financial stability. If citizens, companies and financial institutions would be able to hold large amounts of retail CBDC, this would likely affect banks' refinancing needs. As central banks attempt to avoid such disintermediation, a scenario with unrestricted holdings seems unlikely though.[6]

Whereas central banks operate, or at least closely regulate, payment systems in the wholesale space, private actors play a larger role in retail payments. Thus far, central banks only provide cash as a physical means of payment. Therefore, retail CBDC could shift the balance between public and private sector activity in payments. Public and private infrastructures often exist as complements, which means that the division of labor leverages comparative advantages. For example, central banks are able to provide infrastructures for large-value payments with default-proof central bank money, while the private sector has an advantage at the customer interface in relation to user convenience and customer service. However, public and private systems sometimes also compete with each other, for example in the provision of instant payments. A retail CBDC could lead to a larger role of public actors in the payments market. At the same time, central banks want to encourage competition in the market. The Eurosystem has started investigating a retail digital euro variant, highlighting different scenarios that could motivate its issuance as well as discussing the role of the private sector, risks and trade-offs (see European Central Bank, 2020).

A retail variant could be of interest in a wholesale context if the line between wholesale and retail is increasingly blurred. Instant payments and retail CBDC could eat into turnover of wholesale payments, which could affect the profitability of wholesale payment systems. Nevertheless, the implications of retail transactions moving to other systems for liquidity needs are likely small on aggregate. This is shown by Hellqvist and Korpinen (2021) for liquidity needs when moving to instant payments, but the effects are shown to vary across individual banks. In combination with results in Chapter 2, this suggests that moving to instant payment settlement in retail has a different trade-off compared to wholesale payments. As liquidity needs for payment funding are high in RTGS systems, immediate settlement comes at the cost of higher liquidity needs. In contrast, instant payments require low amounts of liquidity and immediate settlement thus does not come with the same trade-off. Tiering can be seen as netting at a participant level and a tool for participants to save liquidity in wholesale systems, whereas in retail systems these benefits are small. Meanwhile, the benefits for consumers and merchants are large. At the point of sale, transactions can be settled immediately, without the risk of insufficient funds upon settlement. Instant payments make consumer to consumer transactions more efficient, such as private sales or splitting restaurant bills.

[6] Bindseil (2020) discusses different proposals, such as the introduction of a limit on holdings and a tiered remuneration based on the amount of holdings.

The implications of Chapter 2 on wholesale CBDC are less straightforward. If access and business logic do not change, but only the underlying technology, the results pointing to benefits of tiered settlement apart from a risk perspective still hold. If wholesale CBDC would reduce liquidity saving mechanisms in the system, the liquidity saving of tiering implies a higher share of tiering to be beneficial. If access is widened beyond participants today, the benefits of liquidity savings could decrease. Non-bank corporations are likely to settle payments with lower values. Relative to the size of new participants, the liquidity needs and in turn potential savings could still be high. Given setup costs for system participation and active liquidity management, a tiered structure is likely preferable for at least some corporations.

As the studies here have highlighted, system dynamics are often complex and do not evolve in a vacuum. This is true for systems operated by the public and the private sector. Analyzing system dynamics employing transaction data in changing market conditions can thus contribute to well-functioning payment systems. Establishing analytical capabilities in a CBDC sphere while ensuring adequate levels of data protection and privacy for its users will be challenging for central banks around the world.

The digital age has transformed the world of payments and the face of money. Changes range from increased use of cashless payments to alternative models of running a payment network. The innovation of cryptotokens, such as Bitcoin, has gathered attention in finance and popular culture due to stories of fabulous wealth. At the same time, the promise of decentralized "currencies" as a new way to supply money appear ill-fated. A store of value requires trust. Stability is not achieved via a fixed or limited supply in dynamic economies. So-called stablecoins as a response to high volatility, in essence borrow trust and stability from the underlying assets. While the face of money may change, its soul anchored in trust will remain.[7]

With the introduction of a retail CBDC, central banks can establish a trustworthy form of money in the digital sphere. However, the design could jeopardize hard won trust. CBDC may not be accepted or security breaches could undermine trust. Public institutions need to develop a product satisfying consumer demands to gain acceptance. Privacy and security are key issues. Not everyone will be confident in the safeguarding of data by a public institution. Clear rules and plain communication will be key to gain a comparative advantage in relation to the innovative force of private initiatives.

Importantly, CBDC should foster innovation in settlement that enables seamless and convenient payments at any place and point in time with any entity or person. This ubiquity could improve financial inclusion. For the wider economy, the aim is to synchronize the flows of payments with the flow of goods and services. Example applications are synchronizing the provision of services where settlement takes place immediately after delivery. This could bring efficiency in the context of book-keeping and reconciliation. The automated settlement takes place between parties when agreed-upon "trigger events" occur, e.g. sensors confirming a certain temperature was maintained during the transport of goods or oracles providing external information such as flight arrivals. The internet of things and machine to machine payments require efficient and programmable payments. Technologies like distributed ledgers show promising advancements. Companies may use synchronization to improve customer experience. For the public sector, programmable

[7]The analogy stems from the speech "Digital currencies and the soul of money" by Agustín Carstens, at the Goethe University's Institute for Law and Finance (ILF) conference, 18 January 2022.

payments could help ensure regulatory compliance and improve auditing.

As the philosopher Marshall McLuhan said: “It is the framework which changes with each new technology and not just the picture within the frame.” For central banks, this means adapting and proactively implementing innovative technology. However, new technology also requires vigilance in areas such as cyber resilience and quantum computing. The fruits of innovation should be reaped while keeping a stable footing.

6.7 Recent developments and beyond

The most recent developments are not yet reflected in the studies here and the future remains uncertain as to how persistent some behavioral changes in response to evolving market conditions described below will turn out to be. Near-time availability of payments data puts researchers and analysts in a position to quickly evaluate how government actions and central bank stances affect the economy and financial markets.

The years 2020 and 2021 were characterized by the global Covid-19 pandemic. The effects on payments in wholesale systems have been manifold. The decline in real economic activity may translate to lower volumes in wholesale payment systems, while heightened financial market activity may increase values settled. The injection of liquidity via expanded monetary policy measures affects market players' behavior in wholesale systems. As shown in Chapter 2, higher levels of available liquidity may lead banks to manage liquidity less actively and thrifty.

In the retail space, consumers are changing the way they pay, relying less on cash as a payment medium. At the same time, central bank money in the form of cash is used as a store of value by households as a response to uncertainty, thus increasing the demand for cash even as its use in transactions declines (for a recent description of some developments, see Auer et al., 2020).

In terms of conducting research, the pandemic may be seen as a natural experiment. When the dust settles, the pandemic in all likelihood will lead to research putting developments in perspective and informing policymakers on the effectiveness of measures taken in some haste. In Europe, this includes the fiscal programs SURE (Support to mitigate Unemployment Risks in an Emergency) and NextGenerationEU. The programs affect cross-border flows and exposures as they involve the issuance of bonds by the EU commission and a distribution among member states in the form of grants and loans. The outbreak of the pandemic has also put on a hold a normalization of an expansive monetary policy stance that has driven markets since the global financial crisis. Unprecedented high amounts of liquidity and negative interest rates change incentives for market participants. Some of the observed behavior by banks in the studies, such as less emphasis on efficient liquidity management, is likely to change when excess liquidity decreases over time.

Innovation and the evolution of financial markets and the monetary policy environment will continue to affect payment systems. In all likelihood, it seems that payment economics will increase in importance and policy-relevant research questions will be in no short supply.

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The economic analysis of financial market infrastructures has gained increasing interest. Financial market infrastructures provide the underlying network of the financial system and are critical for the smooth functioning of financial markets. The thesis includes four separate research projects unified by the notion that data from FMIs can be highly useful to gain a better understanding of system dynamics, but also offer valuable insights on financial market developments in general. The chapters rely heavily on data from TARGET2, the Eurosystem's large-value payment system.

Chapter 2 shows that a higher share of tiered payments from client banks reduces liquidity consumption by settlement banks by giving them more leeway. System designers and overseers should weigh benefits and risks of tiering carefully. Chapter 3 identifies operational outages of participants using an algorithmic approach. The developed algorithm provides a hitherto absent data set on outages that is useful for evaluating compliance with reporting requirements and risk assessment. Chapter 4 investigates changes in the collateral framework and technical aspects of collateral mobilization. A shift towards domestic channels reflects a home bias, especially during the sovereign debt crisis. Due to high inflows, culminating in the Bundesbank's escalating TARGET2 claims, funding requirements and collateral stocks fell. Chapter 5 investigates why and how data sets on the unsecured interbank money market differ. The systematic approach highlights that different data captures cross-border loans, loans of different banking classes and recurring daily loans unevenly. The analysis is useful for developing reporting frameworks and extracting money market loans from payments data. The last chapter highlights policy implications and trends in payments.

Jan Paulick (1985) is a principal expert in the division Strategy, Policy and Oversight in the Directorate General Payments and Settlement Systems at Deutsche Bundesbank. His work focuses on quantitative analysis of financial market infrastructures as well as the implications of digital money and blockchain technology. He holds a M.A. in International Economics from the University of Göttingen and studied abroad at UC Santa Cruz and Delhi School of Economics before joining the Bundesbank in 2013.

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