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

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Non-technical summary

Research Question

Considerable resources have been devoted to gathering data for the measurement of money market activity. However, little is known about the differences between available data and the structural effects of methodological choices. We use the novel dataset Money Market Statistical Reporting (MMSR) and compare it to data derived from a Furfine-type algorithm and survey data.

Contribution

The study focuses on three different means of measurement and aspects within those categories: survey data, a "Furfine-type" algorithm, and reported transaction data. The comparison of EONIA data, identified loans from TARGET2 data and only recently available MMSR data highlights differences in methodology and scope which cause differences in aggregate indicators. Importantly we are able to compare transaction level reported MMSR data with identified individual loans from TARGET2 for Germany. Furthermore, differences resulting from technical specifications of two different algorithmic approaches are investigated.

Results

We argue that the uncertainty in money market activity critically depends on the technical specifications of measurement, the policy and market environment. Differences between data sources depend on sampling, coverage and the structure of the banking system.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. Policymakers need to be aware of the methodological differences of available data. Different data sources exhibit similar trends, but important deviations occur due to their scope which could lead to differing policy conclusions.

Nichttechnische Zusammenfassung

Fragestellung

Für das Erfassen von Daten zur Messung der Aktivität am Geldmarkt wird erheblicher Aufwand betrieben. Über die Unterschiede zwischen den verfügbaren Daten und die strukturellen Auswirkungen methodischer Unterschiede ist jedoch wenig bekannt. Wir verwenden den seit kurzem verfügbaren Datensatz Money Market Statistical Reporting (MMSR) und vergleichen ihn mit Daten, die mithilfe eines Furfine-Algorithmus und Umfragedaten abgeleitet werden.

Beitrag

Die Studie konzentriert sich auf drei unterschiedliche Messmethoden und Aspekte innerhalb dieser Kategorien: Umfragedaten, einen "Furfine"-Algorithmus und gemeldete Transaktionsdaten. Der Vergleich von EONIA-Daten, identifizierten Geldmarktkrediten aus TARGET2-Daten und erst kürzlich verfügbaren MMSR-Daten zeigt Unterschiede in Methodik und Umfang auf, die zu Unterschieden bei aggregierten Indikatoren führen. Insbesondere vergleichen wir gemeldete MMSR-Daten auf Transaktionsebene mit identifizierten Transaktionen aus TARGET2 für Deutschland. Darüber hinaus werden Unterschiede untersucht, die sich aus technischen Spezifikationen zweier verschiedener algorithmischer Ansätze ergeben.

Ergebnisse

Wir zeigen, dass Unsicherheit hinsichtlich Geldmarktaktivität entscheidend von den technischen Spezifikationen der Messung, dem Politik- und Marktumfeld abhängt. Die Unterschiede zwischen den Datenquellen hängen von der Stichprobe, der Abdeckung und der Struktur des Bankensystems ab. Die Abweichungen in Bezug auf Volumen und Zinssätze sind auf die asymmetrische Messung von Transaktionen zurückzuführen, die insbesondere einzelne Kategorien von Banken, grenzüberschreitende Kredite und bestimmte Arten von Krediten betreffen. Diese Unterschiede sind zum Teil erheblich und wirken sich auf die Gesamtzinssätze und -volumina aus. Selbst grundlegende Fragen wie der Anteil grenzüberschreitender Transaktionen hängen davon ab, welche Daten verwendet werden. Diese blinden Flecken und strukturellen Unterschiede können sich auf die Berechnung von Benchmark-Zinssätzen auswirken. Entscheidungsträger sollten sich der methodischen Unterschiede der verfügbaren Daten bewusst sein. Die Trends, die sich aus verschiedenen Datenquellen ableiten lassen, sind ähnlich, jedoch treten aufgrund ihres Messumfangs wichtige Abweichungen auf, die zu unterschiedlichen Schlussfolgerungen führen könnten.

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

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Abstract

Considerable resources have been devoted to gathering data for the measurement of money market activity. 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 and 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.

Keywords: Money Market, Overnight interest rates, Measurement methodology

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

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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 the transmission of monetary policy to be evaluated. 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 amounts of research.

From a commercial bank's perspective, interbank money markets are a vital tool to cover short-term financial needs. Interbank lending rates are also 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 has been paid to how the data are generated and how the methodology used to produce different available 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 comprehensively compare different data sources and methods of data elicitation. In particular, data generated from Furfine-type algorithms have not been matched to a comprehensive transaction-level dataset of reported unsecured transactions.

Our paper contributes to the literature on general measurement methodology by comparing three 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 and 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 that are frequently not settled in

[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.

central bank money but 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 as 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 are not always clear beforehand and 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. One source of data may be preferred over another to avoid certain blind spots and chose the optimal measurement methodology depending on the research question. Policymakers should consider differing methodologies when assessing money market developments. However, given the discretionary nature of policy choices it is not possible to structurally evaluate how different data would affect policy outcomes.

2 Measuring the money market

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, Perez-Quiros, and Sicilia, 2001).[4] Central banks set policy rates that are transmitted to the short-term interbank money market (see Nautz and Scheithauer, 2011). From there, interest rates are transmitted 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 crucial 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). For the euro area, EONIA was replaced by a

[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.`

new reference rate based on MMSR data, called €STR. [6] A principle driving force behind this 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 not to be 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.[7]

When defining a benchmark, the choice of market segments and reporting entities is crucial for regulators and has been discussed extensively in various jurisdictions.[8] 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.

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, Bräuning, and Lelyveld (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.

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,

[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 for its euro short-term rate and the previously available document, ESTER methodology and policies - European Central Bank, at `ecb.europa.eu.`

[7]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`.

[8]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.

and reported data.

Survey data

As a first data source, 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. As an additional shortcoming, survey data are notoriously unreliable, as they may not be backed by actual transactions. This may result in incorrect data, or even cases of outright manipulation.

The use of actual transactions rather than quotes obtained via surveys was initiated after cases of manipulation of the LIBOR and EURIBOR benchmark rates came to light (see, amongst others, Mollenkamp and Whitehouse, 2008; Duffie and Stein, 2015; Wheatley, 2012; Eisl, Jankowitsch, and Subrahmanyam, 2017). In contrast to EURIBOR data, survey data on EONIA are supposed to be based on actual transactions rather than expert judgements and should therefore be less prone to tampering. However, as underlying transactions are not reported at granular level, there is still scope for misreporting. Such behavior is facilitated by one-sided (lender only) reporting, which does not allow for the data to be cross-checked.

Furfine-type algorithm

As a second data source, 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. Additional conditions and refinements have been suggested to improve the original implementation by Furfine, for example, by Demiralp, Preslopsky, and Whitesell (2004, 2006). Moreover, the basic working of the algorithm has been expanded to include different maturity bands by Kuo, Skeie, Vickery, and Youle (2013), for instance.

Some authors, in particular Armantier and Copeland (2012), have published critical assessments referring to the quality of the data generated by this methodology, based on a loan-by-loan level evaluation for the Fed funds market. 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. The main drawback of the studies is the limited availability of loan-level data for comparison. When alternative data sources such as regulatory balance sheet data are used to construct datasets for comparison, differences in definitions and scope arise that do not allow for a validation. Rempel (2016) proposes another estimation of the vulnerability of the algorithm to false identifications and suggests methodological improvements using Canadian payment systems data.

Furfine-type algorithms have been 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.[9] At the same time, 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).

The reliability of the data generated by Furfine-type algorithms and consequently the varied results produced by different validation exercises depend on payment system characteristics, market customs and the monetary policy environment, as well as the market and banking system structure in different jurisdictions, but is also affected by the availability of information within payments data. As Furfine (2001) mentions, data from Fedwire does not necessarily include information on actual counterparties, but rather the settlement agents. By contrast, European TARGET2 data include information on the originators and beneficiaries and implemented in the algorithm of Frutos, Garcia-de Andoain, Heider, and Papsdorf (2016) and in further-developed versions of the algorithm described in Arciero, Heijmans, Heuver, Massarenti, Picillo, and Vacirca (2016). This information has been employed in several studies on money market dynamics (see, amongst others, Abbassi, Bräuning, Fecht, and Peydró, 2014; Gabrieli and Georg, 2014; Manganelli, Heider, Hoerova, and Garcia-de Andoain, 2016)

The remainder of the paper will focus on the euro area and therefore on the two implementations of Furfine-type algorithms by Arciero et al. (2016) and Frutos et al. (2016). Based on the results of the partial validations with data from national money market trading platforms of Arciero et al. (2016) and Frutos et al. (2016), the implementation of Furfine-type algorithms seems effective for countries in the euro area. The algorithms were continuously improved by their developers and other researchers. Particularly relevant was 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).

The datasets resulting from the implementations by Arciero et al. (2016) and Frutos et al. (2016) have been used as the basis for a variety of literature and to support policymakers; see, for example, Heijmans, Heuver, and Gorgi (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

[9] Millard and Polenghi (2004) apply a similar algorithm for the UK, Hendry and Kamhi (2009) for Canada, Guggenheim, Kraenzlin, and Schumacher (2011) for Switzerland, Akram and Christophersen (2013) for Norway, and Abildgren, Albrechtsen, Kristoffersen, Nielsen, and Tommerup (2018) for Denmark.

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 data source, regulators require banks to report actual transactions. In contrast to survey data, reporting is obligatory for panel banks. Data are not reported as an aggregate number but 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.[10]

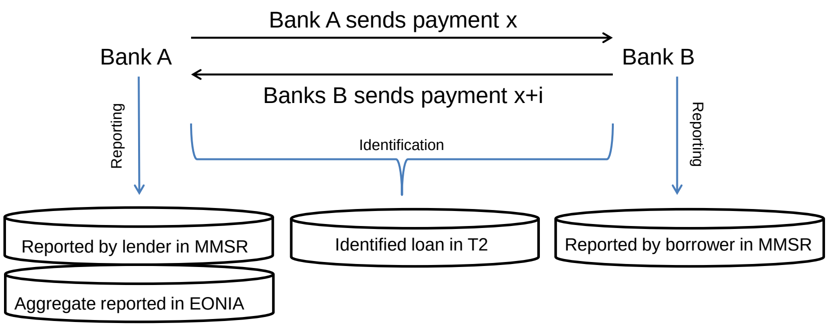
The fact that the newly established reference rate €STR - replacing the survey-based EONIA - is based on MMSR data shows that as well as having the advantage of providing granular high-frequency data, the regulatory reporting is also perceived as a more reliable source for the calculation of reference rates. In the first public consultation for developing a euro unsecured overnight interest rate, MMSR data have been assessed with regard to data sufficiency and representativeness and were deemed appropriate (see European Central Bank, 2017).

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 the available data date back further. At the same time, differences in the underlying datasets have to be taken into account in order to avoid misinterpretation of results. Eisenschmidt, Kedan, and Tietz (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. To our knowledge, no other studies have yet employed transaction-level MMSR data in the unsecured segment.

Figure 1 summarizes how interbank money market loans are captured by the three different data sources.

[10] 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 detailed parameters for the reporting in order to improve the quality of the data.

Figure 1: Stylized example of loan coverage in data sources



3 Data

We use one dataset from each of three different data sources that differ in terms of methodology, scope, sample size and other attributes. For a summary of data properties, see Table 1. As discussed in the previous section, the data can be categorized as survey data, data generated by a Furfine-type algorithm or reported data.

First, EONIA comprises survey data. All overnight lending transactions of panel banks are included in its calculation. Data are reported by each bank as an aggregate volume and a value-weighted interest rate. We use the aggregate values and rates that are publicly available.

Second, we use loan-level data identified from TARGET2 with two different types of Furfine (1999) algorithms by Arciero et al. (2016) and Frutos et al. (2016) as developed for the Eurosystem (referred to as T2 data).[11] The datasets used for our analysis may differ 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. Given the similarity of the datasets for the two implementations, Table 1 describes the implementation by Frutos et al. (2016), and we use this data for comparisons with MMSR because the differences between the implementations are more subtle than those between different forms of data elicitation.

Third, reported data under MMSR include aggregate values, volumes and rates that are available publicly. Official €STR data will be published starting in 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, as mentioned above, €STR also contains banks' borrowing from other financial institutions. For comparability, we use the calculated rates without the trimming and interbank data only. Importantly, our paper also draws on the confidential transaction-level MMSR data for Germany.[12] Our original dataset of the German sample consists of 118 reporting agents with reported unsecured money market

[11]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.

[12]DOI 10.12757/Bbk.mmsr.0716_0419.01.01.

loans, compared with 52 reporting agents on the European level, as the Bundesbank collects additional reporting agents' data.[13]

Table 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 participants in TARGET2, Active 938 participants (total BICs), 104 participants (German BICs)	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 onwards	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[14]	Day of trade

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.[15]

[13]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).

[15]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

The sample varies quite widely, ranging from 28 panel banks for EONIA to 52 reporting agents for MMSR on a European level, and 938 participants (total BICs over the whole time period) active in the money market, as identified from TARGET2 data. Note that T2 data potentially covers all participants in TARGET2.[16] In addition, in 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 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.[17]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 flows of funds 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 system).

A related aspect is the consolidation of banking groups. All datasets aim to 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.[18] How-

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.

[16]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 51,557 credit institutions around the world (80 percent of which are located in the EEA) were accessible via TARGET2 at the end of 2017; see TARGET Annual Report 2017, at www.ecb.europa.eu.

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

[18]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

ever, 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 outstanding amount on cash and savings accounts with a notice.[19] 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 have retained these transactions in the following sections as they are actively used in the German market and in order to investigate the degree to which they are reflected in T2 data.

4 Comparison

Rather than an evaluation or validation of data, the analysis refers to a comparison of the data. Due to methodological differences among the available data, deviations between the datasets used are to be expected. It is therefore not possible to validate one in relation to another. Rather, we focus on comparing the datasets and identifying structural differences empirically. 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.

We systematically compare the data sources with each other. In a first step, we compare aggregates highlighting the differences in results. In the next steps, we control for known deviations in order to identify remaining sources of differences, by comparing two Furfine-type algorithm implementations, replicating EONIA with Furfine-type algorithm data and most importantly, comparing T2 data and MMSR data on a transaction level.

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.

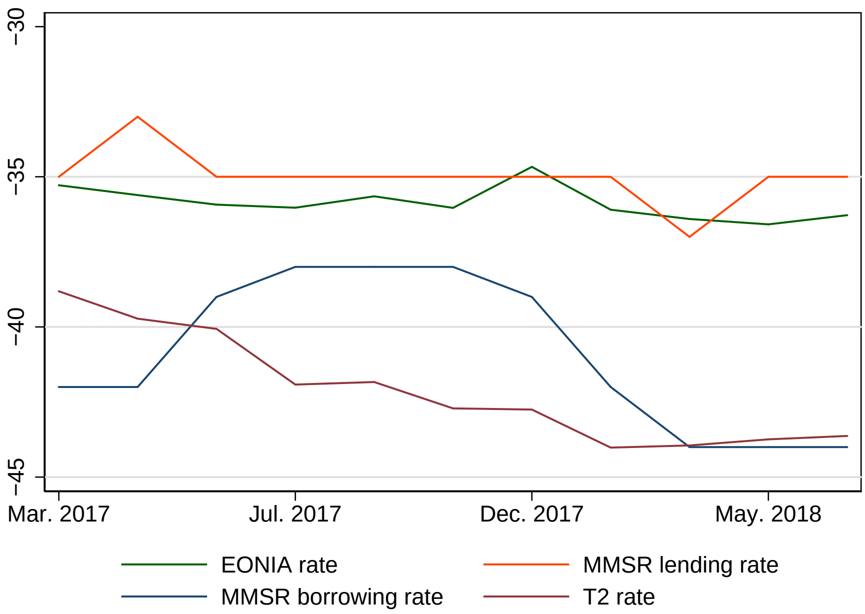
[19]See Reporting instructions for the electronic transmission of money market statistical reporting, December 2018. The inclusion of CACM transactions was also subject of the first public consultation (European Central Bank, 2017). While some respondents indicated a preference for including CACM transactions 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.

4.1 Aggregates

Comparing aggregate rates from the different data sources shows that there are marked differences in trends as well as absolute levels (Figure 2). The differences are in the order of a couple of basis points. However, given the size of the market we consider them to be substantial. Furthermore, the dynamic over time differs between data sources. 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. 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 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 of the data sources. The MMSR borrowing rate lies markedly below the lending rate. Rates from T2 data lie below the borrowing rate and in between the borrowing and lending rates in the beginning of 2017 and 2018.

Figure 2: Aggregate rates

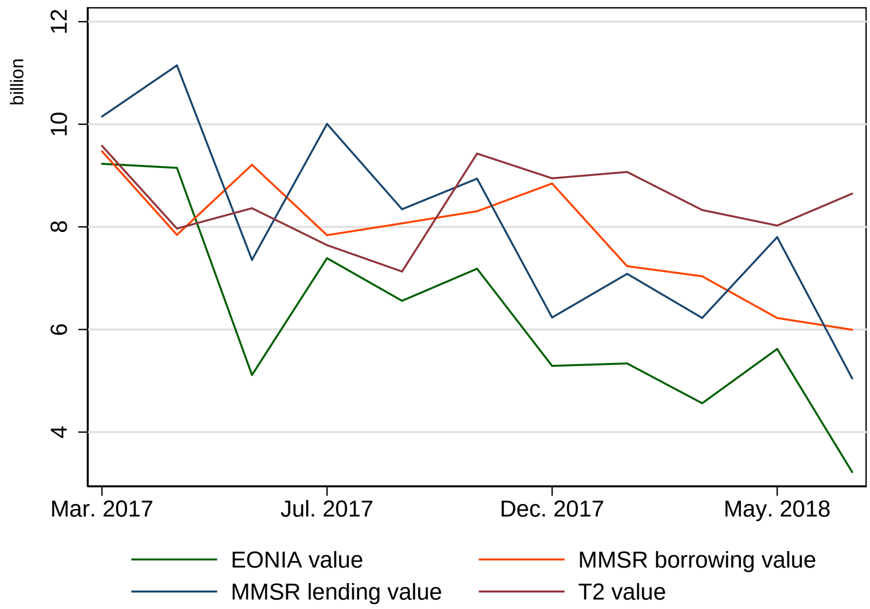


The comparison of interbank borrowing and lending rates illustrates that on average, euro area banks borrow at lower rates in the money market than they lend. The same observation can be made for the German reporting agents and the German extended sample. The main reason for this is that the MMSR borrowing side captures more loans with very low interest rates. The difference stems mainly from transactions with counterparties outside Germany and the euro area. 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, Bräuning, and Schulze (2017), 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 (30 percent of loans) and are virtually non-existent in the lending transactions (0.2 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. This is in line with the rationale above, as T2 data are not subject to this reporting bias due to the fact that 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 very similar dynamics, but with a constantly higher value of MMSR loans (Figure 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 absolute terms as well as in their evolution.

Somewhat surprisingly, T2 overall values lie below MMSR values at times, even though there is no sample restriction on the banks captured in T2 data. The underlying reasons for this are discussed when comparing loan-level T2 and MMSR data.

Figure 3: Aggregate values



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 appear to play a strong role.

4.2 Differences in Furfine-type implementations

For the Eurosystem, two different Furfine-type algorithms have been applied by Arciero et al. (2016) and Frutos et al. (2016), henceforth referred to as A1 and A2 respectively. In practice, Furfine-type algorithms apply a multitude of conditions and refinements to the basic matching process, taking into account specific market conventions and the technical features of the payment system. These refinements can include rounding to basis points according to market customs, a minimum payout or excluding certain categories of payments. By these additions, the algorithm is calibrated in a way that optimizes the occurrence of false positive and false negative matches. False positives are loans that are incorrectly identified by the algorithm as money market loans. False negatives are matches that are not identified as money market loans by the algorithm when in fact they should be. This calibration poses a challenge inasmuch as data for validation are often not or only partly available; it is precisely this lack of data which forms the rationale for developing the algorithm in the first place.

The implementations differ slightly from each other in the details of the applied filters; we are therefore able to assess the impact and importance of the conditions and refinements in relation to each other. We limit the comparison to overnight loans, as only A1 identifies loans with a maturity of up to one year. For comparison, we match identical loans, i.e. loans identified in both algorithm implementations. We use payment ID numbers as the criterion for identical loans, whereby both payout and payback transactions must have the same unique transaction ID.

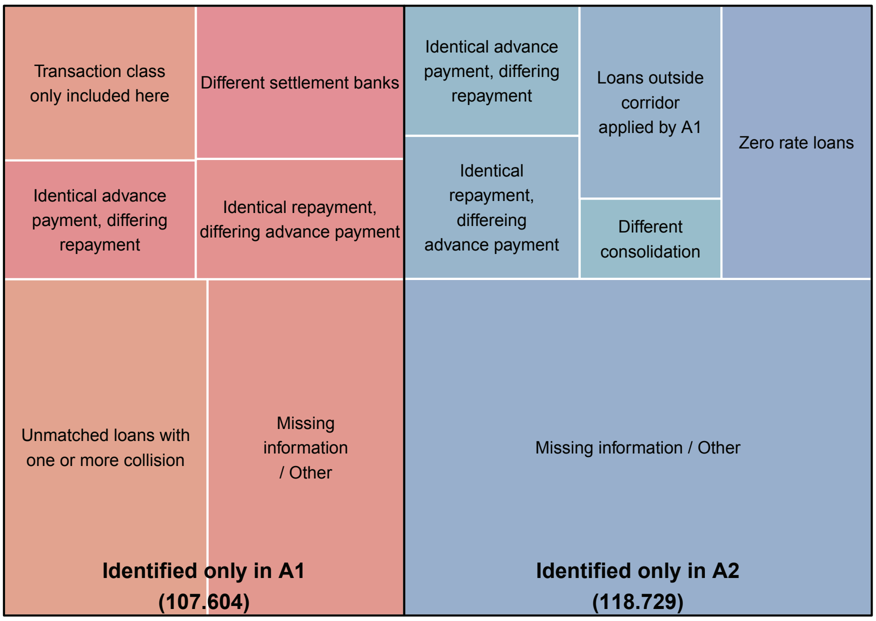
We find 81.9 percent (1,026,045 loans) of the identified loans to be identical in both databases. Of the remaining loans, 8.6 percent were only included in A1 and 9.5 percent were only included in A2. The effect of several differences in the technical specifications of the implementations as causes for the unmatched loans is quantified in Figure 4 in a treemap chart. In more than half of the cases we are not able to identify the driving factors of deviations. Since there are overlaps and feedback loops between the different causes of deviation, a clean separate accounting is not possible. Due to the sequential nature of the algorithms, differences may be amplified in the process. Furthermore, since some information is not available we are unable to fully account for all deviations. Nevertheless, we are able to identify the main causes of deviation and give an approximation of the share of loans affected.

Two main methodological differences can be identified if, in addition to the mere number of unmatched transactions, the implications for results and in particular aggregate indicators calculated based on the different data are taken into account.

As the A1 implementation applies a corridor of plausible loan rates, the implementation by A2 is less restrictive. At the same time, A1 is able to identify loans with longer maturities in addition to overnight loans. Both differences are interlinked. Potentially, an overnight loan that lies above the corridor might be matched by A1 with another potential repayment further down the line, resulting in a loan with longer maturity with a rate within the corridor. Meanwhile, A2 potentially matches outgoing payments of loans with a longer maturity as an overnight loan above the corridor, if in addition to the potential longer maturity repayment another potential repayment is found for overnight maturity and a rate above the corridor.

There is a close relationship within the data, comparing loans above the corridor of A2 with loans where A1 identified longer maturities while the same payment leg was used by A2 for identification of an overnight loan. A1 and A2 exhibit a very high degree of correlation in terms of volume as well as value. There is a clear peak for above-corridor loans and differing maturities in late 2011 (results available upon request). Whilst it might be possible that banks tried to acquire longer-term loans in times of stress, it seems

Figure 4: Causes for deviations of unmatched loans



Note: Table A1 in the Appendix provides a description of the sources of deviation. The size of rectangles corresponds to the share of concerned loans.

more likely that banks in distress would pay higher markups. Even though these loans account for only a small share, they affect aggregate results in crisis episodes.

As a conclusion regarding the practical implementation aspects of Furfine-type algorithms, we argue that the uncertainty surrounding money market loans extracted from payment transactions critically depends on the technical specifications of the algorithm, the monetary policy and market environment. The last decade has seen not only a financial and sovereign crisis, but also an expansionary monetary policy stance. The optimal design of Furfine-type algorithms changes with market conditions and constant revisions, such as accounting for negative interest rates. Comparing two implementations designed for the Eurosystem which diverge on several features shows that cross-checks between them can lead to a better understanding of the money market dynamics. This is especially true in times of stress and market turmoil.

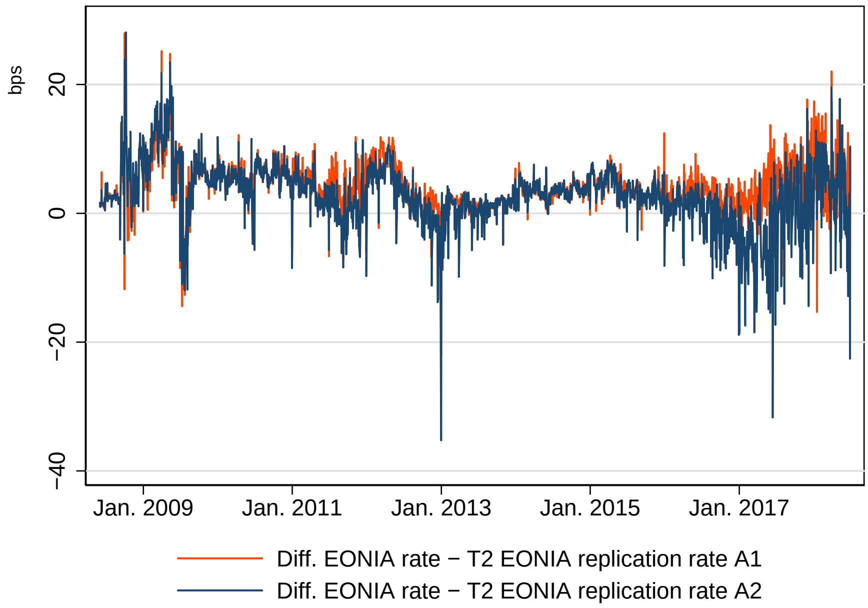
4.3 Replicating EONIA with Furfine-algorithm data

Similarly to Arciero et al. (2016), we compare data of Furfine-type algorithms to EONIA. As the coverage of both data sources is different, T2 data have been adjusted in order to replicate EONIA: only money market loans identified in TARGET2 by banks which are part of the EONIA survey panel have been included in the calculation, taking into account the evolution of the panel composition over time (Figure 5).[20] Compared to Arciero et al.

[20]It should be noted that our replication does not include fallback arrangements in the event of a contingency situation when the number of panel banks reporting non-zero volumes is less than or equal to four. As such cases are very infrequent, this should not affect the results.

(2016), we use a longer time horizon of available data.[21]

Figure 5: T2 EONIA replication, rates

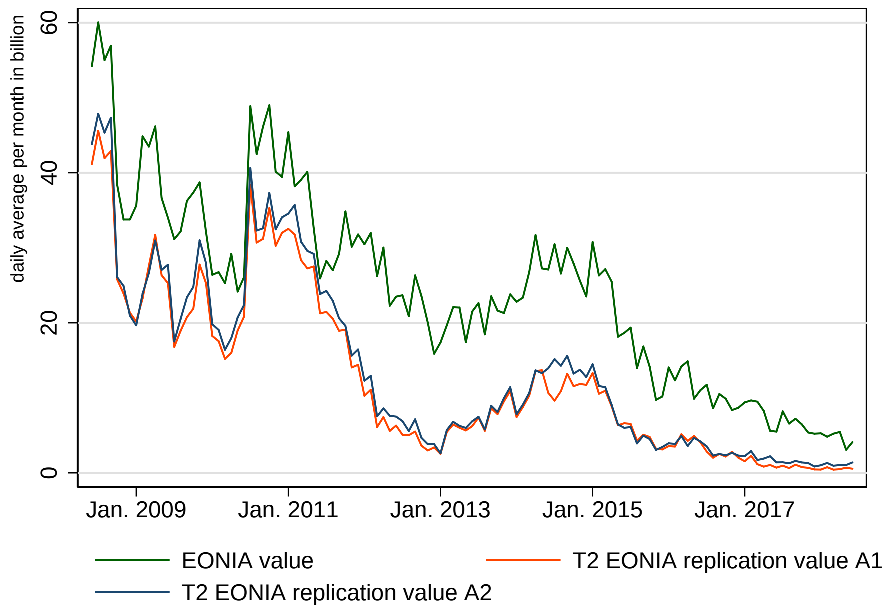


Two main observations can be made: First, as already discussed in Arciero et al. (2016), the rate based on T2 data is generally slightly lower than the published EONIA rate. The difference is around 4 basis points for A1 and A2 on average for the data until end-2015. Second, starting in 2016, the differences to the EONIA rate and between the two different Furfine-type algorithm implementations increase and the pattern of deviations appears less structural. In addition, the difference between the two implementations is much larger for the replicated EONIA panel than in the general comparison for all transactions in the previous section. The main reason for the increased divergences is the reduced activity in the unsecured interbank market in general and by the EONIA panel members in T2 in particular. The lower the number of transactions and active banks, the larger the impact of individual transactions and potential false positives or negatives.

As shown in Figure 6 and Figure 7, the value reported and the number of banks in the EONIA panel decrease over time. At the same time, the decline in the number of banks from the panel for which a money market loan is identified in T2 is more pronounced, i.e. the share of banks from the EONIA panel with no money market loans identified in T2 data increases. This does not necessarily mean that these banks have been inactive. Another explanation is the increased importance in the EONIA panel of banks for which no transactions can be identified by a Furfine-type algorithm. This second explanation

[21] It should be kept in mind that also due to the continuous improvement of the algorithms our results may differ from those in Arciero et al. (2016) for the overlapping time horizon. This is mainly the case for the replicated value, which is systematically higher than the reported value, whilst it is lower with the updated dataset. This can be explained by the updated dataset having been generated using the originator and beneficiary of transactions instead of the sender and receiver. Arciero et al. (2016) therefore expect an upward bias in their data because of sending and/or receiving banks acting on behalf of others. Our results confirm this reasoning.

Figure 6: T2-EONIA replication, values



seems plausible as the value of the EONIA banks replicated in T2 also shows a stronger decrease than the value reported.

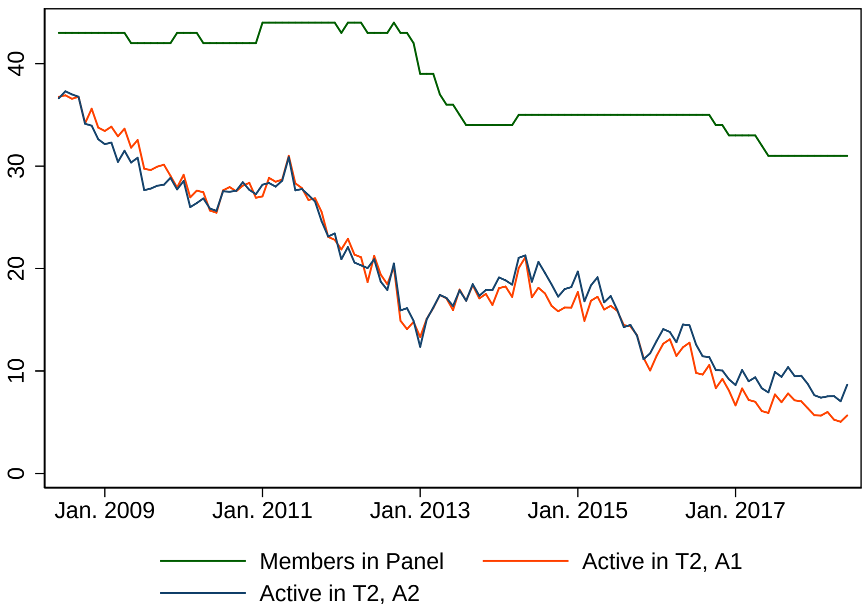
The comparison with aggregate EONIA data shows that differences between A1 and A2 are small compared to the differences with EONIA data based on a different methodology. For the sake of simplicity and as we focus on the overnight market, we henceforth concentrate on one implementation, namely A2 of Frutos et al. (2016), for the transaction level comparison with MMSR data.

4.4 Transaction level comparison of Furfine-type and reported data

We directly compare the German sample of MMSR and T2 data on a loan level. We only use loans where either the lender or borrower of a transaction is a German reporting agent or German TARGET2 participant. 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 or different 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 make use of the same BIC, which is also captured by our extended

Figure 7: EONIA panel members and activity in T2



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.

The available 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).[22]

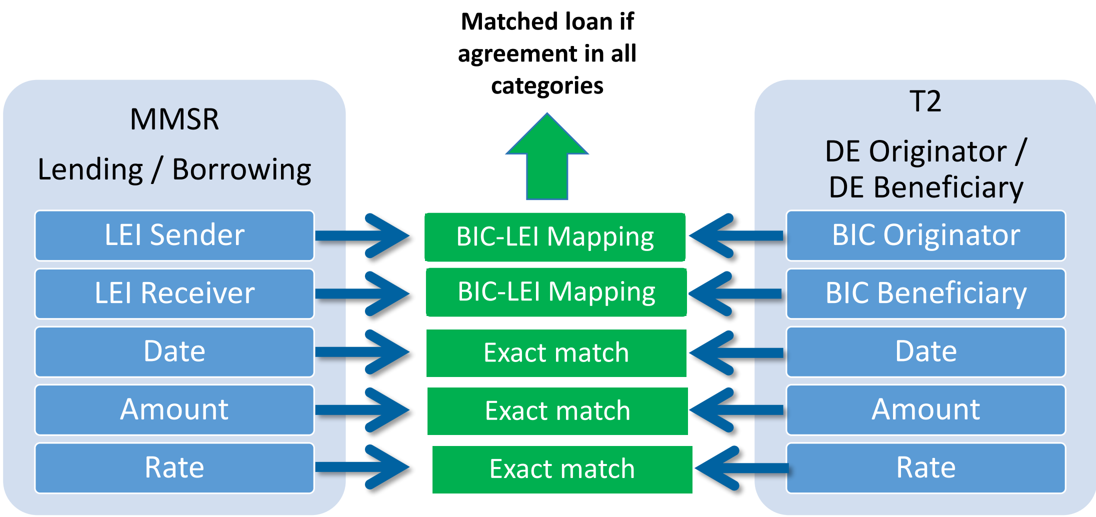
In addition to the ex ante filter necessary to align the data scope, we control for explainable unmatched transactions. We apply an additional ex post filter, taking into account CACM transactions reported under MMSR.[23]

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, it is sometimes the case that only immediately available balances are referred to as "pure fed funds", as opposed to continuing contracts. A similar

[22]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 little to no 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.

[23]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.

Figure 8: Matching of German MMSR and T2 data



reasoning has been applied in the discussion for the unsecured overnight reference rate, where CACM transactions are excluded as instruments for its calculation (see European Central Bank, 2018).

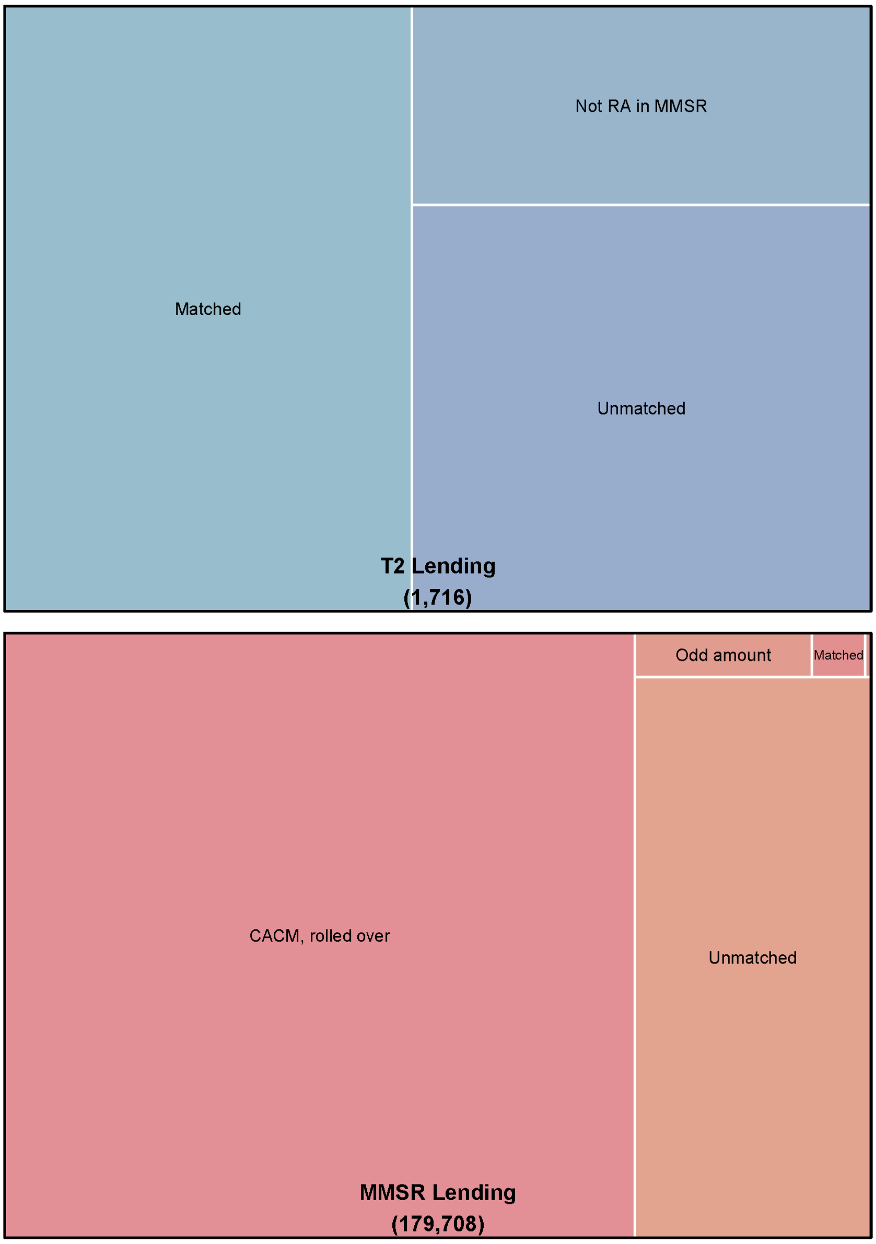
However, instead of simply dropping all CACM transactions, we identify and filter only those with an unchanged amount from one day to another in each lender-borrower pair. In other words, we only keep those CACM transactions when there is a change in the amount, i.e. an active change in the underlying 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.[24] 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 data; these are caused by the methodological differences of the underlying data sources. 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 9 and Figure 10 summarize the matching results for the borrowing and lending sides respectively in treemaps.

The following main observations can be made: First, the explainable differences be-

[24] 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 9: Overview of matches and deviations MMSR-T2, lending



Note: Table A2 in the Appendix provides a description of the sources of deviation. The size of rectangles corresponds to the share of concerned loans.

Figure 10: Overview of matches and deviations MMSR-T2, borrowing

Note: Table A2 in the Appendix provides a description of the sources of deviation.

tween 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 generally not settled in TARGET2.

Second, the results for T2 and MMSR data still differ significantly taking into account the explainable unmatched transactions. In general, the ratio of matched transactions is higher in T2 data than in the MMSR data. 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. In addition, we find a much higher number of lending transactions in MMSR, while T2 data includes more borrowing transactions for Germany. This can be attributed to differences in which loans are captured in the datasets.

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.

For the remainder of this paper, we consider only matched and remaining unexplained unmatched transactions. Figure 11 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 (excluding the explainable differences). We find that around 90 percent of T2 loans are matched with MMSR loans on the lending side and 60 percent on the borrowing side. Looking at matches from the perspective of MMSR data, the ratios are markedly lower, ranging from about 15 percent to just above 30 percent for the borrowing side. On the lending side, an even smaller share of loans is matched with T2 loans, which stems from the fact that MMSR data includes a substantially larger number of loans than T2 data.

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 2 and Table 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 effect of the explanatory variables (Table 3 and Table 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.[25] Such loans might not be settled in TARGET2, but rather in the internal giro system, thus decreasing chances of being matched.

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

Table 2: Probit model, lending side

	(1)	(2)	(3)	(4)	(5)
	Match result MMSR lending				
Reporting agent banking group					
Regional and commercial banks	-0.599***	-0.617***	-0.186*		
	(0.138)	(0.136)	(0.107)		
Landesbanken	0.034	-0.022	0.337***		
	(0.135)	(0.132)	(0.101)		
Savings banks	-0.946***	-1.013***	-0.412***		
	(0.159)	(0.155)	(0.131)		
Credit cooperatives	-0.408**	-0.460***	-0.409***		
	(0.160)	(0.157)	(0.127)		
Mortgage banks	-0.755***	-0.810***	-0.215		
	(0.191)	(0.186)	(0.165)		
Banks with special tasks	-0.531***	-0.562***	0.054		
	(0.206)	(0.202)	(0.183)		
Foreign banks and others	2.677***	2.595***	2.628***		
	(0.215)	(0.212)	(0.163)		
Big banks (reference group)					
Loan characteristics					
Loan amount (mio)	0.001***			0.000	
	(0.000)			(0.000)	
Rate of loan (bp)	-0.001			-0.001	
	(0.002)			(0.002)	
Rate below deposit facility	-1.508***	-1.493***		-0.830***	-0.780***
	(0.287)	(0.271)		(0.180)	(0.164)
Zero rate loan	-	-		-	-
Instrument type CACM	-0.746***	-0.773***		-0.771***	-0.777***
	(0.047)	(0.046)		(0.044)	(0.043)
Within giro system	-1.055***	-1.049***	-0.921***	-0.875***	-0.872***
	(0.042)	(0.039)	(0.037)	(0.033)	(0.032)
Constant	-1.215***	-1.088***	-1.745***	-1.392***	-1.352***
	(0.139)	(0.127)	(0.097)	(0.057)	(0.023)
Observations	45,834	45,834	46,237	45,834	45,834
Pseudo R2	0.256	0.255	0.196	0.164	0.164

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

Table 3: Average marginal effects, lending side

	Match result MMSR lending				
Reporting agent banking group					
Regional and commercial banks	-0.010**	-0.009**	-0.004		
	(0.004)	(0.004)	(0.003)		
Landesbanken	0.009**	0.009**	0.013***		
	(0.004)	(0.004)	(0.003)		
Savings banks	-0.014***	-0.013***	-0.008***		
	(0.004)	(0.004)	(0.003)		
Credit cooperatives	-0.005	-0.006	-0.007***		
	(0.005)	(0.004)	(0.003)		
Mortgage banks	-0.012***	-0.011***	-0.005		
	(0.004)	(0.004)	(0.004)		
Banks with special tasks	-0.009*	-0.007	0.002		
	(0.005)	(0.005)	(0.005)		
Foreign banks and others	0.409***	0.396***	0.543***		
	(0.046)	(0.046)	(0.050)		
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	-0.017***	-0.016***		-0.017***	-0.015***
	(0.001)	(0.001)		(0.001)	(0.001)
Instrument type CACM	-0.020***	-0.021***		-0.023***	-0.023***
	(0.001)	(0.001)		(0.001)	(0.001)
Within giro system	-0.061***	-0.058***	-0.050***	-0.045***	-0.044***
	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)

Standard errors in parentheses are calculated using delta-method.
Zero rate loans excluded from calculation.
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Probit model, borrowing side

	(1)	(2)	(3)	(4)	(5)
	Match result MMSR borrowing				
Reporting agent banking group					
Regional and commercial banks	0.372***	0.574***	-0.798***		
	(0.074)	(0.072)	(0.053)		
Landesbanken	0.482***	0.570***	0.420***		
	(0.035)	(0.034)	(0.030)		
Savings banks	-0.995***	-0.737***	-1.255***		
	(0.066)	(0.063)	(0.059)		
Credit cooperatives	-0.336***	-0.087	-0.554***		
	(0.075)	(0.072)	(0.061)		
Mortgage banks	-0.938***	-0.585***	-1.330***		
	(0.093)	(0.090)	(0.081)		
Banks with special tasks	-0.027	0.051	-0.168***		
	(0.046)	(0.045)	(0.042)		
Foreign banks and others	1.507***	1.698***	1.240***		
	(0.125)	(0.122)	(0.117)		
Big banks (reference group)					
Loan characteristics					
Loan amount (mio)	-0.002***			-0.001***	
	(0.000)			(0.000)	
Rate of loan (bp)	-0.021***			-0.019***	
	(0.002)			(0.002)	
Rate below deposit facility	0.412***	0.828***		0.969***	1.257***
	(0.044)	(0.035)		(0.035)	(0.026)
Zero rate loan	-1.718***	-2.292***		-1.159***	-1.661***
	(0.248)	(0.240)		(0.242)	(0.233)
Instrument type CACM	-2.106***	-1.907***		-1.860***	-1.714***
	(0.054)	(0.053)		(0.054)	(0.054)
Within giro system	-1.665***	-1.508***	-1.705***	-1.577***	-1.487***
	(0.056)	(0.055)	(0.050)	(0.051)	(0.052)
Constant	-1.387***	-1.034***	-0.511***	-1.570***	-1.083***
	(0.081)	(0.036)	(0.027)	(0.069)	(0.022)
Observations	24,433	24,433	24,433	24,433	24,433
Pseudo R2	0.445	0.429	0.275	0.398	0.386

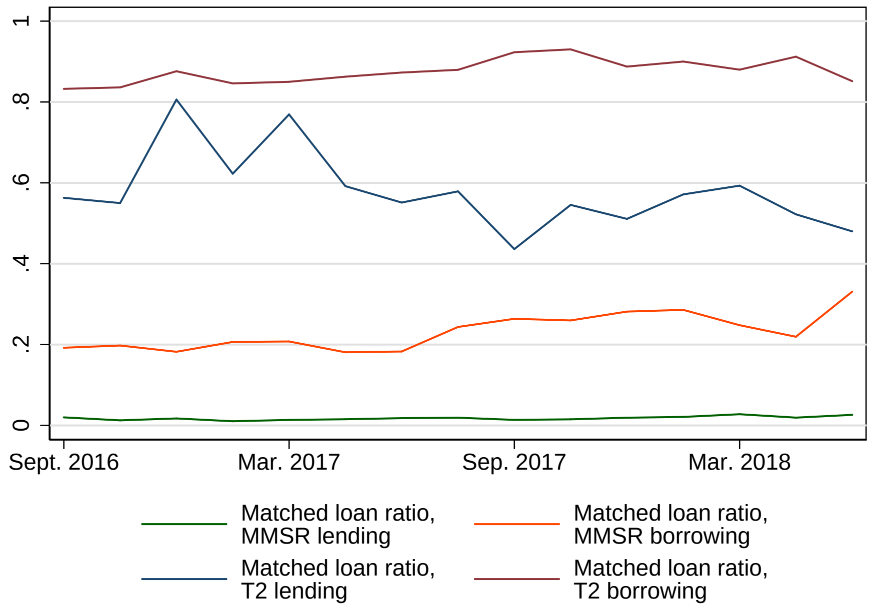
Table reports coefficients and standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Average marginal effects, borrowing side

	(1)	(2)	(3)	(4)	(5)
	Match result MMSR borrowing				
Reporting agent banking group					
Regional and commercial banks	0.073***	0.112***	-0.146***		
	(0.015)	(0.015)	(0.009)		
Landesbanken	0.096***	0.112***	0.116***		
	(0.007)	(0.007)	(0.008)		
Savings banks	-0.134***	-0.100***	-0.185***		
	(0.007)	(0.007)	(0.007)		
Credit cooperatives	-0.056***	-0.015	-0.113***		
	(0.012)	(0.012)	(0.011)		
Mortgage banks	-0.129***	-0.085***	-0.189***		
	(0.010)	(0.011)	(0.008)		
Banks with special tasks	-0.005	0.009	-0.040***		
	(0.008)	(0.008)	(0.010)		
Foreign banks and others	0.321***	0.362***	0.363***		
	(0.028)	(0.027)	(0.034)		
Loan characteristics					
Loan amount (mio)	-0.000***			-0.000***	
	(0.000)			(0.000)	
Rate of loan (bp)	-0.003***			-0.003***	
	(0.000)			(0.000)	
Rate below deposit facility	0.071***	0.151***		0.190***	0.253***
	(0.008)	(0.007)		(0.007)	(0.005)
Zero rate loan	-0.190***	-0.211***		-0.157***	-0.191***
	(0.011)	(0.005)		(0.020)	(0.010)
Instrument type CACM	-0.254***	-0.240***		-0.236***	-0.225***
	(0.003)	(0.003)		(0.003)	(0.004)
Within giro system	-0.226***	-0.210***	-0.243***	-0.234***	-0.221***
	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)

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

Figure 11: Matched loan ratios



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 3 and Table 5 we conclude that differences are economically meaningful, as the effect on matching probabilities is quite substantial for some banking classes as well as 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 likely to be matched. Economically highly significant effects are also observed for CACM transactions, loans with a rate at zero or below the deposit facility.

As expected, the giro system dummy is substantive and negative in all specifications. This is in line with the hypothesis that MMSR data contain loans not settled in TARGET2. In that sense, the covered loans depend on the banking group structure, which appears as one of the main reasons for the observed deviations. The specific banking class a reporting agent belongs to has additional effects on the matching outcomes in the model. Within banking classes, savings banks, credit cooperatives and mortgage banks have a reduced probability of matched loans for their reported transactions.

Regarding the impact of overall monetary policy conditions, the rate of the individual loan has little impact on matching outcomes. However, zero rate loans are either never matched and excluded (lending) or reduce the probability of matching (borrowing). This is in line with the intuition 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, but the number of loans below the deposit facility rate is very low in the model data (0.8 percent of loans versus 38 percent in the borrowing data) and the number of matches is almost negligible. Loans below the deposit facility rate are unlikely to be reported on the lending side, which explains why remaining reported transactions can be considered special cases or even falsely reported data and therefore are not present in T2 data. Borrowing below the deposit facility rate is a possibility for the arbitrage of banks with access to central bank accounts and the standing facilities. Therefore, lending below the deposit facility rate is reasonable only for banks that do not have access to standing facilities. 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 segments of the market that are captured by the data differ depending on these factors. Based on the pseudo R-squared, these factors explain a substantial share of deviations, in particular on the borrowing side.

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 than loans between parties transacting in central bank money.

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 and size Table 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. Unsurprisingly, rate differences are high for zero rate loans and loans below the deposit facility. Big banks stand out as their lending and borrowing rates are relatively far apart from each other and from overall rates, hinting that big banks can borrow and lend liquidity at more favorable terms compared to market rates. Marked 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 few loans. High matching ratios are also observed for big banks, banks with special tasks and Landesbanken on the borrowing side.

Policymakers and researchers may find this illustration of matches and rate differences useful when deciding what data source to use for specific market studies. Keeping in mind uneven measurement, studies on the market structure may be heavily influenced by the inclusion or exclusion of loan categories and banking classes. For example, network topologies may differ significantly in terms of number of links and the importance of nodes in the network.

In addition to the structured econometric model, individual cases of frequent combinations of senders and receivers with no matches at all have been investigated. Detailed results cannot be reported due to confidentiality reasons, but the results are widely in line with the rationale presented so far. A particularly interesting observation was 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, 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

Table 6: German sample by banking and loan categories

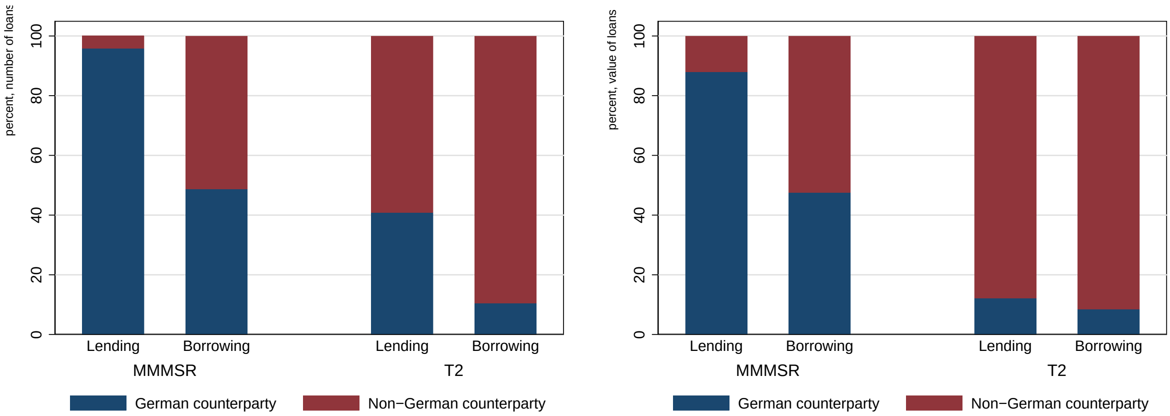
	Rate (bp)	**Rate diff.**	**Number of loans**	**Amount (in mio)**	**Matched, percent**
Lending side. MMSR					
Big banks	-58.4	-22.3	543	40,654	4.1
Foreign banks and others	-33.2	3.0	122	2,117	81.1
Banks with special tasks	-36.0	0.2	198	10,347	4.5
Mortgage banks	-38.0	-1.8	400	17,072	2.5
Credit cooperatives	-26.5	9.7	10,920	108,395	0.2
Savings banks	-36.0	0.2	2,676	84,888	0.6
Landesbanken	-36.4	-0.2	28,092	1,113,285	1.9
Regional and commercial banks	-35.7	0.5	3,286	264,323	2.7
Within giro system	-36.0	0.2	36,417	1,124,513	0.7
Instrument type CACM	-32.7	3.4	22,079	379,781	0.4
Zero rate loan	0.0	36.2	403	14,788	0.0
Rate below deposit facility	-75.1	-38.9	380	31,326	1.6
Overall	-36.2		46,237	1,641,080	1.7
Borrowing side. MMSR					
Big banks	-25.7	13.1	2,442	228,058	30.5
Foreign banks and others	-32.3	6.5	146	6,219	76.7
Banks with special tasks	-42.1	-3.2	1,698	129,464	24.9
Mortgage banks	-37.6	1.3	1,006	46,479	3.3
Credit cooperatives	-36.6	2.2	1,811	98,251	6.0
Savings banks	-37.4	1.5	6,382	387,886	0.7
Landesbanken	-45.6	-6.7	9,521	568,408	36.6
Regional and commercial banks	-25.3	13.5	1,427	26,609	9.5
Within giro system	-37.9	1.0	7,794	458,812	0.8
Instrument type CACM	-37.7	1.1	4,389	109,394	1.5
Zero rate loan	0.0	38.8	900	13,649	0.2
Rate below deposit facility	-46.6	-7.8	9,339	631,469	47.2
Overall	-38.8		24,433	1,491,374	20.8
T2					
Lending	-40.8		1,716	269,056	47.0
Borrowing	-43.6		6,676	389,120	82.5

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 12). 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 88 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 transactions 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 tend to borrow from counterparties abroad that do not report these granted 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.

Figure 12: Counterparty locations for loans by German reporting agents



As shown, this is also reflected in the MMSR lending rate, which is generally above the borrowing rate. Loans with rates below the deposit facility rate are mainly being carried out by foreign banks that are not reporting agents. When calculating lending and borrowing rates for German originators or, respectively, beneficiaries with T2 data, it can be observed that the lending rate is much closer to the borrowing rate. This can be considered to confirm the observations, as loans not reported under the MMSR due to an external booking location are still identified in T2 data based on the settlement location.

Even though this difference appears rather technical, substantial deviations arise from the different concepts of settlement location versus booking location of money market loans.

5 Policy implications

The analysis has highlighted some inherent differences in measurement when applying different methodologies and scope. Blind spots and structural differences may affect the values 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. Such transactions are legally not classified as intra-group, but may be closer to loans within a banking group in economic terms. Measuring the size and scope of overall money market activity critically depends on whether the data include these loan types or not.

Loans with foreign counterparties are represented unevenly across as well as 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. Dynamics in the money market may be driven by specific trends affecting different segments of the market. 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 foreign banks or specific banking classes. This could affect studies on fragmentation, for example, as cross-border transactions are captured unevenly across as well as within the datasets. 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 not 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 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 a cost-benefit analysis and comparative studies.

6 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 the monetary policy affect which loans are captured in different datasets and thus measuring the size of money market activity which is key for monetary policy decisions. 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 fundamental 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 datasets and consider cross-checking results with different datasets. 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.

Appendix

Table A1: Sources of deviation of Furfine-type implementations (Figure 3)

Transaction class only included here	Certain transaction classifications are not treated as potential money market loans in A2, but are included in A1.
Different settlement banks	A1 considers loans with differing settlement banks for the advance and repayment, as long as the ultimate sender and receiver agree. A2 only considers loans where both the settlement agents and ultimate sender and receiver agree for the advance and repayment transactions.
Identical advance payment, differing repayment	The advance payment agrees in both implementations, but has been matched with a different repayment transaction.
Identical repayment, differing advance payment	The repayment agrees in both implementations, but has been matched with a different advance payment.
Unmatched loans with one or more collision	Loans that have not been matched, where A1 provides the information that several potential transaction pairs have been identified but only one is kept as a match. This may cause coincidental differences as multiple matches would be possible.
Loans outside corridor applied by A1	A1 uses a more restrictive interest rate corridor than A2. Therefore, loans outside the applied corridor are only found in A2.
Different consolidation	The sorting of intra-group transactions differs as different assumptions for banking group consolidation are employed. Loans listed here have been sorted as intra-group in the other implementation.
Identified as longer maturity in A1	Either the advance or repayment transaction leg has been identified as being part of a longer maturity loan in A1.
Zero rate loans	Loans with a zero interest rate. A2 identifies those based on an empirical strategy, whereas A1 ignores them.
Missing information / Other	There is no straightforward explanation for unmatched loans, or information is not available to quantify effects. This might be partly explained by the sequential nature of the algorithms that cause different outcomes later on.

Table A2: Sources of deviation of MMSR and T2 (Figure 9 and Figure 10)

CACM, rolled-over	Call account/call money (CACM) transactions that are rolled-over transactions, meaning that there is no change in the underlying amount.
Unmatched	Unmatched transaction where none of the other reasons apply.
Odd amount	Odd amounts are assumed not to occur in the Furfine-type implementations.
Not in T2	Reporting agent does not have a TARGET2 account.
Matched	Transactions for which all details are matching in MMSR and T2.
Not RA in MMSR	TARGET2 participant that is not a reporting agent under MMSR.

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