The original sin: fragmentation in the money market and its transmission to the credit market[*]

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Abstract

The aim of this paper is twofold. First, we develop a country-specific indicator of fragmentation for the euro area unsecured overnight money market. Second, we use this indicator to assess the impact of fragmentation on the transmission of monetary policy to the credit market. Our findings indicate notable fragmentation in the euro area, with Italian banks, for example, paying an approximately 8 basis point premium over German banks. Furthermore, we show that fragmentation in the money market transmits along the monetary policy transmission chain, particularly affecting the credit market, where fragmentation premia pass through proportionately to new loan rates.

JEL-Classification: G1, E5.

Keywords: Money markets, fragmentation, credit market.

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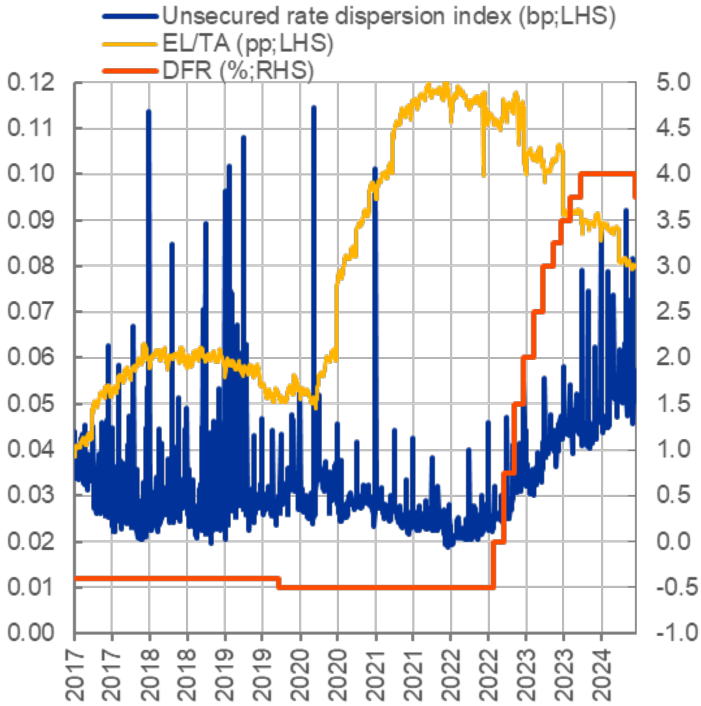
1 Introduction

The unsecured overnight (ON) money market is crucial for monetary policy, serving as the first leg in the monetary policy transmission mechanism. In the euro area (EA), a well-functioning money market implies the absence of fragmentation –meaning that reserves are able to flow between banks and countries without impediments. Consequently, the rate charged for unsecured overnight loans should not vary systematically across countries after controlling for differences in banks' characteristics that would justify rate differentials. In contrast, money market fragmentation can undermine monetary policy transmission, limiting its effectiveness in steering broad credit conditions for households and firms.

Figure 1 shows that, since 2022, unsecured ON rates have become more dispersed. This period marked the start of the monetary policy normalization cycle, namely the lift of policy rates from the negative territory and the gradual compression of the Eurosystem's balance sheet. Both of these factors contributed to stronger incentives for trading in the money market, leading to greater dispersion in rates. This increase in dispersion underscores the significant relationship between the monetary policy cycle and money market dynamics, as well as the importance of accurately identifying market fragmentation.

We argue that a substantial part of this increase in rate dispersion is linked to country-specific factors, which have become more prominent as policy rates have risen after the extended period at the lower bound. Additionally, as liquidity conditions shift from an ample to a more balanced state, jurisdictional factors tied to the borrowing bank are likely to play a more influential role in market activity and pricing. The aim of this paper is twofold. First, we use transaction-level data from the money market statistical reporting (MMSR) dataset from January 2017 to June 2024 to develop a country-specific indicator of fragmentation for the EA's unsecured overnight market. Our focus on the unsecured money market reflects not only its critical role in monetary policy but also its unique features, which make it well-suited for quantifying fragmentation. Given the very short maturity, this market is relatively immune to uncertainty related to the future path of monetary policy and instead reflects counterparty risk and precautionary liquidity hoarding. The unsecured segment allows to focus on the market for reserves, abstracting from the demand for collateral. We also test for fragmentation in the part of the secured segment that is driven by the demand for liquidity, i.e., where the specific asset pledge to the transaction is not relevant. Second, we use the fragmentation indicator to assess the impact of fragmentation on the transmission of monetary policy to the credit market.

Figure 1: Euro area unsecured overnight market dispersion



Note: Unsecured rate dispersion index computed following Duffie and Krishnamurthy (2016). EL/TA: euro area aggregate excess liquidity over total assets of the banking system. DFR: deposit facility rate of the ECB.
Source: ECB and author calculations.

We provide evidence of fragmentation in the euro area. Over the sample period, Italian banks have, on average, paid positive premia of approximately 8 basis points (bps), respectively, compared to German banks. In contrast, Dutch banks have received a "discount" of about 6 bps relative to German banks. Moreover, time-varying country fragmentation indicators show that fragmentation has indeed increased over the recent hiking cycle, especially for countries paying on average positive fragmentation premia (Italy and Spain). From the analysis in the General Collateral (GC) repo market, we find no evidence of fragmentation in this market, suggesting that this may be closely related to credit risk at the country level. In the second part of the analysis, we find that money market fragmentation is transmitted along the monetary policy transmission chain to the credit market, with 1 bp fragmentation premium getting passed through in full to interest rates on new loans to firms.

This paper is structured as follows. Section 2 describes the data and the identification strategy. Section 3 constructs the country-specific indicator of money market fragmentation. Section 4 evaluates how relevant is money market fragmentation for the transmission of monetary policy in the credit market. Section 5 concludes.

2 Data and empirical strategy

In this section, we first describe the data and their sources. Second, we outline the empirical strategy used to estimate money market fragmentation.

2.1 Data, sample selection and summary statistics

We use transaction-level data from the MMSR dataset, which includes a sample of approximately 50 euro area reporting agents (banks). This dataset provides detailed information on various euro money market segments: secured, unsecured, foreign exchange swaps, and overnight index swaps.[1] Notably, the MMSR forms the basis for calculating the euro short-term rate (ESTR), which serves as the key benchmark interest rate and reflecs the wholesale unsecured overnight borrowing costs of banks in the euro area.

Our focus is on the same market segment used to compute the ESTR. Specifically, we select unsecured, fixed-rate deposit transactions with ON maturity, where reporting banks (borrowers) engage with financial institutions as counterparties (lenders). Reporting banks are exclusively from the euro area, but their counterparties can be banks or non-banks, from the euro area or outside. We collect data spanning January 2017 to June 2024 but exclude the last business day of each month to avoid potential distortions from reporting-related requirements.

We organize our data as a daily-frequency panel dataset with the lender-borrower (counterparty-bank) pair as unit of observation. The same lender-borrower pair can trade more than once in the same day, but in the majority of cases, all transactions share the same borrowing rate, allowing us to aggregate volumes into a single daily observation per lender-borrower pair. If even one transaction for a given pair and day has a differing borrowing rate, we exclude all transactions for that pair on that day. This exclusion affects only about 0.5% of total transactions and volumes.[2]

We merge MMSR data with bank-level data to account for borrower characteristics. For this purpose, we draw on multiple data sources: the IBSI dataset for bank balance sheet information,

[1] See https://www.ecb.europa.eu/stats/financial_markets_and_interest_rates/money_market/html/index.en.html for more details about the MMSR.

[2] Afonso and Lagos (2015) argues that transaction rates can differ over the day. Given that our focus is on structural differences coming from the country location of the bank, we abstract from issues related to intraday microstructure of the market.

Finrep for supervisory data, and standard financial market data providers for market-related information.

2.2 Conceptual framework

The empirical setting is motivated by the 'law of one price', which states that assets with identical payoffs and risks should have the same price. In a perfectly integrated market, given the same counterparty and controlling for differences in banks' credit risk, the rate charged for unsecured overnight interbank loans should not vary systematically across countries. Thus, fragmentation can be defined as the (positive or negative) premia paid by banks due to their country-location and not justified by differences in the banks' profiles (Garcia-de Andoain et al., 2014). Let $y_{b,l,t}$ denote the borrowing rate paid on unsecured overnight loans by bank b to borrow from lender l on day t and decompose it into a risk-free rate y_t, a risk premium based on the bank's characteristics $y_{b,t}$ and a country (or country-group) premium $y_{c,t}$:

$$y_{b,l,t} = y_t + y_{r,t} + y_{c,t}. \tag{1}$$

Perfect integration implies that $y_{c,t} = 0$ for all countries c and at each point in time t.

2.3 Empirical framework and identification

Equation 1 constitutes the basis of our empirical specification,

$$y_{l,b,t} - y_t = \alpha_{l,t} + \alpha_{c,f} + X_{b,t}\beta + \epsilon_{l,b,t}. \tag{2}$$

The dependent variable, $y_{l,b,t} - y_t$, denotes the spread between the borrowing rate paid on unsecured overnight loans by bank b to borrow from lender l on day t and the Deposit Facility Rate (DFR). $\alpha_{l,t}$ are the lender-day fixed effects, which are a powerful way to control for time-varying heterogeneity at the lender level and constitute the core of our the identification strategy, because they allow us to compare transaction prices among different banks borrowing from the same lender on the same day. This approach is similar to strategies used in the banking literature to account for loan demand using loan-level data (Khwaja and Mian, 2008). Our coefficient of interests are the bank country-time fixed effects $\alpha_{c,f}$, as they capture whatever remains in differences paid by a bank to a given borrower in a given day that cannot be explained by any factor related to the bank but can be attributed to the country where the bank is located; they can be estimated at any preferred frequency f.

Finally, matrix $X_{b,t}$ includes bank time-varying characteristics, to control for bank specific factors that may influence the dependent variable. The ON unsecured market serves as a mechanism for absorbing idiosyncratic liquidity shocks. Consequently, a bank's vulnerability to these liquidity shocks is a key determinant of the interest rate. To account for this, we include the bank's daily excess reserves as a share of its total assets. Riskier banks are expected to pay a higher rate, even for very short-term maturity transactions where the probability of default is very little (Furfine, 2001). We control for the bank's credit risk by incorporating the bank's daily credit default swaps (CDS) and its Tier 1 capital ratio. However, since we focus on the ON segment, characteristics related to credit risk are likely to have limited relevance in explaining price differences. The rate is also determined by the bargaining power of the bank, which we proxy by the bank size measured by the logarithm of total assets (Afonso and Lagos, 2015).[3] The frequency with which a relationship between a borrower and a lender is established is a significant determinant of the interest rate, likely serving as an "insurance" mechanism against adverse events that could drive an institution out of the market. To account for this "relationship lending" factor, we include a variable that measures the frequency of trading over a 30-day period, as suggested by Furfine (2001) and Bräuning and Fecht (2016). Additionally, we control for the bank's funding structure by incorporating the ratio of market funding to total assets, which can increase banks' vulnerability to external shocks (Afonso et al., 2011). Finally, over the last decade the overnight unsecured market has operated under a regime of ample aggregate reserves. As a result, unsecured transactions are less influenced by the borrower side and more by the lender side. Specifically, the demand for deposits from institutions without access to the central bank has been a key driver of transactions in this market. Consequently, banks may encounter balance sheet constraints that are reflected in overnight transaction rates. To account for this effect, we include the bank leverage ratio (LR) in our analysis.

In addition to idiosyncratic bank characteristics, there are factors related to the country in which a bank operates that can also influence the pricing of ON unsecured transactions. The first factor is the relationship between the banks and their sovereign bonds, stemming, for example, from shared vulnerabilities to economic shocks or factors such as financial repression and carry trades. This sovereign-bank interaction can manifest as a home bias in banks' bond portfolios

[3]We also consider a measure of bank size relative to the country banking sector and results hold the same.

(Becker and Ivashina, 2017; Ongena et al., 2019; Acharya and Steffen, 2015). We account for this home bias by including the share of domestic sovereign bond holdings relative to the bank's total sovereign bond holdings. Moreover, we include the share of domestic bank bond holdings over total bond holdings of the bank, to control for systemic risk of the banking sector at the country level.

Table 1 reports the number of observations in the raw MMSR dataset and in our baseline estimation sample. The fixed effects we use in the analysis place particular demands on the data, especially for those countries with fewer reporting banks. Having lender-day fixed effects implies that per day each lender needs to have at least two transactions with two different banks. Adding to these the country-time fixed effects implies that these two banks need to be from different countries and we need at least two transactions from two banks of the same country over the preferred time horizon.

Table 1: Number of observations and banks in MMSR dataset and in estimation sample

	Raw data		Baseline estimation sample	
	Observations	Banks	Observations	Banks
DE	277,210	14	110,180	10
ES	24,399	5	14,716	5
FR	241,127	9	113,952	8
IT	14,413	3	6,386	3
NL	63,792	4	9,291	2
Others	75,766	9	35,082	6

To test and improve the internal validity and robustness of our baseline results, we further restrict the estimation sample. First we only include only cross-border transactions, as domestic and cross-border transactions can be priced differently.[4] Second, we refine the sample by including only banks directly supervised by the European Central Bank (ECB). Specifically, we focus on banks selected based on size or cross-border activity criteria. This restriction ensures that our sample comprises institutions of systemic importance, enhancing the comparability of entities.[5] We recognize that banks may be not randomly assigned across countries of the euro area. The correlation between a country's banking sector and national factors can be more pronounced for smaller banks with limited international connections, making it difficult to understand how

[4] Abbassi et al. (2022) show that cross-border transactions are penalized relative to domestic, although more in terms of volumes than prices. Freixas and Holthausen (2004) rationalize this finding based on an asymmetric information problem across borders.

[5] See https://www.bankingsupervision.europa.eu/banking/list/criteria/html/index.en.html for more information about the significance criteria.

location-specific factors influence a bank's borrowing rate independently of its own characteristics. Additionally, banks under national supervisory authorities may experience slight regulatory differences across countries, despite a shared regulatory framework (Ampudia et al., 2019). By including only the biggest and more integrated SSM banks, we minimize these idiosyncratic factors in transaction pricing.

The drawback of the identification strategy is the limited number of banks in some countries, risking confounding the banks with the country (Table 1). However, these are large banks that represent the majority of the money market of the respective country. Moreover, when comparing the main characteristics of the banks across countries in Table 2, it is not clear that we can isolate countries depending only on these characteristics.

Table 2: Descriptive statistics at bank level for MMSR reporting agents (mean and standard deviation).

Country		Total Assets (TA) ml€	Adjusted EL /TA	Debt securities issued/TA	Dom.sov.bond/ tot.sov.bond	Dom.MFI bond/ tot.MFI bond	LCR	Capital ratio Tier 1	Leverage ratio	#banks
DE	mean	382720	0.084	0.221	0.569	0.474	2.35	5.6	17.2	15
	std.dev.	326741	0.052	0.201	0.447	0.181	2.79	2.3	3.4	
ES	mean	482901	0.073	0.104	0.809	0.521	1.90	5.4	14.4	6
	std.dev.	255137	0.048	0.029	0.102	0.302	0.47	0.7	1.2	
FR	mean	766282	0.086	0.140	0.640	0.64	1.5	4.4	15.2	9
	std.dev.	530808	0.050	0.095	5.804	0.362	0.20	1.3	2.7	
IT	mean	510176	0.070	0.113	0.622	0.480	1.70	5.4	16.3	3
	std.dev.	247893	0.050	0.023	0.138	0.216	0.23	0.6	1.4	
NL	mean	584420	0.100	0.260	0.250	0.289	1.61	6.6	22.9	4
	std.dev.	326053	0.058	0.269	0.407	0.226	0.28	2.0	10.2	
Total	mean	533133	0.084	0.179	0.586	0.502	1.94	5.4	16.9	46
	std.dev.	409623	0.052	0.173	3.019	0.284	1.85	1.9	5.1	

3 Measuring money market fragmentation

In this section, we present results from two exercises: one estimating time-invariant country-specific fixed effects and the other estimating time-varying fixed effects for two country groups. For both cases, we report results only for countries with sufficient observations to ensure robust estimation — namely, Spain, France, Germany, Italy, and the Netherlands. Observations from other countries remain in the estimation sample to aid inference, though their results are not reported.

3.1 Time-invariant results

In this first exercise, we employ Equation 2 to estimate the time-invariant, country-specific average fragmentation premia relative to Germany. This is achieved by omitting the time index

Table 3: Baseline result: country-specific average fragmentation premium relative to Germany.

	(1) Trans rate - DFR	(2) Trans rate - DFR	(3) Trans rate - DFR	(4) Trans rate - DFR
ES	2.207**	3.470***	0.982	1.444
	(0.851)	(0.993)	(1.215)	(1.564)
FR	-0.499	-1.556	-0.778	-1.244
	(0.699)	(1.223)	(1.351)	(1.391)
IT	8.802***	7.329***	10.353***	10.696***
	(1.725)	(1.861)	(1.651)	(1.406)
NL	-6.022***	-9.787***	-4.818***	-3.455***
	(0.787)	(1.804)	(1.295)	(0.976)
Controls	yes	yes	yes	yes
Fixed effects	Lender-day	Lender sector -location-day	Lender-day	Lender-day
Sample	Full	Full	SSM banks	SSM banks and cross-border trans
N	289607	587476	150990	127848
adj. R^2	0.592	0.751	0.540	0.623

Note: Panel fixed-effects regressions. Sample period: January 2017 to June 2024. Results reported for countries for which there is enough data available for a robust estimation. Bank controls included but not reported. Standard errors in parentheses clustered at the bank-borrower level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

from the country fixed effects, α_c. The results, shown in Table 3, refer to various estimation samples. Column 1 presents the baseline outcomes, indicating that, all else equal, Italian and Spanish banks incur higher borrowing costs of approximately 9 and 2 basis points, respectively, relative to their German counterparts. Conversely, Dutch banks benefit from a discount of around 6 basis points relative to German banks. French banks experience no significant premium compared to German banks when borrowing in the unsecured overnight market. Results are robust across different specifications, with the exception of Spain for the restricted sample. In column 2, we relax the constraints on the lender-day fixed effect and instead include lender-sector and location-day fixed effects, which more than doubles the estimation sample. We obtain similar results in terms of signs but somewhat different magnitudes. In the following two columns, we use progressively more restricted samples than in the baseline estimation. In column 3, we limit the sample to banks supervised by the SSM (see Section 2.3). In column 4, we further restrict the sample by excluding domestic transactions. Given the restrictiveness and the homogeneity of the banks included in the estimation sample, results in column 4 can be considered as lower bounds for the estimates of the fragmentation premia.

Finally, we use Oster (2019)'s method to evaluate the robustness of our results regarding omitted variable. We find that for all countries dummies, the potential additive value of unobservables is negligible, with the exception of The Netherlands. Thus, we can confidently say that we adequately control for relevant factors that may influence the pricing of overnight unsecured transactions.

3.2 Fragmentation in the repo market

Despite the bank level variables included in the regression to control for the credit risk of the bank and the restriction to only SSM supervised banks, one could still argue that the country fragmentation premium reflects factors related to credit risk of the country and that can be measurable. A similar transaction with collateral should cover for credit risk of the borrowing bank, thus overcoming this concern. Although credit risk exposure is quite limited in the unsecured overnight market, given that it is highly unlikely that one observes a sudden shock from one day to another that can cause a default in the loan, we extend the analysis to the overnight (including tom-next and spot-next) General Collateral (GC) repo market. GC transactions are collateralised with a set or basket of securities that can be substituted for one another without changing the repo rate much, if at all. This means that the driver of the transaction is the demand or supply of cash, not of the collateral, i.e., are cash-driven transactions, not collateral-driven transactions. Thus, the GC segment parallels the unsecured market, as the broad motivation to get involved in a transaction would be the same.

The repo market has increased its relevance over the last few years, reflecting several factors going from increased risk aversion, changes in regulation and monetary policy measures (Corradin et al., 2020; ECB, 2023). However, a large part of the market reflects collateral-driven repo transactions. When looking only at cash-driven transactions, GC repo columes are still lower than the ON unsecured market but with an increasing trend (Figure 2). New participants entry costs to the repo market are also higher than to the unsecured market, especially for transactions with CCP, which can limit GC market activity for smaller institutions. As excess liquidity reduces and incentives to fund liquidity in the market increase, the GC segment will likely continue to see an increase in activity in particular due to lower regulatory costs than in the unsecured market.[6] Thus, given the relevance of the repo market, we should also monitor the extent to which fragmentation is also priced in this market.

We follow a similar identification strategy as before, but we extend to take into account the

[6]For example, some repo transactions can be netted out for the computation of the leverage ratio.

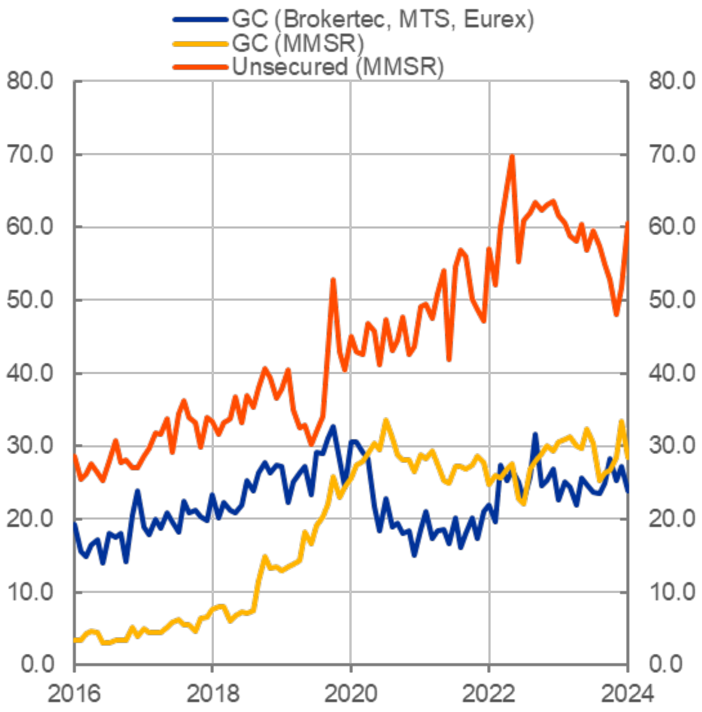


Figure 2: Volumes in GC repo and unsecured market

Note: Daily average volumes of ON transactions over the month. MMSR only includes borrowing transactions with financial institutions from reporting banks.
Source: ICAP (Brokertec), MTS, Eurex, MMSR and author calculations.

additional dimension that determines the transaction: the collateral. Although GC securities can be replaced, there is usually a list of specific securities that are eligible to a given basket and that comply with a set of restrictions. For example, government bonds issued by Germany. Given that we have information of the ISIN underlying the repo, we extend the regression equation 2 to include this information and estimate:

$$y_{l,b,i,t} - y_t = X_{b,t}\beta + D_{b,i,t}\gamma + \alpha_{l,t} + \alpha_{i,t} + \alpha_c + \epsilon_{l,b,i,t}. \tag{3}$$

where besides the lender l and the bank b identifying the transaction in day t, we also have now the collateral i. We include ISIN-month fixed effects to take into account the different pricing of the repo depending on the collateral. We assume that the effect of collateral characteristics can change over time, but with a lower frequency than the transaction frequency, ie, over the month instead of every day. We also include a dummy variable $D_{b,i,t} = 1$ whenever the issuer of the security is from the same country as the borrowing bank, given the existence of a premium when the risk of the borrower is correlated with the risk of the collateral (Barbiero et al., 2024). With this specification, we are comparing transactions from the same lender with the same collateral to different banks from different countries.

Results for the estimate of the time-invariant country fragmentation premium relative to German banks are shown in table 4 for the countries with enough observations to be able get a viable estimate of the premium. All columns show the results of the main specification (equation 3), changing only the sample used. In column (1) we have the full sample of banks, in column (2) we restrict to SSM supervised banks and in column (3) we additionally exclude domestic transactions. In all regressions, we do not find any significant estimated country premium. When we control for credit risk with collateralized transactions there is no longer any heterogeneity across countries in the euro area. Thus, results suggest that fragmentation is linked to credit risk at the country level.

3.3 Time-varying results

To explore the evolution of fragmentation over time, we re-estimate Equation 2 and construct a time-varying, country-group specific fragmentation indicator. The parameters of interest remains $\alpha_{c,f}$, now estimated at a monthly frequency. Although $\alpha_{c,f}$ could theoretically be estimated using dummy variables, the high number of fixed effects renders this approach computationally

Table 4: Baseline result: country-specific average fragmentation premium in the overnight GC repo market relative to Germany.

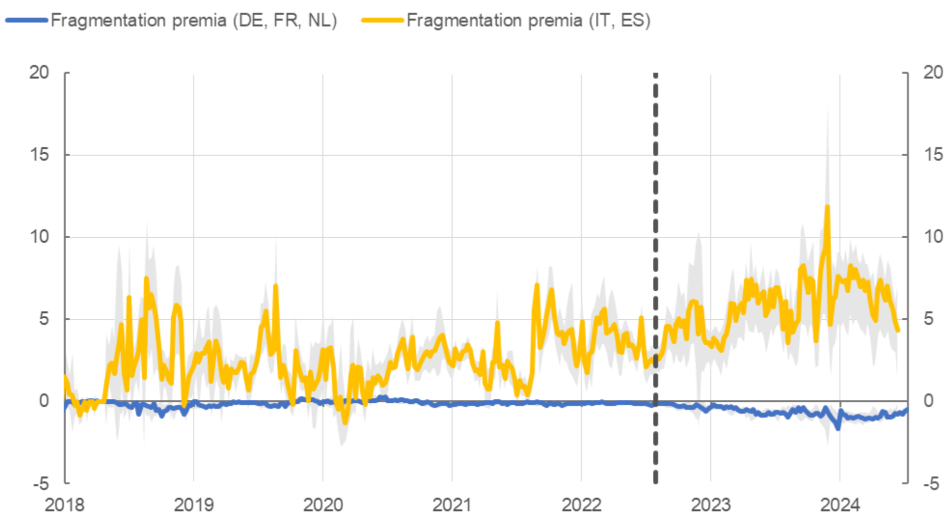
	(1) Trans rate - DFR	(2) Trans rate - DFR	(3) Trans rate - DFR
ES	-1.490	-7.965	-6.479
	(2.648)	(6.201)	(7.040)
FI	-3.194	19.325*	-1.208
	(2.806)	(9.917)	(3.216)
FR	-5.104	19.470*	1.348
	(3.523)	(10.525)	(4.711)
IT	-2.844	-2.489	0.812
	(2.870)	(4.013)	(4.040)
Controls	yes	yes	yes
Fixed effects	Lender-day, band, isin-month	Lender-day, band,isin-month	Lender-day, band,isin-month
Sample	Full	SSM banks	SSM banks& cross-border
N	425862	362607	259044
adj. R^2	0.956	0.960	0.952

Note: Panel fixed-effects regressions. Sample period: January 2017 to June 2024. Results reported for countries for which there is enough data available for a robust estimation. Bank controls included but not reported. Standard errors in parentheses clustered at the bank-borrower level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

intensive and may reduce the numerical accuracy. Therefore, we allow the fixed effects to be absorbed by the estimation procedure and subsequently use bootstrapping techniques to retrieve the relevant fixed effects and calculate their standard errors. This approach also enables us to construct time-varying country-specific fragmentation indicators for all included countries, including Germany –an important feature for policy makers and monitoring efforts, particularly as aggregate excess liquidity continues to decline. These indicators capture the positive or negative premia that banks face for being in a particular country, beyond what would be expected based solely on bank characteristics, lender conditions, and daily market factors.

Figure 3 presents the fragmentation indicators for two country groups. Group 1 comprises Germany, France, and the Netherlands, while Group 2 includes Spain and Italy. Grouping the countries is necessary due to confidentiality requirements in the MMSR data, and the country allocations are based on the sign of the country-specific coefficients shown in Table 3. The results indicate that fragmentation for the two groups remained relatively stable, albeit at different levels, until the first half of 2022. For Germany, France, and the Netherlands, fragmentation levels were nearly zero, whereas for Spain and Italy the average country premium was approximately 3 basis points. However, with the start of the ECB's hiking cycle in the summer of 2022, there is evidence of an increase in absolute fragmentation levels for both groups. This intensification reached its peak during the height of the rate-hiking cycle, marking the most pronounced period of fragmentation observed to date.

Figure 3: Fragmentation indicators



Notes: This figure depicts the estimated average premium (in bps) for borrowing by banks from two country groups. The gray areas indicate the 90% confidence interval based on standard errors clustered at the bank level.

4 How relevant is money market fragmentation along the transmission chain?

The fragmentation premia observed in the unsecured ON money market likely reflect persistent cross-country differences within the monetary union that have the potential to get transmitted to other markets. For instance, if Italian banks, on average, pay 8 basis points more than German banks for short-term unsecured funding, this premium may influence broader banking activities, and particularly the credit markets. In the second part of this analysis, we test whether country-specific fragmentation premia impact the interest rates banks set on loans to non-financial corporations. We assume uniform fragmentation premia across banks within each country. Our focus is on the credit market, as this segment plays a central role in the monetary policy transmission mechanism, ultimately impacting the real economy. Specifically, we examine loans to non-financial corporations, which are more responsive to the business cycle and thus expected to be more synchronized across the euro area. By contrast, loans to households tend to be influenced by more idiosyncratic factors. Additionally, we analyze new business interest rates, which reflect the interest rates on new loans issued within the reporting period, capturing the most current lending conditions. We obtain monthly data on new business interest rates at the bank level from the IMIR dataset. The final dataset for this exercise runs from January 2017 to

June 2024 and includes banks from France, Germany, Italy, Spain, and The Netherlands.

We employ the following regression specification:

$$i_{b,t}^{NFC} = \beta_0 F_{c,t} + OIS\ 3m_t + X_{b,t-1}\beta_1 + Z_{c,t}\beta_2 + \alpha_b + \epsilon_{b,t}, \tag{4}$$

where $i_{b,t}^{NFC}$ is bank b's new business loan rate to non-financial corporations, weighted average over month t. The rate is benchmarked against the relevant risk-free rate, which we take to be the 3-month Overnight Index Swap (OIS) rate ($OIS\ 3m_t$). The primary coefficient of interest, β_0, captures the effect of the country-level fragmentation premia ($F_{c,t}$) estimated in the previous section. For this specific exercise, we use Equation 2 and estimate fragmentation premia at the monthly frequency for the 6 countries included in the analysis. To mitigate endogeneity concerns, we include a set of bank-level controls $X_{b,t-1}$, lagged one period. The bank controls included are the composite deposit interest rate of the bank, the share of ECB funding over total assets, the share of sovereign domestic bond holdings over total sovereign bond holdings, the share of domestic MFI bond holdings over total bond holdings, the share of debt securities issued over total assets, the tier 1 capital ratio, the leverage ratio and the average rating from the four largest credit rating agencies. Additionally, we include bank fixed effects, (α_b) to account for unobserved bank-specific characteristics, such as business model. To control for country-specific macroeconomic conditions, we include GDP growth (interpolated at the monthly frequency), inflation, and a proxy for non-financial corporation (NFC) loan demand from the Bank Lending Survey ($Z_{c,t}$). This specification is aligned with Altavilla et al. (2019), where the authors investigate the impact of interbank rate uncertainty on bank lending rates to firms.

Table 5 shows the results. Column 1 includes the country-premium estimated from the baseline sample (corresponding to column 1 in Table 3) and column 2 the estimation from the most restricted sample (corresponding to column 4 in Table 3). The results across these two columns are comparable. An increase in the country premium is linked to a proportional rise in loan interest rates to NFCs. These findings indicate that fragmentation in the money market plays a significant role in the transmission of monetary policy, particularly influencing credit conditions for firms.

Table 5: Transmission of fragmentation premia to new business loan rates to NFC.

	(1) NFC loan rate	(2) NFC loan rate
$F_{c,t}$	1.087*	
	(0.501)	
$F_{c,t}$ restr.		0.882*
		(0.422)
Bank FE	Yes	Yes
#banks	47	47
N	2748	2650
adj. R^2	0.909	0.909

Note: Panel fixed-effects regressions. All controls included but not shown. Variables defined in [INCLUDE A TABLE WITH VARIABLES]. Standard errors in parentheses clustered at the bank level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5 Conclusion

In the first part, this paper examined the degree of fragmentation in the Euro Area's overnight unsecured money market from January 2017 to June 2024, constructing a country-specific fragmentation indicator. In the second part, it assessed whether this money market fragmentation get transmitted through the monetary policy transmission chain, affecting other markets.

The findings confirm the presence of fragmentation within the euro area. Italian and Spanish banks face positive fragmentation premia of approximately 8 and 2 basis points, respectively, compared to German banks, compared to what should be priced in based on bank-specific characteristics alone. In contrast, Dutch banks experience a discount of around 6 basis points relative to German banks. The premia seems to reflect credit risk at the country level, given that when credit risk is properly accounted for with collateralized transactions, we no longer find significant differences in prices across countries.

The time-varying country-specific fragmentation indicator reveals that countries with positive premia on average (such as Italy and Spain) saw increased fragmentation throughout the recent rate-hiking cycle. The second part of the analysis shows that money market fragmentation does pass through the monetary policy transmission chain and that it is proportionately transmitted to the new loan rates offered to firms.

References

Abbassi, P., Bräuning, F., Fecht, F., and Peydró, J.-L. (2022). Cross-border interbank liquidity, crises, and monetary policy. *Journal of International Economics*, 139(C).

Acharya, V. V. and Steffen, S. (2015). The "greatest" carry trade ever? understanding eurozone bank risks. *Journal of Financial Economics*, 115(2):215–236.

Afonso, G., Kovner, A., and Schoar, A. (2011). Stressed, not frozen: The federal funds market in the financial crisis. *The Journal of Finance*, 66(4):1109–1139.

Afonso, G. and Lagos, R. (2015). Trade dynamics in the market for federal funds. *Econometrica*, 83(1):263–313.

Altavilla, C., Carboni, G., Lenza, M., and Uhlig, H. (2019). Interbank rate uncertainty and bank lending. Working Paper Series 2311, European Central Bank.

Ampudia, M., Beck, T., Beyer, A., Colliard, J.-E., Leonello, A., Maddaloni, A., and Marqués-Ibáñez, D. (2019). The architecture of supervision. Working Paper Series 2287, European Central Bank.

Barbiero, F., Schepens, G., and Sigaux, J. (2024). Liquidation Value and Loan Pricing. *Journal of Finance*, 79(1):95–128.

Becker, B. and Ivashina, V. (2017). Financial Repression in the European Sovereign Debt Crisis*. *Review of Finance*, 22(1):83–115.

Bräuning, F. and Fecht, F. (2016). Relationship Lending in the Interbank Market and the Price of Liquidity*. *Review of Finance*, 21(1):33–75.

Corradin, S., Eisenschmidt, J., Hoerova, M., Linzert, T., Schepens, G., and Sigaux, J.-D. (2020). Money markets, central bank balance sheet and regulation. Working Paper Series 2483, European Central Bank.

Duffie, D. and Krishnamurthy, A. (2016). Passthrough efficiency in the fed ' s new monetary policy setting ? In *Designing Resilient Monetary Policy Frameworks for the Future. Federal Reserve Bank of Kansas City, Jackson Hole Symposium.*

ECB (2023). Euro money market study 2022. Technical report, European Central Bank.

Freixas, X. and Holthausen, C. (2004). Interbank Market Integration under Asymmetric Information. *The Review of Financial Studies*, 18(2):459–490.

Furfine, C. H. (2001). Banks as monitors of other banks: Evidence from the overnight federal funds market. *The Journal of Business*, 74(1):33–57.

Garcia-de Andoain, C., Hoffmann, P., and Manganelli, S. (2014). Fragmentation in the Euro overnight unsecured money market. *Economics Letters*, 125(2):298–302.

Khwaja, A. I. and Mian, A. (2008). Tracing the impact of bank liquidity shocks: Evidence from an emerging market. *American Economic Review*, 98(4):1413–42.

Ongena, S., Popov, A., and Van Horen, N. (2019). The invisible hand of the government: Moral suasion during the european sovereign debt crisis. *American Economic Journal: Macroeconomics*, 11(4):346–79.

Oster, E. (2019). Unobservable selection and coefficient stability: Theory and evidence. *Journal of Business & Economic Statistics*, 37(2):187–204.