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Peering beyond the veil: A dissection of aggregate bank lending rate movements into pricing and composition effects using credit-level data*

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Abstract

Compared to 2021, the aggregate bank lending rate to firms in the euro area increased strongly during the monetary tightening and easing cycle of 2022-25. However, it rose up to 1.5 percentage points less than the rise in policy and money market rates. We approach this gap using granular credit registry data, revealing how changes in the composition and pricing of credit translate into developments of the aggregate rate. The tool we use is standard in labor economics, but scarcely used outside that context: the Oaxaca-Blinder decomposition. We are the first to apply it to analyze the development of an aggregate variable over time in the loan pricing literature. We find that changes in the pricing of credit compared to 2021 were the main reason why a gap opened up. Compositional shifts in firm and credit characteristics and changes in banks' market shares had minor effects. Our micro-level insights have implications for policy makers, bankers and debtors, as they help understand what shapes aggregate pass-through patterns and the strength of monetary policy transmission. Moreover, our approach opens up promising new applications in the loan supply literature.

Keywords: Credit pricing, euro area, monetary policy transmission, interest rate pass-through

JEL classification: E52, E43, E44, E58, G20, G21.

*Contact address: Wilhelm-Epstein-Strasse 14, 60431 Frankfurt am Main, Germany. Phone: +49 (0)69 9566 11964. Email: Paul.Reimers@bundesbank.de, Henrike.Michaelis@bundesbank.de. We thank Refet Gürkaynak, Olivier De Jonghe, Christiane Baumeister, Joachim Winter, Sebastian Bredl, Tim Hagenhoff, Ulrike Busch and our colleagues from the Bundesbank's Economics and Research departments for insightful discussion and helpful comments. In addition to comments and discussions, Tim Hagenhoff also provided us with a very helpful code to assess the role of bank characteristics in pass-through heterogeneity. The views expressed in this paper are those of the authors and do not necessarily coincide with the views of the Deutsche Bundesbank or the Eurosystem.

1 Introduction

As inflation surged from 2021 onward, central banks around the world tightened their monetary policy. In the euro area, for example, policy rates increased by up to 4.5 percentage points (PP) during the 2022-25 tightening and easing cycle. Wherever bank lending is a key step in the transmission process, policy makers, bankers, and debtors closely observed the extent to which money market rates and bank lending rates co-moved with policy rates. Money market rates closely mimicked the rise in the ECB’s policy rates. Regarding bank lending rates to non-financial corporations (henceforth ‘firms’), a stylized fact from pass-through studies is that these typically do not increase in lockstep (de Bondt, Mojon, and Valla, 2005; Belke, Beckmann, and Verheyen, 2013; Holton and d’Acri, 2018). This was also the case after 2021: Aggregate statistics that we compute based on credit registry data point to an increase in the bank lending rate to firms of up to 3 PP. This is approximately 1.5 PP less than the increase in policy and money market rates.

What explains the increase in the aggregate bank lending rate, and why did it not rise in lockstep with policy and money market rates? This is what we address in our paper. For central bankers, these are important questions when assessing the strength of transmission via banks and its determinants, particularly if the pass-through of monetary policy impulses to bank lending rates is stronger or weaker than historical patterns. For banks and firms, these questions are also highly relevant: Both form expectations about the development of interest income and financing costs during monetary policy cycles, and adjust their loan pricing and financing strategies accordingly.

To answer these questions, it is crucial to have a detailed understanding of the factors that shape the development of aggregate bank lending rates. We therefore approach them from a micro-perspective, using credit-level registry data (AnaCredit). In this regard, we connect most closely to Altavilla, Gürkaynak, and Quaedvlieg (2024), who use the same database to study the determinants of bank lending rates. Our data comprises 42 million financing arrangements originating between euro area banks and firms from April 2021 to August 2025, and provides information on a large set of firm- and credit-level variables. Using this type of granular data, we focus on two factors shaping the increase in the aggregate bank lending rate to firms and the gap that opened up.

First, compared to 2021, the *composition of lending* changed: ‘which banks’ financed ‘which firms’ and ‘how’ evolved during the tightening and easing phases of 2022-25. For example, lending shifted between banks, with some banks exhibiting increasing shares in the credit market and other banks decreasing market shares. Moreover, lending shifted towards larger and less risky firms, and across sectors of economic activity. Finally, the typical financing arrangement changed over time: The average financing amount, maturity, and interest rate fixation all decreased. So far, the literature lacks systematic evidence on the many types of compositional shifts that occur, be it over time or specifically during 2022-25. We set out to document them and pinpoint how they contributed to the development of the aggregate bank lending rate.

Second, the *credit pricing structure* also changed during 2022-25. We view bank lending rates as being set on the basis of a bank-specific fixed component of credit pricing, which reflects the refinancing costs banks face. To this fixed component, banks add a mark-up that consists of premia and discounts to account for firm and credit characteristics. We mirror such a credit pricing structure using OLS with bank fixed effects, which

we estimate on a monthly basis from 2021 onward. One of the major patterns we find concerns how banks priced larger financing amounts: They were associated with lower rates in 2021, but the coefficient quantifying that discount decreased afterwards. Premia and discounts changed for other determinants of bank lending rates as well. We set out to quantify the extent to which such pricing patterns exerted up- or downward pressure on the development of the aggregate rate and, hence, the gap.

Overall, we consider a multitude of factors that could influence the aggregate rate’s increase and explain why it did not increase in lockstep with policy and money market rates. Disentangling this requires a structured and systematic approach. We implement the Oaxaca-Blinder decomposition to do so (Oaxaca, 1973; Blinder, 1973), a method that is well established in the labor market literature.¹ One reason is that the data necessary to implement it has been available for decades. As the availability of granular firm-financing data increases, so do the opportunities to investigate how developments at the firm and credit level translate to aggregate banking statistics (micro-macro nexus). The setup we propose is particularly interesting because, by design, it is able to do just that.

The innovation we present here is to implement the Oaxaca-Blinder decomposition to explain the development of an aggregate statistic *over time*. The essence of what we do is as follows. First, we model and estimate the determinants of bank lending rates on a monthly basis using OLS. This is to estimate a time-varying credit pricing structure. We then show how to decompose the increase in the aggregate bank lending rate compared to 2021 into ‘pricing effects’ and ‘composition effects’. Pricing effects arise because, compared to 2021, the OLS coefficients changed in 2022-25. To compute the pricing effects, we assume that the composition remained constant over time (as in 2021). Composition effects arise because the composition of lending changed compared to 2021. To compute these effects, we assume that the credit pricing structure in 2021 was the same as in 2022-25. This setup can easily be extended to decompose the differential increase in the aggregate bank lending rate compared to any policy or money market rate. For our implementation we choose the 3-month (3M) Euribor.

To the best of our knowledge, we are the first to implement the Oaxaca-Blinder decomposition in such an over-time context and in the loan pricing literature. Ours is thus an exemplary analysis that opens up promising new microdata applications in banking, monetary policy, and supervision. For example, the approach can be easily applied to other aggregates, such as the development of credit amounts or debtor PD, or it can be used in cross-country studies.

We find that composition effects were minor, while changes in the credit pricing structure substantially dampened the increase in the aggregate bank lending rate after 2021. The aggregate rate would have increased up to 1.5 PP more if credit pricing had remained as in 2021. That is, pricing effects account for the bulk of the gap between the aggregate bank lending rate and policy or money market rates. Changes in the composition of lending dampened the increase in the aggregate rate, too, but only by up to -0.15 PP.

To better understand what shapes our main findings, we then quantify the contribu-

¹See Weichselbaumer and Winter-Ebmer (2006); Olivetti and Petrongolo (2008). The approach is typically implemented to analyze the determinants of gender wage gaps. It uses OLS to decompose mean wage differences between two groups, typically men versus women. First, an explained part that arises from group differences in the characteristics that determine wages (the composition effect); second, an unexplained part that arises from different coefficients on wage determinants.

tions of individual components of the credit pricing structure. One key element shaping the pricing effect is the extent to which banks’ fixed components of credit pricing (the bank fixed effects) increased during the tightening. To decompose the gap, our setup benchmarks the change in the bank fixed effects against the change in the 3M Euribor. In essence, this reflects the degree to which banks passed through the increase in refinancing costs. We find that banks’ fixed components of credit pricing were adjusted less than one-to-one, and this *dampened* the increase in the aggregate rate by up to 2.25 PP. Put simply, the gap between the aggregate bank lending rate and 3M Euribor opened up because the pass-through of changes in the 3M Euribor to banks’ fixed component was weak.

However, given the size of the gap, this cannot be the full story, because the gap was smaller than 2.25 PP. This means that changes in the pricing of other determinants of bank lending rates must have exerted *upward pressure* on the aggregate rate, such that the gap closed again to a certain extent. The key contributor exerting upward pressure on the aggregate rate results from the pricing of larger credit amounts. As mentioned above, the discount on the credit amount decreased. Compared to 2021 this made credit with a given financing amount more expensive. If the discount had remained as large as in 2021, and assuming that average credit amounts were constant, then the aggregate bank lending rate would have increased up to 1.3 PP less. Composition-wise, the reduced discount was flanked by a reduction in the average credit amount, which we consider to be the ‘intensive margin’ of financing (‘how much’ financing is provided conditional on a financing agreement). This exerted further upward pressure on the aggregate rate. In addition, we find that the yield curve inversion temporarily dampened the increase in the aggregate, but this was counteracted by a lower average rate fixation. Lastly, changes in the pricing of instrument types exerted upward pressure on the aggregate rate.

Finally, we present an example of how our results can be used to expand what is known about the transmission of monetary policy via banks. One opportunity lies in identifying how the aforementioned changes in the pricing of certain firm- and credit-level characteristics shape aggregate interest rate pass-through patterns (de Bondt et al., 2005). Our decomposition makes this a straightforward task. This is because the development of banks’ fixed component of credit pricing is a natural starting point to think about the pass-through of monetary policy to bank lending rates. To pinpoint the extent to which individual elements of the credit pricing structure shaped the pass-through, we construct rates for counterfactual scenarios. In these scenarios, only certain elements of the credit pricing structure (fixed component, selected discounts/premia) are as in 2022-25 while the remaining pricing elements remain as in 2021. For each of the counterfactuals, we then compute pass-through measures. Based solely on the development of banks’ fixed component of credit pricing, the aggregate pass-through would have been lower than we would have expected from aggregate pass-through estimates. The reason why the pass-through to the aggregate rate was higher is that banks reduced the discount on larger credit amounts and increased the relative cost of widely used financing instruments.

The paper is structured as follows. Section 2 links our paper to the previous literature and highlights our contributions. Section 3 describes the data and provides stylized facts that motivate our paper. We show how to implement the Oaxaca-Blinder decomposition in an over-time context to address our research question in Section 4. Section 5 presents our results. In Section 6 we discuss the implications of our results and conclude.

2 Related literature

We systematically investigate how credit- and firm-level developments translate into the development of aggregate bank lending rates. Due to the absence of granular credit data for the euro area, it was previously not possible to carry out this exercise.

Previous studies limited their analyses to identifying and quantifying selected channels of monetary policy that could affect the quantity and price of bank lending. In doing so, they paved the way for the part of our work that focuses on the prevalence and importance of compositional shifts for movements in the aggregate rate. This is because the compositional shifts we focus on are symptoms of the identified monetary policy channels. For example, [Kashyap and Stein \(2000\)](#), [Kishan and Opiela \(2000\)](#), [Van den Heuvel \(2002\)](#), and [Gambacorta \(2005\)](#) find that the transmission of monetary policy to bank lending volumes varies depending on banks' capital levels, liquidity, and size (the bank balance-sheet-channel). Evidence based on credit-level variation is scarce, but confirms that bank capital is related to the approval of credit applications, volumes, and riskiness ([Jiménez, Ongena, Peydró, and Saurina, 2012, 2014](#)). Moreover, the credit supply of reserve-rich banks is less sensitive to a monetary policy tightening ([Fricke, Greppmair, and Paludkiewicz, 2024](#)). If such bank balance-sheet-channels were at work during the monetary tightening and easing phases of 2022-25, then measurable shifts in banks' market shares should be an observable symptom. Our contribution is to pinpoint the extent to which such shifts affected the development of the aggregate rate.

Similarly, the firm balance-sheet-channel should bring about changes in the composition of lending across firm and credit characteristics. This is because a tightening of monetary policy impacts debtors' net worth and creditworthiness, exacerbating agency costs ([Bernanke and Gertler, 1995](#)). Using credit-level data, this should become visible via a shift in lending towards debtors that are more financially sound ([Bernanke, Gertler, and Gilchrist, 1996](#)), secured credit, or through greater reliance on pre-existing lending relationships ([Petersen and Rajan, 1994](#)). In addition, the macroeconomic and credit market repercussions of monetary policy impulses do not necessarily affect all debtors equally. The impact may differ depending on firm age or sector of economic activity ([Durante, Ferrando, and Vermeulen, 2022](#)), reliance on short- versus long-term financing, or country of origin. Some firms may be better able to maintain funding access than others ([Chodorow-Reich, Darmouni, Luck, and Plosser, 2022](#)). Finally, it may be possible to mitigate rising agency costs by using financing arrangements with more favorable terms for the bank (less flexibility in drawing funds or faster amortization, for example).

Overall, the existing literature suggests that compositional shifts may occur along many dimensions, be they banks' market shares, firm characteristics, or credit characteristics. Our study documents such shifts and quantifies how they contributed to the development of the aggregate rate.

In our decomposition, one source of pricing effects is when a bank's fixed component of credit pricing does not move in lockstep with policy or market rates. This is a natural starting point for understanding the pass-through of monetary policy to aggregate bank lending rates and connects our work to [de Bondt et al. \(2005\)](#), [Belke et al. \(2013\)](#) and [Horvath, Kotlebova, and Siranova \(2018\)](#). These studies document the stylized fact that the long-run pass-through of changes in policy and market rates to bank lending rates is incomplete (typically around 70-90%). However, the studies rely on macro-based ap-

proaches and thus cannot address the role that specific determinants play in shaping the extent of the pass-through and, hence, the gap. Regarding possible specific determinants, we connect to previous studies that attribute heterogeneity in the pass-through of monetary policy to bank-level variation (this is because, in our setup, the fixed component of credit pricing is bank-specific). Evidently, the bank balance sheet channel affects not only lending volumes, but also pricing dynamics (Holton and d’Acri, 2018; Altavilla, Canova, and Ciccarelli, 2020). Gambacorta and Mistrulli (2014), one of the few studies to examine credit pricing using bank- and firm-level data, further supports this. We contribute to this literature by pinpointing the role that individual firm- and credit-level determinants of bank lending rates play in shaping the pass-through of monetary policy.

The other source of pricing effects is when the discounts and premia that capture the influence of firm- and credit-level characteristics on bank lending rates change over time. Put simply, banks can respond to higher agency costs either by being more selective in whom they finance and how (‘extensive margin’ of financing) or by financing smaller amounts (‘intensive margin’), as shown above. Alternatively, they can adjust credit pricing to account for these increased costs. So far, however, the lack of micro data has hindered research into the influence of firm- and credit-level characteristics. Berger and Udell (1995) shed light on the role of relationship lending, which is one of the few determinants of lending rates to have been investigated early using micro data. Chodorow-Reich et al. (2022) document the differences in credit pricing depending on firm size. Kosekova, Maddaloni, Papoutsis, and Schivardi (2024) show how bank lending rates vary across euro area countries, financing types, relationship lending, maturity, and firm size. We connect most closely to Altavilla et al. (2024), who attribute the variation in bank lending rates to firms to country-, bank-, firm-, and credit-level heterogeneity. We contribute to this literature by documenting how pricing changed compared to 2021, and by quantifying how these changes influenced the development of the aggregate rate and the gap.

3 Data and motivational facts

Our analysis relies on the AnaCredit credit registry. The data contains harmonized contract-level information on financing obligations between non-financial corporations (‘firms’) and banks in the euro area. It is available on a monthly basis and includes attributes at the level of the individual firm and the financing contract. Banks must report all claims against a particular firm when they exceed the sum of 25,000 euros.

3.1 Data processing and sampling

We draw all new financing contracts² originating between firms and banks from June 1st 2019 onward. The type of debt instrument must be a loan, credit line (also revolving), trade receivable, overdraft, or finance lease (see Kosekova et al., 2024 for an overview of instrument types). For simplicity, in the following we refer to these different types of financing contracts as ‘credit’.

²The first unique combination of creditor, debtor, contract and instrument ID (in AnaCredit, a ‘contract’ can encompass multiple financing arrangements, which are referred to as instruments).

Table 1: Descriptive statistics

		Distribution (2019/06-2025/08)				2021*	2022 ff.
		Mean Std. Dev	p(5)	Median	p(95)	Mean	Mean
Sample	Annualized rate	3.6%	0.0%	4.3%	8.0%	2.0%	4.1%
	# of Obs.	2.3%	61,274,838			6,371,961	35,737,252
Original data	Annualized rate	3.5%	0.0%	4.0%	8.2%	2.0%	3.9%
	# of Obs.	2.5%	83,706,438			9,002,761	47,416,038
Sample Coverage			73%			71%	75%

Notes: Based on new lending data in AnaCredit. ‘Original data’ refers to the new financing data after outlier detection and after dropping reporting issues. The size of the sample is smaller because it requires data availability along all variables that we use later on in the analysis. *April - December 2021, which is the benchmark we impose later on in the analysis due to computational limitations.

We exclude credit issued by multiple banks. The data must contain information on the firm- and credit-level characteristics that enter the decomposition exercise.³ We filter outliers using a multivariate outlier-detection procedure. Based on the remaining data, we impute the debtor’s probability of default (PD) (for about 50% of the financing arrangements, which we exclude in a robustness exercise in [Section 5.5](#)), and the number of years until the next reset of the interest rate (0.5% of the data). We provide distributional statistics for all the attributes used in [Tables 4 and 5](#) in the Appendix. At the time of writing, several banks had unresolved reporting issues that affected the identification of *new* financing arrangements. We exclude these banks because such issues make it difficult to identify shifts in banks’ market shares and how such shifts affected the development of the aggregate rate. For similar reasons, we restrict our sample to banks that issued at least one credit in every month after 2021 (1,197 distinct banks).

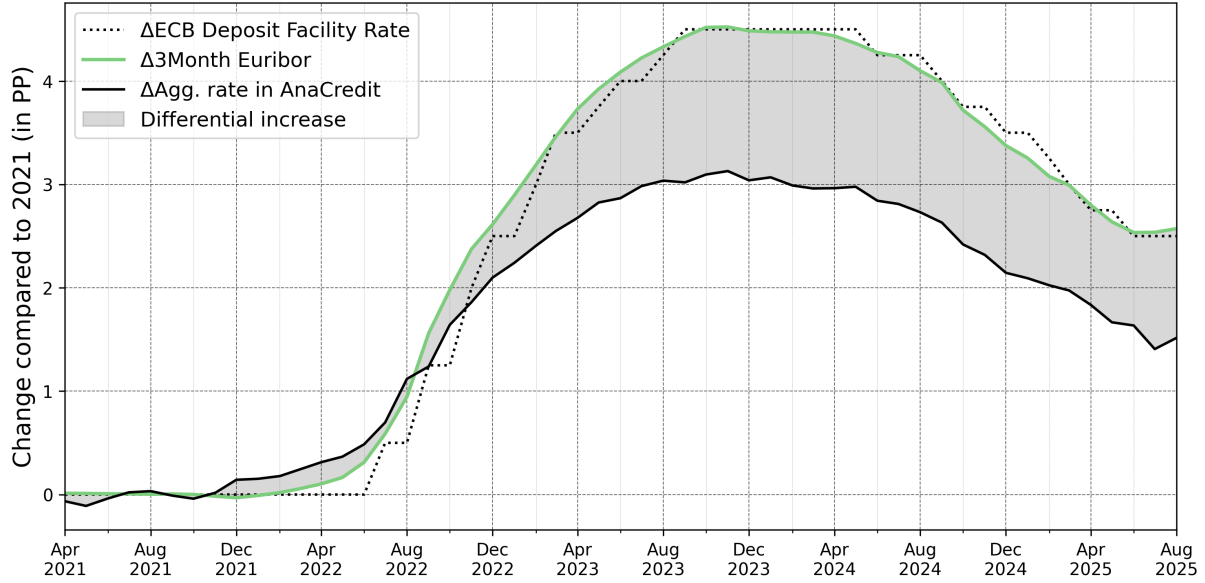
[Table 1](#) gives an overview of the data. Our main analysis uses data from April 2021 onward, totaling 42 million observations. The sample covers around 71 - 75% of the original data and replicates the distributional patterns of lending rates: In our sample, the lending rate also averaged 2.0% in 2021 (amount-weighted); after 2021 it was 2.1 PP higher, averaging 4.1% (compared to 3.9%). Official bank lending rate statistics provide a similar picture, with rates having increased from 1.6% to 3.9%.⁴

In [Figure 1](#) we compare the increase in the aggregate bank lending rate in AnaCredit with the increase in policy rates and the 3M Euribor. Compared with 2021, the ECB’s

³Credit level information includes the interest rate, amount, duration of rate fixation, maturity, whether the financing amount is secured, type of amortization, purpose of financing (working capital facility or not). Firm-level information includes the debtor’s probability of default (PD), economic sector, and $\ln(\text{number of employees} + 1)$.

⁴[MFI Interest Rate Statistics](#) (MIR): Rates for loans to corporations, series key MIR.M.U2.B.A2A.A.R.A.2240.EUR.N; and rates for revolving loans, overdrafts, convenience, extended credit card to corporations, key MIR.M.U2.B.A2Z.A.R.A.2240.EUR.N.

Figure 1: The differential increase during the 2022-25 tightening and easing cycle



Notes: Based on AnaCredit data and own calculations. Benchmark to calculate the changes is April - December 2021 (the period we use later on due to computational limitations).

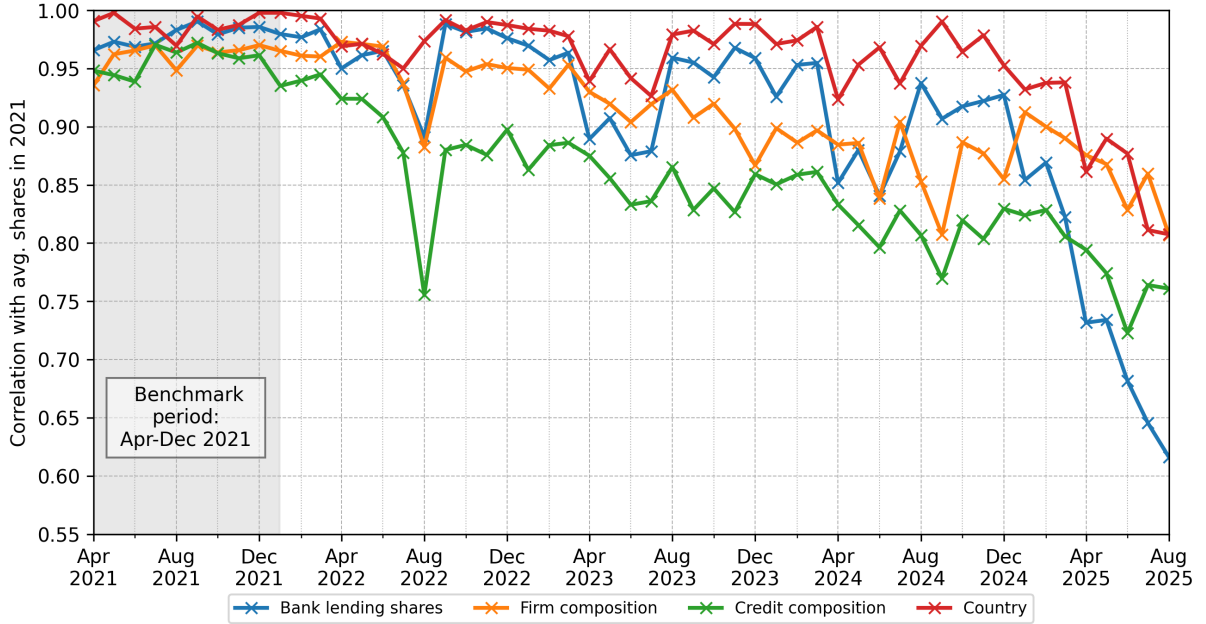
deposit facility rate and the 3M Euribor both increased by up to 4.5 PP. Regarding the development of the aggregate bank lending rate to firms, existing studies provide the stylized fact that the pass-through of changes in money market or policy rates to the bank lending rate is incomplete (de Bondt et al., 2005; Belke et al., 2013; Holton and d’Acri, 2018; Horvath et al., 2018). Thus, one should not expect the aggregate bank lending rate to rise in lockstep with money market and policy rates, but a gap to open up. Indeed, in our data the aggregate bank lending rate increased less, by up to 3 PP. The gray shaded area highlights the gap that arose due to the differential increase and that amounted to up to 1.5 PP.

Understanding what is behind the increase in the aggregate bank lending rate and why it did not rise in lockstep with policy and market rates is central to the debate on the strength of monetary policy transmission via banks. So far, assessments of the strength of transmission have been confined to the use of macrodata, for example by contrasting the pass-through of monetary impulses with historical patterns. Due to the limited availability of microdata, it was previously not possible to identify what exactly shapes the incomplete pass-through and, hence, the opening of the gap. We set out to add insights to the discussion by exploiting the granular nature of AnaCredit to identify micro-level factors that lie behind the ‘veil of the aggregate’ and shape macro patterns. In this regard, our interest in shifts in the composition of lending and in changes in the credit pricing structure originates from two motivational facts.

3.2 Compositional shifts in lending

First, the composition of lending in AnaCredit exhibits changes along multiple determinants of bank lending rates. Figure 2 provides a condensed summary of these composi-

Figure 2: Changes in the composition of lending compared to 2021



Notes: Based on AnaCredit data and own calculations. Correlation of lending shares over time. Lending shares are computed on a monthly basis for clusters defined by either the country, bank, firm or credit-level variables, then correlated with those in April - December 2021 (benchmark).

tional changes. For the red line, we correlate the market shares of total lending in each country after 2021 with the market shares that prevailed on average from April to December 2021 (our benchmark period). This shows the similarity of the lending composition across countries over time. Similarly, for the blue line we correlate banks' market shares in each month with those that prevailed on average in our benchmark period. For the green and orange lines, we cluster observations along firm and credit attributes, respectively, and calculate the clusters' lending shares. We then correlate the lending shares of the clusters after 2021 with those that prevailed in our benchmark period.

For a long time, the correlation of lending shares across countries remained close to one. Lending shifts did occur across countries after 2021, but these were minor: Spain's lending share increased, while Italy's decreased (see Table 5 in the Appendix).

Compared to this, bank lending shares shifted more substantially (blue line), particularly from 2025 onward. We expect that lending shifts arose during the tightening phase as symptoms of the bank balance sheet channel (Kashyap and Stein, 2000; Kishan and Opiela, 2000). Furthermore, lending may also have shifted within-country (rather than across-countries) if firms compared financing offers from multiple banks as interest rates began to rise. If they managed to identify and obtain funding from relatively cheaper banks, this could have dampened the increase in the aggregate rate.

We also construct clusters along firm characteristics (orange line, based on firm size, sector, and debtor PD, among other factors). Here, too, the composition changed from mid-2022 onward. This is due to an increase in credit to, on average, larger and less risky firms, and less credit to the real estate sector (in line with the firm balance sheet channel of monetary policy). We expect that such compositional shifts may have dampened the

increase in the aggregate rate.

The green line in [Figure 2](#) illustrates that, compared with 2021, the composition of credit-level attributes changed the most (we cluster the data along credit amount, duration of rate fixation, relationship lending, and instrument and amortization type, among others). One reason is that the average credit amount decreased, as did the average duration of rate fixation, maturity, and the share of arrangements without a pre-existing creditor-debtor relationship. Changes in the credit composition were particularly pronounced in August 2022, when firms secured funding just before the first hike in policy rates. Given that the yield curve inverted during the tightening phase, we expect that a shorter average duration of rate fixation may have exerted upward pressure on the increase in the aggregate.

A final note on the aforementioned shifts in the composition of lending: Our use of firm- and credit-level financing data highlights that there are two margins to how monetary policy impacts firm financing. We refer to the first as the ‘extensive’ margin of financing: ‘who’ receives ‘what type’ of financing. This is closely related to the aforementioned compositional shifts across firm- and most credit-level characteristics. The second is the ‘intensive’ margin. This is the amount of financing provided, conditional on a financing agreement being in place. The compositional shift that is most important for this margin is the decline in the average credit amount. Investigating how the firm balance-sheet-channel impacts both of these margins and aggregate financing patterns is a promising avenue for future research.

3.3 Changes in the credit pricing structure

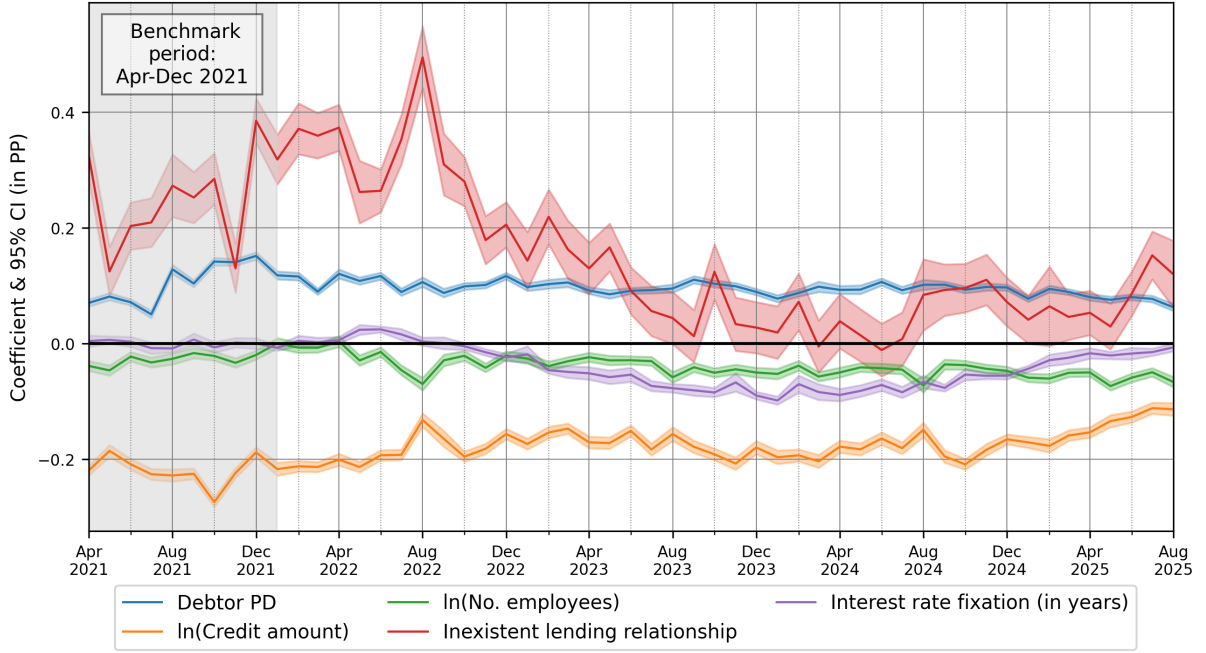
Our second motivational fact is that the credit pricing structure changed over time. We deduce this from OLS estimations that we run on a monthly basis from 2021 onward. The underlying specification describes the correlation between bank lending rates and a set of firm- and credit-level variables, including the firm PD, relationship lending, $\ln(\text{number of employees} + 1)$, as well as the duration of rate fixation and the $\ln(\text{amount})$ (see [Appendix Table 4](#) and [Table 5](#) for a complete overview of the variables included). We include bank fixed effects to control for unobserved bank-specific factors.⁵ Although we include a large set of regressors, we may be omitting important variables. In addition, our specification raises concerns about simultaneity. Both issues could bias our OLS estimates. We thus caution against interpreting the estimates as anything beyond mere correlations.

We plot the development of the coefficients for five selected characteristics in [Figure 3](#). These can be thought of as premia and discounts that banks require to price credit- and firm-level characteristics. It becomes clear that some coefficients remained broadly stable, while others changed more substantially.

Regarding credit-level determinants of lending rates, higher credit amounts are associated with lower interest rates (orange line). We attribute this to fixed-cost depression. The discount on larger amounts decreased from about -0.2 basis points (BP) per percent

⁵Essentially, all OLS coefficients are time-varying because we implement the regression on a monthly basis, and the bank fixed effects thus capture time-specific factors as well. In principle, time-varying coefficients could be estimated by using the full data and including interactions of all regressors and fixed-effects with monthly dummies. This would have allowed us to perform proper statistical testing of the differences in coefficients over time. However, computational limitations restrict us from doing so.

Figure 3: Changes in the pricing of credit and firm characteristics since 2021



Notes: Based on AnaCredit data and own calculations. Coefficients and significance intervals computed from monthly OLS regressions including bank fixed effects. The continuous and categorical variables included in the estimation are listed in [Table 4](#) and [Table 5](#).

higher credit amount to about -0.15 BP after 2021. Note that the discount was smallest at the onset of the tightening phase, mid-2022, and at the end of our sample period. We expect that the decline of the discount exerted upward pressure on the aggregate bank lending rate. The coefficient on the duration of rate fixation was close to zero in 2021 (purple line) but turned negative towards the end of 2022 (in light of the yield curve inversion). As of mid-2024 and as the yield curve steepened again, the coefficient increased again until the end of the period considered here. Taken individually, this pricing change should have dampened the increase in the aggregate rate after 2021, but mostly in between the tightening and easing phases of monetary policy. Lending arrangements without pre-existing debtor-creditor relationships came at higher costs (again, note the peak at the onset of the tightening). The coefficient reflects the spread arising from informational asymmetries ([Berger and Udell, 1995](#)) and is consistent with evidence that longer relationships contribute to lower lending rates ([Gambacorta and Mistrulli, 2014](#); [Kysucky and Norden, 2016](#)). According to our results, the premium associated with the absence of a prior relationship decreased after 2021, and also turned insignificant for a while.

Regarding firm-level determinants of lending rates, we confirm that a higher debtor PD is associated with higher bank lending rates ([Gambacorta and Mistrulli, 2014](#); [Altavilla et al., 2024](#)). In 2021, the risk premium amounted to about 10 BP per 1 PP higher PD. After 2021, this coefficient decreased slightly, which may have exerted downward pressure on the aggregate rate. The coefficient on the number of employees is negative (in line with [Chodorow-Reich et al., 2022](#); [Altavilla et al., 2024](#)) and appears to have declined slightly

over time. This suggests that the aforementioned compositional shifts in firm size, rather than the associated pricing, may have influenced the development of the aggregate rate.

In summary, we find evidence for compositional shifts along firm- and credit-level characteristics that are related to lending rates. Similarly, we observe that the credit pricing structure changed. Our aim is to quantify how compositional and pricing changes contributed to the increase in the aggregate bank lending rate and its gap to market and policy rates. This essentially means identifying which of the many determinants were most influential. In doing so, we also aim to pinpoint the extent to which contributions from changes in composition and pricing could have opposite effects (for example, due to substitution strategies). Next, we show how this can be done based on an over-time application of the Oaxaca-Blinder Decomposition.

4 The ‘over-time’ Oaxaca-Blinder decomposition

Oaxaca (1973) and Blinder (1973) both independently formulated a method to decompose group-level differences in means. In principle, the idea is to decompose differences in the average outcome of two groups into an ‘explainable’ component (related to differences in the composition of both groups) and an ‘unexplainable’ component (how differently characteristics influence the outcome variable). So far, its main application has been in labor economics, where it is used to decompose gender or racial wage gaps (Weichselbaumer and Winter-Ebmer, 2006; Olivetti and Petrongolo, 2008; Karapanagiotis and Reimers, 2024).

Here, we deviate from the perspective of differences between groups. Instead, we propose implementing the decomposition over time.⁶ This translates into a decomposition of the change in the aggregate bank lending rate compared to a benchmark period.

Our starting point is the OLS specification to derive the stylized facts in Section 3. For simplicity, we recur to matrix notation, giving

$$\mathbf{r}_t = \mathbf{X}_t^C \boldsymbol{\beta}_t + \mathbf{X}_t^F \boldsymbol{\delta}_t + \mathbf{B}_t \boldsymbol{\omega}_t + \boldsymbol{\epsilon}_t. \quad (1)$$

This mirrors a credit pricing structure in which banks set rates based on an individual fixed component, to which they add premia and discounts to account for credit and firm characteristics.

We estimate Equation 1 separately for different points in time, which is why the coefficients have subscript $\mathbf{t}$. The vector $\mathbf{r}_t$ has length $\mathbf{N}_t$. It contains the annualized bank lending rate $r_{t,l,f,b}$ of each newly agreed credit contract l in period t , between firm f and bank b . $\mathbf{X}_t^C$ is a $N_t \times C$ matrix where C denotes the number of credit-level attributes. This includes the $\ln(\text{amount})$, maturity and rate fixation (both in years), and dummies to identify the type of instrument, the type of amortization, and whether the credit serves as a working capital facility. $\mathbf{X}_t^F$ is a $N_t \times F$ matrix where F is the number of firm characteristics. This includes the sector of activity, probability of default (PD), $\ln(\text{number of employees} + 1)$, and whether a lending relationship pre-existed between firm f and bank b . The coefficients in $\boldsymbol{\beta}_t$ and $\boldsymbol{\delta}_t$ are the associated parameters. $\mathbf{B}_t$ is a binary

⁶Over-time applications of the Oaxaca-Blinder decomposition are scarce and limited to analyses of labor market outcomes (Gomulka and Stern, 1990; Juhn, Murphy, and Pierce, 1993; Fitzenberger, Kohn, and Wang, 2011). To the best of our knowledge, we are the first to apply the Oaxaca-Blinder decomposition in such a way in the loan pricing literature.

$N_t \times B$ matrix to identify the bank $b \in \{1, 2, \dots, B\}$ associated with each credit. The parameters in ω_t are the bank fixed effects. We exclude firm fixed effects because most firms do not engage in multiple financing arrangements in a typical single month (firm fixed effects would hence leave little variation in firm-level attributes).

The discussion in [Fortin, Lemieux, and Firpo \(2011\)](#) highlights that multiple assumptions are central to our undertaking. Regarding the structural form of the credit pricing function, we assume that the credit pricing structure in [Equation 1](#) is linearly additive in inputs. Second, we assume overlapping support. This is to rule out that the set of inputs (the firm- and credit-level characteristics) determining bank lending rates changes over time. And third, the (admittedly questionable) assumption of zero conditional mean ($E[\epsilon_t | \mathbf{X}_t^C, \mathbf{X}_t^F, \mathbf{B}_t] = 0$).⁷ Combined, these assumptions allow us to compute the aggregate rate $\bar{r}_t$ as the linear combination of average outcomes of $\bar{\mathbf{X}}_t^C$, $\bar{\mathbf{X}}_t^F$, and bank lending shares $\Delta \bar{\mathbf{B}}_t$.

Now consider two points in time, $t_2 > t_1$, where t_1 represents a benchmark period. The differential increase between the aggregate bank lending rate and a money market (or policy) rate MR can be decomposed as

$$\begin{aligned}
& \Delta \bar{r}_{t_2-t_1} - \Delta MR_{t_2-t_1} && \text{Differential increase} \\
&= \underbrace{\Delta \bar{\mathbf{X}}_{t_2-t_1}^C \hat{\beta}_{t_2} + \Delta \bar{\mathbf{X}}_{t_2-t_1}^F \hat{\delta}_{t_2}}_{\substack{\text{Changes in } \emptyset \text{ credit} \\ \& \text{ firm characteristics}}} + \underbrace{\Delta \bar{\mathbf{B}}_{t_2-t_1} \hat{\omega}_{t_2}}_{\substack{\text{Shifts in bank} \\ \text{lending shares}}} && \text{Composition effect} \\
&+ \underbrace{\bar{\mathbf{X}}_{t_1}^C \Delta \hat{\beta}_{t_2-t_1} + \bar{\mathbf{X}}_{t_1}^F \Delta \hat{\delta}_{t_2-t_1}}_{\substack{\text{Changes in discounts} \\ \& \text{ premia}}} + \underbrace{\bar{\mathbf{B}}_{t_1} (\Delta \hat{\omega}_{t_2-t_1} - \Delta MR_{t_2-t_1})}_{\substack{\text{Pass-through} \\ \text{Benchmark} = 1:1}} && \text{Pricing effect}
\end{aligned} \tag{2}$$

The first part on the right-hand side of [Equation 2](#) is the ‘composition effect’. It quantifies the change in the aggregate bank lending rate resulting from changes in the composition of lending. These take the form of changes in the means of continuous credit and firm characteristics, and changes in the shares of categorical credit and firm attributes ($\Delta \bar{\mathbf{X}}_{t_2-t_1}^C$, $\Delta \bar{\mathbf{X}}_{t_2-t_1}^F$). Moreover, banks’ shares of total lending also shifted over time ($\Delta \bar{\mathbf{B}}_{t_2-t_1}$). We separate the three terms to highlight that we can compute the contributions of individual explanatory variables to the development of the aggregate rate. This is because, by assumption, the credit pricing structure is linearly additive.

Intuitively, a negative composition effect arises when the composition of lending shifts towards cheaper characteristics over time. Such shifts could have dampened the increase in the aggregate bank lending rate during the tightening and, hence, strengthened the opening of the gap between both rates. For example, we envision that in the face of rising interest rates, firms could have tried to set credit terms in more favorable ways: by

⁷Assuming zero conditional mean is questionable given obvious endogeneity concerns in [Equation 1](#), for example regarding the simultaneous relationship between the credit amount and the bank lending rate: Under fixed cost depression, higher amounts should bring about lower rates, but basic economics dictate that lower rates may simultaneously bring about a higher demand for credit. As mentioned briefly in the introduction, our results emphasize the importance of changes in mean credit amounts and changes in the discount applied to larger credit amounts for the development of the aggregate bank lending rate. In [Section 5.5](#) we therefore test whether our results are robust when we instrumentalize the credit amount.

substituting comparatively more expensive credit attributes for cheaper ones. In addition, banks may have shied away from financing firms with high PDs or firms from certain economic sectors. Finally, firms could have sought financing offers from multiple banks and chosen the most favorable one (all else equal, this will be the offer from the bank with the lowest fixed component of credit pricing).

The second part on the right-hand side of [Equation 2](#) quantifies the contribution of changes in the credit pricing structure to the change in the aggregate bank lending rate. The ‘pricing effect’ arises from changes in the premia or discounts that banks apply to account for credit and firm characteristics, $\Delta\hat{\beta}$ and $\Delta\hat{\delta}$. Intuitively, a negative pricing effect indicates that lower premia or higher discounts compared to the benchmark period dampened the increase in the aggregate rate.

The key to quantifying the contributions of individual variables is linearity in the credit pricing structure. However, the zero conditional mean assumption must hold. Otherwise, a detailed decomposition does not produce interpretable results ([Fortin et al., 2011](#)). To see why, consider the case in which an OLS coefficient suffers from endogeneity bias. In our setting, this is likely to be the case for the coefficient on the credit amount. The bias would then confound how a larger credit amount is related to the lending rate. Worse still, the extent of the bias could change over time. Such a case would be misleading, as it would attribute part of the development of the aggregate rate to changes in the pricing of credit amounts, rather than the factors or mechanics that remained unaccounted for. We return to this particular issue regarding the credit amount in [Section 5.5](#).

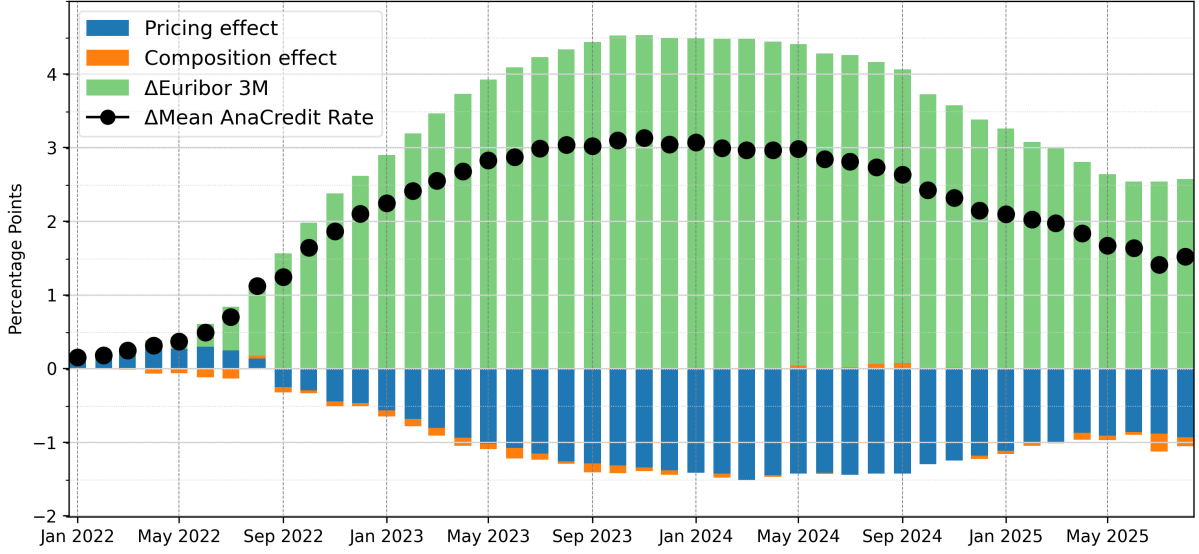
In addition, the pricing effect arises from changes in the bank fixed effects, which reflect banks’ individual fixed components of credit pricing. Before going into details, we note a potential issue related to the interpretation of these parameters. The mere fact that one has to choose a reference category leads to an identification problem in the decomposition ([Oaxaca and Ransom, 1999](#)). Essentially, changes in the bank fixed effects can be due to changes in the pricing of the reference categories when estimating [Equation 1](#). This has the potential to distort the contributions of individual categorical attributes in the decomposition exercise. To avoid this, we normalize the coefficients post-estimation ([Yun, 2005](#); [Kröger and Hartmann, 2021](#)).⁸ The fixed effects then incorporate the mean coefficient of all attributes of a categorical variable, while the normalized coefficients for the attributes express deviations from that mean.

Our focus on the opening of the gap between both rates requires us to put the change in the money market or policy rates MR into perspective on the right-hand side of [Equation 2](#) as well. We do so by deducting the change in MR from the change in the bank fixed effects. By construction, the decomposition thus imposes the benchmark that fixed effects and money market rate move in lockstep. This reflects a scenario in which an increase in the interest rate environment is fully passed through to banks’ fixed component of credit pricing.⁹ When the pass-through is less (or more) than 1, a gap opens up between the

⁸This involves adjusting the dummy coefficients of categorical attributes and the bank-specific constants. First, for each categorical variable, we compute the mean of all coefficients associated with its attributes. In doing so, we impose that the coefficient for the reference category is zero. We then deduce the mean from the respective coefficients (including the reference coefficient). The normalized coefficients represent deviations from the ‘grand mean’ coefficient of all attributes associated with a categorical variable (Jann, 2008, p. 462). We ensure that the normalized and original model are equivalent by adding the means to the bank-specific intercepts.

⁹Following [de Bondt et al. \(2005\)](#), this would occur through an increase in banks’ refinancing costs.

Figure 4: Pricing and Composition effects since 2022



aggregate bank lending rate and the policy or money market rate.

In terms of implementation, we use weighted-least-squares to estimate the parameters in Equation 1, with credit amounts as weights. We do so to best replicate the movement of aggregate bank lending rates from official statistics. We also use credit amounts as weights to compute $\bar{\mathbf{X}}_t^C$, $\bar{\mathbf{X}}_t^F$ and $\Delta\bar{\mathbf{B}}_t$. For the money market or policy rate MR we choose the 3M Euribor. This is because it compromises between the average rate fixation of bank lending to firms in the euro area and the short horizon of policy rates. As a benchmark and due to computational limitations, we choose the period from April to December 2021. This allows for a clear-cut separation of the benchmark period and the monetary policy tightening and easing phases, but comes at the cost that lending in 2021 was still influenced by Covid policies (such as government guarantees or subsidized lending). For the periods after 2021 we retrieve the coefficients, mean attributes, as well as bank lending shares on a monthly basis.

5 Results

We begin by visualizing the overall results of the decomposition. The green bars in Figure 4 illustrate the change in the 3M Euribor: Compared to 2021, it had increased by up to 4.5 PP by the third quarter of 2023. In contrast to this, the aggregate bank lending rate to firms in AnaCredit increased by up to 3 PP, opening a gap between the development of both rates that amounted to up to 1.5 PP.

The blue bars in Figure 4 quantify the pricing effect. It is negative for most of the observation period, reaching nearly -1.5 PP in early 2024. That is, the slower increase of the aggregate rate compared to the 3M Euribor seems to be mainly due to pricing effects. The orange bars quantify the composition effect. It was also negative for most of the observation period, but small, typically ranging between -5 and -15 BP. In summary, pricing and composition effects both dampened the increase in the aggregate bank lending rate. This widened the gap between the aggregate bank lending rate and the 3M Euribor.

From [Figure 4](#) we cannot identify the main contributors of the pricing and composition effects. This is what we do next.

5.1 Credit- and firm-level determinants of the aggregate rate

[Figure 5](#) plots the five credit- and firm-level determinants with the largest contributions to the development of the aggregate rate. We start with the determinants whose compositional and pricing changes exerted, in net terms, upward pressure on the increase in the aggregate rate. Afterwards, we turn to those determinants that dampened the rise.

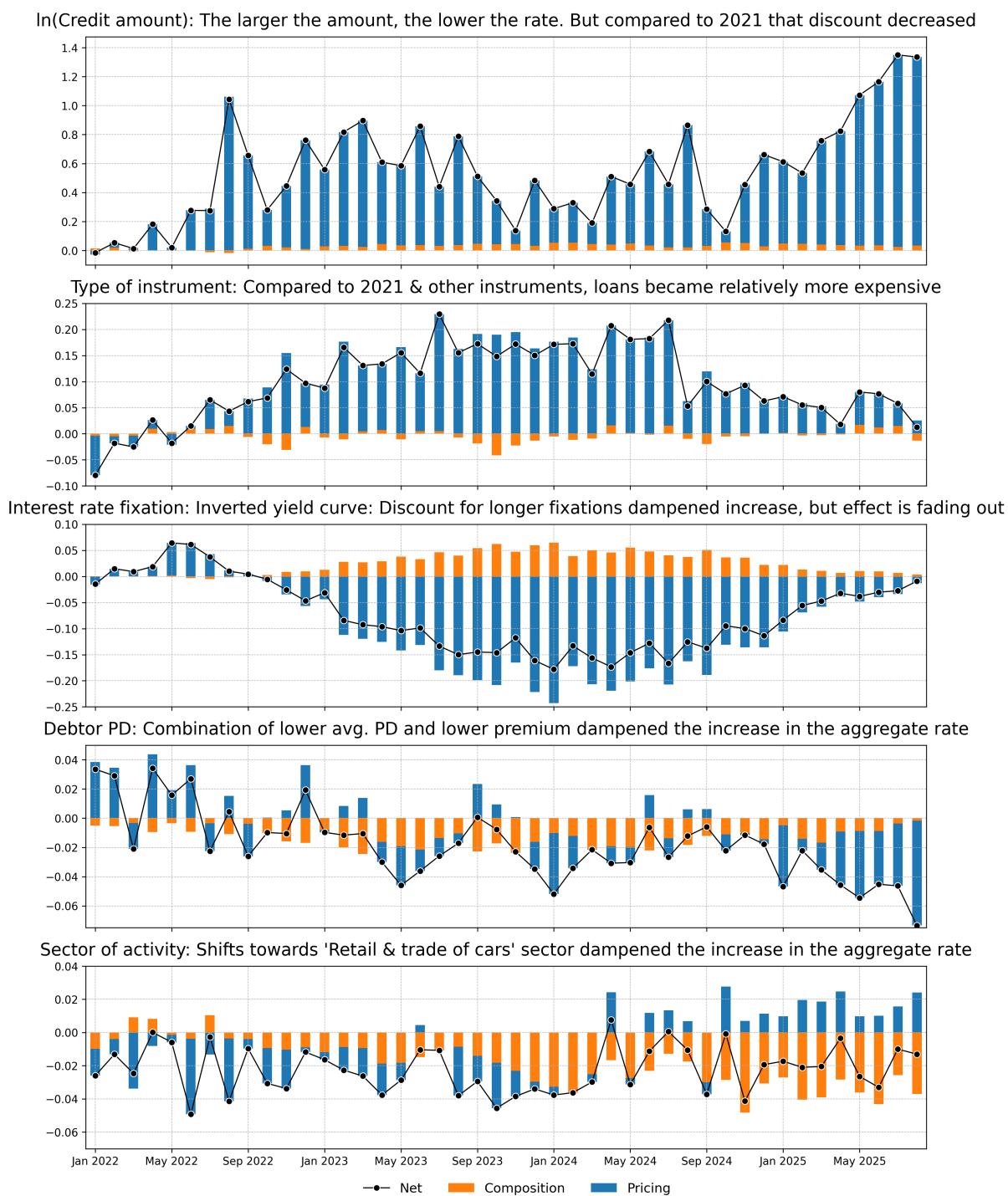
Of all the firm- and credit-level determinants, the largest contribution came from changes in the pricing of credit amounts. In [Section 3](#) we observed that the higher the amount, the lower the interest rate. Although this discount prevailed throughout 2021-2025, the coefficient's magnitude changed: the discount decreased from -0.2 BP per percent higher credit amount in 2021 to approximately -0.15 BP in 2022-23, and even less in 2025 ([Figure 3](#)). The positive blue bars in the top panel of [Figure 5](#) show that the increase in the aggregate rate would have been up to 1.3 PP lower if the discount on credit amounts had remained as large as in 2021. We find that this effect is particularly pronounced during the tightening phase (until September 2023) and after the monetary policy stance eased (mid-2024 onward). In between, the discount re-approached its values from 2021. This is why the pricing effect is lower then.

To compute the pricing effect, we assume that the average credit amount remained constant at its 2021 level ([Equation 2](#)). However, average credit amounts actually decreased during 2022-25. That is, monetary policy affected the intensive margin of financing. As a result, debtors did not benefit as much from the credit amount discount as they could have if amounts had remained as large as in 2021. Compositional changes with respect to credit amounts thus also exerted upward pressure on the rise of the aggregate rate.

The second most important contribution came from changes in the pricing of the different instrument types. Due to normalization, the coefficients quantify premiums or discounts relative to the average cost of all instrument types. We observe that in 2021, the cost of a loan was about 50 BP below the average cost of all instrument types. However, that discount narrowed during the tightening phase. By mid-2023, the cost of a loan had converged with the average cost of all instrument types. The cost remained so until mid-2024, but then declined again in light of the monetary policy easing phase (it did not reach 2021 levels, though). Due to the large share of loans in the data, its pricing change exerted considerable upward pressure on the increase in the aggregate rate during the tightening (up to +30 BP), but this effect faded during the easing (see [Appendix Figure 10](#)). For credit lines, the pattern is similarly symmetric: Costs first increased to exceed the average across instrument types, which exerted upward pressure on the aggregate rate; but entering the easing phase, the cost decreased below the average, which explains the drop in the blue bars from April 2024 onward.

Next, we focus on the duration of the interest rate fixation. The dark line in the middle panel of [Figure 5](#) shows that its net contribution became relevant in 2023 and dampened the increase in the aggregate rate. This is because the yield curve inverted in light of market expectations about policy rate cuts in the (then already foreseeable) easing phase. As a consequence, longer rate fixations were associated with lower interest rates. Without this pricing effect, the increase in the aggregate bank lending rate would

Figure 5: Contributions of selected firm- and credit-level determinants



Notes: Based on AnaCredit data and own calculations.

have been up to 25 BP higher. However, the inversion of the yield curve came with shorter average rate fixation periods: compared to 2021 the average fixation decreased by up to 6 months in 2022-25. This means that lending benefited less from the yield curve inversion than it could have if rate fixations had remained as long as in 2021. This exerted upward pressure on the increase in the aggregate rate (up to 5 BP), and is reflected by the positive orange bars. The inverted hump shape in the figure shows how the contribution of this determinant declined as the yield curve steepened again in 2025. When assessing the strength of monetary policy transmission, this is a pattern of symmetry that should be taken into account, as it tends to counteract monetary policy impulses.

Regarding the debtor PD, we find that composition and pricing effects both dampened the increase in the aggregate bank lending rate. Compared to 2021 the average debtor PD was up to 25 BP lower in 2022-25, decreasing during the tightening phase and returning to 2021 values in 2025. This pattern is in line with the firm balance-sheet-channel of monetary policy, and shows how monetary policy tightening and easing impulses transmit to the extensive margin of financing. Given that banks require a premium to compensate for debtor risk, the hump-shape pattern in the average debtor PD dampened the increase in the aggregate rate, but then faded during the easing phase. Moreover, we find that the coefficient quantifying the premium for higher default probabilities decreased by a few basis points. This reduction further dampened the increase in the aggregate rate, but seems to be particularly prevalent in 2025, following the monetary easing. Combined, changes in the average debtor PD and its pricing dampened the rise of the aggregate rate by up to 5 BP.

In the bottom panel, we focus on firms' sectoral composition. The orange bars show that, after mid-2022, sectoral shifts dampened the increase in the aggregate rate. These originate from a shift in lending towards firms engaged in wholesale and retail trade of cars. Throughout most of the period considered, and compared to the average cost of credit across all economic sectors, lending to that sector was the cheapest. This is why shifts towards that sector dampened the increase in the aggregate rate. Regarding the upward pressure due to pricing effects, we find that these tend to be due mostly to higher premia for firms in industrial sectors and in wholesale and retail trade (excluding cars).

Finally, for the remaining determinants, the contributions are minor. Composition-wise, a noteworthy contribution stems from shifts in lending towards working capital facilities from the end of 2023 onward. This dampened the rise in the aggregate rate by 2 to 3 BP. In addition, the share of secured loans increased, which slightly dampened the increase throughout 2022-25. Pricing-wise, working capital facilities also became cheaper compared to 2021, which further dampened the rise in the aggregate rate (by about 5 BP). We find that the discount applicable to firms with more employees increased somewhat from mid-2023 onward, which dampened the rise in the aggregate rate.

5.2 Lending shifts within and across countries

Changes in bank lending shares constitute part of the composition effect. They enter [Equation 2](#) via $\Delta \bar{\mathbf{B}}_{t_2-t_1} \hat{\omega}_{t_2}$. The first term, $\Delta \bar{\mathbf{B}}_{t_2-t_1}$, captures the extent to which banks' market shares shifted compared with 2021. $\hat{\omega}_{t_2}$ are banks' fixed components of credit pricing (the normalized bank fixed effects).

Our analysis includes banks in the euro area. The variation of lending shares over

time can, therefore, originate from lending shifts both within and across countries. In the regression, we cannot separate these directly, as including country fixed effects on top of bank fixed effects would cause multicollinearity. We thus separate the contribution of within- versus across-country lending shifts to the composition effect after estimation. For simplicity, we switch from matrix to scalar notation. Let $b_i, i \in \{1, \dots, B^c\}$ denote the lending share of bank i , and let Δb_i be the change in the share over time. The change in the lending share of country c is then

$$\Delta b^c = \sum_{i=1}^{B^c} \Delta b_i$$

Also, let $\hat{\omega}_i$ denote the (normalized) OLS estimate for the fixed effect of bank i , ω^c the average fixed effect of all banks in country c (weighted by credit amounts, as in the OLS estimation), and C the set of all countries. The contribution of shifts in banks' lending shares to the composition effect can then be decomposed as

$$\sum_{c \in C} \sum_{i=1}^{B^c} \Delta b_i \hat{\omega}_i = \sum_{c \in C} \Delta b^c \omega^c + \sum_{c \in C} \sum_{i=1}^{B^c} \Delta b_i (\hat{\omega}_i - \omega^c). \quad (3)$$

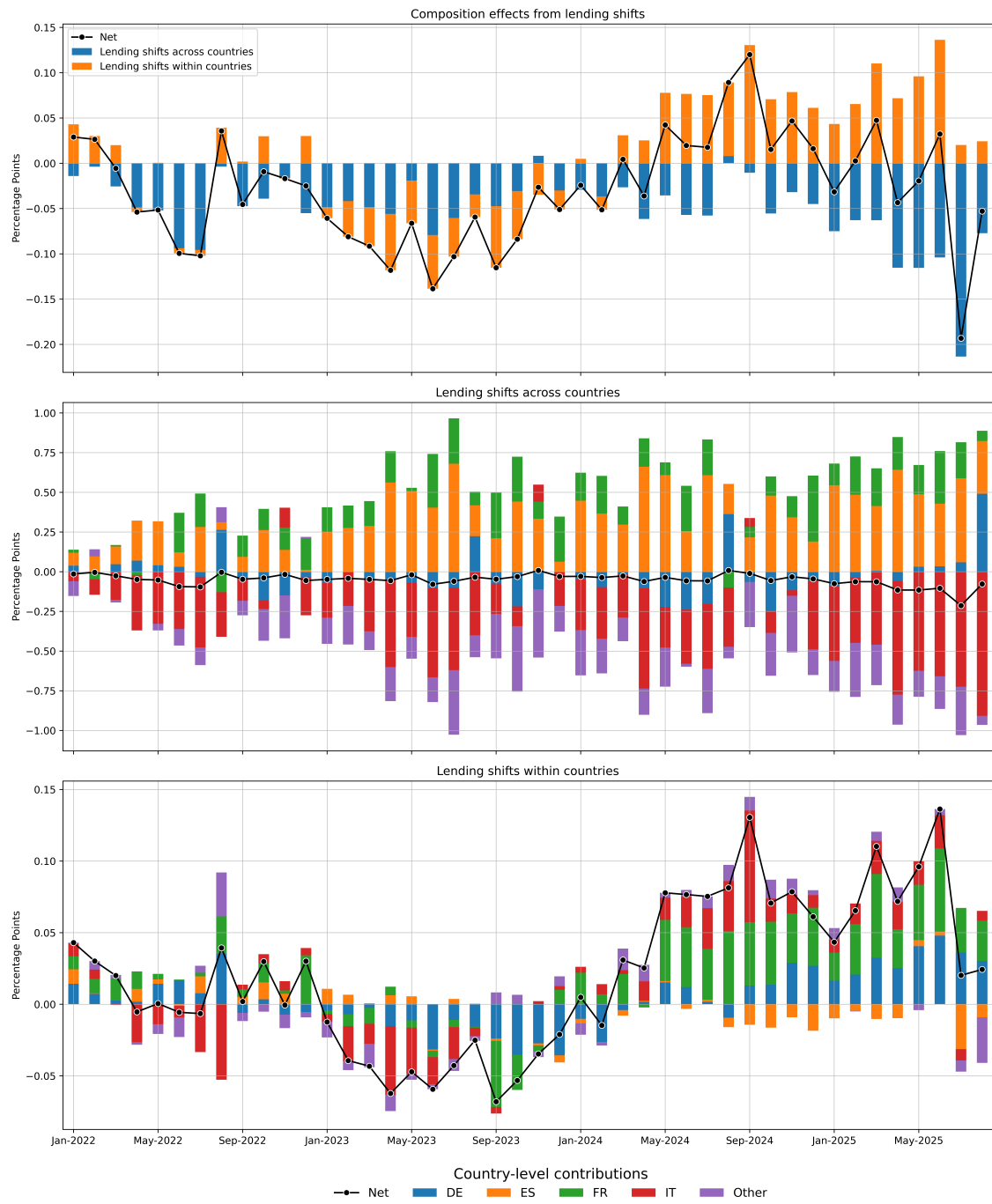
The first term on the right-hand side of Equation 3 quantifies the contribution of lending shifts *across* countries. Shifts toward countries where banks' average fixed component of credit pricing is lower than the euro area average dampen the increase in the aggregate rate. In contrast, shifts toward countries with a higher average fixed component of credit pricing exert upward pressure on the aggregate rate. The second term quantifies the contribution of lending shifts *within* countries. Lending may shift toward banks with lower fixed components of credit pricing than the domestic average, which dampens the increase in the aggregate rate. Conversely, shifts towards banks with relatively expensive fixed components of credit pricing amplify the increase in the aggregate rate.

The top panel of Figure 6 shows that the contribution of lending shifts across countries (blue bars) is negative throughout the period considered, typically ranging from -5 to -12 BP.¹⁰ In other words, the increase in the aggregate rate would have been 5 to 12 BP higher if the lending composition across countries had remained as in 2021. Consequently, the gap between the aggregate rate and the 3M Euribor would have been 5-12 BP smaller. In our data, lending shifted mainly away from Italy (hence the negative red bars in the middle panel) and towards Spain and France (positive bars). Compared with the other countries, Italian banks' average fixed component of credit pricing was highest throughout 2022-25, while that of French banks was lowest, and that of Spanish banks was below average (though not consistently). Thus, lending did indeed shift towards relatively cheaper countries, which dampened the increase in the aggregate rate (black line).

Regarding lending shifts across banks within the same country, we find mixed contributions at the onset of the tightening in 2022. Afterwards, lending shifts within countries dampened the increase in the aggregate rate by up to -7 BP (orange bars in the top panel, and black line in bottom panel). From mid-2024 onward, as monetary policy entered the

¹⁰The average bank fixed effect declined strongly in Spain in July 2025, which explains the trough then.

Figure 6: Contributions of lending shifts across and within countries



easing phase, within-country lending shifts exerted upward pressure (up to +14 BP).

The bottom panel of [Figure 6](#) shows that this pattern is broadly visible across countries. Most exhibit positive as well as negative contributions in the second half of 2022. We attribute the large bars in August 2022 to firms being less price-sensitive while attempting to rapidly secure funding at the onset of the tightening. By 2023, the tightening had had time to transmit to bank lending rates. Shifts towards banks with lower fixed components of credit pricing than their domestic competitors dampened the increase in the aggregate rate. Such shifts occurred in most of the countries we consider. We interpret this as evidence that borrowers, facing rising interest rates, compared multiple financing offers from different banks before selecting the cheapest one. By mid-2024, the last tightening impulse had faded, and monetary policy began to ease its stance. Within-country lending shifts then exerted upward pressure on the development of the aggregate rate everywhere except in Spain. In Italy and France the bank fixed effects then clustered more densely around their respective country means. This translates into a scenario where firms' potential gain from comparing multiple credit offers declined, disincentivizing them from seeking alternative banks as funding sources. Thus the pressure to shift lending towards comparably cheaper banks decreased.

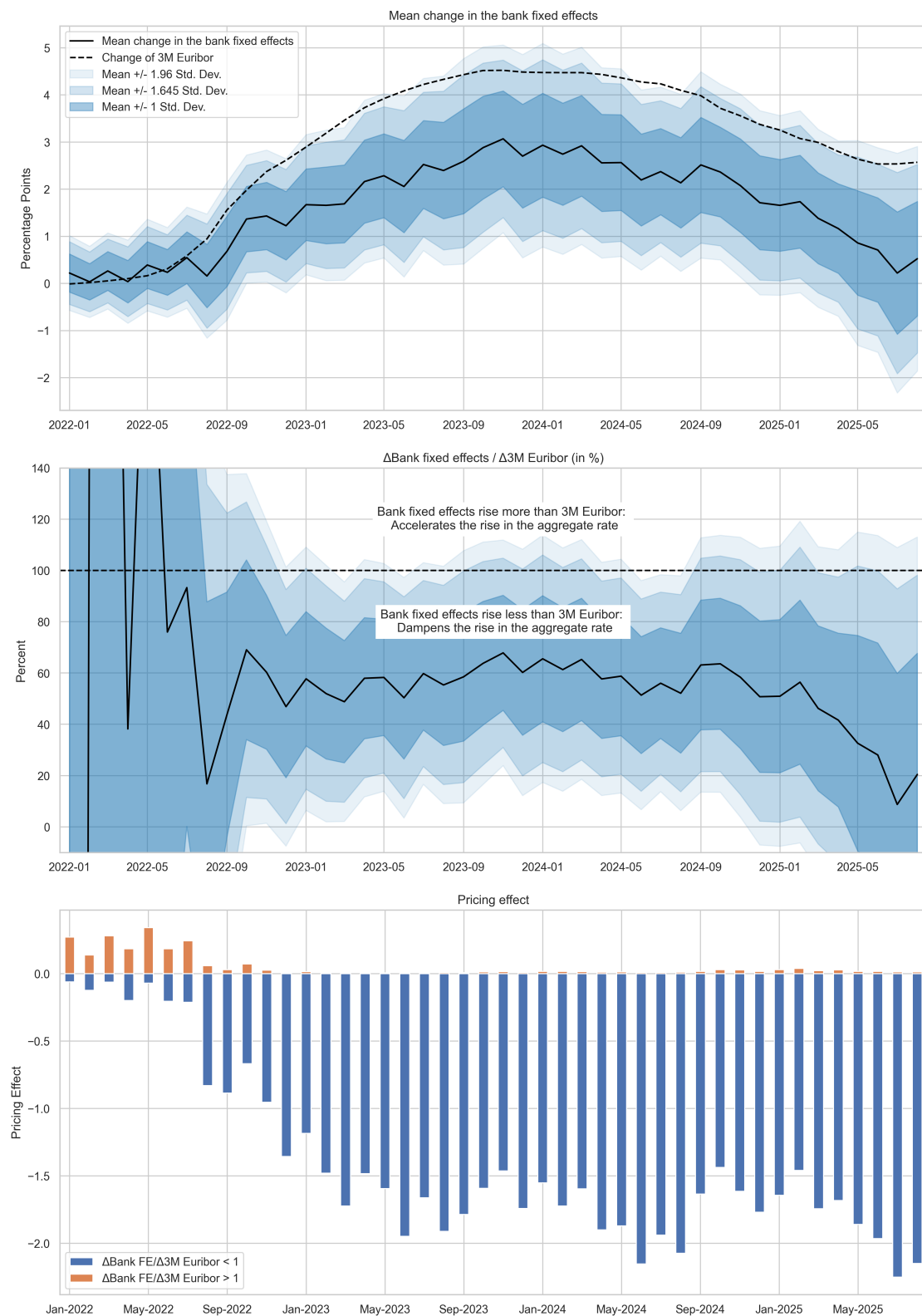
5.3 How pass-through and banks' fixed components of credit pricing shape the pricing effect

Next we focus on the development of the bank fixed effects. Viewed through the lens of our OLS model, these are a bank-specific fixed component of credit pricing. To this fixed component, banks add premia and discounts to account for firm and credit characteristics. By construction, assessing the differential increase in [Equation 2](#) requires us to benchmark the development of the bank fixed effects against the development of the 3M Euribor. This benchmarking establishes a natural starting point to think about the pass-through of money market rates to bank lending rates. Conceptually, this pass-through materializes because banks' refinancing costs co-move with the former ([de Bondt et al., 2005](#)). We find that benchmarking is a key factor shaping the pricing effect in our decomposition.

To see why, consider first the top panel of [Figure 7](#). This displays the change in the average bank fixed effect and the change in the 3M Euribor, both compared to our benchmark period in 2021. The increase in the average bank fixed effect during the tightening phase was hump-shaped. It peaked at +3 PP at the end of 2023. As the monetary policy stance eased from mid-2024 onward, the average bank fixed effect decreased again. By mid-2025 it was only 1 PP higher than in 2021. Compared to the bank fixed effects, the increase in the 3M Euribor was steeper and higher. Clearly, the increase in the bank fixed effects did not follow the increase in the 3M Euribor in lockstep, resulting in a gap opening up between the two series.

The middle panel of [Figure 7](#) visualizes the extent to which the two variables co-moved. This is based on a simple measure of pass-through for which we divide the change in the average bank fixed effect by the change in the 3M Euribor. The changes in both variables during the first half of 2022 were minor and moved in opposite directions at times. This resulted in very volatile pass-through, but we include that period for the sake of transparency and completeness. The data smoothenes after the first policy rate hike in July 2022. We then find that for every 1 PP increase in the 3M Euribor compared to 2021,

Figure 7: Changes in the bank fixed effects, pass-through and pricing effect



Notes: Average bank fixed effects computed using credit amounts as weights.

the mean bank fixed effect increased by between 0.40 PP and 0.65 PP. The average pass-through after July 2022 was about 50%. For banks that increased their fixed component of credit pricing more strongly (+1 standard deviation above the average change in the bank fixed effects), the pass-through averaged about 80%; for those that increased their fixed component less (-1 standard deviation), it averaged 20%.

Now consider the bottom panel of [Figure 7](#). For the pricing effect the key distinction is whether the pass-through is less than 100% or stronger. If a bank’s fixed component of credit pricing increased by less, then this bank’s pricing contributed to widening the gap between the aggregate rate and the 3M Euribor. If it rose by more, its pricing widened the gap in the opposite direction (i.e., widened the spread with the opposite sign). In the bottom panel, we separate both. We find that right around the announcement of the first policy rate hike in July, the upward and downward contributions balanced each other out. Going forward, however, the bulk of banks’ fixed components of credit pricing exhibited a pass-through of less than 100%.¹¹ The negative blue bars reflect the extent to which this dampened the increase in the aggregate bank lending rate compared to the 3M Euribor. The increase in the aggregate rate would have been 1.5 to 2.25 PP higher if the pass-through of changes in the 3M Euribor to banks’ fixed component of credit pricing had been 100% for all banks. Everything else equal, the gap between the aggregate bank lending rate and the 3M Euribor would either not have opened or even been reversed.

5.4 What shapes aggregate pass-through patterns?

These results raise multiple questions. The first emerges from our finding that for each 1 PP change in the 3M Euribor, banks’ fixed component of credit pricing increased on average by only 0.5 PP. The aggregate bank lending rate in AnaCredit, however, increased on average by 0.7 PP. This signals that the pricing of firm- and credit-level characteristics was a key determinant shaping aggregate pass-through patterns. How can our decomposition results help understand how the different credit pricing components (fixed component, discounts/premia) shape the pass-through patterns we observe for the aggregate bank lending rate?

To address this, we evaluate the development of counterfactual aggregate rates for the typical financing arrangements that prevailed in each month during the 2022-25 monetary tightening and easing cycle. That is, we take the composition of lending as given in 2022-25. What we vary to compute the counterfactuals are the discounts and premia that banks use to price credit and firm characteristics (those from 2021 or those in the months thereafter). Similarly, we vary which fixed components of credit pricing banks use.

First, we compute the aggregate rate of typical financing arrangements that prevailed in 2022-25, but using the pricing structure of 2021. On average, this counterfactual rate would have been 0.1 PP lower than the aggregate rate in 2021 (row 1 in [Table 2](#)). The pass-through of changes in the 3M Euribor to the counterfactual rate would have been -2%. Both values reflect the dampening contribution of compositional shifts to the aggregate rate. Next, we compute the counterfactual rate of typical financing arrangements that would have been priced using the discounts and premia from 2021, but those premia and discounts would have been added to banks’ fixed components for 2022-25 (third row).

¹¹We find that the pass-through was greater than 100% for a number of banks, though: in 2023 to 2025 this typically concerned between 30-50 banks out of 1,197 banks in our sample.

Table 2: How pricing effects shape aggregate pass-through patterns

Underlying rate	Δ	$\frac{\Delta \text{Rate}}{\Delta \text{Euri3M}}$	ECM*
	(PP)	(%)	(%)
Aggr. bank lending rate in AnaCredit	+2.1	70%	79%
Counterfactual aggr. rate: Assuming composition as in 2022-25...			
...but credit pricing (fixed component + discounts/premia) as in 2021	-0.1	-2%	-
...fixed component as in tightening, all discounts/premia as in 2021	+1.5	53%	77%
...fixed component & rate fixation pricing as in 2022-25	+1.5	50%	67%
...fixed component & amount discount as in 2022-25	+2.1	70%	81%
...fixed component & instrument type pricing as in 2022-25	+1.7	56%	82%

Notes: *Average coefficients for the long-run pass-through (estimated as in [Holton and d'Acri \(2018\)](#), using error correction models with different reference rates).

The average increase would have amounted to 1.5 PP and the pass-through to 53%. This again highlights the importance of the development of banks' fixed components of credit pricing for the development of the aggregate rate. Next, we additionally allow discounts and premia for individual characteristics to be as in 2022-25 as well. Allowing the rate fixations to be priced as in 2022-25, the pass-through is 3 PP lower than the aforementioned 53%, at 50%. This is because of the yield curve inversion. If, instead, the credit amount discount is allowed to be as in 2022-25, then the pass-through is higher, at 70%. Similarly, if pricing of instrument types is as in 2022-25 the pass-through is higher as well, at 56%.

These counterfactual results show that there is more to the transmission of monetary policy than a mere passing-through of changes in banks' refinancing costs to bank lending rates ([de Bondt et al., 2005](#)): In a scenario where banks' mark-ups over refinancing costs (i.e. the discounts and premia to account for credit- and firm-level characteristics) were constant, banks' fixed components of credit pricing would have had to increase more substantially. Otherwise, it would not be possible to reproduce the actual increase in the aggregate bank lending rate. Our results show that mark-ups are, in fact, not constant. Instead, mark-ups increased to compensate for the insufficient rise in banks' fixed components of credit pricing. In particular, mark-ups increased due to lower discounts on larger credit amounts and due to an increase in the relative cost of widely used financing instruments (loans), among others. In turn, this implies that the monetary impulses of 2022-25 were therefore transmitted very differently, depending on the type of firm and financing arrangement.

We next make an exemplary case of how our decomposition results can be used in monetary policy. Column 4 in [Table 2](#) shows *long-run* pass-through estimates that we compute using error correction models (ECMs). This is a type of model that has shaped the understanding of the pass-through of monetary policy to bank lending rates, and that helps assess the strength of transmission compared to historical patterns. However, earlier works tended to estimate these models on a macro-level, using aggregate data (see for

example de Bondt et al., 2005, Belke et al., 2013 and Holton and d’Acri, 2018, who use data aggregated at the bank level). The problem is that by construction, the contributions of micro-level shifts in the composition of individual credit and firm characteristics to changes in aggregate bank lending rates remain concealed in macro-based approaches.¹² So do contributions of changes in the pricing of individual characteristics. Based on our decomposition, however, we can shed light on this.

To do so, we apply the panel ECM approach of Holton and d’Acri (2018) to our aggregate rate in AnaCredit. We find that, on average across a suite of models with different (money) market rates, the long-run pass-through estimate is 79% (last column of Table 2).¹³ Next, we apply the ECMs to the counterfactual rates we computed above. If we allow only banks’ fixed components of credit pricing to be as in 2022-25 (discounts and premia as in 2021), then the long-run pass-through is 77%. Compared to this, if the interest rate fixation is priced as in 2022-25 as well, the long-run pass-through is about 10 PP lower; using the credit amount discounts from 2022-25 it is 4 PP higher; and pricing instruments as in 2022-25 leaves it 5 PP higher. We thus tend to emphasize the benefit for policy and decision makers of approaching macro patterns from the micro-level. In our case, doing so unveils the dimensions that shape the long-run pass-through of changes in money market rates to aggregate bank lending rates and that would otherwise remain hidden.

The second question that arises concerns the high dispersion in the development of banks’ fixed components of credit pricing (middle panel of Figure 7). In light of Holton and d’Acri (2018), Altavilla et al. (2020) and Altavilla et al. (2024), we consider it possible that variation at the bank level may help explain the pass-through heterogeneity we observe. We therefore match bank-level information from the ECB’s individual Balance Sheet Items database with the bank fixed effects from our decomposition. This includes deposits to firms and households, capital as a (questionable) proxy for CET1, liquidity, and central bank reserves (all as shares of total assets). We then re-estimate the panel ECMs from above, but accounting for bank-level heterogeneity.

The results are not particularly insightful regarding how the pass-through is associated with bank characteristics. For example, we do not find sizable differences between the pass-through of banks with high versus low shares of firm and household deposits (measured as 75th vs 25th percentile). The same holds for banks with high versus low capital, liquidity, or central bank reserves (significant differences occasionally exist, but are not as sizable as in Holton and d’Acri, 2018). One reason could be that heterogeneity in credit- and firm-level characteristics systematically coincides with heterogeneity in

¹²In their simplest form, existing macro-based pass-through estimates from ECMs impose that the aggregate bank lending rate (r_t) is a mark-up (α) over marginal funding costs. Typically, funding costs are proxied using money market rates (mr_t): $r_t = \alpha + \beta mr_t$. Implemented within an ARDL model and given cointegration, β quantifies the long-run pass-through of changes in market rates to changes in bank lending rates. The contributions of micro-level shifts remain disguised because the aggregate approach cannot capture the influence of time-varying credit amounts, interest rate fixation periods, or sectoral compositions, to name a few determinants of lending rates. If such compositional and pricing changes coincide systematically with movements of market rates, they will influence β but remain disguised.

¹³For better comparability with previous estimates we estimate a suite of ECMs with reference rates ranging from daily (ESTR) to 10 maturities (see Appendix Table 6). For market rates with a 1-year term, the long-run pass-through ranges from 69% to 74%, for 2-year terms it is about 85%. Using 10-year OIS swaps, it is more than 100%.

bank characteristics.¹⁴ Alternatively, it could be that the heterogeneity in pass-through relates to other bank-level variables. We find that for banks that incur high deposit rates, the pass-through is nearly 12 PP higher than for banks incurring low deposit rates. The informative value of this result is limited, however, as it hinges on a smaller sample of banks and endogeneity concerns. We leave this aspect to future research.

5.5 Robustness

Implementing the decomposition using AnaCredit requires us to make various decisions regarding data cleaning and imputation, filtering of banks, and specifying the underlying OLS model. In addition, a number of reporting issues could affect our results. To check whether our results are robust, we run the decomposition using alternative specifications and data samples. For an overview of our robustness exercises, consider [Table 3](#).

In our baseline sample, we rely on nearly 42 million financing contracts reported by 1,197 banks (row 1). In the row below, we give the decomposition results for a specification that includes $\ln(\text{debtor turnover})$, $\ln(\text{debtor balance sheet total})$ and the debtor age as additional regressors. We find that the size of the composition and pricing effects remain as in the baseline. The individual contribution of age is negligible. But the contributions are considerable for the other two variables and originate in both cases on the pricing side. For debtor turnover, the contribution ranges from +30 to +80 BP, while for debtor balance sheet it ranges from -25 to -125 BP (see [Appendix Figure 11](#)). However, we advise caution regarding these findings, as the coefficient on $\ln(\text{balance sheet total})$ is volatile and insignificant for most of April to December 2021.

Of the assumptions we make to implement the decomposition, exogeneity of the credit amount is the one we question the most. It is likely that bank lending rates and credit amounts are simultaneously determined or that unobserved factors are at play. For example, under fixed-cost depression, higher amounts should be associated with lower rates. However, lower rates may simultaneously bring about a lower supply of credit by banks (and a larger demand by firms). We therefore caution against interpreting the credit amount coefficient as being causal. What is even more concerning is the possibility that the extent of the bias could have changed after 2021. Our results, which emphasize the importance of changes in the discount applied to larger credit amounts for the development of the aggregate bank lending rate, could then be misleading.

We therefore decide to implement the decomposition based on instrumentalizing the credit amount. To do so, we exploit the panel structure of our data: we use as an instrument the credit amounts that firms contracted in new financing arrangements prior to April 2021 (our panel goes back to June 2019). Where possible, we compute the mean amount at the individual firm level and by instrument type. Where only a single financing arrangement is available for a firm and instrument type, we use that. We argue in favor of using past values as these should be a reliable indicator of firms' credit demand going forward in time. In fact, first stage estimates point to the relevance of the instruments

¹⁴After controlling for firm and credit-level characteristics, the bank fixed effects would then exhibit only little or no further co-variation with the bank-level characteristics we contemplate here. But of all the bank-, firm- and credit-level characteristics, what is then the determinant factor? We leave this question as a possible avenue for future research to identify the pass-through determinants within a joint approach.

Table 3: Robustness

	Obs. (Mio.)	Δ Mean rate	Pricing effect	Composition effect	Individual contributions (net)			
					ln(credit amount)	Instrument type	Δ Bank FEs	Lending shifts across banks
Baseline	42,109,213	2.05	-0.85	-0.05	0.58	0.09	-1.38	-0.03
Robustness of specification								
Specification incl. turnover, balance sheet size & age	38,177,973	2.07	-0.81	-0.07	0.81	0.08	-1.41	-0.06
Instrumentalizing credit amount (2SLS)	34,199,461	2.10	-0.82	-0.05	0.72	0.12	-1.61	-0.03
Robustness to selection of banks								
Only banks with <1% market share	21,204,353	2.13	-0.80	-0.02	0.09	0.01	-0.84	0.02
Only banks with >1% market share	20,904,860	1.91	-0.9	-0.13	1.04	0.14	-1.85	-0.11
Excl.: banks that are automotive subsidiaries	31,059,604	2.04	-0.85	-0.06	0.71	0.06	-1.48	-0.04
Robustness to cleaning measures								
Excl. off-balance sheet amounts	40,168,987	2.07	-0.81	-0.07	0.50	0.20	-1.36	-0.03
Excl.: rate & outstanding amount = 0	41,71,642	2.09	-0.79	-0.06	0.61	0.14	-1.39	-0.03
Excl.: imputed debtor PD	18,867,633	2.03	-0.87	-0.06	0.74	0.17	-1.60	-0.05

(we follow the textbook approach and include all firm- and credit-level variables in the first stage, plus firm age, to control for firm behavior). Our premise is that since the past credit amounts are predetermined, the source of endogeneity stemming from the feedback of bank lending rates on the supply of credit via banks should be eliminated. Unfortunately, relying on the panel structure of AnaCredit to compute our instrument comes at the cost of reducing the sample. This is because we can only compute the instrument for incumbent firms, not for firms that took out bank financing only from April 2021 onward.

Our findings suggest that the coefficient on credit amount in [Equation 1](#) is indeed biased. Compared to the simple OLS estimates (averaging -0.25 in 2021 and -0.12 to -0.2 afterwards), the 2SLS coefficients are more negative (averaging -0.3 in 2021 and -0.14 to -0.3 afterwards). This suggests that under the simple OLS setup, the estimates are biased upward from the positive but unaccounted relationship between banks' credit supply and lending rates. Importantly, we are relieved to find that the coefficient on the credit amount continues to exhibit an upward pattern: this is the decline of the credit amount discount over time, which drives our decomposition results in the baseline. Consequently, we are able to maintain our results. Compared to the baseline, we merely find that the contributions of the credit amount variable and of a reduced pass-through to banks' fixed component of credit pricing are both amplified.

We next check the robustness of our results to the selection of banks. In rows 4 and 5 we include only small banks (a market share from April 2021 onward of less than 1%) versus only large banks (share of more than 1%). Our results for the size of the composition and pricing effects remain unaffected. Regarding the contribution from credit amounts and a reduced pass-through to banks' fixed component of credit pricing, there is heterogeneity: We see that for the sample of large banks, the contributions are amplified compared to the baseline. For small banks, the contributions are diminished, but still sizable. The reason for this heterogeneity is that the decrease in the credit amount discount is substantially more pronounced for large banks. The exercise also shows that the upward pressure from changes in the allocation and pricing of instrument types originates predominantly from large banks. Our results remain the same overall when we exclude banks that are subsidiaries of automotive companies (row 6).¹⁵ Only the upward contribution from credit amounts is slightly amplified compared to the baseline.

In the remaining rows, we check the sensitivity of our results to cleaning measures and data imputations. Row 7 summarizes the results if we restrict the decomposition to only outstanding amounts, rather than outstanding plus off-balance sheet amounts (our baseline). This essentially excludes undrawn credit facilities. Our results regarding the size of the composition and pricing effects remain unaffected, with only the contributions from certain determinants change somewhat. In row 8 we address an issue related to a reporting requirement imposing that an interest rate of 0% should be reported when an interest calculation is possible, but has not yet been carried out. We address this issue by excluding all observations in which the reported rate and the outstanding amount are zero. Our results remain in line with the baseline. Otherwise, one major decision we made was to impute the debtor PD in case it is not reported.¹⁶ When we instead rely only on data with a reported debtor PD, the sample size is less than half of the baseline (and more concentrated on large firms). However, the overall size of the composition and the pricing effects remain similar to the baseline. However, we find that the contribution from changes in the pricing of credit amounts is amplified compared to the baseline, as is the contribution from a low pass-through of changes in the 3M Euribor to banks' fixed component of credit pricing.

One limitation concerns the robustness of the contributions of lending shifts across domestic banks (within the same country) to the development of the aggregate rate. When running the above robustness checks, we found that, in most cases, lending shifts within countries dampened the rise of the aggregate rate in 2023 and exerted upward pressure from 2024 onward, as in the baseline. However, in some instances, the contributions differed in size (see Appendix [Figure 12](#)). We also found that, in individual countries, the dampening contribution from shifts across domestic banks hinged on the contributions of a small number of large banks. For this reason, we advise caution regarding how domestic shifts in banks' market shares dampened the rise of the aggregate.

Finally, we note that our results are robust to using sub-samples of financing arrange-

¹⁵We exclude them because car financing by such banks accounts for a substantial and increasing share of the data (about 11 million financing arrangements in our baseline sample). Hence, our results could be prone to the pricing policies of such banks.

¹⁶We do so by clustering the data along credit and firm attributes, then computing the mean debtor PD for those observations where the clustering information is available, and finally using these means to fill in the missing values within the same clusters.

ments with rate fixations that are either variable, up to 6 months, or above 6 months (we then use, as a benchmark, the ECB’s deposit facility rate, the 3M Euribor, and the 12M Euribor, respectively). We do so in light of the shortcoming of our main decomposition, which benchmarks all financing arrangements against the same money market rate (3M Euribor), although their rates may have shorter or longer fixations. Our findings reappear in all three sub-samples. What this disaggregated approach reveals, however, is that the contribution from more expensive pricing of certain instrument types is driven mostly by financing arrangements with rate fixations above 6 months.

6 Discussion and conclusion

We started from the motivational fact that, during the 2022-25 monetary tightening and easing cycle, the aggregate bank lending rate to firms in the euro area increased up to 1.5 PP less than the 3M Euribor. Our decomposition uses granular credit data to systematically separate the contributions of changes in the composition and pricing of credit to the opening of the gap. The setup translates micro-level patterns into the aggregate level, offering a way to identify the contributions of individual determinants of bank lending rates and to characterize the transmission of monetary policy via banks.

We find that banks adjusted their fixed components of credit pricing by less than the increase in the 3M Euribor, which was a key factor behind the opening of the gap. According to the literature, banks adjust their fixed components of credit pricing to pass through changes in refinancing costs, but this pass-through tends to be incomplete. Therefore, the opening of a gap is not entirely surprising. However, the lesson learned from our decomposition is that the transmission of monetary policy to bank lending rates involves more than just a passing through of refinancing costs: changes in mark-ups also play a critical role. Specifically, the premia and discounts that banks apply to account for firm and credit characteristics changed. Overall, these changes exerted upward pressure on the development of the aggregate bank lending rate, partially offsetting the effect of the weak increase in banks’ fixed components of credit pricing. Without these adjustments, the gap would have amounted to up to 2.25 PP, rather than 1.5 PP.

The changes in premia and discounts that we document imply that banks implement credit pricing adjustments during monetary tightening and easing phases. These adjustments may be strategic to tailor lending terms to different firm and financing profiles and to better manage risk and profitability, for example. As a consequence, monetary policy impulses were transmitted to bank lending rates differently depending on the type of firm and financing arrangement. Firms should be aware that such adjustments may occur, as they affect how banks assess their individual characteristics and the cost of their preferred financing arrangements. Understanding and anticipating these adjustments can help firms optimize their financing strategies, negotiate better terms, and align demand for and the supply of credit.

Our micro-based perspective is also useful for monetary policy, as it unveils how individual determinants of bank lending rates shape aggregate interest rate pass-through patterns. So far, understanding of pass-through patterns has largely been derived from macro analyses that apply error correction models to bank lending rates at the aggregate or bank level. For central bankers, such macro-based approaches are useful tools because

they provide a way to benchmark the development of aggregate rates against historical patterns. They thereby point towards the strength of transmission. The shortcoming of macro-based approaches, however, is that they conceal the influence of changes in the composition or pricing of individual determinants of bank lending rates on the pass-through. Using micro data and our decomposition, we can shed light on this. For example, counterfactual analyses based on our decomposition results reveal that the reduction of the discount for larger credit amounts exerted upward pressure on the pass-through, reinforcing transmission. This highlights the importance of micro-level insights in complementing macro-based approaches to better understand and assess monetary policy transmission.

So far, the literature lacks comparable evidence on compositional shifts and pricing changes during other monetary policy tightening and easing phases. This hinders policy-makers, bankers, and debtors in evaluating whether the compositional shifts and pricing changes that we document for 2022-25 were in line with broader historical patterns. Such considerations extend to the contributions of compositional shifts and pricing changes to the development of the aggregate bank lending rate and the gap. Given this, we emphasize the importance of building historical evidence and continuing to leverage the opportunities that emerge as more granular financing data becomes available.

We conclude with a suggestion for future research. We find that lending shifted across banks, as one would expect based on the bank balance-sheet-channel of monetary policy. Lending also shifted along dimensions that are central to the firm balance-sheet-channel. For example, we observe a decrease in firms' average probability of default and shifts in the shares of economic sectors. Regarding the transmission of monetary policy, this indicates that the tightening affected the extensive margin of bank lending ('which firms' are financed). However, we also observe that banks reduced the discount on larger credit amounts and that this coincided with a decline in average financing amounts. Monetary policy thus affected financing along the intensive margin ('how large' is financing, conditional on a financing agreement) as well. Granular financing data such as AnaCredit offers an opportunity to better differentiate between these two margins of bank lending. Thus, one avenue for future research would be to apply the decomposition to bank lending amounts, rather than to the price of bank lending.

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A Appendix

Table 4: Descriptive statistics for continuous variables

Attribute	Distribution (2019/06 - 2025/08)				Means		
	Mean Std. Dev	p(5)	Median	p(95)	2021*	Post 2021	Δ Mean
Annualized rate	3.6% 2.3%	0.0%	4.3%	8.0%	2.0%	4.1%	2.1 PP
Amount (in thousands)	68.6 22.8	0.1	18.2	262.5	74.4	66.6	-7.8
# of Employees	515 8,924	1	32	2,088	275	568	293
Interest rate fixation (in years)	2.1 4.19	0.0	0.2	5.1	2.5	2.02	-0.48
Maturity (in years)	3.74 6.32	0.1	0.4	5.1	4.2	3.6	-0.6
Debtor PD	1.89% 4.19%	0.15%	1.60%	5.88%	2.0%	1.86%	-0.14

Notes: Based on new lending data in AnaCredit, means and standard deviations are computed using amounts as weights. *April - December 2021, which is the benchmark we impose later on in the analysis due to computational limitations.

Table 5: Distribution and changes of categorical variables

Attribute		Full sample*		Apr. - Dec. 2021		Post 2021		Δ Share	Δ Rate
		Share (in %)	Mean rate	Share (in %)	Mean rate	Share (in %)	Mean rate		
Country	AT	3.0	3.3	3.5	1.9	2.8	3.9	-0.7	1.9
	BE	5.3	3.8	6.6	2.9	4.9	4.1	-1.7	1.3
	DE	17.9	3.7	18.4	2.0	17.8	4.2	-0.6	2.2
	ES	16.3	3.6	12.5	1.9	17.4	3.9	4.9	2.0
	FI	1.3	3.9	1.4	2.1	1.3	4.5	0.0	2.3
	FR	19.3	3.1	17.3	1.5	19.8	3.5	2.6	2.0
	IE	0.8	4.7	0.9	3.5	0.8	5.0	0.0	1.5
	IT	29.6	3.9	33.0	2.0	28.7	4.4	-4.3	2.5
	NL	1.8	4.1	2.0	2.7	1.7	4.5	-0.3	1.8
	PT	2.8	3.9	2.7	2.6	2.8	4.3	0.2	1.6
	Other	1.9	3.5	1.9	1.9	1.9	3.8	0.1	1.9
Type of instrument	Credit lines	23.4	3.6	24.3	2.0	23.2	4.1	-1.0	2.1
	Loans	47.8	3.6	47.1	1.7	47.9	4.1	0.9	2.3
	Finance leases	5.2	3.5	4.6	2.1	5.3	3.9	0.8	1.8
	Overdrafts	1.6	4.9	1.9	3.3	1.5	5.4	-0.4	2.1
	Revolving credit	11.5	3.9	11.0	2.6	11.6	4.2	0.5	1.7
	Trade receivables	10.5	3.4	11.2	2.2	10.4	3.8	-0.8	1.6
Type of amortisation schedule	Bullet	35.1	3.5	32.0	1.9	35.9	3.9	3.9	2.0
	Fixed	12.0	3.4	12.6	1.9	11.9	3.9	-0.7	2.0
	French/German	25.4	3.5	24.8	1.8	25.5	4.0	0.7	2.2
	Other	27.5	4.0	30.5	2.2	26.7	4.5	-3.8	2.3
Purpose of loan	Working Capital Facility	25.4	3.9	27.1	2.4	24.9	4.4	-2.1	2.0
	Other	74.6	3.5	72.9	1.8	75.1	4.0	2.1	2.1
Lending relationship	Existent	87.9	3.9	83.3	2.6	89.1	4.3	5.9	1.7
	Inexistent	12.1	4.8	16.7	3.3	10.9	5.2	-5.9	1.9
Protection	Secured	50.4	3.8	53.0	2.2	49.5	4.3	-3.6	2.1
	Unsecured	49.6	3.4	47.0	1.7	50.5	3.9	3.6	2.1
Sector of activity	Industry	26.6	3.4	28.4	1.7	26.2	3.9	-2.2	2.1
	Wholesale and Retail Trade (excl. Cars)	18.4	3.6	18.2	1.9	18.4	4.0	0.2	2.1
	Wholesale and Retail of Cars	12.6	3.9	9.0	1.9	13.5	4.3	4.5	2.3
	Service	20.0	3.8	20.3	2.3	19.8	4.2	-0.5	1.9
	Real Estate	12.9	3.6	14.8	2.1	12.5	4.1	-2.3	2.0
	Construction	4.0	4.0	3.9	2.5	4.1	4.4	0.1	1.9
	Primary Sector	3.8	3.5	3.5	1.8	3.9	4.0	0.4	2.1
	Others	1.7	3.7	1.8	2.1	1.7	4.2	-0.2	2.1

Notes: Own calculations based on new lending data in AnaCredit, using amounts as weights. Differences in shares and rates are rounded to first decimal. *Full sample contains all data from June 2019 ff.

Figure 8: Composition effects by firm- and credit-level characteristics, and from lending shifts across banks

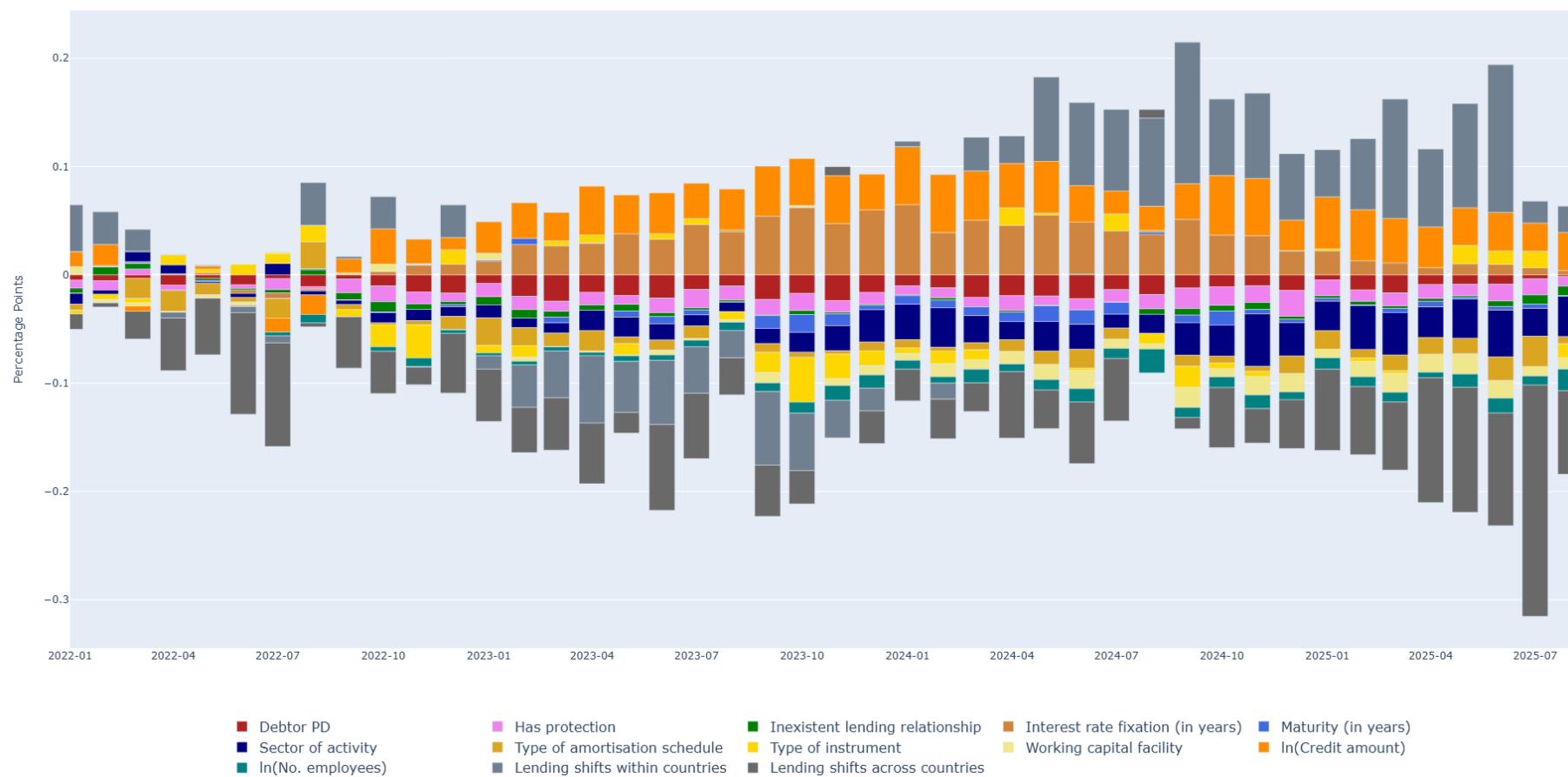


Figure 9: Pricing effects by firm- and credit-level characteristics, and from an incomplete pass-through

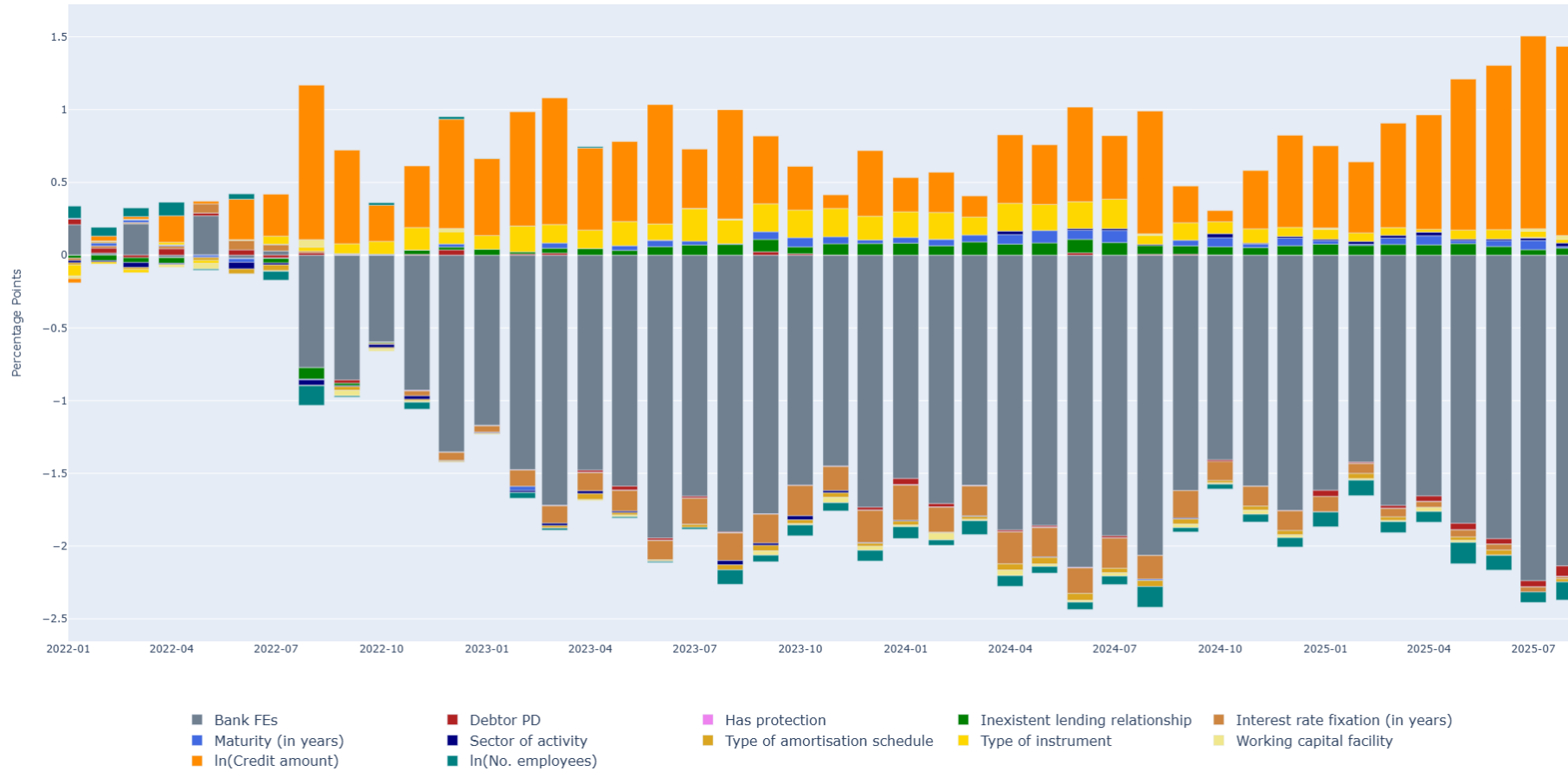
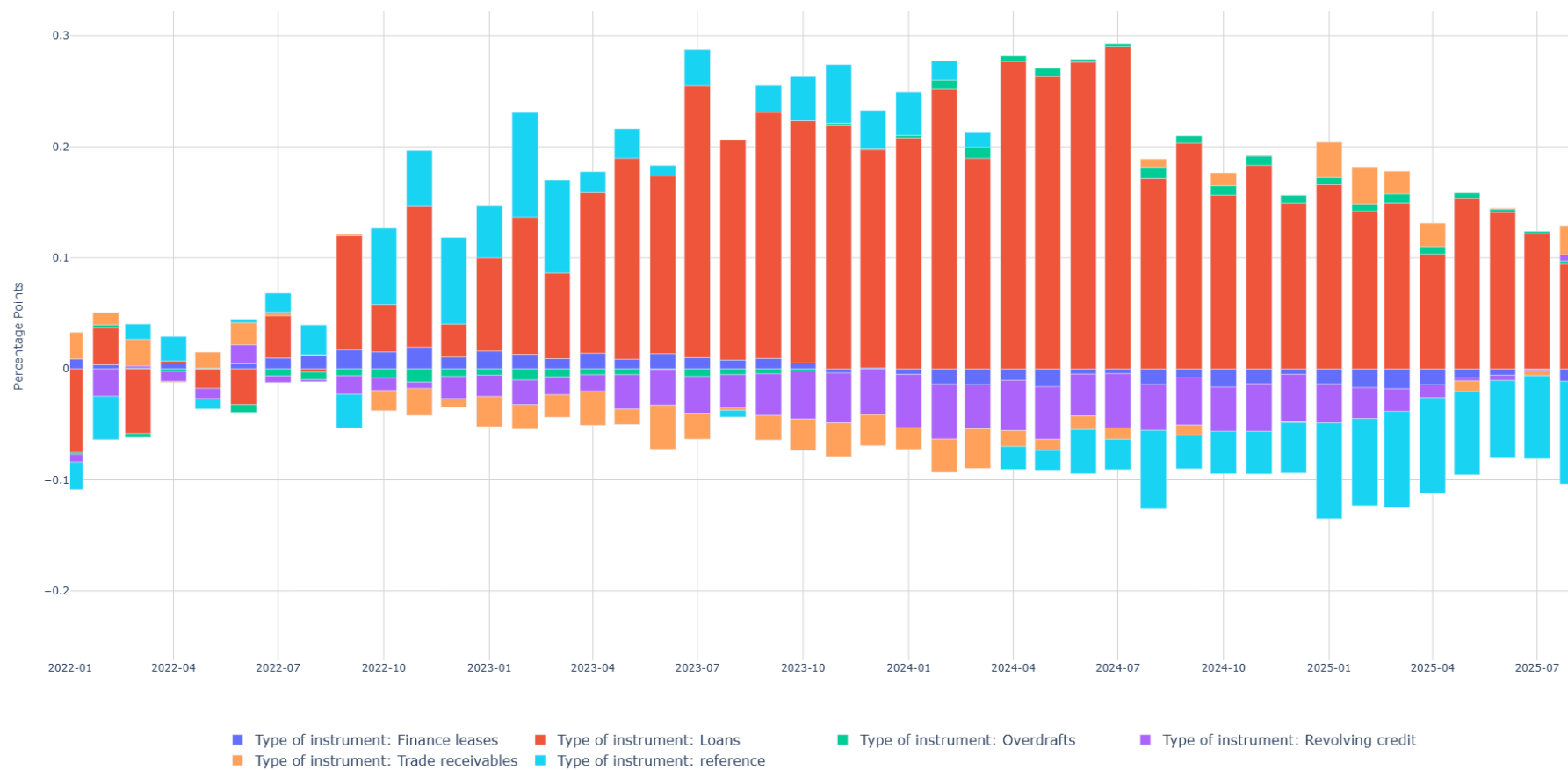


Figure 10: The contribution of changes in the pricing of instrument types (baseline exercise)



Notes: Reference category are credit lines.

Figure 11: Contributions of selected determinants in the extended specification

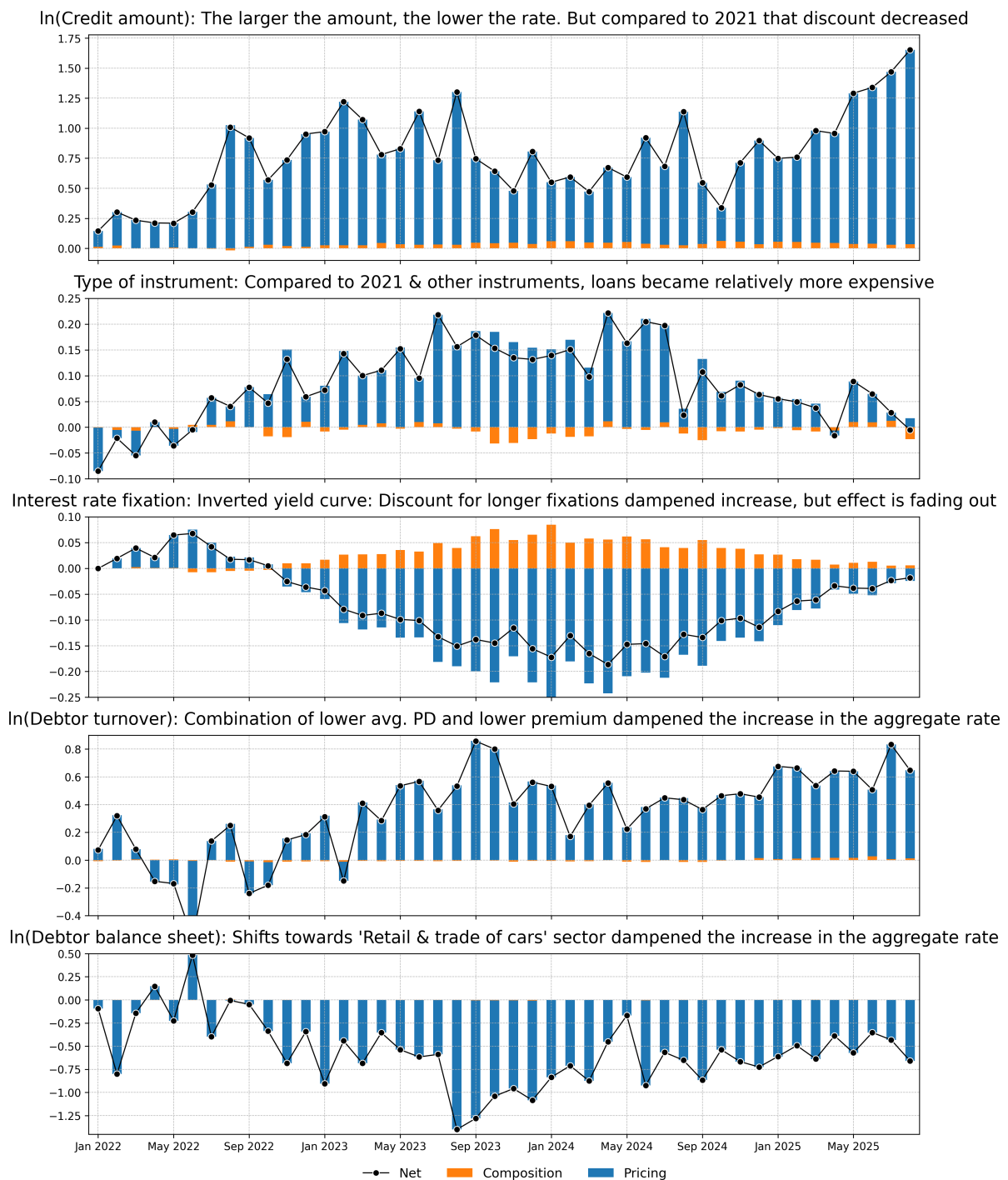


Table 6: ECM-based long-run pass-through measures for different reference rates

Underlying rate/Reference rate	ESTR	Euribor					EA Bond				OIS				
		1D	7D	1M	3M	6M	1y	1y	2y	5y	10y	1y	2Y	5Y	10Y
Aggr. bank lending rate in AnaCredit	0.56	0.57	0.59	0.62	0.65	0.68	0.73	0.86	1.0	0.94	0.71	0.85	1.08	1.15	
Counterfactual aggr. rate: Assuming composition as in 2022-25...															
...but credit pricing (fixed component + discounts/premia) as in 2021	-	-	-	-	-	-	-	-	-0.01	-0.01	-	-	-0.01	-0.01	
...fixed component as in 2022-25, all discounts/premia as in 2021	0.54	0.55	0.57	0.61	0.63	0.66	0.7	0.84	0.97	0.92	0.69	0.82	1.04	1.12	
...fixed component + rate fixation pricing as in 2022-25	0.49	0.5	0.5	0.54	0.58	0.6	0.64	0.74	0.82	0.71	0.62	0.73	0.91	0.94	
...fixed component + amount discount as in 2022-25	0.61	0.62	0.65	0.67	0.68	0.7	0.76	0.88	0.99	0.94	0.73	0.86	1.07	1.15	
...fixed component + instrument type pricing as in 2022-25	0.61	0.62	0.65	0.67	0.68	0.7	0.76	0.88	0.99	0.94	0.73	0.86	1.07	1.15	

Note: Coefficients shown only if significant at a 10% level. H0 assumption of non-stationarity typically rejected for 80-85% of the panel IDs (banks) in the sample.

Figure 12: Robustness exercises - details

	# of Obs.	Year	Δ Mean AnaCredit Rate	Pricing ef- fect	Composi- tion effect	ln(Credit amount)	Individual contributions (net)			
							Type of instrument	Pass- through < 1:1	Lending shifts within countries	Lending shifts across countries
Baseline	42,109,213	2022	0.87	0.02	-0.05	0.33	0.03	-0.32	0.01	-0.04
		2023	2.82	-1.07	-0.09	0.59	0.15	-1.62	-0.04	-0.04
		2024	2.74	-1.39	0.01	0.44	0.14	-1.76	0.06	-0.04
		2025	1.77	-0.95	-0.08	0.96	0.05	-1.82	0.07	-0.10
Specification incl. turno- ver & balance sheet size	38,177,973	2022	0.88	0.03	-0.04	0.51	0.02	-0.29	0.01	-0.04
		2023	2.91	-1.00	-0.07	0.89	0.14	-1.50	-0.03	-0.04
		2024	2.74	-1.33	-0.05	0.68	0.13	-1.73	0.01	-0.05
		2025	1.73	-0.94	-0.14	1.15	0.04	-2.10	0.03	-0.14
2SLS to instrumentalize credit amounts	34,199,461	2022	0.86	0.02	-0.06	0.33	0.04	-0.38	0.01	-0.04
		2023	2.86	-1.03	-0.09	0.46	0.16	-1.56	-0.06	-0.05
		2024	2.80	-1.34	0.02	0.51	0.19	-1.93	0.04	-0.03
		2025	1.88	-0.94	-0.06	1.57	0.10	-2.58	0.08	-0.09
Only banks with <1% market share	21,204,353	2022	0.74	-0.13	-0.02	0.01	0.04	-0.20	0.03	-0.02
		2023	2.86	-1.08	-0.04	0.20	0.12	-1.31	-0.01	-0.02
		2024	2.88	-1.24	0.00	0.14	-0.02	-1.23	0.04	-0.01
		2025	2.03	-0.76	0.00	-0.01	-0.10	-0.62	0.07	-0.02
Only banks with >1% market share	20,904,860	2022	1.05	0.21	-0.05	0.69	-0.03	-0.41	0.01	-0.07
		2023	2.77	-1.07	-0.15	0.94	0.10	-1.79	-0.04	-0.11
		2024	2.53	-1.58	-0.01	0.72	0.29	-2.21	0.06	-0.06
		2025	1.31	-1.18	-0.31	1.80	0.20	-2.99	0.12	-0.34
Excl.: Banks that are au- tomotive subsidiaries	31,059,604	2022	0.89	0.05	-0.05	0.37	0.03	-0.31	0.01	-0.04
		2023	2.91	-1.04	-0.03	0.78	0.12	-1.73	-0.01	-0.02
		2024	2.71	-1.41	0.00	0.62	0.09	-1.92	0.03	-0.03
		2025	1.66	-0.99	-0.15	1.09	0.00	-1.97	-0.01	-0.11
Excl. off-balance sheet amounts	40,168,987	2022	0.86	0.01	-0.04	0.23	0.08	-0.27	0.02	-0.04
		2023	2.85	-1.02	-0.11	0.50	0.27	-1.61	-0.05	-0.04
		2024	2.79	-1.33	-0.01	0.35	0.29	-1.72	0.05	-0.04
		2025	1.79	-0.91	-0.10	0.92	0.17	-1.83	0.07	-0.10
Excl.: Rate = 0 & out- standing amount = 0	41,711,642	2022	0.88	0.04	-0.05	0.33	0.04	-0.32	0.02	-0.04
		2023	2.88	-1.01	-0.10	0.63	0.20	-1.64	-0.04	-0.04
		2024	2.79	-1.32	-0.01	0.49	0.21	-1.79	0.06	-0.04
		2025	1.82	-0.88	-0.10	1.00	0.11	-1.83	0.07	-0.10
Excl.: Imputed debtor PD	18,867,633	2022	0.98	0.12	-0.04	0.21	0.06	-0.11	0.02	-0.05
		2023	2.79	-1.11	-0.08	0.72	0.14	-1.77	-0.02	-0.09
		2024	2.63	-1.49	-0.01	0.92	0.24	-2.40	0.05	-0.04
		2025	1.71	-0.99	-0.10	1.10	0.23	-2.10	0.01	-0.06