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Address: 9, Instytutska Street, Kyiv, 01601, Ukraine
E-mail: journal@bank.gov.ua

PREFACE BY THE EDITOR-IN-CHIEF

Dear readers,

This issue of the ***Visnyk of the National Bank of Ukraine*** focuses on themes that become increasingly relevant during the war. Our authors examine the FX market's reaction to central bank communications and the transmission of interest rates in Ukraine.

In the first paper, *Impact of Central Banks' Communications on FX Market Dynamics*, Tetiana Yukhymenko and Oleh Sorochan explore the online presence of the National Bank of Ukraine (NBU) using Google Analytics and a unique textual dataset. The authors assess various types of central bank communications based on visitor popularity, topics or references related to the NBU governor, and other characteristics that enable them to classify central bank messages. Utilizing this data, they apply a local projection model to analyze the relationship between NBU communications and FX market dynamics, concluding that central bank communications have a notable influence on market behavior.

The second paper, *Interest-Rate Pass-Through in Ukraine: Estimates and Determinants*, by Nadiia Shapovalenko and Artem Vdovychenko, estimates the strength of long-run interest rate pass-through in Ukraine. The authors present findings on linear estimates and asymmetric transmission, which differ based on the direction of changes in interbank rates, as well as time-varying estimates.

The Visnyk of the National Bank of Ukraine encourages researchers and policymakers to support and continue the discussion initiated by the authors in this issue. We also invite submissions of original research papers, particularly those focusing on economic policies during the war and post-war reconstruction of the economy. Our journal welcomes high-quality research papers on a range of topics, including but not limited to monetary policy, financial regulation, integrated policy frameworks, international financial support, the labor market, and migration.

Best regards,
Andriy Tsapin

IMPACT OF THE CENTRAL BANK'S COMMUNICATIONS ON FX MARKET DYNAMICS[1]

TETIANA YUKHYMENKO[a], OLEH SOROCHAN[a]

[a]National Bank of Ukraine
E-mail: tania.iukhymenko@gmail.com
Oleh.Sorochan@bank.gov.ua

Abstract This study explores the impact of central bank communications on FX market dynamics. Our main results suggest that the NBU's statements and press releases on monetary policy issues do indeed matter. We find that exchange rate movements and volatility are negatively correlated with the volumes of publications by the NBU on its official website. However, this effect is noticeably larger for volatility than for exchange rate changes. The impact of communications on FX developments is strongest a week after a news release, and it persists further. Furthermore, these indicators turn out to be more sensitive to monetary policy announcements than NBU updates overall.

JEL Codes E58, E71, C55

Keywords central bank communications, monetary policy, FX market, text analysis

1. INTRODUCTION

The role of central bank communications has grown rapidly in recent decades. Today, central banks (CBs) use various communication tools widely in order to better manage expectations and achieve policy objectives (Casiraghi, 2022). Communications work through building greater trust in CB decisions and reducing uncertainty in the market, particularly about the future direction of monetary policy. By being more predictable for the markets, CBs make market reactions more predictable for themselves, and thereby strengthen their influence on economic developments (Blinder et al., 2008). Unsurprisingly, a wide strand of literature has already been devoted to the impact of communications on macrofinancial outcomes, including FX market dynamics. However, most studies so far have focused on the markets of advanced economies with stable macroeconomic environments and a developed financial infrastructure. Our study aims to answer whether CB communications can effectively steer market behavior in the complex and turbulent environment of an emerging market – such as that of Ukraine.

To evaluate the impact of CB communications, researchers typically examine financial market reactions. There is abundant evidence that CB communications have a significant impact on asset prices and yield moves. For instance, it has been proved that the Fed's communications through statements, minutes, and speeches affect both the volatility of U.S. asset prices and trading volumes (Hayo et al., 2008; Rosa, 2011). Monetary policy announcements may also explain variations in asset prices in other advanced markets, like the Euro area (Leombroni et al., 2021) or the UK (Mumtaz et al, 2023). However, asset market responses may be weak and uncertain in emerging markets with undeveloped or illiquid securities markets (Eklou, 2023; Kamin et al., 1998). Therefore, bond and stock price moves would be a poor proxy for evaluating CB communications in these cases. Therefore, taking into account the insufficient level of development of the Ukrainian securities market, in our study we primarily focused on the reactions of the FX market.

CBs keep a close eye on FX developments, which are extremely important for achieving policy goals. The exchange rate channel is considered to be a very powerful link of monetary transmission in emerging countries (Stone et al., 2009), and Ukraine is no exception (Zholud et al., 2019). Excessive ER volatility may be an issue of high concern, as it negatively affects a range of macroeconomic variables, including inflation, trade, and investments (Weber, 2017). Moreover, the negative impact of exchange rate volatility is exacerbated during currency crises (Brouwer, 2004), which are rather common in emerging markets. In contrast, lower ER volatility improves monetary transmission and reinforces confidence in the local currency, contributing to low and stable inflation (Velarde and Montoro, 2022). For this reason, CBs try to shape the reactions of the FX market through using both actual and verbal interventions. Many CBs use communications as

[1] The authors thank Professor Oleksandr Talavera from the University of Birmingham for the academic supervision of this paper. This research took place through the coaching program under the Bilateral Assistance and Capacity Building for Central Banks (BCC), financed by SECO, and the Graduate Institute in Geneva.
The views expressed in this paper are solely those of the authors and do not necessarily reflect those of the National Bank of Ukraine.

a primary policy instrument for reducing excessive market fluctuation (Fratzscher, 2005). Several empirical studies have shown a smoothing impact of communications on ER volatility in the Czech Republic (Fišer and Horváth, 2009), India (Goyal and Arora, 2012), China (Ning et al., 2016), and Poland (Brzeszczyński et al., 2017). We also studied whether monetary policy communications smooth sentiments on the currency market in Ukraine.

Recent scientific papers on Ukraine have already shown that there is a distinct connection between the NBU's communications and FX market behavior (Gao et al., 2023; Ivanytskyi, 2022). In particular, research by Gao et al. (2023) highlights the power of communications sentiment and its impact on overall ER volatility and the black market premium during the full-scale russian invasion of Ukraine. We extend these findings by discovering a significant correlation between the volumes of NBU publications on its official website and ER movements and volatility. Our results clearly suggest that the NBU's communications efforts contribute to smoothing sentiment on the currency market. The impact of these efforts peaks within a week of publication and persists throughout the observed horizon. Communications related to monetary policy have a greater impact on both ER movements and volatility compared to other messages. However, the general effect of communications on ER volatility turned out to be much more tangible than the effect on ER changes. This insight suggests that market factors may have a greater impact on ER fluctuations, while behavioral factors may play a larger role in determining volatility.

Another finding of our paper concerns references to the governor in the NBU's communications. Although mentioning the governor does not appear to have a clear-cut impact on volatility or ER movements, it is likely to enhance the smoothing effect on the FX market during the first week. This means that markets attribute additional weight to the governor's voice. This finding echoes the results of some other papers, which demonstrate heightened attention to market-related speeches and remarks by the governors of the ECB (Istrefi et al., 2022) and Fed (Biefang-Frisancho and Howells, 2007). The additional weight of high-ranking communications is also confirmed by other researchers. For instance, in the United States, the financial markets react more strongly to a statement from the chairman than to ones from other Fed officials (Ehrmann and Fratzscher, 2005), while the vice chairman's voice has more influence compared to other Board members, and voting regional Fed presidents affect markets more than non-voting ones do (Hayo et al., 2008). While the influence of the governors' words also depends greatly on their personalities (Narain and Sangani, 2023), their potential to attract more market attention is undisputed and should be used judiciously in communications.

The findings presented here have significant implications for both policymakers and financial market participants. Policymakers can use this insight to strategically craft and disseminate communications – particularly those related to monetary policy – to mitigate potential fluctuations in the currency market. Furthermore, the study's results propose straightforward and practical measures to enhance the effectiveness of central bank communications. Specifically, the NBU should publish monetary policy news more frequently at the start of the week if they are not linked to the Monetary Policy Committee's decision schedule. In addition, including references to the governor in the messages augments the impact of communications.

The paper is organized as follows. Section 2 briefly describes communications in the NBU. Section 3 covers data exploration and the methodology applied to assess the impact of communications on the FX market dynamics. Empirical results on this impact are provided in Section 4. Section 5 provides a summary.

2. NBU COMMUNICATION INSIGHTS

Since the adoption of inflation targeting and the transition to a floating exchange rate in 2015, the NBU has seen communications as an important instrument for achieving policy goals. Transparency, consistency, proactivity, and clarity of communications have been integral principles of the NBU's strategy. Given that, the NBU's communications toolkit has been significantly improved and expanded in recent years. The current arsenal includes monthly *Macroeconomic and Monetary Reviews*, quarterly *Inflation Reports*, semiannual *Financial Stability Reports*, *Annual Reports*, press briefings on key decisions, monetary policy releases, *Summaries of MPC* discussions, commentaries on inflation and GDP, and other publications. The NBU also holds regular meetings with experts, market participants, the business community, and foreign investors. Interviews and columns by Board members and experts of the NBU, and off-record meetings with journalists are widely used for the better transmission of key messages to key audiences. Educational outreach is conducted through seminars for university professors, and lectures and contests for students. The NBU maintains a strong presence on social media platforms (Facebook, Twitter, Instagram, YouTube, Telegram), and makes layered communications to tailor content to the needs of diverse audiences. A Transparency Award from *Central Banking* marked the progress of the NBU's communications system in 2019.

Through this multifaceted approach, the NBU strives to reduce market uncertainty and promote informed decision-making. This is crucial in the turbulent and rapidly changing economic landscape of Ukraine. The last decade alone brought the annexation of Crimea, subsequent russian aggression in eastern Ukraine, the COVID-19 crisis, and a full-scale russian invasion. Each of these events struck a huge blow to the Ukrainian economy. Despite these challenges, the NBU has remained committed to openness. Following the russian invasion, the NBU made some modifications to its monetary regime but maintained consistent communications practices. Consistent proactive communications were required to ease the unprecedented level of uncertainty during the war. External research has proved the effectiveness of this approach. The Semantic Index developed by Morgan Stanley shows high consistency between the words used and policy moves of the NBU during wartime (Slyusarchuk et al., 2023). For its part, congruous communications by the NBU and correct wording helped to mitigate the shocks of war, in particular by smoothing the reactions of the Ukrainian FX market (Gao et al., 2023). The NBU's broad communications toolkit and its successful implementation in a fast-changing economic environment make it a valuable case study for studying the potential of CB communications.

3. DATA AND METHODOLOGY

3.1. Data Overview

The NBU maintains a strong online presence through its official website and social media platforms, providing essential information to the public. The Wayback Machine shows that the NBU website was launched in the 1990s, initially containing limited information on banking legislation, the NBU's structure, exchange rates, etc. In 2019, the NBU launched a new website with improved functionality and expanded content. Most of the important information messages were transferred to its News section, but a significant part remains in the archive and can only be accessed through a website search.

Similarweb.com suggests that the NBU's website receives 1.4-2 million monthly users. Time spent on the NBU website increased from 100 seconds in 2022 to 200 seconds in 2023. However, 60% of visitors leave the site after viewing the first page. This could be due to the nature of the information of interest to visitors, such as the exchange rate, which is located on the home page. Thus, one-third of the visitors who are more interested in other information viewed an average of 10 pages (up from 4.2 pages in 2022). When compared to the other state organizations' websites (Figure 1), such as those of the President, the Government, and the Parliament, this website has higher results, except for the Tax Service website, which can be explained by the fact that this agency gives access to its electronic services through its website.

With such a large audience, central banks' websites provide new tools for communicating monetary policy messages to a wide range of audiences, while at the same time improving the public's access to central bank information.

This study analyzes the online presence of the NBU using Google Analytics, and uses website data as independent external variables.

Google Analytics is a web analysis service provided by Google that allows website owners to track and analyze various aspects of their online presence. This service anonymously collects and processes information about website visitors, including their geographic location, devices and browsers used, traffic sources, and specific actions taken on the website. Attempts have been made to use Google Analytics data to measure the impact of CB communications on the public's information demand, which in turn affects inflation expectations. For instance, Jung and Kühl (2021) used European Central Bank (ECB) website traffic as a proxy for visitors' engagement with its communications.

This research utilized a unique Google Analytics dataset, which includes daily views of the NBU website from January 2014 to December 2022. The dataset focuses on the *News and Official Announcements* sections of the NBU website. Data points were filtered to exclude days and pages with less than 10 views, resulting in a sample of 158,000 data points. Further refinement addressed duplication issues caused by variations in URLs. A dataset of 142,000 data points representing 7,098 news items in Ukrainian was ultimately obtained after data cleaning. The primary analysis indicates that each page received an average of 20 days of visits and was viewed approximately 3,500 times. Notably, page views experienced a surge in February 2022. Thus, specific pages related to supporting the Armed Forces of Ukraine and humanitarian aid garnered a significant portion of website views (see Appendix A, Figure 9). As this topic is specific and remote from traditional central bank functions, this section will be excluded from the study.

We collected textual data for almost every news item by using links to publications on the NBU website from Google Analytics data. Unfortunately, after the transition to the new version of the website, some of the data became unavailable in the archive. However, the share of these articles is only 5.6%, which is an acceptably low level for the research.

Various characteristics of communications, such as their content and tone, can significantly impact assessment results. Gorodnichenko et al. (2023) found that even nonverbal communications can affect various financial indicators. To investigate heterogeneity, we evaluated

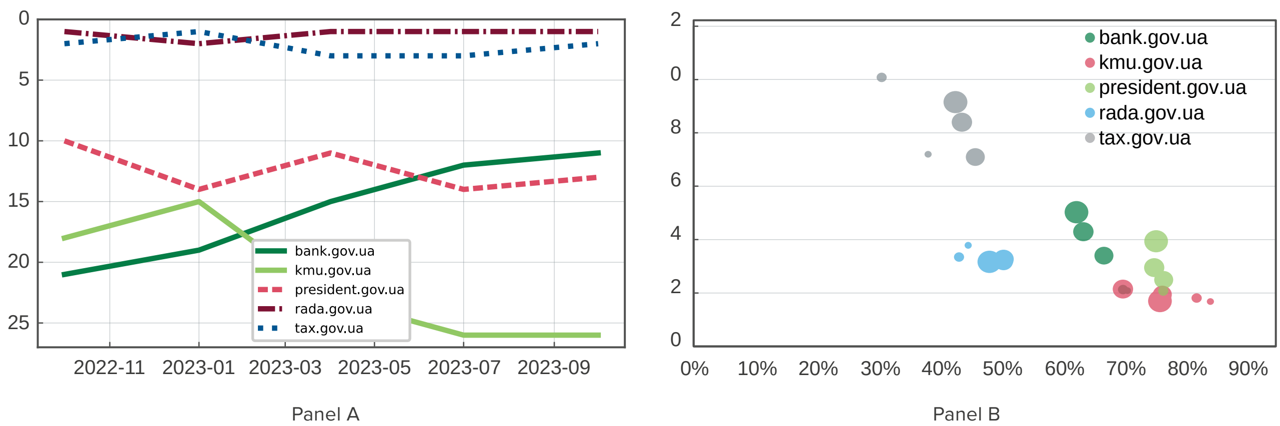

Figure 1. Ranking of Sites in Category Government in Ukraine (*panel A*) and Bounce Rate and Average Pages visited (*panel B*)

Note: The y-axis on *panel A* represents the rank of the website based on the number of visits, while the x-axis represents the date. The y-axis on *panel B* represents the number of pages opened by a single visitor per visit. The x-axis shows the bounce rate, which indicates the percentage of visitors who view only one page per visit. The larger markers denote more recent data.
Source: similarweb.com

various types of central bank communications, with regard to the topic, references to the governor in the text, the popularity of articles on the website among visitors, the stage of monetary policy, and so on. The new site features numerous articles with tags, which are specific words or phrases used in search queries to find relevant information on a particular topic or subject. These keywords include monetary policy, financial stability, numismatics, payments, and more (see Appendix B, Figure 9). In total, we identified 40 keywords, including monetary policy, financial stability, numismatics, and payments. Some articles have two or more tags, which makes it possible to trace the relationships between topics and identify more aggregated groups. In the end, we implemented a binary classification based on the proposed tags (monetary/non-monetary) to focus on monetary publications.

However, nearly 3K articles lack tags. To fix this, we utilized the BERT model (Devlin, 2019) to classify the remaining data. Due to the morphological complexity of the Ukrainian language, the text required thorough cleaning before further analysis. Therefore, the text of each article was lemmatized using the Pymorphy2 library (Korobov, 2015). Pymorphy2 returns the normal form of a word, including the nominative singular for nouns and adjectives, and the indefinite present tense for verbs. In addition, prepositions and particles were removed from the text, along with the most frequently used words using a list of stopwords. On average, articles on the NBU website contain 302 words (the median is 252 words).

The model was trained on existing data with the following characteristics: maxlen=200, max_features=100000, preprocess_mode='bert'. The validation sample size was 20%. The model appears to perform reasonably well even considering the non-uniformity of the sample (see Table 1). Additionally, the validation accuracy is slightly higher than the training accuracy, indicating that the model is generalizing well to new, unseen data. The low loss values suggest that the model's predictions closely match the true values, both in the training and validation sets. Our model classified 94 additional publications, in addition to the 472 already identified.

We also used a dictionary-based approach to distinguish articles that mention the governor.

All the publications were divided into two categories using a dictionary approach: those that mention the NBU governor's name and those that do not. The NBU website contains 762 messages that mention the governor, 74 of which are related to monetary policy.

3.2. Econometric Specification

Local projections are linear regressions that project observations of an endogenous variable at different periods over a chosen horizon onto observed exogenous variables. This method is well suited for capturing the heterogeneous effects of economic variables over time, and offers a nuanced and dynamic perspective (Jorda, 2005). In the context of our research objectives, this methodology allows for a granular examination of the impact of central bank communications on the FX market dynamics. Local projections provide the flexibility to incorporate short-term and long-term effects, capturing the multifaceted nature of economic relationships across varying temporal scales. The sensitivity of local projections to changes in the economic landscape enhances the model's ability to reflect evolving dynamics, making it an ideal choice for studying a dynamic economic system. Local projections are commonly used in economic research due to their advantages. For example, Gao et al. (2023) used local projections to prove that NBU's announcements significantly impacted FX market agents; Carrière-Swallow et al. (2023) estimated the variance of the rate of pass-through from the exchange rate to domestic prices across states of the economy.

To evaluate the effect of central bank communications on macroeconomic outcomes, we created the subsequent local projections model:

$$y_{t+h} = \theta_h\, CB_t + \gamma_h\, y_t + \varepsilon_{t+h};\;\; h = 0, 1,\ldots, H, \tag{1}$$

where y is the dependent variable (the macroeconomic outcome being studied), *CB* – publications of the central bank measured as the number of released messages on the website, ε is a residual, *h* – horizon, and *t* is a point of time. θ is a coefficient vector, which according to the local projections' method is interpreted as a sequence of impulse responses to a structural shock.

We used the volume of publications on the NBU's website (expressed as a natural logarithm) as an

Table 1. Model Results of NBU Messages Classification Using BERT

	Precision	Recall	F1-score	Support
Monetary	0.71	0.56	0.63	87
Non-monetary	0.95	0.98	0.96	808
Accuracy			0.94	895
Accuracy (training)			0.91	3580
Loss			0.16	895
Loss (training)			0.24	3580
Macro avg	0.83	0.77	0.80	895
Weighted avg	0.93	0.94	0.93	895

Note: Leveraging BERT's zero-shot classification capabilities allowed the model to classify messages without needing extensive task-specific training data. The model demonstrates robust performance in classifying NBU messages, with an overall accuracy of 94% on the validation set, which exceeds the training accuracy of 91%. This suggests effective generalization to new data. The precision, recall, and F1-score metrics indicate that while the model excels in identifying non-monetary messages (precision of 0.95 and recall of 0.98), it faces challenges with monetary messages, showing a lower precision of 0.71 and recall of 0.56. The macro average scores highlight a balanced performance across classes, with an F1-score of 0.80. The loss values – 0.16 for validation and 0.24 for training – indicate that the model's predictions are closely aligned with true outcomes.

exogenous variable. Given the significant volatility of this indicator and dependence on its popularity on the day of the week (see Appendix A for more details), we use the sum of publications for seven days. The time series successfully passed stationarity tests, affirming the stability and constant statistical properties of the data over time.

The study aims to understand the intricate connections between central bank communications and economic variables. Traditional macroeconomic indicators, such as inflation or GDP, are published infrequently, either on a monthly or quarterly basis, and exhibit a considerable lag in their release. This temporal discrepancy poses challenges in isolating the distinct influence of individual central bank events on overall indicators. Furthermore, the transient nature of interest in central bank news complicates this task. Local projections are also most justified for use on high-frequency data.

Therefore, the focus of the investigation shifts to macroeconomic indicators with higher frequency. As the Ukrainian stock market remains in its early stages of development, the exchange rate of the hryvnia against foreign currencies, particularly the U.S. dollar, is used. Following Ukraine's departure from the fixed exchange rate system in 2014, a gradual relaxation of currency constraints and a shift towards inflation targeting ensued. Nonetheless, the NBU reinstated the fixed exchange rate mechanism in late February 2022 due to the large-scale military intervention by russia in Ukraine. Taking into account the very volatile nature of the grey cash exchange rate, we use it in our study (see Figure 2). The analysis utilized the change in the hryvnia/dollar exchange rate on the cash market and the seven-day volatility of the hryvnia exchange rate. The use of these variables instead of the exchange rate is also justified from the point of view of statistical properties. The volatility of the exchange rate and its change passed stationarity tests, unlike the exchange rate indicator.[2]

We estimated impulse responses by using local projections on the sample from 1 January 2014 to 31 December 2022.

4. ESTIMATION AND RESULTS

At first, we calculated impulse response coefficients for exchange rate volatility and ER change to CB messages.

The evolution of the results for the impulse response coefficient θ_h from equation 1 on ER indicators as a function of the lag length h is plotted in Figure 3. The lag parameter h ranges from 0 to 30 days after the publication date.

We found out that the publications of the NBU on its official website have a negative correlation with both exchange rate movements and volatility. The coefficient's negative sign indicates an inverse relationship between the number of CB messages on its website and ER volatility. This suggests that a 1% increase in the number of any messages by the CB is associated with a 0.4% decrease in ER volatility in one week (see Figure 3, Panel A). Publications on monetary policy have a stronger impact on both indicators than other messages. A 1% increase in the number of monetary policy messages leads to a 1.2% decrease in ER volatility in 7–10 days (see Figure 3, Panel A). This effect reaches a maximum in about a week and persists throughout the entire observed horizon. All these results are significant at the 5% level.

Therefore, the communications published by the NBU may smooth sentiment on the currency market to a noticeable extent. This can be attributed to the characteristics of the audience reading each particular news item, and to other events occurring in the economy. In particular, people who are responsible for setting the

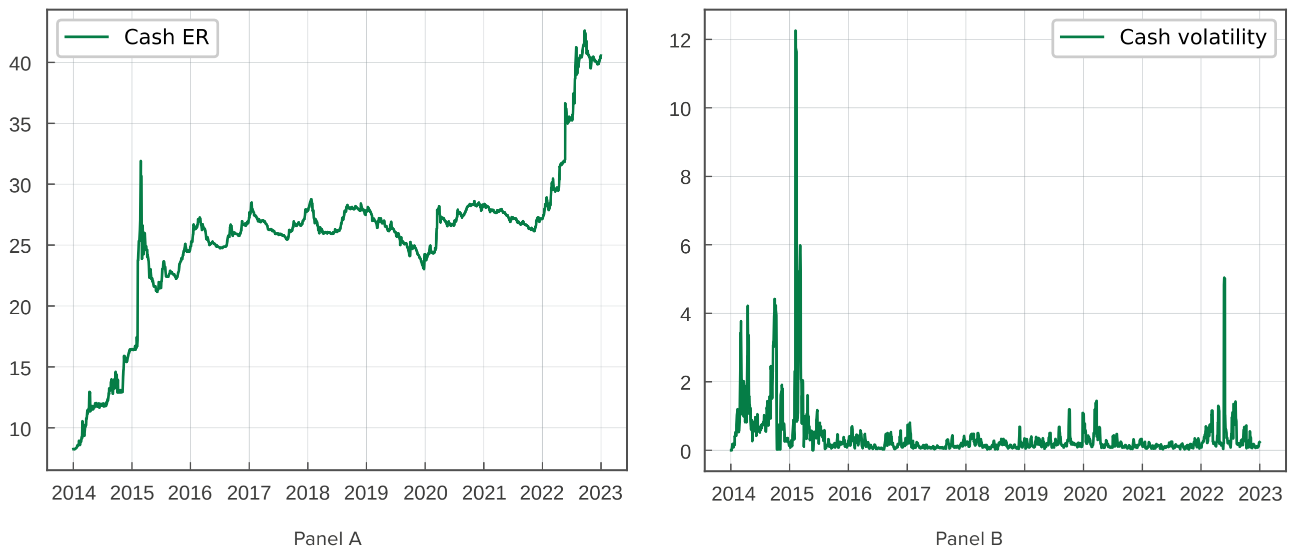

Figure 2. Cash ER (*panel A*) and ER Volatility (*panel B*)

Note: *Panel A* Shows the evolution of the UAH/USD exchange rate. After the transition to a floating exchange rate in 2014, the cash and official exchange rates were virtually identical. However, the forced fixing of the exchange rate in February 2022 due to russia's full-scale invasion led to a widening of the spread. *Panel B* shows the evolution of the seven-day volatility of the UAH/USD exchange rate.
Source: NBU, minfin.com.ua

[2] DF ER change = -10.212 (p-value = 0.000), DF ER volatility = -5.613 (p-value = 0.000).

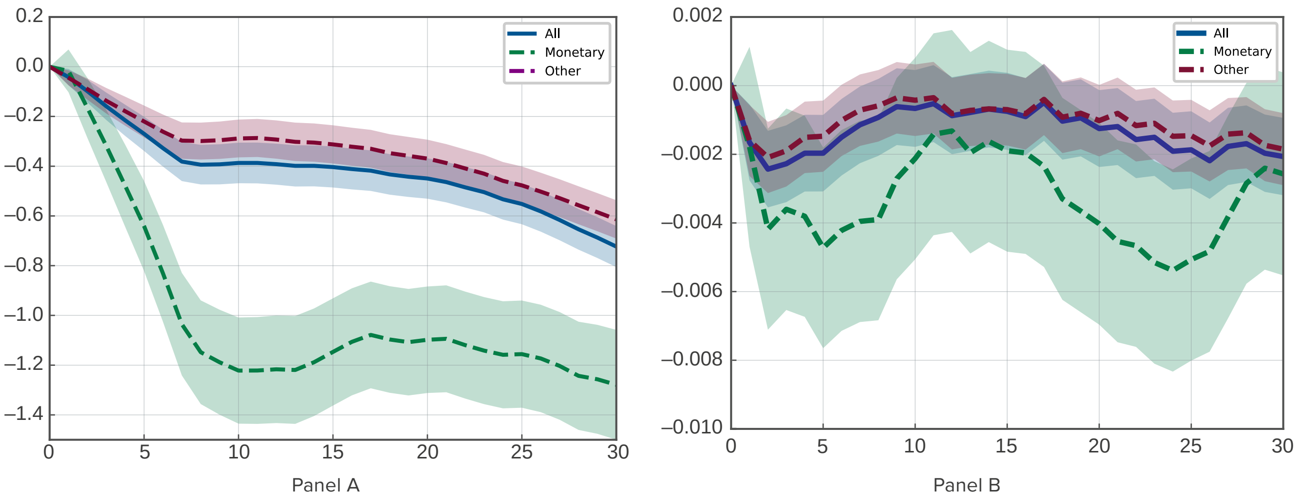

Figure 3. Daily Evolution of the Impulse Response Coefficient for ER Volatility (*panel A*) and ER Change (*panel B*) to Central Bank Messages

Note: This figure shows the results of estimating the sentiment coefficient θ from equation 1 for the time shift h varying between publication day (0) and 30 days after the announcement. The y-axis is the response to a number of publications (in logs). The x-axis is the time shift parameter. The shaded fields, show the 95% confidence interval. The dark-solid line represents the coefficients for all publications, the light-dotted line represents the coefficients for monetary publications, and the dark-dotted line represents the coefficients for monetary publications. The estimates of the coefficients can be seen in Appendix C, Table 1a-1b.

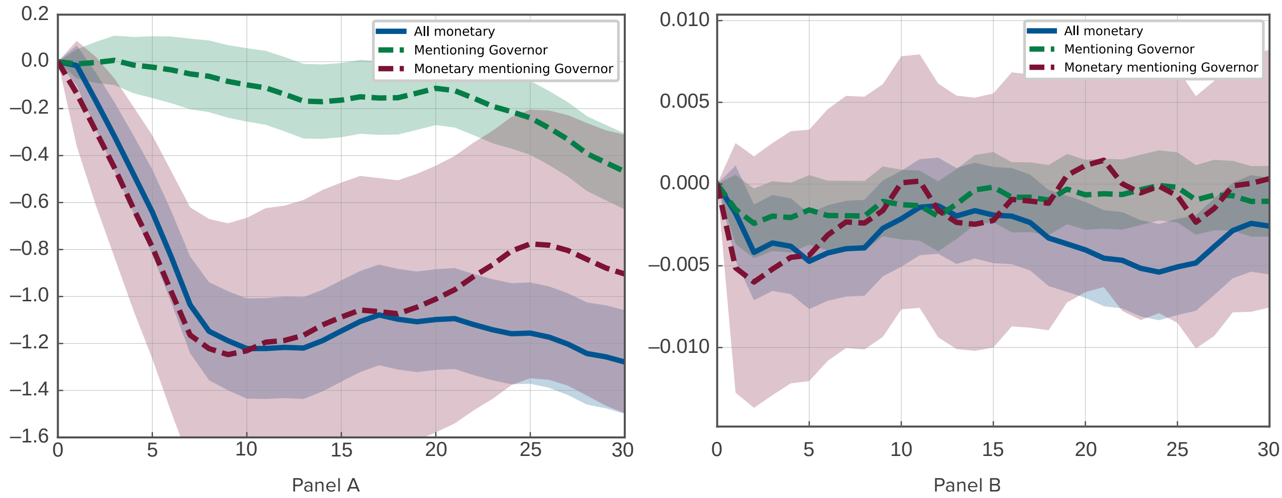

Figure 4. Daily Evolution of the Impulse Response Coefficient on CB Messages in which the Governor is Mentioned or Not Mentioned

Note: *Panel A* shows the reaction of cash ER volatility and panel B shows the reaction of change in ER. These figures show the results of estimating the sentiment coefficient θ from equation 1 for the time shift h varying between publication day (0) and 30 days after the announcement. The y-axis is the response to the number of publications (in logs). The x-axis is the time shift parameter. The shaded fields show the 95% confidence interval. The dark-solid line represents the coefficients for all publications, the light-dotted line represents the coefficients for monetary publications, and the dark-dotted line represents the coefficients for monetary publications. The estimates of the coefficients can be seen in Appendix C, Table 2a-2b.

trend in trading volumes in the forex market are more likely to read specialized news rather than news in general.

On the other hand, the effect of the NBU's news on the exchange rate changes is much smaller than for volatility. Within 3-5 days after publication, an increase of 1% in the number of overall news items, as well as monetary policy news in particular (in logarithm value terms) will reduce the exchange rate insignificantly – by 0.002% and by 0.004% respectively (see Figure 3, Panel B). This may suggest that exchange rate changes are more dependent on market factors, while volatility is more often determined by behavioral factors. This could be interpreted as an increase in transparency or effective communications by the central bank, leading to greater stability in exchange rates and reducing the impact of speculative or panic-driven behavior.

At the second stage, aimed to identify patterns and properties of publications that may affect the impact of communications on exchange rate indicators. These properties may include the content or the level of reader attention.

In particular, we assumed that the central bank governor's authority and attention to specific events could affect the assessment's results.

Figure 4 demonstrates that, in general, references to the governor in NBU communications do not have

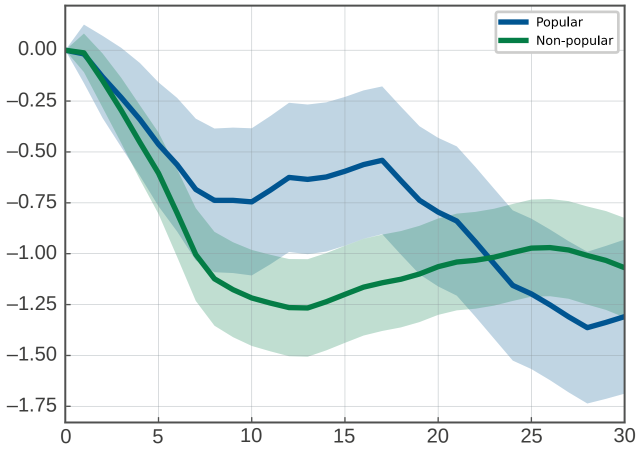

Figure 5. Evolution of the Impulse Response Coefficient to CB Messages by Popularity

Note: Figure shows the reaction of cash ER volatility. This figure shows the results of estimating the sentiment coefficient θ from equation 1 for the time shift h varying between publication day (0) and 30 days after the announcement. The y-axis is the response to a number of publications (in logs). The x-axis is the time shift parameter. The shaded fields show the 95% confidence interval. The dark-solid line represents the coefficients for all publications, the light-dotted line represents the coefficients for monetary publications, and the dark-dotted line represents the coefficients for monetary publications. The estimates of the coefficients can be seen in Appendix C, Table 3.

an impact on volatility or exchange rate movements. However, if the governor is mentioned in monetary policy news, it is likely to accelerate the smoothing effect of the NBU's publications on the FX market during the first week. The maximum effect on volatility is achieved at least one day earlier when mentioning the governor. This may indicate greater attention and trust in messages, which contain the governor's direct or indirect speech. Meanwhile, the coefficients for monetary publications that mention the governor have a high degree of uncertainty. This uncertainty is due to the limited number of observations. Nevertheless, we believe that it is a good idea to mention the governor in such publications for enhanced precision and impact. During periods of significant shocks, time can be important in offsetting the negative impact on the economy.

The news has been divided into two categories based on the number of views, below and above the median. On average, monetary policy news is viewed less frequently (see Appendix A, Figure 12). It was discovered that news with a larger number of views had a lower impact on FX market volatility (Figure 5). A 1% increase in the number of popular messages leads to only a 0.75% decrease in ER volatility in the first week. A 1% rise in non-popular news converts to a significant 1.25% drop in volatility. This may be because monetary policy news, which as we have already noted is more likely to reduce volatility, receives fewer views.

5. DISCUSSION AND CONCLUSIONS

This study examines the impact of central bank communications, specifically those published on the NBU website, on FX market indicators. Local projections, a method that captures both short-term and long-term effects, were used to identify nuanced patterns in the impact of central bank communications on various indicators. The study shows a clear correlation between the NBU's statements and press releases on monetary policy issues and the behavior of the FX market. The negative correlation between exchange rate movements, volatility, and the volume of NBU publications suggests that an increase in the central bank's communications activity is associated with a decrease in FX market volatility. Notably, monetary policy announcements have a more pronounced impact compared to overall publications, resulting in a statistically significant larger decrease in FX volatility within 7–10 days.

The analysis showed that while exchange rate changes are minimally affected in the short term, volatility experiences a more substantial reduction. We also examined the role of specific communications characteristics, such as references to the governor and message popularity, on FX market indicators. Emphasizing the importance of key figures in central bank communications, mentioning the governor in monetary policy news was found to enhance the smoothing effect on the FX market. In particular, the effect of such messages seems to be faster.

Our research confirms the results of previous studies that communications are important and can influence the behavior of financial market participants (Fratzscher, 2005; Fišer and Horváth, 2009; Goyal and Arora, 2012; Ning et al., 2016; Brzeszczyński et al., 2017; Gao et al., 2023), but also provides empirical insights into the complex relationship between central bank communications and FX market indicator dynamics. The implications of our findings are significant for policymakers and financial market participants. Policymakers can strategically shape and disseminate communications, especially those related to monetary policy, to mitigate currency market fluctuations. This is especially important in times of crisis or other shocks when it is necessary to react quickly and accurately. The importance of clear and targeted messaging is underscored by the differential influence of communications themes on inflation expectations, with monetary policy announcements playing a pivotal role. Practical measures to enhance the effectiveness of NBU communications include the more frequent publication of monetary policy news early in the week, and incorporating references to the governor in messages. These recommendations aim to improve the precision and impact of central bank communications.

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APPENDICES

APPENDIX A. GOOGLE ANALYTICS

Before the full-scale invasion, NBU webpage views rarely exceeded 200K per month. However, in February 2022, the uncertainty and open communication policy of the NBU prompted people to visit the site more often. In addition, a significant share of the views was collected by two pages “Special Account” and “Special Account for Humanitarian Aid” containing account details to support the Armed Forces of Ukraine and humanitarian aid to Ukrainians. In the 311 days from the launch of this page until the end of 2022, it was viewed almost 11 million times, which is about 43% of all views of the NBU website over nine years.

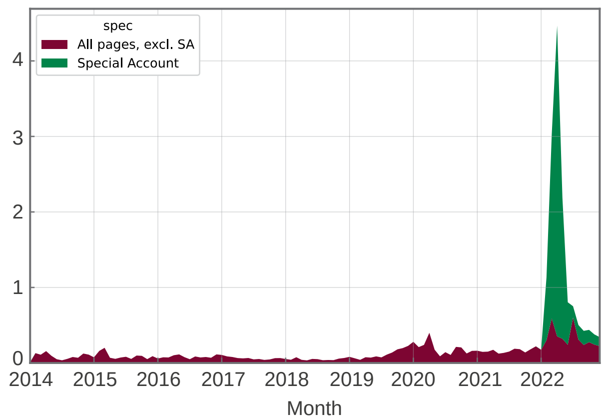

Figure 6. Total Number of Views per Month, million

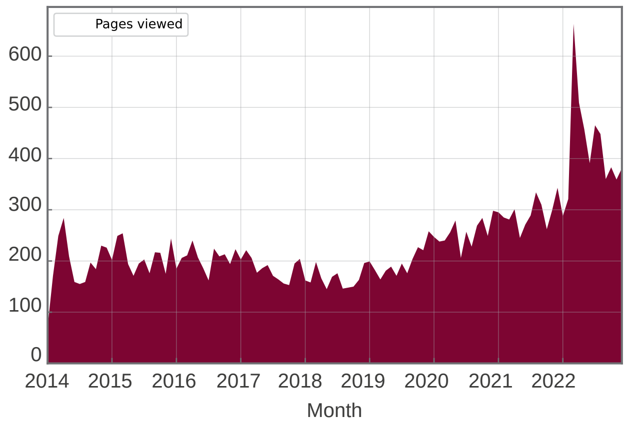

Figure 7. Pages Viewed per Month

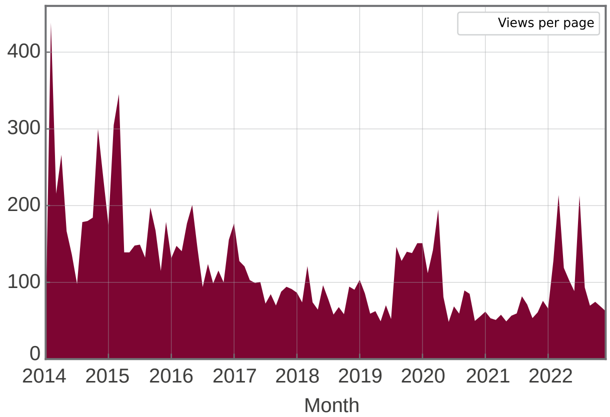

Figure 8. Average Page Views per Month (excl. Special Account Page

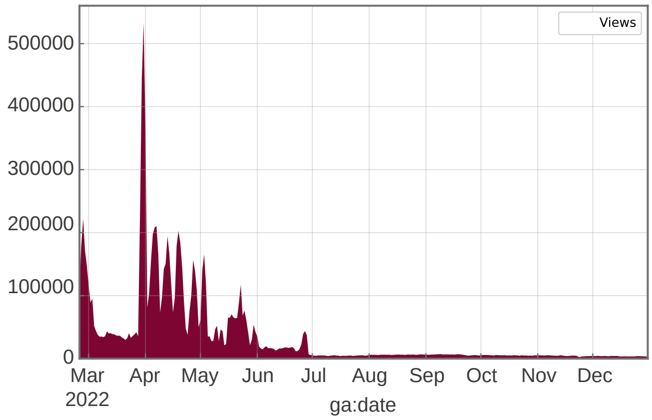

Figure 9. Views of Special Account Page per Day

Views of the NBU’s pages are expected to be highest in the first days after publication on the website (Figure 10). Interestingly, on average, the next day after the publication there is a significant increase in views compared to the first day. However, this is explained by the views of 39% of articles being significantly shifted to the next day: Among other things, this can be explained by the time of publication during the day – evening news is likely to be viewed more the next day. Unfortunately, the exact date and time of publication are not available for most articles, so the issue of the exact time will not be considered in this study. Therefore, the study will be based on daily data.

Page views largely depend on the day of the week. First, on weekends, the NBU website publishes much less news. Second, the number of visitors on weekends drops sharply.

We looked at the difference between the trajectory of views of all news on the NBU website and news related to monetary policy only. On average, monetary policy news is viewed less frequently, and views drop sharply two days after publication. This can be explained by the fact that very often monetary policy news is published on Thursday, in conjunction with meetings of the monetary policy committee and the announcement of decisions. As shown in Figure 11, on weekends views are much lower for all news.

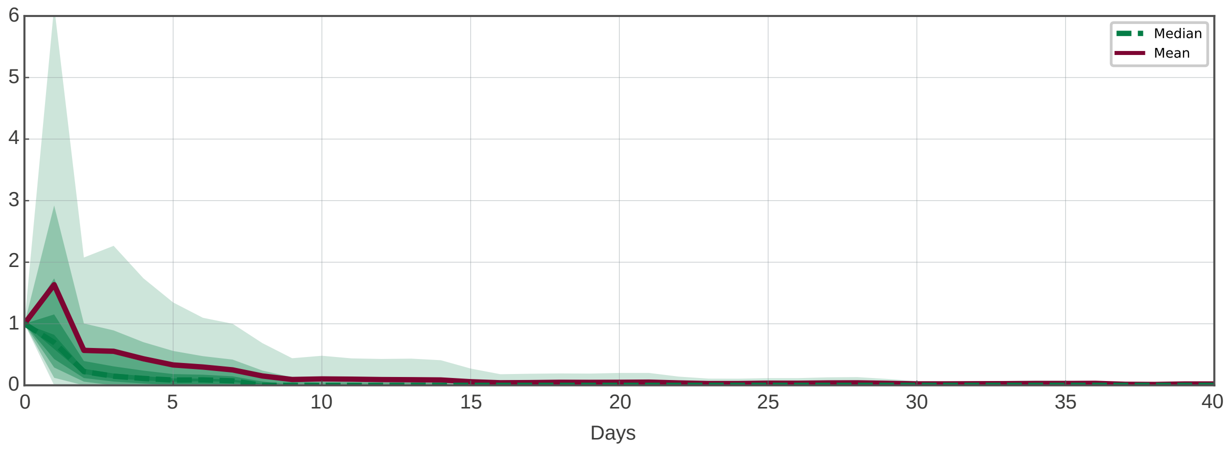

Figure 10. Average Interest on Pages by Days (publication day = 1)

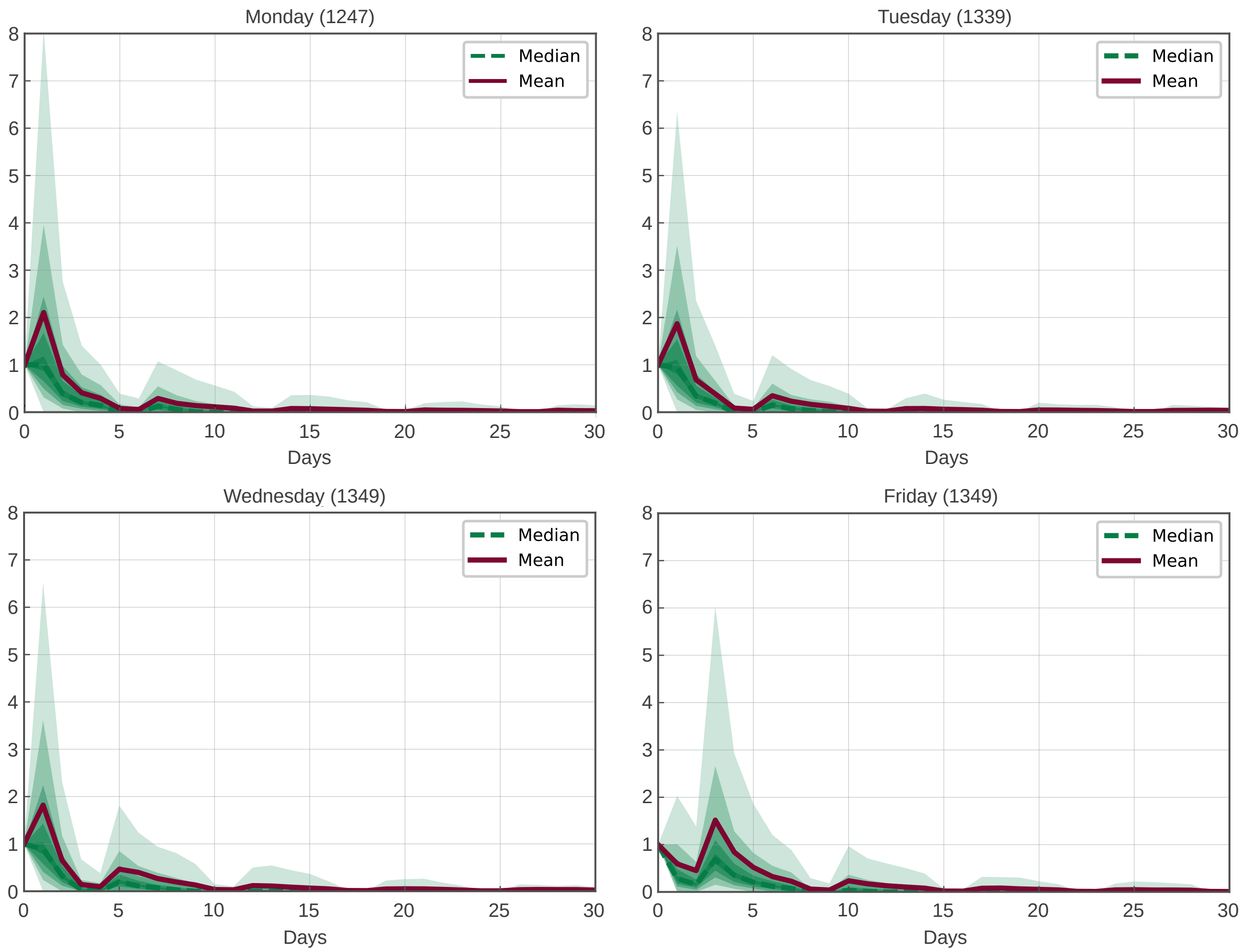

Figure 11. Average Interest in Pages by Days (publication day = 1) Depending on Day of the Week when the News was Published (number of published news in parentheses)

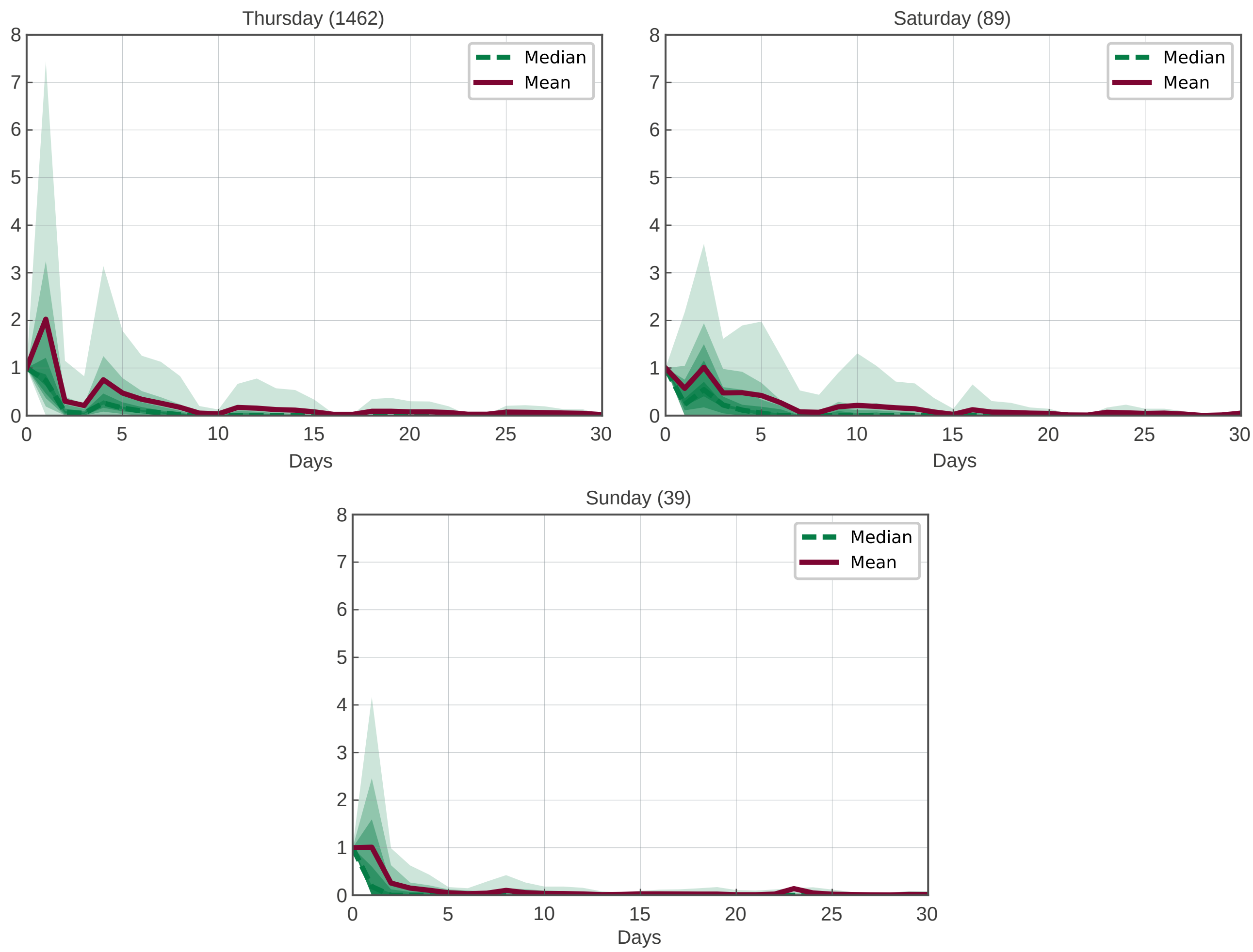

Figure 11 (continued). Average Interest in Pages by Days (publication day = 1) Depending on Day of the Week when the News was Published (number of published news in parentheses)

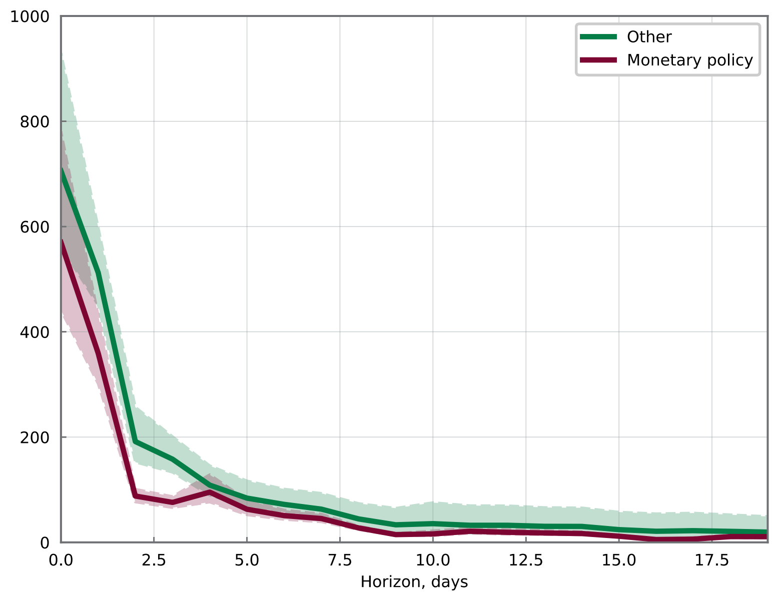

Figure 12. Average Interest in Pages by topic, views per page

APPENDIX B. WHAT THE NBU SAYS

Some keywords are very similar and occur for the same news, so we have combined them into groups (for example, monetary policy and monetary policy decisions). Nevertheless, there are significant interconnections between different topics, as shown in Figure 5.

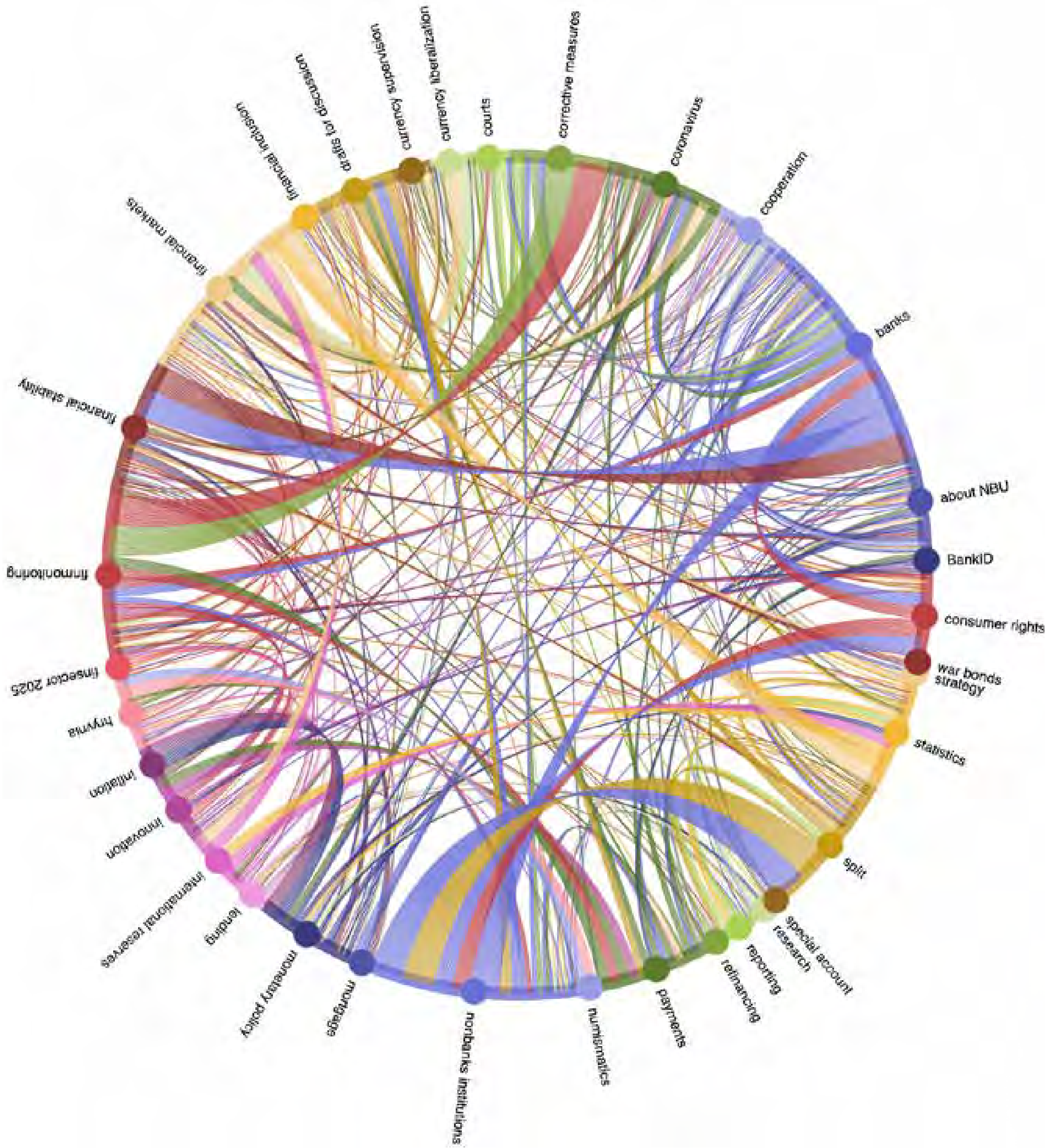

Figure 13. Chord Diagram for Keyword Interlinks between News on the NBU website (the width of the lines corresponds to the number of shared news items).

An interactive version of this diagram can be downloaded here: https://github.com/taniaghub/CB_communications/blob/main/Figure_B1.html

APPENDIX C. IMPULSE RESPONSES BY LOCAL PROJECTIONS

Table 2a. Results of Model Estimation for Equation (1) for Different Lag Length Values of the Parameter *h* for the Cash Volatility

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Total publications																
publications	0.000***	- 0.042**	- 0.098***	- 0.159***	- 0.216***	- 0.270***	- 0.328***	- 0.381***	- 0.394***	- 0.392***	- 0.387***	- 0.387***	- 0.392***	- 0.399***	- 0.398***	- 0.403***
p-value	(0.000)	(0.037)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cash_volatility	1.000***	0.928***	0.852***	0.775***	0.696***	0.616***	0.529***	0.439***	0.413***	0.389***	0.365***	0.350***	0.335***	0.327***	0.336***	0.345***
p-value	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R squared	1.000	0.864	0.733	0.613	0.501	0.399	0.304	0.220	0.199	0.179	0.159	0.148	0.138	0.133	0.139	0.146
Sample size	3,286	3,285	3,284	3,283	3,282	3,281	3,280	3,279	3,278	3,277	3,276	3,275	3,274	3,273	3,272	3,271
Monetary publications																
publications	0.000	- 0.017	- 0.166**	- 0.319***	- 0.479***	- 0.641***	- 0.831***	- 1.035***	- 1.148***	- 1.188***	- 1.222***	- 1.221***	- 1.217***	- 1.219***	- 1.188***	- 1.147***
p-value	(0.351)	(0.750)	(0.024)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cash_volatility	1.000***	0.929***	0.853***	0.776***	0.697***	0.616***	0.528***	0.437***	0.409***	0.385***	0.361***	0.345***	0.331***	0.323***	0.332***	0.341***
p-value	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R squared	1.000	0.864	0.733	0.612	0.499	0.398	0.303	0.221	0.202	0.184	0.166	0.155	0.144	0.139	0.144	0.149
Sample size	3,286	3,285	3,284	3,283	3,282	3,281	3,280	3,279	3,278	3,277	3,276	3,275	3,274	3,273	3,272	3,271
Other publications																
publications	0.000***	- 0.045**	- 0.090***	- 0.137***	- 0.179***	- 0.220***	- 0.261***	- 0.297***	- 0.299***	- 0.296***	- 0.288***	- 0.287***	- 0.293***	- 0.302***	- 0.305***	- 0.312***
p-value	(0.000)	(0.016)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cash_volatility	1.000***	0.928***	0.853***	0.776***	0.698***	0.618***	0.532***	0.442***	0.417***	0.393***	0.369***	0.354***	0.339***	0.331***	0.340***	0.348***
p-value	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R squared	1.000	0.864	0.733	0.612	0.500	0.397	0.301	0.215	0.193	0.173	0.154	0.142	0.132	0.128	0.134	0.141
Sample size	3,286	3,285	3,284	3,283	3,282	3,281	3,280	3,279	3,278	3,277	3,276	3,275	3,274	3,273	3,272	3,271

Table 2a (continued). Results of Model Estimation for Equation (1) for Different Lag Length Values of the Parameter *h* for the Cash Volatility

	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
Total publications															
publications	- 0.411***	- 0.418***	- 0.433***	- 0.442***	- 0.449***	- 0.464***	- 0.485***	- 0.504***	- 0.533***	- 0.552***	- 0.582***	- 0.616***	- 0.654***	- 0.687***	- 0.723***
p-value	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cash_volatility	0.352***	0.361***	0.363***	0.365***	0.366***	0.359***	0.356***	0.355***	0.354***	0.350***	0.345***	0.335***	0.324***	0.303***	0.282***
p-value	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R squared	0.152	0.160	0.163	0.165	0.167	0.163	0.164	0.165	0.168	0.168	0.169	0.166	0.164	0.156	0.149
Sample size	3,270	3,269	3,268	3,267	3,266	3,265	3,264	3,263	3,262	3,261	3,260	3,259	3,258	3,257	3,256
Monetary publications															
publications	- 1.106***	- 1.078***	- 1.097***	- 1.108***	- 1.098***	- 1.094***	- 1.119***	- 1.142***	- 1.158***	- 1.156***	- 1.173***	- 1.203***	- 1.243***	- 1.257***	- 1.279***
p-value	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cash_volatility	0.350***	0.360***	0.362***	0.364***	0.365***	0.359***	0.356***	0.355***	0.355***	0.352***	0.348***	0.338***	0.328***	0.308***	0.288***
p-value	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R squared	0.153	0.159	0.161	0.163	0.164	0.159	0.158	0.158	0.159	0.157	0.154	0.149	0.143	0.131	0.119
Sample size	3,270	3,269	3,268	3,267	3,266	3,265	3,264	3,263	3,262	3,261	3,260	3,259	3,258	3,257	3,256
Other publications															
publications	- 0.322***	- 0.330***	- 0.347***	- 0.358***	- 0.369***	- 0.387***	- 0.409***	- 0.430***	- 0.459***	- 0.477***	- 0.502***	- 0.529***	- 0.557***	- 0.585***	- 0.614***
p-value	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cash_volatility	0.356***	0.365***	0.367***	0.369***	0.369***	0.362***	0.359***	0.358***	0.357***	0.354***	0.349***	0.339***	0.328***	0.308***	0.287***
p-value	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R squared	0.147	0.155	0.158	0.160	0.162	0.159	0.159	0.161	0.164	0.164	0.164	0.161	0.157	0.148	0.139
Sample size	3,270	3,269	3,268	3,267	3,266	3,265	3,264	3,263	3,262	3,261	3,260	3,259	3,258	3,257	3,256

Note: ***, **, * indicate statistical significance levels at 1%, 5%, and 10%.

Table 2b. Results of Model Estimation for Equation (1) for Different Lag Length Values of the Parameter *h* for the Cash Volatility

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Total publications																
publications	0.000*	- 0.002**	- 0.002***	- 0.002***	- 0.002***	- 0.002***	- 0.002**	- 0.001*	- 0.001	- 0.001	- 0.001	- 0.001	- 0.001	- 0.001	- 0.001	- 0.001
p-value	(0.066)	(0.014)	(0.000)	(0.001)	(0.004)	(0.004)	(0.027)	(0.093)	(0.175)	(0.368)	(0.329)	(0.442)	(0.199)	(0.250)	(0.317)	(0.273)
ER change	1.000***	0.126***	- 0.059***	0.002	0.049***	- 0.090***	0.083***	0.059***	- 0.038**	- 0.057***	0.053***	- 0.001	- 0.025	0.066***	0.078***	- 0.010
p-value	(0.000)	(0.000)	(0.001)	(0.929)	(0.005)	(0.000)	(0.000)	(0.001)	(0.031)	(0.001)	(0.002)	(0.973)	(0.149)	(0.000)	(0.000)	(0.574)
R squared	1.000	0.018	0.007	0.003	0.005	0.010	0.009	0.005	0.002	0.003	0.003	0.000	0.001	0.005	0.006	0.000
Sample size	3,286	3,285	3,284	3,283	3,282	3,281	3,280	3,279	3,278	3,277	3,276	3,275	3,274	3,273	3,272	3,271
Monetary publications																
publications	0.000	- 0.002	- 0.004**	- 0.004**	- 0.004**	- 0.005***	- 0.004**	- 0.004**	- 0.004**	- 0.003	- 0.002	- 0.001	- 0.001	- 0.002	- 0.002	- 0.002
p-value	(0.226)	(0.315)	(0.019)	(0.044)	(0.033)	(0.008)	(0.018)	(0.027)	(0.029)	(0.129)	(0.234)	(0.428)	(0.460)	(0.273)	(0.362)	(0.289)
ER change	1.000***	0.127***	- 0.058***	0.003	0.050***	- 0.090***	0.084***	0.060***	- 0.038**	- 0.057***	0.053***	0.000	- 0.025	0.066***	0.078***	- 0.010
p-value	(0.000)	(0.000)	(0.001)	(0.869)	(0.004)	(0.000)	(0.000)	(0.001)	(0.031)	(0.001)	(0.002)	(0.982)	(0.157)	(0.000)	(0.000)	(0.585)
R squared	1.000	0.017	0.005	0.001	0.004	0.010	0.009	0.005	0.003	0.004	0.003	0.000	0.001	0.005	0.006	0.000
Sample size	3,286	3,285	3,284	3,283	3,282	3,281	3,280	3,279	3,278	3,277	3,276	3,275	3,274	3,273	3,272	3,271
Other publications																
publications	0.000**	- 0.002**	- 0.002***	- 0.002***	- 0.002**	- 0.001**	- 0.001	- 0.001	- 0.001	0.000	0.000	0.000	- 0.001	- 0.001	- 0.001	- 0.001
p-value	(0.012)	(0.011)	(0.001)	(0.003)	(0.017)	(0.020)	(0.109)	(0.259)	(0.354)	(0.576)	(0.502)	(0.580)	(0.198)	(0.255)	(0.284)	(0.271)
ER change	1.000***	0.126***	- 0.059***	0.002	0.050***	- 0.090***	0.083***	0.060***	- 0.038**	- 0.057***	0.053***	0.000	- 0.025	0.066***	0.078***	- 0.010
p-value	(0.000)	(0.000)	(0.001)	(0.928)	(0.005)	(0.000)	(0.000)	(0.001)	(0.032)	(0.001)	(0.002)	(0.978)	(0.147)	(0.000)	(0.000)	(0.572)
R squared	1.000	0.018	0.007	0.003	0.004	0.009	0.008	0.004	0.002	0.003	0.003	0.000	0.001	0.005	0.007	0.000
Sample size	3,286	3,285	3,284	3,283	3,282	3,281	3,280	3,279	3,278	3,277	3,276	3,275	3,274	3,273	3,272	3,271

Table 2b (continued). Results of Model Estimation for Equation (1) for Different Lag Length Values of the Parameter *h* for the Cash Volatility

	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
Total publications															
publications	- 0.001	0.000	- 0.001	- 0.001	- 0.001*	- 0.001*	- 0.002**	- 0.002**	- 0.002***	- 0.002***	- 0.002***	- 0.002***	- 0.002**	- 0.002***	- 0.002***
p-value	(0.185)	(0.472)	(0.130)	(0.169)	(0.066)	(0.080)	(0.021)	(0.028)	(0.005)	(0.006)	(0.001)	(0.010)	(0.013)	(0.004)	(0.003)
ER change	- 0.026	0.089***	0.028	- 0.017	- 0.084***	0.071***	0.026	0.000	- 0.059***	- 0.071***	- 0.141***	0.028	0.143***	0.009	- 0.017
p-value	(0.141)	(0.000)	(0.112)	(0.327)	(0.000)	(0.000)	(0.131)	(0.983)	(0.001)	(0.000)	(0.000)	(0.114)	(0.000)	(0.616)	(0.326)
R squared	0.001	0.008	0.002	0.001	0.008	0.006	0.002	0.001	0.006	0.007	0.022	0.003	0.023	0.003	0.003
Sample size	3,270	3,269	3,268	3,267	3,266	3,265	3,264	3,263	3,262	3,261	3,260	3,259	3,258	3,257	3,256
Monetary publications															
publications	- 0.002	- 0.002	- 0.003*	- 0.004**	- 0.004**	- 0.005**	- 0.005***	- 0.005***	- 0.005***	- 0.005***	- 0.005***	- 0.004**	- 0.003	- 0.002	- 0.003
p-value	(0.273)	(0.187)	(0.065)	(0.041)	(0.024)	(0.011)	(0.009)	(0.004)	(0.003)	(0.005)	(0.007)	(0.033)	(0.110)	(0.181)	(0.153)
ER change	- 0.025	0.089***	0.028	- 0.017	- 0.084***	0.071***	0.027	0.001	- 0.058***	- 0.070***	- 0.140***	0.028	0.144***	0.010	- 0.016
p-value	(0.147)	(0.000)	(0.109)	(0.329)	(0.000)	(0.000)	(0.124)	(0.970)	(0.001)	(0.000)	(0.000)	(0.104)	(0.000)	(0.566)	(0.365)
R squared	0.001	0.009	0.002	0.002	0.008	0.007	0.003	0.003	0.006	0.007	0.022	0.002	0.022	0.001	0.001
Sample size	3,270	3,269	3,268	3,267	3,266	3,265	3,264	3,263	3,262	3,261	3,260	3,259	3,258	3,257	3,256
Other publications															
publications	- 0.001	0.000	- 0.001	- 0.001	- 0.001	- 0.001	- 0.001*	- 0.001*	- 0.001**	- 0.001**	- 0.002***	- 0.001**	- 0.001**	- 0.002***	- 0.002***
p-value	(0.197)	(0.527)	(0.147)	(0.205)	(0.107)	(0.203)	(0.067)	(0.084)	(0.020)	(0.022)	(0.005)	(0.027)	(0.030)	(0.007)	(0.004)
ER change	- 0.026	0.089***	0.028	- 0.017	- 0.084***	0.071***	0.027	0.001	- 0.059***	- 0.071***	- 0.141***	0.028	0.143***	0.009	- 0.017
p-value	(0.140)	(0.000)	(0.113)	(0.327)	(0.000)	(0.000)	(0.128)	(0.974)	(0.001)	(0.000)	(0.000)	(0.113)	(0.000)	(0.619)	(0.323)
R squared	0.001	0.008	0.001	0.001	0.008	0.006	0.002	0.001	0.005	0.006	0.022	0.002	0.022	0.002	0.003
Sample size	3,270	3,269	3,268	3,267	3,266	3,265	3,264	3,263	3,262	3,261	3,260	3,259	3,258	3,257	3,256

Note: ***, **, * indicate statistical significance levels at 1%, 5%, and 10%.

Table 3a. Results of Model Estimation for Equation (1) for Different Lag Length Values of the Parameter *h* for the Cash ER Volatility Depending on Governor Mentions in Text

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Monetary publications																
publications	0.000	- 0.017	- 0.166**	- 0.319***	- 0.479***	- 0.641***	- 0.831***	- 1.035***	- 1.148***	- 1.188***	- 1.222***	- 1.221***	- 1.217***	- 1.219***	- 1.188***	- 1.147***
p-value	(0.351)	(0.750)	(0.024)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ER volatility	1.000***	0.929***	0.853***	0.776***	0.697***	0.616***	0.528***	0.437***	0.409***	0.385***	0.361***	0.345***	0.331***	0.323***	0.332***	0.341***
p-value	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R squared	1.000	0.864	0.733	0.612	0.499	0.398	0.303	0.221	0.202	0.184	0.166	0.155	0.144	0.139	0.144	0.149
Sample size	3,286	3,285	3,284	3,283	3,282	3,281	3,280	3,279	3,278	3,277	3,276	3,275	3,274	3,273	3,272	3,271
Governor publications																
publications	0.000**	- 0.010	- 0.003	0.006	- 0.015	- 0.023	- 0.035	- 0.052	- 0.062	- 0.084	- 0.099	- 0.112	- 0.139	- 0.168*	- 0.171*	- 0.164*
p-value	(0.020)	(0.794)	(0.948)	(0.931)	(0.839)	(0.771)	(0.684)	(0.567)	(0.501)	(0.371)	(0.297)	(0.243)	(0.150)	(0.082)	(0.077)	(0.088)
ER volatility	1.000***	0.930***	0.856***	0.781***	0.704***	0.626***	0.541***	0.452***	0.427***	0.403***	0.379***	0.364***	0.349***	0.341***	0.350***	0.359***
p-value	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R squared	1.000	0.864	0.732	0.610	0.496	0.392	0.292	0.205	0.182	0.163	0.144	0.133	0.123	0.117	0.123	0.130
Sample size	3,286	3,285	3,284	3,283	3,282	3,281	3,280	3,279	3,278	3,277	3,276	3,275	3,274	3,273	3,272	3,271
Monetary governor publications																
publications	0.000	- 0.136	- 0.294	- 0.453*	- 0.625**	- 0.790***	- 0.979***	- 1.164***	- 1.222***	- 1.248***	- 1.231***	- 1.194***	- 1.187***	- 1.165***	- 1.121***	- 1.088***
p-value	(0.664)	(0.320)	(0.125)	(0.051)	(0.018)	(0.006)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
ER volatility	1.000***	0.929***	0.855***	0.779***	0.702***	0.623***	0.537***	0.448***	0.423***	0.399***	0.375***	0.359***	0.345***	0.337***	0.346***	0.355***
p-value	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R squared	1.000	0.864	0.732	0.611	0.497	0.393	0.295	0.208	0.186	0.166	0.147	0.135	0.125	0.120	0.125	0.131
Sample size	3,286	3,285	3,284	3,283	3,282	3,281	3,280	3,279	3,278	3,277	3,276	3,275	3,274	3,273	3,272	3,271

Table 3a (continued). Results of Model Estimation for Equation (1) for Different Lag Length Values of the Parameter *h* for the Cash ER Volatility Depending on Governor Mentions in Text

	16	17	18	19	20	21	22	23	24	25	26	27	28	29
Monetary publications														
publications	- 1.106***	- 1.078***	- 1.097***	- 1.108***	- 1.098***	- 1.094***	- 1.119***	- 1.142***	- 1.158***	- 1.156***	- 1.173***	- 1.203***	- 1.243***	- 1.257***
p-value	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ER volatility	0.350***	0.360***	0.362***	0.364***	0.365***	0.359***	0.356***	0.355***	0.355***	0.352***	0.348***	0.338***	0.328***	0.308***
p-value	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R squared	0.153	0.159	0.161	0.163	0.164	0.159	0.158	0.158	0.159	0.157	0.154	0.149	0.143	0.131
Sample size	3,270	3,269	3,268	3,267	3,266	3,265	3,264	3,263	3,262	3,261	3,260	3,259	3,258	3,257
Governor publications														
publications	- 0.150	- 0.155	- 0.154	- 0.134	- 0.114	- 0.123	- 0.156	- 0.190**	- 0.213**	- 0.239**	- 0.283***	- 0.331***	- 0.392***	- 0.430***
p-value	(0.118)	(0.104)	(0.107)	(0.159)	(0.233)	(0.196)	(0.103)	(0.047)	(0.026)	(0.012)	(0.003)	(0.001)	(0.000)	(0.000)
ER volatility	0.367***	0.376***	0.378***	0.381***	0.382***	0.375***	0.373***	0.372***	0.372***	0.370***	0.366***	0.356***	0.347***	0.328***
p-value	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R squared	0.135	0.142	0.144	0.145	0.146	0.141	0.140	0.140	0.140	0.138	0.136	0.130	0.124	0.112
Sample size	3,270	3,269	3,268	3,267	3,266	3,265	3,264	3,263	3,262	3,261	3,260	3,259	3,258	3,257
Monetary governor publications														
publications	- 1.058***	- 1.064***	- 1.073***	- 1.046***	- 1.011***	- 0.971***	- 0.915***	- 0.865**	- 0.807**	- 0.776**	- 0.782**	- 0.804**	- 0.842**	- 0.879**
p-value	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.005)	(0.008)	(0.013)	(0.020)	(0.026)	(0.025)	(0.022)	(0.017)	(0.014)
ER volatility	0.363***	0.372***	0.375***	0.377***	0.378***	0.372***	0.370***	0.369***	0.369***	0.367***	0.363***	0.353***	0.343***	0.324***
p-value	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R squared	0.137	0.144	0.146	0.147	0.148	0.143	0.141	0.140	0.140	0.138	0.135	0.128	0.122	0.109
Sample size	3,270	3,269	3,268	3,267	3,266	3,265	3,264	3,263	3,262	3,261	3,260	3,259	3,258	3,257

Note: ***, **, * indicate statistical significance levels at 1%, 5%, and 10%.

Table 3b. Results of Model Estimation for Equation (1) for Different Lag Length Values of the Parameter *h* for the Cash ER Change Depending on Governor Mentions in Text

	0	1	2	3	4	5	6	7	8	9	10	11	12	13		14
Monetary publications																
publications	0.000	- 0.002	- 0.004**	- 0.004**	- 0.004**	- 0.005***	- 0.004**	- 0.004**	- 0.004**	- 0.003	- 0.002	- 0.001	- 0.001	- 0.002	- 0.002	- 0.002
p-value	(0.226)	(0.315)	(0.019)	(0.044)	(0.033)	(0.008)	(0.018)	(0.027)	(0.029)	(0.129)	(0.234)	(0.428)	(0.460)	(0.273)	(0.362)	(0.289)
ER change	1.000***	0.127***	- 0.058***	0.003	0.050***	- 0.090***	0.084***	0.060***	- 0.038**	- 0.057***	0.053***	0.000	- 0.025	0.066***	0.078***	- 0.010
p-value	(0.000)	(0.000)	(0.001)	(0.869)	(0.004)	(0.000)	(0.000)	(0.001)	(0.031)	(0.001)	(0.002)	(0.982)	(0.157)	(0.000)	(0.000)	(0.585)
R squared	1.000	0.017	0.005	0.001	0.004	0.010	0.009	0.005	0.003	0.004	0.003	0.000	0.001	0.005	0.006	0.000
Sample size	3,286	3,285	3,284	3,283	3,282	3,281	3,280	3,279	3,278	3,277	3,276	3,275	3,274	3,273	3,272	3,271
Governor publications																
publications	0.000	- 0.002	- 0.002*	- 0.002	- 0.002	- 0.002	- 0.002	- 0.002	- 0.002	- 0.001	- 0.001	- 0.001	- 0.002	- 0.001	0.000	0.000
p-value	(0.135)	(0.229)	(0.063)	(0.132)	(0.114)	(0.222)	(0.138)	(0.136)	(0.133)	(0.416)	(0.333)	(0.311)	(0.131)	(0.348)	(0.783)	(0.886)
ER change	1.000***	0.127***	- 0.058***	0.003	0.051***	- 0.089***	0.084***	0.060***	- 0.037**	- 0.057***	0.054***	0.000	- 0.025	0.066***	0.078***	- 0.009
p-value	(0.000)	(0.000)	(0.001)	(0.855)	(0.004)	(0.000)	(0.000)	(0.001)	(0.033)	(0.001)	(0.002)	(0.981)	(0.154)	(0.000)	(0.000)	(0.599)
R squared	1.000	0.017	0.004	0.001	0.003	0.008	0.008	0.004	0.002	0.003	0.003	0.000	0.001	0.005	0.006	0.000
Sample size	3,286	3,285	3,284	3,283	3,282	3,281	3,280	3,279	3,278	3,277	3,276	3,275	3,274	3,273	3,272	3,271
Monetary governor publications																
publications	0.000	- 0.005	- 0.006	- 0.005	- 0.004	- 0.004	- 0.003	- 0.002	- 0.002	- 0.002	0.000	0.000	- 0.002	- 0.002	- 0.002	- 0.002
p-value	(0.470)	(0.270)	(0.200)	(0.267)	(0.339)	(0.351)	(0.504)	(0.621)	(0.612)	(0.731)	(0.987)	(0.969)	(0.734)	(0.619)	(0.602)	(0.637)
ER change	1.000***	0.127***	- 0.058***	0.003	0.051***	- 0.089***	0.084***	0.060***	- 0.037**	- 0.057***	0.054***	0.000	- 0.025	0.066***	0.078***	- 0.009
p-value	(0.000)	(0.000)	(0.001)	(0.856)	(0.004)	(0.000)	(0.000)	(0.001)	(0.034)	(0.001)	(0.002)	(0.996)	(0.159)	(0.000)	(0.000)	(0.593)
R squared	1.000	0.017	0.004	0.000	0.003	0.008	0.007	0.004	0.001	0.003	0.003	0.000	0.001	0.004	0.006	0.000
Sample size	3,286	3,285	3,284	3,283	3,282	3,281	3,280	3,279	3,278	3,277	3,276	3,275	3,274	3,273	3,272	3,271

Table 3b (continued). Results of Model Estimation for Equation (1) for Different Lag Length Values of the Parameter *h* for the Cash ER Change Depending on Governor Mentions in Text

	15	16	17	18	19	20	21	22	23	24	25	26	27	28	
Monetary publications															
publications	- 0.002	- 0.002	- 0.003*	- 0.004**	- 0.004**	- 0.005**	- 0.005***	- 0.005***	- 0.005***	- 0.005***	- 0.005***	- 0.004**	- 0.003	- 0.002	0.000***
p-value	(0.273)	(0.187)	(0.065)	(0.041)	(0.024)	(0.011)	(0.009)	(0.004)	(0.003)	(0.005)	(0.007)	(0.033)	(0.110)	(0.181)	(0.000)
ER change	- 0.025	0.089***	0.028	- 0.017	- 0.084***	0.071***	0.027	0.001	- 0.058***	- 0.070***	- 0.140***	0.028	0.144***	0.010	0.000***
p-value	(0.147)	(0.000)	(0.109)	(0.329)	(0.000)	(0.000)	(0.124)	(0.970)	(0.001)	(0.000)	(0.000)	(0.104)	(0.000)	(0.566)	(0.000)
R squared	0.001	0.009	0.002	0.002	0.008	0.007	0.003	0.003	0.006	0.007	0.022	0.002	0.022	0.001	0.000
Sample size	3,270	3,269	3,268	3,267	3,266	3,265	3,264	3,263	3,262	3,261	3,260	3,259	3,258	3,257	0
Governor publications															
publications	- 0.001	- 0.001	- 0.001	0.000	- 0.001	- 0.001	- 0.001	0.000	0.000	0.000	- 0.001	- 0.001	- 0.001	- 0.001	0.000***
p-value	(0.535)	(0.536)	(0.453)	(0.814)	(0.614)	(0.650)	(0.624)	(0.788)	(0.951)	(0.875)	(0.455)	(0.608)	(0.582)	(0.419)	(0.000)
ER change	- 0.025	0.089***	0.029	- 0.016	- 0.083***	0.072***	0.028	0.002	- 0.057***	- 0.069***	- 0.139***	0.029*	0.144***	0.010	0.000***
p-value	(0.151)	(0.000)	(0.103)	(0.350)	(0.000)	(0.000)	(0.113)	(0.924)	(0.001)	(0.000)	(0.000)	(0.097)	(0.000)	(0.556)	(0.000)
R squared	0.001	0.008	0.001	0.000	0.007	0.005	0.001	0.000	0.003	0.005	0.019	0.001	0.021	0.000	0.000
Sample size	3,270	3,269	3,268	3,267	3,266	3,265	3,264	3,263	3,262	3,261	3,260	3,259	3,258	3,257	0
Monetary governor publications															
publications	- 0.001	- 0.001	- 0.001	0.001	0.001	0.001	0.000	- 0.001	0.000	- 0.001	- 0.002	- 0.001	0.000	0.000	0.000***
p-value	(0.843)	(0.825)	(0.804)	(0.911)	(0.809)	(0.757)	(0.997)	(0.909)	(0.979)	(0.878)	(0.619)	(0.753)	(0.982)	(0.993)	(0.000)
ER change	- 0.025	0.090***	0.029	- 0.016	- 0.083***	0.072***	0.028	0.002	- 0.057***	- 0.069***	- 0.139***	0.029*	0.144***	0.011	0.000***
p-value	(0.152)	(0.000)	(0.102)	(0.353)	(0.000)	(0.000)	(0.111)	(0.923)	(0.001)	(0.000)	(0.000)	(0.097)	(0.000)	(0.547)	(0.000)
R squared	0.001	0.008	0.001	0.000	0.007	0.005	0.001	0.000	0.003	0.005	0.019	0.001	0.021	0.000	0.000
Sample size	3,270	3,269	3,268	3,267	3,266	3,265	3,264	3,263	3,262	3,261	3,260	3,259	3,258	3,257	0

Note: ***, **, * indicate statistical significance levels at 1%, 5%, and 10%.

Table 4. Results of Model Estimation for Equation (1) for Different Lag Length Values of the Parameter *h* for the ER Volatility Depending on the Popularity of Messages

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Popular publications (views>median)															
publications	0.000	- 0.018	- 0.131	- 0.232	- 0.340**	- 0.463**	- 0.563***	- 0.684***	- 0.738***	- 0.738***	- 0.745***	- 0.688***	- 0.625***	- 0.635***	- 0.623***
p-value	(0.151)	(0.836)	(0.285)	(0.117)	(0.044)	(0.013)	(0.005)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.005)	(0.005)	(0.005)
Cash_volatility	1.000***	0.930***	0.855***	0.780***	0.703***	0.624***	0.539***	0.450***	0.425***	0.401***	0.377***	0.362***	0.347***	0.339***	0.348***
p-value	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R squared	1.000	0.864	0.732	0.610	0.496	0.393	0.294	0.207	0.185	0.166	0.147	0.135	0.124	0.119	0.125
Sample size	3,286	3,285	3,284	3,283	3,282	3,281	3,280	3,279	3,278	3,277	3,276	3,275	3,274	3,273	3,272
Unpopular publications (views<median)															
publications	0.000***	- 0.013	- 0.149*	- 0.296***	- 0.453***	- 0.605***	- 0.801***	- 1.004***	- 1.123***	- 1.177***	- 1.217***	- 1.242***	- 1.265***	- 1.267***	- 1.236***
p-value	(0.000)	(0.820)	(0.066)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cash_volatility	1.000***	0.929***	0.854***	0.777***	0.699***	0.618***	0.531***	0.440***	0.413***	0.389***	0.364***	0.349***	0.334***	0.326***	0.335***
p-value	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R squared	1.000	0.864	0.733	0.611	0.498	0.396	0.300	0.217	0.198	0.180	0.162	0.152	0.142	0.137	0.141
Sample size	3,286	3,285	3,284	3,283	3,282	3,281	3,280	3,279	3,278	3,277	3,276	3,275	3,274	3,273	3,272

Table 4 (continued). Results of Model Estimation for Equation (1) for Different Lag Length Values of the Parameter *h* for the ER Volatility Depending on the Popularity of Messages

	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29
Popular publications (views>median)															
publications	- 0.595***	- 0.562**	- 0.541**	- 0.641***	- 0.738***	- 0.796***	- 0.840***	- 0.942***	- 1.049***	- 1.156***	- 1.197***	- 1.251***	- 1.310***	- 1.363***	- 1.337***
p-value	(0.007)	(0.011)	(0.014)	(0.004)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cash_volatility	0.357***	0.365***	0.374***	0.376***	0.378***	0.379***	0.373***	0.370***	0.369***	0.369***	0.366***	0.362***	0.353***	0.342***	0.324***
p-value	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R squared	0.131	0.136	0.143	0.145	0.148	0.149	0.145	0.144	0.144	0.146	0.144	0.142	0.136	0.130	0.116
Sample size	3,271	3,270	3,269	3,268	3,267	3,266	3,265	3,264	3,263	3,262	3,261	3,260	3,259	3,258	3,257
Unpopular publications (views<median)															
publications	- 1.200***	- 1.164***	- 1.143***	- 1.125***	- 1.099***	- 1.064***	- 1.041***	- 1.032***	- 1.017***	- 0.994***	- 0.973***	- 0.970***	- 0.982***	- 1.009***	- 1.033***
p-value	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cash_volatility	0.344***	0.352***	0.362***	0.365***	0.367***	0.369***	0.362***	0.360***	0.360***	0.360***	0.358***	0.353***	0.344***	0.334***	0.315***
p-value	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R squared	0.147	0.151	0.158	0.159	0.160	0.160	0.154	0.152	0.151	0.151	0.148	0.145	0.139	0.133	0.120
Sample size	3,271	3,270	3,269	3,268	3,267	3,266	3,265	3,264	3,263	3,262	3,261	3,260	3,259	3,258	3,257

Note: ***, **, * indicate statistical significance levels at 1%, 5%, and 10%.

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INTEREST RATE PASS-THROUGH IN UKRAINE: ESTIMATES AND DETERMINANTS

NADIIA SHAPOVALENKO[a], ARTEM VDOVYCHENKO[a]

[a]National Bank of Ukraine
E-mail: nadiia.shapovalenko@bank.gov.ua
artem.vdovychenko@bank.gov.ua

Abstract In this study, we apply ARDL models to estimate the strength of long-run interest rate pass-through in Ukraine. We focus on the transmission of the overnight interbank interest rate to the rates on term deposits of households and loans to non-financial corporations – both in national currency. Controlling for macroeconomic indicators and bank financial variables we obtain bank-level time-varying estimates of transmission and run a set of panel regressions to analyze the determinants of pass-through strength. Besides linear estimates, we report asymmetric transmissions, which differ depending on the decrease or increase in the interbank rate, and time-varying estimates for transmission.

JEL Codes E43, E52, E58

Keywords interest rate transmission, determinants of transmission, ARDL, panel data

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1. INTRODUCTION

The strength of interest rate pass-through[1] is an important characteristic of monetary policy efficiency. Deposit rates[2] affect households' decisions on consumption, savings and their demand for foreign currencies. Credit rates[3] determine business activity and the population's propensity to consume, driving aggregate demand in an economy. These decisions significantly influence GDP, exchange rates, and inflation dynamics, which in turn demonstrate how effectively a central bank is achieving its goals. In 2016 the National Bank of Ukraine moved to an inflation targeting regime. Under this framework, the interest rate channel plays an important role in monetary transmission. Therefore, estimating the strength of pass-through and understanding its functioning becomes an essential issue.

Understanding transmission is even more important from the monetary policy perspective if there is a switch to a hybrid monetary regime, as happened in Ukraine after the full-scale military invasion of russia. This regime was introduced in the first days of the invasion and it assumes a smooth transition from a fixed exchange rate back to inflation targeting. The new goal of monetary policy in such a period of transition is to support "flexible exchange rate sustainability". To achieve this goal, the NBU sets its interest rate at a level that makes assets denominated in national currency attractive to households. Following this logic, monetary decisions help to control both – inflation and demand for foreign currency. These circumstances increase the motivation to study transmission, especially in a nonlinear framework. The central bank needs to know whether the reaction of deposit rates is symmetrical for a decrease/increase of the key rate. If deposit rates are more responsive to key rate decreases, then the monetary authorities must be careful in loosening monetary policy as the attractiveness of assets in domestic currency can be lost very fast. Another important issue is the reaction of the banks regarding to their size and ownership status. Under these conditions, many questions can be asked regarding transmission estimates.

In this study, we estimate the strength of transmission from changes in the overnight interbank rate (IR) to deposit and credit rates in Ukraine over a range of horizons. Our estimates are based on the application of ARDL models. Extending previous studies on interest rate transmission for Ukraine, we apply nonlinear regressions that allow us to estimate asymmetry in transmission and its change over

[1] In this paper, we use the concepts of interest rate pass-through and transmission of interbank interest rate to banks' rates interchangeably.
[2] Hereafter under deposits, we mean term deposits of households (HH) in national currency (hryvnias).
[3] Hereafter under credits, we mean loans to non-financial corporations (NFC) in national currency (hryvnias).

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time. We estimate transmission strength and its dynamics both at the level of the whole banking system and at the level of individual banks. Estimates of time-varying transmission allow us to run panel regression to detect the determinants of pass-through at the macroeconomic and bank levels. The results are useful to the monetary authorities, as we demonstrate recent tendencies in the dynamics of pass-through strength and analyze the characteristics of banks that affect pass-through.

The rest of this paper is organized as follows: Section 2 presents a review of the literature on transmission estimates and the analysis of its determinants. Section 3 presents the methodology for estimating transmission strength and discusses the variables we use as potential determinants. Section 4 provides data characteristics. Section 5 reports the main results of our estimates for Ukraine. Conclusions are presented in Section 6.

2. LITERATURE REVIEW

Most studies of interest rate pass-through show that the reaction of market rates is sluggish and incomplete over the long run. Incomplete transmission is seen especially in deposit rates, which are included in banks' expenses and for this reason are rigid to increase. In theory, pass-through would be complete in an environment of full information, perfect competition, and risk-neutral banks (Gigineishvili, 2011). In the literature, imperfect transmission is usually explained by a low level of competition between banks, the availability of alternative sources of funding, the rigidity of banks' costs, or the high elasticity of consumer demand with respect to interest rate adjustments. Additional reasons are the possible deterioration of the creditworthiness of borrowers, implicit interest rate fixing for clients involved in long-term relationships with banks, the structure of bank rates where long-term contracts can dominate, and uncertainty over the future dynamics of money market rates (Mojon, 2000). However, there are also arguments for long-run transmission over unity, mostly applicable to credit rates. Under high credit risks, banks may not ration credits but increase the risk premium for loans instead (Bondt, 2005). This “overshooting” reflects the asymmetry of information between banks and borrowers (Sørensen and Werner, 2006).

Interest rate transmission is also found to be asymmetric in different aspects, while asymmetry itself is often the object of empirical studies. For instance, pass-through to credit rates is higher in the periods when money market rates (MMRs) are increasing than when they are decreasing (Mojon, 2000). Asymmetry works in the opposite direction for deposit rates, which are less rigid for decrease, suggesting that banks hold some degree of pricing power in the markets. Sander and Kleimeier (2002, 2004) demonstrate that asymmetries exist not only in the direction of rate changes but also in the severity of the interest rate shock. This “threshold” reaction means that banks take into account menu costs and transmit changes in market rates of a minimum size. Aristei and Gallo (2014) use a Markov-switching vector autoregressive model to show that the interest rate pass-through during periods of financial distress is lower than in normal times.

Cross-country studies found a large amount of variability in interest rate transmission strength between economies. Based on a literature survey, Mishra and Montel (2012) conclude that monetary policy transmission is much weaker in developing countries than in advanced economies. This typical conclusion from empirical studies initiated an important strand of the literature devoted to the differences in the strength of transmission. In a pioneering paper, Cottarelli and Kourelis (1994) examine lending rate stickiness across a panel of countries. They attribute the terminated and incomplete response of lending rates to MMR changes to financial structure, certain characteristics of which create frictions that prevent full adjustment. Among such characteristics, the authors identify factors affecting demand for loans and the ability of banks to change rates quickly: the level of competition between banks, barriers to market entry, alternatives to bank loans, and administratively set discount rates. Adjustment costs and uncertainty also slow down the lending rate response, as banks can perceive MMR changes as only temporary. Cottarelli and Kourelis (1994) estimate the degree of lending rate stickiness for 31 industrial and developing countries by regressing respective rates against distributed lags of the money market and discount rates in each country. Stickiness is measured as the degree of response of lending rates to changes in MMRs at different time lags. In the second stage, they regress a cross-section of stickiness measures against a set of country-specific financial system features. Specifically, it is shown that the variation in lending rate stickiness is explained by the existence of a sizable market for short-term monetary instruments, the degree of capital mobility, constraints on bank competition, private sector ownership of the banking system, the volatility of MMRs, and the level of inflation. A two-stage empirical procedure, in which pass-through measures are first estimated, and then regressed on a set of determinants, has become the standard approach in recent decades. For instance, Mojon (2000) analyzes the heterogeneity of transmission from MMRs to retail bank rates (25 credit rates and 17 deposit rates) for the six largest countries in the euro area (Belgium, Germany, Spain, France, Italy, and the Netherlands). To estimate the pass-through effect, he runs an error correction model with distributed lags for each kind of retail rate where the MMR is the only explanatory variable. In the second stage, the author builds a panel of retail bank markets and run panel regressions accounting for the heterogeneity of transmission measures across countries and over time. Analysis of the determinants of the pass-through focuses on four sets of variables: the monetary policy regime, competition among banks, competition from non-banking financial sectors, and the rigidity of bank costs. The fourth group of factors is particularly interesting, given that the rigidity of the costs is not frequently analyzed in studies on this topic. Mojon (2000) assumes that a higher share of operating costs in the total costs of a bank should imply a smaller pass-through. Unlike funding costs, operating costs are weakly related to the movements of MMRs. It is also argued that a bank that relies on traditional deposits is more likely to have more rigid funding costs (meaning lower pass-through to credit rates) than a bank that prefers debt as a source of funding. Their empirical evidence shows that the structure of bank costs matters. Specifically, higher staff costs result in a smaller degree of pass-through to credit rates.

Studies of IR transmission to bank rates have been carried out earlier in Ukraine. One paper, by Hlazunov et al (2023), is focused on the transmission of the key policy rate to deposit and credit rates depending on the banking sector's structure. The authors differentiate their estimates based on loan and deposit maturities, as well as the ownership status of the banks. Assuming that a bank's efficiency depends on its type of ownership, they conclude that less efficient banks have more powerful transmission to deposit rates and weaker pass-through to credit rates. The interest rate pass-through is lower for deposits and loans with higher maturities.

From the perspective of an analysis of the monetary transmission mechanism in Ukraine, it is worth discussing whether policy tools (such as reserve requirements) can be effectively used to enhance transmission. The literature on this topic is rather scant, and conclusions differ depending on the specific tool chosen. For instance, Ma and Wang (2014) based on the results from a DSGE model for China, found that institutional constraints (such as a high deposit reserve requirement and quantitative limits on the loan-to-deposit ratio or caps on loans) increase the cost of rebalancing assets and liabilities, or directly limit asset allocation. These restrictions thus weaken the transmission of policy rates to deposit and lending rates. However, Terrier et al (2011) argue that reserve requirements can be a useful instrument to bring the interbank rate close to the policy rate under conditions of excessive liquidity or stress in the financial system. Generally speaking, the variables used in empirical literature to explain heterogeneity in monetary policy transmission across countries or individual banks can be grouped into macroeconomic factors, financial structure characteristics, and the balance sheet characteristics of individual banks (Sørensen and Werner, 2006; Leuvensteijn et al, 2008; Gigineishvili, 2011; Saborowski and Weber, 2013; Stanisławska, 2015; Leroy and Lucotte, 2016).

In studies on interest rate transmission, the standard set of macroeconomic determinants usually includes inflation, the exchange rate regime, and the business cycle. The financial structure of an economy affects transmission through competition in the banking system, the development of the nonbanking sector, the share of state-owned or foreign banks, the level of non-performing loans, and the level of liquidity in the banking system. The returns on equity and assets, net interest margin, cost-to-income ratio, cost structure, liquidity ratio, capital adequacy ratio, funding structure, and credit portfolio quality belong to control determinants taken from banks' balance sheets.[4]

A comprehensive review of econometric techniques used to estimate interest rate transmission strength and its determinants is presented in Deutsche Bundesbank (2019). The standard approach is to apply some modification of the error correction model (ECM) to time series or panel data to obtain long-run responses of the banks' rates to the MMR. ECM is usually estimated in the form of ARDL, via dynamic OLS (DOLS) or dynamic seemingly unrelated regression (DSUR) approaches (Mojon, 2000; Sørensen and Werner, 2006; Leuvensteijn et al, 2008; Gigineishvili, 2011; Leroy and Lucotte, 2016; Gregor and Melecký, 2018; Fičura and Witzany, 2023). A multivariate approach to the estimation of long-run relationships between interest rates is also popular. Saborowski and Weber (2013) argue that ARDL specifications are not appropriate, as there is feedback from the policy rate to movements in retail rates, meaning that the policy rate is not purely exogenous. Instead, they suggest using the VAR framework for estimates. Specifically, Saborowski and Weber (2013) estimate the panel VAR (PVAR) model, both with and without interaction terms (which are variables potentially affecting transmission), to determine the average pass-through across countries and identify determinants of interest rate transmission. Leroy and Lucotte (2016) also use interaction terms to analyze their impact on transmission in both ARDL and VAR frameworks.

3. ECONOMETRIC APPROACH TO MEASURING THE PASS-THROUGH

3.1. Linear vs Nonlinear ARDL Models

In recent years, the majority of studies have utilized error correction models (ECM) to evaluate interest rate pass-through. The ECM is usually estimated by ARDL models, which enable the examination of both the long-term equilibrium pass-through of MMRs to retail bank rates and the speed at which adjustments occur toward this equilibrium.

To estimate the transmission from MMR x to bank rate y, a standard ARDL(p,q) of a form (1) is reformulated into an error correction form denoted as (2):

$$y_t = c_0 + \sum_{i=1}^{p} \beta_{y_i} y_{t-i} + \sum_{i=0}^{q} \beta_{x_i} x_{t-i} + \epsilon_t, \tag{1}$$

$$\Delta y_t = c_0 + \alpha\left(y_{t-1} - \theta x_{t-1}\right) + \sum_{i=1}^{p-1} \psi_{y_i} \Delta y_{t-i} + \sum_{i=0}^{q-1} \psi_{x_i} \Delta x_{t-i} + \epsilon_t, \tag{2}$$

where θ is the value of long-term equilibrium pass-through and *α* is the speed of correction.

In this study, we analyze θ, which we interpret as a general characteristic of interest rate pass-through. Considering that θ is an asymptotic value of transmission, we extended our analysis by estimating impulse response functions (IRF) for all of the transmissions we estimated. The IRFs show how banks' rates react to an MMR shock. This allows us to analyze pass-through strength at different horizons, disentangling short-, medium-, and long-run effects. At this stage, we ignore the speed of error correction (*α*), indicating how fast banks adjust their rates. This information can be useful for understanding transmission, especially for central banks, as it predicts the dynamics of banking rates in the short term. However, the speed of the banks' reaction is captured at least partially by our estimates of IRFs for different horizons. If a short-term IRF value covers, for example, more than half of the overall pass-through, this indicates a high speed of transmission.

To get information about average transmission values, we first estimate linear ARDLs for economy-level and bank-level data. ARDLs provide straightforward coefficient estimates, making it easier for policymakers and analysts to understand the relationships between the variables. We determine the optimal number of lags using the Bayesian Information Criterion (BIC), as it is commonly used to choose a more parsimonious model.

However, linear models fall short of addressing nonlinearity and asymmetry, which are commonly observed phenomena in economic data. This limitation can lead to misspecification errors, resulting in biased parameter estimates and inaccurate policy implications. Non-linear models offer greater flexibility in capturing complex relationships that cannot be adequately represented by linear models. This flexibility allows for a more accurate representation of economic phenomena with nonlinear patterns.

[4] Overview of relevant studies and potential determinants of transmission are presented in more detail in Appendix A, Tables 2-3.

Specifically, we are interested in the asymmetries associated with the direction of change in the MMR. Commercial banks may exhibit different reactions when the central bank adjusts its interest rates upwards versus downwards. In instances of a central bank raising rates, commercial banks might be quicker to pass on the increased costs to borrowers, resulting in a relatively prompt upward adjustment in lending rates. Conversely, when the central bank lowers interest rates, commercial banks may display a more gradual response, with deposit rates adjusting at a slower pace. The literature exploring asymmetry includes instances where asymmetry is observed, as well as cases where it is not evident. See for example Gambacorta & Iannotti (2007), Sznajderska (2012), Månsson et al. (2013), Apergis et al. (2015).

To verify whether there is an asymmetry in the interest rate pass-through for Ukraine, we apply the NARDL framework proposed by Shin et al. (2014). This approach captures short-term and long-term nonlinearities by representing them as positive and negative partial sum decompositions of the distributed lag variables.

Noting, that any series z_t may be written as $z_t = z^0 + z_t^+ + z_t^-$ where z_t^- and z_t^+ are the partial sum processes of positive and negative changes in z_t:

$$z_t^+ = \sum_{s=1}^{t} \max\left(\Delta z_s, 0\right), \tag{3}$$

$$z_t^- = \sum_{s=1}^{t} \min\left(\Delta z_s, 0\right), \tag{4}$$

with some manipulation (2), may be rewritten as

$$\Delta y_t = c_0 + \alpha\left(y_{t-1} - \left(\theta^+ x_{t-1}^+ + \theta^- x_{t-1}^-\right)\right) + \sum_{i=1}^{p-1} \psi_{y_i} \Delta y_{t-i} + \ldots$$
$$\ldots + \sum_{i=0}^{q-1}\left(\psi_{x_i}^+ \Delta x_{t-i}^+ + \psi_{x_i}^- \Delta x_{t-i}^-\right) + \epsilon_t, \tag{5}$$

where asymmetric long-term equilibrium pass-through is given by the parameters θ^+ and θ^-.

To verify the presence or absence of statistically significant asymmetry, a Wald test with the null hypothesis that $\theta^+ = \theta^-$ is conducted.

NARDL models are specifically designed to handle nonlinear relationships through their inclusion of positive and negative partial sum decompositions of distributed lag variables. This makes them well-suited for capturing asymmetries. However, they may not adequately address certain specific forms of asymmetry or nonlinearity. For example, abrupt changes or complex patterns in the data-generating process might be challenging for traditional models to accommodate. In such cases, the introduction of additional flexibility, such as allowing the coefficients of the model to vary over time, as in models with time-varying parameters, becomes crucial. In the next step of our research, we apply the Bayesian approach to estimate ARDLs with time-varying parameters (TVP) to obtain a time-varying estimate of the long-run pass-through.

3.2. ARDL with Time-Varying Parameters

ARDL models with time-varying parameters (TVP-ARDL) introduce an additional element of flexibility by allowing parameters to change over time. This adaptive approach enables the model to better capture evolving relationships and structural shifts in the data, offering a more nuanced representation of the underlying dynamics.

Furthermore, having time-variant pass-through coefficients enables us to undergo regression analyses involving various sets of explanatory variables (i.e., determinants of pass-through). This process aims to pinpoint variables that demonstrate statistical significance, and meaningful relationships, and yield a satisfactory overall model fit.

The TVP-ARDL model we employ allows for time variation in both the model coefficients and the residual covariance matrix. We use Bayesian inference to estimate the parameters of the model.

For simplicity, consider a model in a form (1) with a time-varying parameters:

$$y_t = c_{t,0} + \sum_{i=1}^{p} \beta_{t,y_i} y_{t-i} + \sum_{i=0}^{q} \beta_{t,x_i} x_{t-i} + \epsilon_t, \quad \epsilon_t \sim N\left(0, \Sigma_t\right). \tag{6}$$

The model can be reformulated as

$$y_t = \overline{X_t}\omega_t + \epsilon_t, \tag{7}$$

where $\overline{X_t} = \left(1 y_{t-1}\ y_{t-2} \ldots y_{t-p}\ x_t\ x_{t-1} \ldots x_{t-q}\right)$

$$\omega_t = \left(c_{t,0}\, \beta_{t,y_1}\ \beta_{t,y_2} \ldots \beta_{t,y_p}\ y_{t-p}\ \beta_{t,x_1}\ \beta_{t,x_2} \ldots \beta_{t,x_q}\right).$$

Coefficients in our model vary in time following a random walk process. Accordingly, the dynamic process for ω_t is:

$$\omega_t = \omega_{t-1} + \nu_t,\ \ \nu_t \sim N\left(0, \Omega\right) \tag{8}$$

While $\Sigma_t = \bar{s}\exp(\lambda_t)$ where $\bar{s}$ is a known scaling term, λ_t is a dynamic process generating the heteroskedasticity of the model.

$$\lambda_t = \gamma\omega_{t-1} + \vartheta_t,\ \ \vartheta_t \sim N\left(0, \phi\right). \tag{9}$$

The parameters to estimate are coefficients $\omega = \{\omega_t : t = 1,..,T\}$, the covariance matrix Ω for the shocks on the dynamic process, the set of dynamic coefficients $\lambda = \{\lambda_t : t = 1,..,T\}$, and the heteroskedasticity parameter ϕ.

The Gibbs sampler algorithm is used for model parameter estimations. For a detailed algorithm, please refer to Dieppe et al. (2016).

The specifications of the estimated TVP-ARDLs align with those estimated in a previous section. Table 1 provides details regarding the estimation process and some parameters.

Table 1. TVP-ARDL Parameters

Total number of iterations	50,000
Burn-in iterations	40,000
Post-burn selection	yes
Frequency of draw selection	20
AR coefficient on residual variance γ	0.85
IG shape on ϕ α_0	0.001
IG scale on ϕ δ_0	0.001

3.3. Determinants of the Pass-Through

Time-varying estimates of transmission allow us to study potential determinants in a panel regression framework with banks as cross-section units and a monthly time domain. Running panel regressions, we include fixed effects to control for the specific features of separate banks and to avoid endogeneity caused by the omitted variables problem. We also control for time-specific shocks, applying two-way fixed effects. However, the latter is not always feasible, as economy-wide variables are invariant in the cross-section dimension, thus time-fixed effects suffer from collinearity. The panel regressions were estimated with different approaches to get standard errors of coefficient robust to clustering, heteroscedasticity, and the autocorrelation of residuals.

Potential determinants of IR pass-through to deposit and credit rates can be grouped into macroeconomic conditions, the structure of assets and liabilities, and the structure of revenues and expenditures (Appendix A).

Macroeconomic Variables

The group of macroeconomic variables includes the level of liquidity in the banking system, the financial stress index (FSI), the Herfindahl-Hirschman index for deposits and credits, inflation, proxies for deposit supply, and credit demand.

We assume that *excessive liquidity* weakens transmission. It reduces incentives for banks to compete for depositors by raising deposit rates. For creditors, high liquidity can reflect a more conservative business model or a lack of investment opportunities.

Economic uncertainty, which we proxy by FSI (Filatov, 2021), potentially negatively affects transmission to deposit rates. Facing uncertainty, banks are less likely to change deposit rates sharply: the risk of deposit outflows prevents them from cutting rates, while there is a risk of a loss of profits from a significant increase in interest costs. For credit rates, the effect on transmission is not obvious. In a low-risk environment banks with weak balance sheets may react to an expansive monetary policy by shoring up liquidity rather than extending credit at lower rates. At the same time, the level of credit risk may also be related to the degree of competition. Even in periods of high uncertainty, banks in a more competitive environment would tend to lend to more risky borrowers to boost their market shares.

Banks *competition* in credit and deposit markets is quantified by the Herfindahl-Hirschman index. Market monopolization hinders transmission, as monopolists care little about the reaction of competitors and the possible loss of customers. However, this effect can be nonlinear in the sense that low competition weakens transmission to credit rates when the IR goes down but enforces pass-through when the rates increase (and vice versa for deposit rates).

The impact of *inflation* on the strength of transmission is explained, in part, by the need to index deposit rates. Higher inflation usually requires a more significant increase in interest rates to keep deposits attractive in real terms and make credit operations profitable. Lower inflation allows for lower rates without the threat of deposit outflows and losses from credits.

Deposits supply and credit demand are pro-cyclical. Economic growth and high credit demand encourage banks to allocate their funds towards riskier projects, meaning higher transmission on credit rates. However, periods of high demand are characterized by underestimated credit risk of borrowers and high competition for market share. These factors may lower real credit rates, decreasing transmission. When deposit supply is high it may be easier for banks to keep rates at their current level without losing clients, which means lower transmission. On the other hand, a high supply may be associated with a more dynamic market, leading to more entries and higher competition, thereby making deposit rates increase.

A separate subgroup of variables characterizes the *actions of the NBU* directed at enforcement of the transmission to deposit rates. The instruments recently used for these goals are the reserve requirement ratio for households' deposits on demand and current accounts, and the NBU's long-term certificates of deposit (CDs). Raising the reserve requirement ratio increases the attractiveness of term deposits for banks by reducing their opportunity cost. This encourages banks to attract term deposits, including by raising interest rates. The option of investing spare liquidity in longer-term CDs with higher yields also creates room for banks to raise deposit rates. Considering the potential importance of these instruments for transmission, we include them in regressions.

Balance Sheet Variables

A high share of non-performing loans is expected to harm transmission to credit rates because banks with weak balance sheets prefer meeting liquidity requirements rather than extending credit portfolios. A reduction in the policy rate may thus have only a limited impact on market rates. The opposite effect can be detected in a highly competitive environment, when banks on average take on more problematic loans, which might explain the positive correlation with the pass-through. *Provisions to assets ratio* is another variable measuring the degree of risks for a bank. Similar to the share of non-performing loans, the level of reserves can have different effects on transmission depending on market concentration.

Funding cost must have a positive correlation with transmission to the deposit rates considering that households' deposits constitute a significant share of banking system liabilities. The impact on transmission to credit rates is questionable. If banks set credit rates by adding a margin over funding costs, then we can assume the positive effects of the cost increase on transmission.

Profit after taxation to equity capital ratio or net interest income to assets ratio (net interest margin) are interpreted as proxies for competition in the market. High profitability in the banking sector often weakens pass-through, since it reflects inadequate competition and market power. In an uncompetitive environment, banks can set higher premiums that deviate from their marginal costs. As a result, lending rates become less elastic due to changes in funding costs.

Own capital to liabilities ratio. A high capital ratio may act as a buffer against market fluctuations and would hence reduce the strength of transmission.

Short-*term securities of the NBU to assets* and *government bonds to assets* can have a positive effect on transmission to credit rates. This may happen because of the crowding-out effect, when banks allocate their resources to government securities and supply fewer credits to the economy. When the demand for credits goes up potential debtors have to compete for resources with the government. This allows the banks to set higher margins.

The deposits to liabilities ratio signals about stability of funding. A bank with a high share of traditional deposits in liabilities is more likely to have more stable funding costs than a bank that funds itself mostly by issuing debt on the capital markets. Potentially, banks with a large and stable share of deposit funding are expected to be less vulnerable to changes in MMRs, thereby leading to a relatively weaker transmission to credit rates.

The Structure of Revenues and Expenditures

Non-interest income share or the *share of interest expenses* reflect the diversification of money flows. A bank with a highly diversified portfolio of activities may be less sensitive to changes in MMRs, meaning a more sluggish pass-through. At the same time, a higher share of non-interest income or expenditures may make transmission stronger. Banks that are less dependent on interest-related income/expenditures adjust interest rates more quickly in response to interbank rate changes. Acting in such a way banks try to capture market share in a competitive environment.

Administrative expenses and *staff costs to gross income* indicate the dependence of expenditures on MMR. Large administrative costs can reflect obstructive regulatory and legal frameworks, undeveloped financial infrastructure, and information asymmetry. To cover these excessive costs and preserve their margins, credit rates would be more responsive to increases in MMR. At the same time, if banks set their interest rates by adding a margin over their costs, then the proportion of costs that are not sensitive to interbank rate fluctuations would reduce the pass-through. A higher share of operating costs in total costs should imply a weaker transmission.

4. DATA

In this study, we interpret the strength of transmission as a response of banks' deposit or credit rates to interbank interest rates. Deposit and credit rates in the estimates are weighted average interest rates on term deposits of HHs in the national currency and weighted average interest rates on credits to NFCs in the national currency respectively. As an interbank rate, we use UONIA, which is the Ukrainian weighted average overnight interbank rate.

The strength of IR pass-through is estimated on monthly data. The samples used are different depending on the goals of the estimates. In ARDLs with constant parameters, we use a sample of 2015 m1 – 2023 m12, which covers the period of the inflation targeting[5] regime in Ukraine, meaning that the interbank rate significantly affected banking rates at that time. The estimates of the TVP ARDLs for the whole economy span a much longer period, which starts at 2006 m1. We use as long a sample as possible to give the Bayesian algorithm a reasonably large training dataset. For panel estimates, where we use bank-level data, the time sample is 2018 m1 – 2023 m12. The start point in 2018 is explained by the availability of reliable monthly data from the balance sheets of Ukrainian banks.

A balanced panel database was formed for the regressions that we use to analyze the transmission determinants. To avoid gaps in the data, we applied a selection procedure to the banks. First, the banks must be functioning during the sample of 2015–2023. Second, less than 30% of gaps in data were allowed for the time series of the banks' interest rates. Some of the banks did not perform credit or deposit operations in certain months. To keep the panel balanced, we filled these gaps by applying a linear spline interpolation.[6] After the selection procedure, we were left with 25 banks for the deposit rate transmission panel and 55 for credit rate transmission.[7]

5. RESULTS

5.1. Linear and Asymmetric Estimates of the Pass-Through: Banking System Level

Linear estimates of long-run pass-through for the whole banking system are presented in Figure 1. Deposit and credit rates are weighted averages of all banks that conducted respective deposit/credit operations in separate months. Figure 1 demonstrates impulse response functions to a 1% UONIA shock, which we derive from the linear ARDL model. The meaning of long-run transmission is the point at which the impulse response function converges. Our estimates show that long-run pass-through is higher for deposit rates, but that credit rates adjust faster.

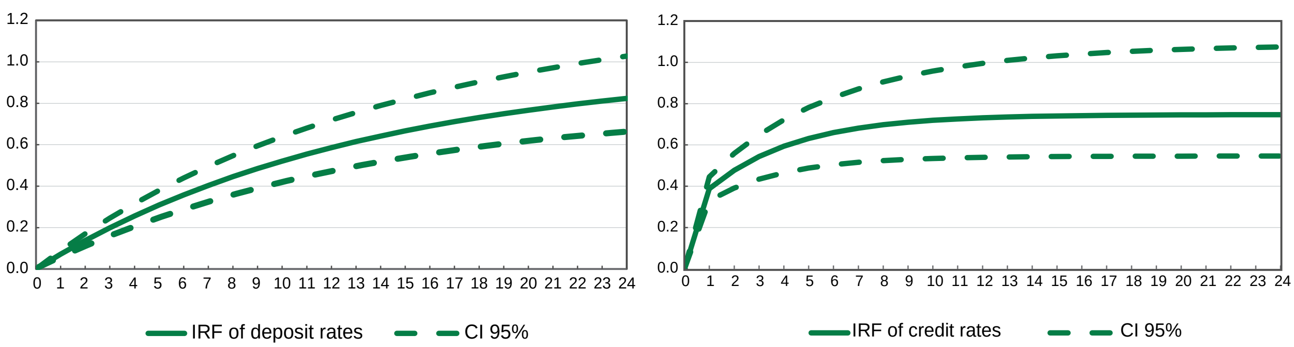

Figure 1. Linear Estimates of Long-Run Transmission, 1% UONIA shock, %, month

[5] Strictly speaking, after the start of the full-scale russian invasion (2022 m2) monetary policy in Ukraine switched to a mixed regime. Under this regime, in different periods exchange rate fixation and controlled exchange rate floating were primary goals. In this period, the NBU's interest rate was mainly used to maintain the attractiveness of domestic currency assets compared to the assets denominated in foreign currencies.

[6] Definitions and basic statistics of variables can be found in Tables 4-5, Appendix A. Macroeconomic variables are the same for each bank. For this reason, the number of observations equals the number of months in the sample. Since the majority of variables coincide for both panels (transmission to credit rates and transmission to deposit rates), we report statistics from the credit rates transmission panel, which contains more banks.

[7] 25 selected banks covered 96% of deposits in 2023, 55 banks – 99% of credits in 2023.

Asymmetric estimates (Figure 2) show us the difference in transmission depending on whether the UONIA changes are positive or negative. Asymmetry is more significant for deposit rates. The banks are usually more willing to cut deposit rates than to raise them (in part due to their wish to reduce interest costs). Therefore, the transmission strength of an increase in the UONIA is smaller than that of a decrease.

The asymmetry of transmission to credit rates is also downward, but not as significant as for deposit rates. Nevertheless, we would expect higher transmission for positive changes in interbank rates, due to the profit maximization motives of banks. Downward asymmetry can be caused by competition factors and the desire of a bank to occupy a larger share of the market. Another possible explanation is the size of a debtor. Big firms can have more favorable credit conditions compared to medium- and small-size companies. Having high market power, big firms might be more aggressive in negotiating a cut in credit rates when market rates go down. To illustrate this possibility, we estimated the IRFs of credit rates for firms of different sizes (Figure 3). Our results show that downward asymmetry in credit rates pass-through mainly comes from the rates for large enterprises.

5.2. Bank-Level Estimates of the Pass-Through

Below, we present the outcomes of the estimated long-run market rate transmission (sample 2015m1–2023m12) at the bank level. Initially, our focus is on the long-run pass-through estimations for household deposit rates, obtained through both ARDL models and an asymmetric ARDL model.

For each bank, we ran the ARDL model with an optimal lag-structure based on the Schwarz criterion. Tables 6–7 report descriptions and testing statistics for the two sets of ARDLs used for the estimation of transmission to deposit and credit rates. In general, the ARDLs obtained indicate the existence of a long-run relationship between IR and respective rates and have adequate properties in terms of autocorrelation or heteroscedasticity of residuals[8].

Figure 4 shows the histogram of the long-run pass-through estimations for the 25 commercial banks chosen in the previous section. In general, the pass-through for the majority of the banks falls within the range of 0.5 to 0.7, with a smaller portion exhibiting higher values of pass-through.

As can be seen in Figure 5, the long-run pass-through to deposit rates is higher for state banks and lower for the banks with foreign private capital. This is due to the influence of various factors. For example, state banks, being under public ownership or control, might have strategic motivations to quickly adjust their deposit rates in response to changes in market rates. On the other hand, banks with foreign private capital may have different risk appetites or operational strategies, leading to a comparatively lower pass-through.

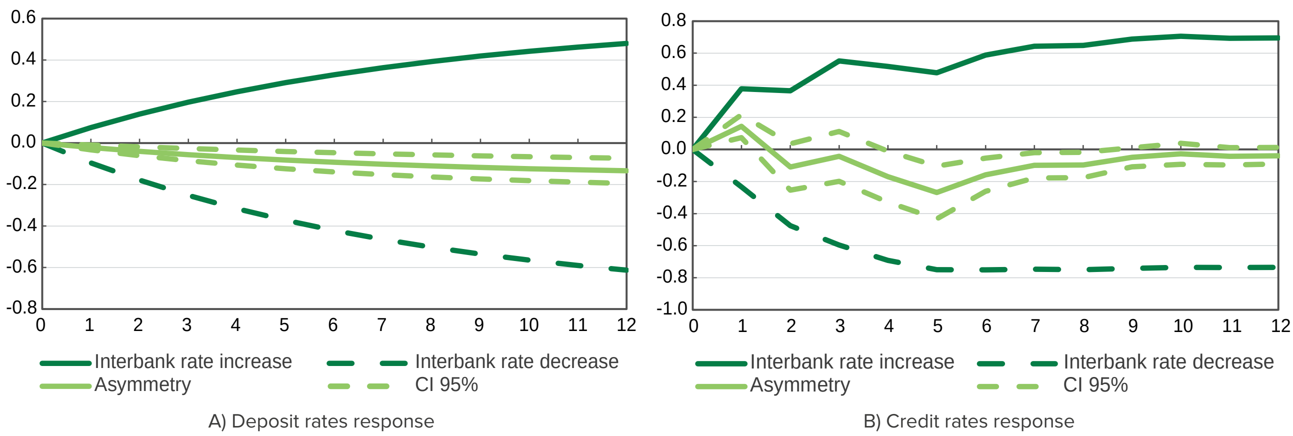

Figure 2. Asymmetric Long-Run Transmission, 1% UONIA shock, %, month

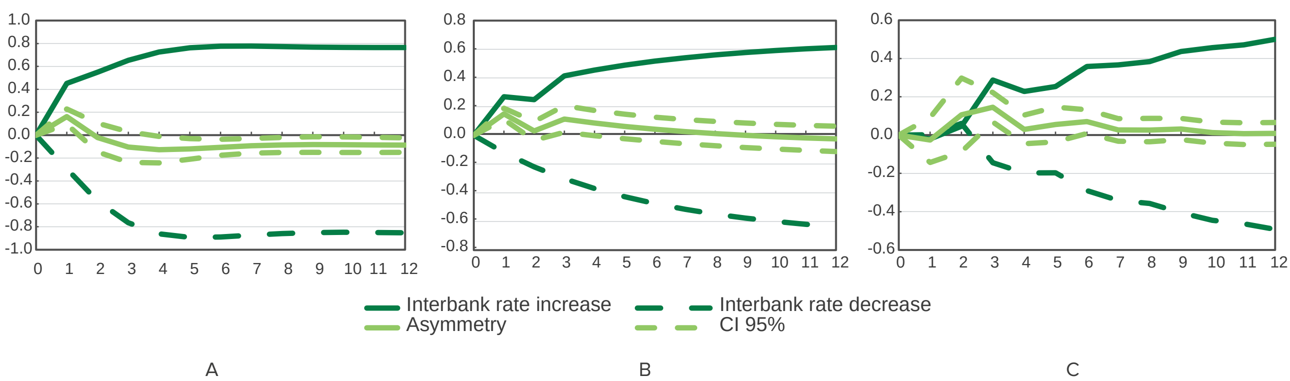

Figure 3. Asymmetric Long-Run Transmission for (A) Large, (B) Medium, and (C) Small Firms, 1% UONIA shock, %, month

[8] A long-run relationship was identified for 20 banks out of 25 for deposit rates, and 49 out of 55 for credit rates. Autocorrelation in residuals was rejected respectively for 19 and for 42 banks. Homoscedasticity was confirmed for 18 and 24 banks respectively.

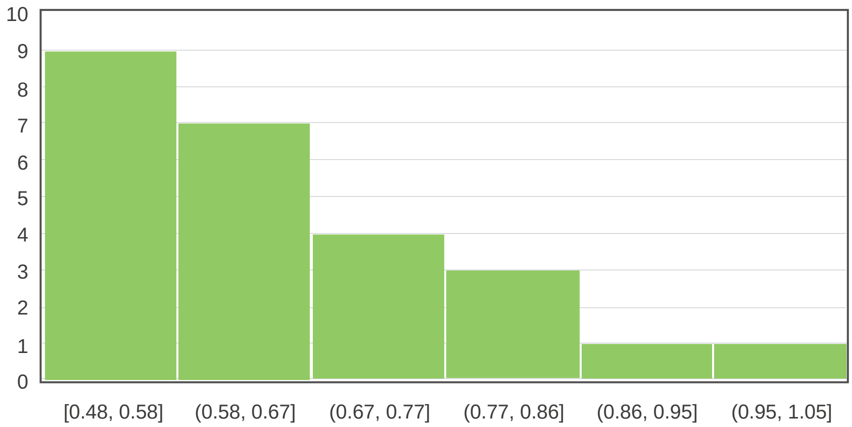

Figure 4. Histogram Plot of the Long-Run Pass-Through for Deposit Rates

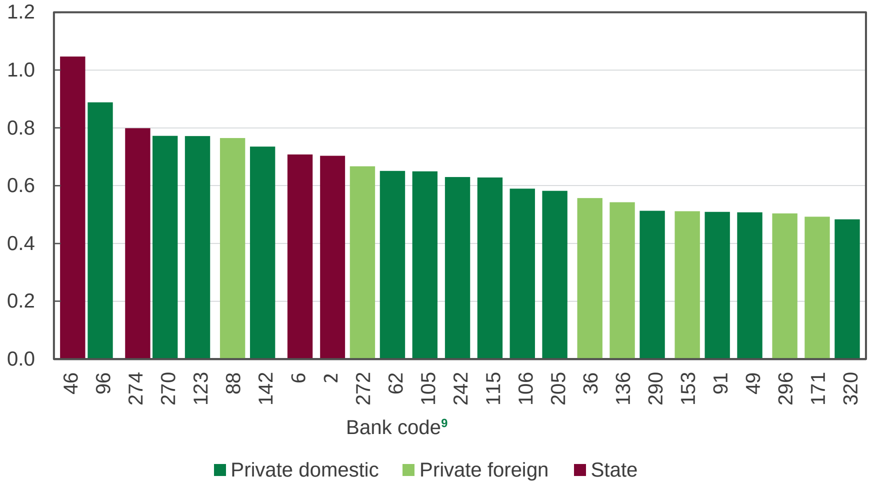

Figure 5. Long-Run Pass-Through to Deposit Rates

Our estimates let us plot relationships between transmission strength and banks' characteristics via scatterplots. Figure 6 plots banks' pass-through and their share of the total amount of deposits. The latter is interpreted as a proxy for market power. Figure 6 indicates that for almost all foreign private banks, there is an increase in transmission with a rise in deposit share. Notably, the state bank that holds nearly half of the deposits exhibits the highest pass-through. However, the relationship between the share of deposits and transmission for private domestic banks appears to be ambiguous, suggesting the presence of other significant factors that influence transmission.

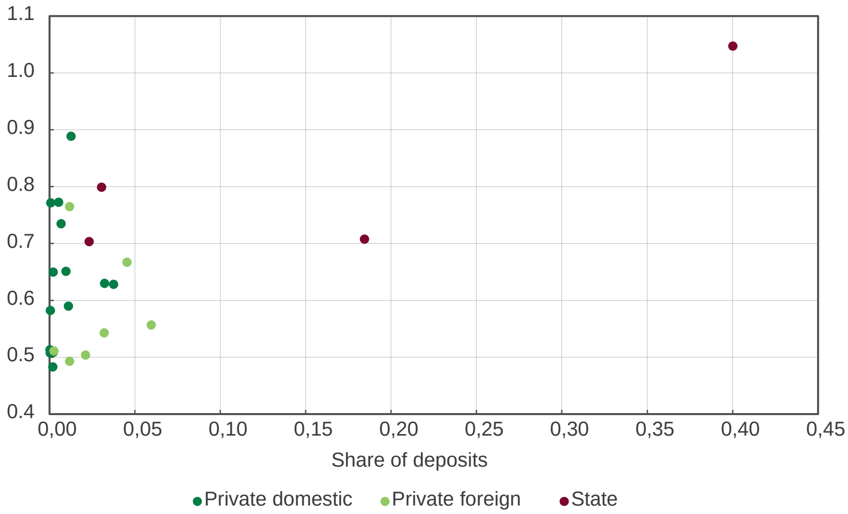

Figure 6. Long-Run Pass-Through to Deposit Rates vs Deposit Shares

[9] Bank codes with respective titles of the banks are reported on the NBU website in the section of balance sheets data.

Figures 7 and 8 (Appendix B) show the results of the estimation of the NARDL model with asymmetry. For the majority of banks, the response to a decrease in the MMR is more pronounced, prompting a swift adjustment of deposit rates downward. Conversely, during rate hikes, there may be a tendency for a more gradual adjustment, as banks seek to avoid increased expenditures. A test of the statistical significance of the asymmetry indicates that none of the instances of positive asymmetry are statistically significant. Furthermore, the test did not identify significant asymmetry in the estimates for banks with high market power.

In Figure 9 (Appendix B), the histogram illustrates long-run pass-through estimations for the 55 commercial banks. The median pass-through to NFC loans surpasses that of deposits. Notably, for NFC loans, a more varied distribution is apparent, featuring cases with both low and high transmission at the extremes.

In contrast to deposit rates, private banks with foreign capital generally exhibit higher transmission for NFC loans than those with domestic capital (Figure 10 in Appendix B). One of the possible explanations for this may be that private banks with foreign capital might have diverse and potentially more extensive funding sources, impacting their flexibility in adjusting lending rates. This could contribute to a more pronounced transmission effect.

The impact of market power remains uncertain. It's worth noting that among all banks (excluding the largest one), those with a loan share above 0.5% exhibit long-run pass-through exceeding 0.65. Figure 11 illustrates that banks with exceptionally high or low pass-through rates typically have a rather small share of loans.

Much like the observed pattern in deposit rates, asymmetry is evident in many banks when it comes to NFC loan rates, with a larger share of banks having a more significant response when the MMR decreases (see Figure 12 in Appendix B). This may be explained by the fact that when the MMR decreases, banks may compete more vigorously for borrowers. As a result, they may be more inclined to adjust loan rates downward promptly to attract and retain customers.

Concerning the statistical significance of the asymmetry, we observe more cases for loan rates: the asymmetry is significant for almost half of all banks (see Figure 13 in Appendix B) and remains notable even among banks with high market power.

To get a general picture of the differences in transmission for banks with different forms of ownership, we ran panel ARDLs for three groups of banks: state, foreign, and domestic private banks. The IRFs presented in Figure 14 (Appendix B) demonstrate that there is no statistically significant difference in transmission to deposit rates for banks with different forms of ownership. However, in the long-run pass-through transmission in state banks is somewhat higher. Transmission to credit rates is much faster and stronger for foreign banks.

5.2. Time-Varying Pass-Through: Aggregated and Bank-Level Estimates

When estimating TVP transmissions we used ARDL specifications for each bank presented in Tables 6-7. Doing this, we assume that only the coefficients of the regression vary in time, while the specification optimized on the whole sample is constant. We consider this assumption as a good trade-off between the simplicity of estimations and the real frequency of changes in the decision rules of the banks. For each TVP-ARDL we estimated time-varying IRFs, which allows us to explore pass-through effects across different horizons. To keep our analysis parsimonious, we use the responses of the banks' rates after 3, 6, 9, and 12 months, and over the long run.

Figure 15 (Appendix B) shows estimations of time-variant long-run pass-through for household deposit rates for 25 banks. While the magnitude of pass-through may vary, the majority of banks exhibit a consistent dynamic pattern: a decline in long-run pass-through since the end of 2019. Nevertheless, from the second half of 2022 onward, there is an observable increase in pass-through – possibly influenced by the measures taken by the NBU to enhance the transmission from the MMR to deposit rates.

Apart from calculating the median pass-through, we also computed the pass-through weighted by the share of deposits. Throughout the entire period, the weighted pass-through consistently appeared lower than the median, suggesting that the largest market participants likely had below-average values of pass-through. This result contrasts with the findings obtained through ordinary ARDL, justifying further investigation. It is noteworthy that asymmetry ARDL yielded results more closely aligned with those from the TVP model.

The magnitude of TVP pass-through for NFC loan rates was found to be higher than that for deposit rates (see Figure 16 in Appendix B). To better comprehend the factors influencing transmission, the obtained TVP pass-through will be subsequently utilized in regression analyses to identify the determinants contributing to the transmission dynamics.

In Appendix B we present more results from TVP estimates. The medians of pass-through strength for different horizons (Figure 17) are positively correlated. This reflects the fact that the IRFs we obtained at the bank level are mostly smooth and monotonic. Kernel densities (Figure 18) indicate that in the short-run both transmissions are close to bimodal distribution, meaning that in our sample there is a sizable group of bank-month estimates that are significantly different from the general median. Over the 12-month horizon bimodality disappears and the median values of the transmissions for deposit and credit rates are close to each other.

The dataset contains several banks that have changed their ownership status between 2015 and 2023.[10] These banks might be interesting objects for separate studies on possible changes in transmission after their ownership changes. However, this question remains out of the scope of

[10] Three banks in the sample for transmission to deposit rates: one changed its status from foreign private to domestic private, one from foreign private to state, and one from private domestic to state. Two banks in the sample for transmission to credit rates: one changed its status from foreign private to state, and one from private domestic to state.

our paper. Figure 19 shows time-varying transmissions across different horizons for the banks where ownership changed. The visual analysis does not indicate significant shifts in transmissions after the ownership transition, compared to the average dynamics of the market.

5.3. Panel Estimates of the Pass-Through Determinants

The results of all of the panel regressions are reported in Appendix A. In Tables 8 – 9 we present regressions for long-run pass-through, which demonstrate our results in general. The specifications we report are regressions containing only bank-level variables, regressions containing only macroeconomic data, and joint estimates. To control for possible autocorrelation and heteroscedasticity in errors, we apply three estimators to each type of specification. In regressions with one-way clusterization, standard errors of coefficients and statistics are robust to both arbitrary heteroscedasticity and arbitrary correlation inside the panel units (banks). The option of two-way clusterization provides us with standard errors that are robust to arbitrary within-panel autocorrelation and arbitrary contemporaneous cross-panel correlation. The third option we use to get consistent standard errors is the application of the Newey-West variance estimator, which gives statistics that are robust to both arbitrary heteroscedasticity and arbitrary autocorrelation. First of all, we pay attention to statistically significant variables in regressions (7) – (9) since they contain the full list of variables. Considering that cluster-robust algorithms can give inconsistent results when the number of clusters is small, we prioritize the results of the Newey-West variance estimator.

We also report regressions for different transmission horizons (Tables 10–11) to study whether some determinants can be significant in the short run. To keep the tables to a reasonable size only regressions with both bank-level and macroeconomic variables are included.

For a deeper understanding of potential cluster heterogeneity, we estimated baseline panel regressions for groups of banks. The banks were divided on the basis of ownership, into state-owned and privately owned. We also applied alternative grouping procedures. Hierarchical clustering using the Lance-Williams algorithm was conducted to cluster banks based on the correlations between the TVP monetary transmission of different banks, for both deposits and credits. Due to sample limitations, only the group with the largest cluster (K1) was considered. The main results for group estimations will be discussed below, with further details available in Figures 20–21.

Transmission to Deposit Rates

Transmission to deposit rates is positively affected by the share of the bank in the deposit market (*hhd_shr*). This result corresponds to the coefficient of market concentration (*hhi_dep*), which is positive. Bigger banks demonstrate higher transmission strength, and a more concentrated market means higher deposit rate transmission. This somewhat counterintuitive result might be explained by the desire of big banks to occupy more market share, which forces them to demonstrate higher transmission. Another possible reason for such a result is the existence of two big players on the market with high transmission estimates (Figure 6). These outliers can bias the general picture significantly.

The coefficient of net interest income to assets ratio (*intrev_a*) has a negative sign and is statistically significant for short horizons. We relate this to a positive correlation between interest expenses and the strength of transmission. More responsive banks pay higher interest rates (at least in periods of interbank rate increase), thus decreasing net interest income.

Provisions to assets ratio (*res_a*) indicate that the banks with more risky assets actively change deposit rates. That may happen because of the desire to attract new funds from households.

Costs paid for funding from households (*fu_cst_hh*) are also positively correlated with transmission strength, reflecting the accounting effects of changes in deposit rates. When transmission is high, banks actively increase\decrease deposit rates in response to respective changes in IR and pay higher\lower costs for acquired funds. Funding costs for resources acquired from the NFCs (*fu_cst_nfc*) are insignificant in the final specification. It means that the policies of the banks on setting rates for HHs and NFCs are independent of each other.

Ratios of administrative and staff costs (*nadmexp_exp*, *persexp_exp*) have positive coefficients, although they are mostly insignificant. These expenses are independent of interest rate fluctuations, meaning that when their shares increase a bank can be more responsive to interbank rate changes without seeing considerable effects on overall expenditures.

The positive effect of the share of interest income (intrev_rev) is an indication of the compensatory behavior of the banks. Having higher transmission to deposit rates (and higher interest expenses respectively), banks try to adjust credit rates more actively to cover the additional costs.

High liquidity negatively affects transmission strength, confirming the assumption that it reduces incentives for banks to attract new funds. On the bank level, we define liquidity as cash and cash equivalents to assets ratio (*liq_a*), while on the macroeconomic level liquidity is the ratio of CDs on banks' balance sheets to liabilities (*liq*). These two measures of liquidity can be used interchangeably in regressions. When we remove the macroeconomic measure of liquidity from regression, bank-level liquidity negatively affects transmission as well (Table 12, regressions 1–3).

The growth of economic uncertainty (*fsi*) decreases transmission, making banks more cautious in rate adjustments. An increase in deposit rates can lead to extra costs for banks, which are undesirable in times of macroeconomic volatility. A decrease in rates can lead to a fast outflow of deposits.

Deposits supply (*rdep_gr*) decreases transmission, demonstrating that banks can get more funding for less cost when deposit inflows are high. CPI has a negative sign in all regressions, contradicting the hypothesis that banks have to maintain real deposit rates at some level via indexation of nominal rates. On the one hand, the negative sign of CPI can be explained by economic uncertainty, which is not fully captured by FSI. In this case, CPI demonstrates uncertainty effects on transmission, when high inflation happens in times of turbulence. On the other hand, the effect of CPI can be nonlinear, depending on the degree of inflation. To show this, we have added the square of CPI in regressions (Table 12, regressions 4–6). Nonlinear modification of regression demonstrates that the impact of CPI becomes positive when inflation exceeds 23.3% (sample mean for 2018m1–2023m12 equals 10.8%, maximum – 26.6%).

The reserve requirement ratio for households' deposits on demand and current accounts (*norm_res*), together with the share of long-term deposit certificates (*dc_100d_shr*), have a positive effect on transmission. These variables are interpreted as instruments used by the NBU to enforce the pass-through. According to the estimates, the impact of the reserve requirement ratio and the attractiveness of long-run NBU deposit certificates are in line with our assumptions.

The results for different groups of banks (Figure 20) show that most factors influence transmission in the same direction, but that the strength of the influence may differ. For example, for state-owned banks, the reserve requirement ratio seems to have a greater influence than the share of long-term deposit certificates, while the opposite is true for private banks. Additionally, inflation has a positive sign in the state-owned group, which aligns with theoretical reasoning.

Transmission to Credit Rates

In the regressions, we have three variables that are proxies for competition in the credit market. Transmission to credit rates becomes stronger with the growth of the market share (*nfcl_shr*) of a bank. The credit market concentration indicator (*hhi_cred*) also has a positive coefficient, meaning that lower competition leads to higher transmission. Net interest income to assets ratio (*intrev_a*) positively affects transmission. The banks generating high net interest rate margins adjust their credit rates more actively (and may be less sensitive in deposit rates (Table 8)) than those with low margins. These effects demonstrate that the market power of a bank increases its ability to adjust credit rates.

A high share of NPLs (*npl_agr*) restricts the reaction of banks to IR fluctuations. The negative effect is explained by liquidity requirements having to be fulfilled, and the need to heal the credit portfolio rather than expanding it. The proportion of NPLs is an indicator of already realized credit risks, which have to be covered by liquidity rationing as resultantly less aggressive policy on the credit market. At the same time, the provisions of the banks approximate the magnitudes of potential risks. The growth of the provisions to assets ratio (*res_a*) indicates an increase in credit portfolio riskiness. A positive coefficient in the regressions indicates that the banks are covering high risks with higher rates and more aggressive reactions to IR changes, increasing pass-through.

A high capital ratio (*vk_liab*) increases the strength of transmission, especially in the short run. Playing the role of a safety buffer, the higher the level of a bank's capital, the more aggressive it can be on the credit market, adjusting interest rates by more. The high share of term deposits (*termdep_liab*) in liabilities provides banks with stable funding costs, making them less vulnerable to changes in market rates and thus leading to weaker transmission to credit rates.

A positive sign for interest expense share (*int_exp*) signals a connection between the credit and deposit rates policies of the banks. As in regressions for deposit rate transmission, banks demonstrating higher interest expenses try to compensate for these costs by actively adjusting credit rates.

High liquidity in the banking system (*liq*) negatively affects transmission. Extra liquidity reflects the risk perception of the banks or low opportunities for new credits. When risks in an economy are considered extremely high, banks prefer more safe and liquid assets and react weakly to IR movements.

Macroeconomic uncertainty (*fsi*) makes transmission stronger. Banks try to account for increased financial risks by actively adjusting credit rates.

Inflation has an insignificant effect on transmission. Nevertheless, the coefficient is negative, which might be explained (as in the case of transmission to deposit rates) by nonlinearities. The inclusion of squared inflation (Table 13) gives a threshold of about 20%, after which banks become more sensitive to inflation, adjusting credit rates.

The variable of credit demand (*rcred_gr*) has a positive sign. In times of high demand, the banks have the opportunity to increase credit rates by more. When demand for credits goes down, banks try to attract clients by lowering rates more aggressively.

Variables testing for the existence of the crowding-out effect (*ovdp_a*, *dc_100d_shr*) have positive coefficients, although only the coefficient of the long-run deposit certificates share is statistically significant in all regressions. This result confirms the crowding-out effect of the relatively long securities allocated by the government and the NBU.

The difference between estimation results for various groups is more pronounced for credit rates compared to deposit rates. For example, for state banks, factors such as lower competition and high capital ratio are more important, whereas excess liquidity does not play a significant role. Conversely, the factor of the crowding-out effect can be observed for private banks and banks from the K1 cluster.

Discussions and Extensions

Our study relies on estimates of transmission strength obtained from ARDL models. This approach has the advantage of simplicity, but it also assumes the exogeneity of the MMR with respect to the banks' rates. This assumption could be too strong, as there is evidence of policy rate endogeneity (Saborowski and Weber, 2013). The estimation of the effects with a VAR model may partially tackle the endogeneity issue, yet bring its own set of challenges. The analysis of transmission determinants also could be conducted in a VAR setup by running PVAR models. We recognize the possibility of another approach to the study of transmission in Ukraine.

In some cases, the results we obtained in the analysis of factors affecting transmission are not coherent with the conventional outcomes of other studies. For instance, the results from the regressions for both transmissions suggest that banks' policies regarding the adjustment of credit and deposit rates are positively correlated. Increasing interest expenses in relative terms results from high transmission to deposit rates. To cover high expenses, the banks add a margin over deposit rates, which leads to higher transmission to credit rates. Tables 14–15 explicitly include credit rate transmissions into regressions for deposit rate transmission and vice versa. The results show that deposit rate transmission is positively correlated with credit rate transmission over different horizons (3, 6, 9, 12 m) confirming that banks with increasing transmission to deposit rates also increase transmission to credit rates.

Transmission to deposit rates is positively affected by market concentration. This result could be driven by two outliers, which are state-owned banks occupying large shares of the market and demonstrating relatively high transmission (Figure 6). To test for this, we excluded these two banks from our estimates (Table 16). The results show that market concentration now negatively affects transmission, as seen in the majority of empirical studies. Considering this, we conclude that the two large banks distort the overall picture. On average, the majority of the banks decrease transmission to deposit rates when the market becomes more concentrated. This finding turns us to the question of the strategies that are used by different banks in setting interest rates. Some banks can increase deposit rates aggressively, demonstrating higher transmission and getting higher shares of the market. If such behavior is true, market concentration will be positively correlated with transmission strength. On the other hand, a negative coefficient of market concentration in regressions can indicate a situation in which big banks actively adjust deposit rates down in response to IR decreases (transmission goes up) and lose some share of the market as their deposits become less attractive. These examples show possible nonlinearity in the relationship between market concentration and transmission strength, depending on the sign of the IR change.

Tables 17–18 present regressions with tests for nonlinear effects of market concentration on transmission to deposit and credit rates depending on the increase/decrease of the IR. We tested variables of market shares (*hhd_shr*, *nfcl_shr*) and market concentration (*hhi_dep*, *hhi_cred*) with a dummy of an IR decrease. The estimates indicate that nonlinearity is more statistically significant for transmission to deposit rates. With market concentration growth, deposit rates become more responsive to an IR decrease. The same effect, though non-significant, is present for the market shares of banks. For credit rates, an increase in market concentration or market share makes banks less responsive to an IR decrease. However, these nonlinearities are weak.

The negative impact of inflation on transmission in linear specification requires deeper analysis. Lower transmission to deposit rates in times of high inflation might be explained by the desire of banks to minimize real interest expenses. But this explanation fails to account for credit rates, as banks must try to maximize real interest incomes. For a better description of transmission, we introduced threshold effects of inflation and expanded our sample to 2015m1–2023m12. The years 2015–2016 are a period of high economic turbulence, with high inflation. This data extension gives us a longer sample for a better understanding of inflationary effects on transmission and higher volatility of inflation for better identification of nonlinear effects. Tables 19–20 contain regression specifications with macroeconomic variables only, as bank-level data is absent for such a long sample. To test for the threshold effects, we include a squared term of CPI. In extended sample results, inflation changes its coefficient to positive in regressions for transmission to deposit rates, while retaining a negative coefficient in regressions for credit rate transmission. The main point is that for the 2015–2023 sample, the effects of inflation lose statistical significance. However, estimates with threshold effects of inflation have high statistical significance and give a threshold of about 16% for both transmissions. A negative impact on transmission under the threshold means that banks try to minimize real interest expenses by adjusting deposit rates and try to retain clients by setting lower credit rates. Over the threshold, banks start to reset deposit rates more actively to retain clients and adjust credit rates by more to maintain real interest income.

6. CONCLUSIONS

Interest rate pass-through in Ukraine shows different patterns for deposit and credit rates. On average, long-run transmission is higher for deposit rates, but banks adjust credit rates more quickly. Transmission is highly nonlinear when it comes to an increase/decrease in the interbank rate. The responses of both deposit and credit rates are downward asymmetrical. For deposit rates, this is explained by the desire of banks to minimize funding costs. Credit rates can be more responsive to an IR decrease because of competition between the banks and the negotiating power of big borrowers.

Whatever their form of ownership, banks on average demonstrate close magnitudes of pass-through – except in transmission to credit rates of foreign banks, which is significantly higher compared to other banks.

The strengths of transmissions to deposit and credit rates are positively correlated. Banks that demonstrate high transmission to deposit rates are also more responsive to IR fluctuations in the credit market.

Time-varying estimates of the long-run pass-through on the bank level allow us to investigate the effects of balance sheet and macroeconomic variables on transmission. Our results show that market concentration increases the responsiveness of deposit and credit rates. For deposit rates, this result is driven by two outliers, which dominate the deposit market and demonstrate high transmission to deposit rates. The exclusion of these outliers yields a negative relationship between market concentration and transmission to deposit rates. We interpret this as evidence that big players try to occupy more market shares by actively decreasing/increasing credit/deposit rates or trying to get monopolistic rent increasing/decreasing rates for credits/deposits when reacting to the respective movements of the interbank rate. However, the rest of the banks demonstrate lower transmission in a concentrated market.

The relationship between market concentration and transmission is highly nonlinear depending on the increase/decrease of the IR. When market concentration goes up, deposit rates become more responsive to an IR decrease, while credit rates demonstrate lower transmission effects.

Increasing the share of NPLs decreases the pass-through to credit rates, preventing banks from accumulating new credits and making them pay more attention to financial sustainability parameters. The riskiness of assets increases transmission strength to both deposit and credit rates. For credit rates, this indicates a more aggressive policy of a bank on the credit market, which, in turn, requires more flexible adjustment of deposit rates to attract additional funding resources. Funding costs are associated with higher transmission to deposit rates, meaning that on average banks need to pay additional expenses for flexibility in the market of deposits. In the short run, the pass-through to credit rates becomes stronger with an increase in the equity capital to assets ratio. Playing the role of a safety buffer, a high capital ratio allows a bank to take on more credit risks. Banks that increase the share of term deposits in their liabilities are less vulnerable to changes in market rates, which leads to weaker transmission to credit rates.

At the macro-level high liquidity negatively affects transmission to both rates. For the deposit market, extra liquidity reduces incentives for banks to attract new funds, while on the credit market it reflects the unwillingness of banks to lend because of high risks. Macroeconomic uncertainty decreases transmission to deposit rates and positively affects transmission to credit rates. In times of high economic volatility, banks try to minimize their costs, and as a result, deposit rates are weakly adjusted. On the other hand, uncertainty is associated with higher credit risks, which banks try to cover with higher rates. Inflation has a statistically significant negative effect on transmission to deposit rates. Moderate inflation allows banks to pay less for deposits in real terms, so rates are rigid. However, we found nonlinear effects: banks start to adjust deposit rates more actively when inflation exceeds 16%. This threshold also works for transmission to credit rates. The growth of deposit supply decreases pass-through, allowing banks to acquire more deposits at lower rates. High demand for credits increases transmission to credit rates.

The results of panel regressions for transmission to deposit rates confirm that the measures taken by the NBU to encourage pass-through had a significant positive effect. The increased reserve requirement ratio for households' deposits on demand and current accounts, together with the ability to allocate liquidity to long-term deposit certificates, made the banks adjust their term deposit rates.

We also found that having government bonds in assets and having a higher share of long-term deposit certificates make transmission to credit rates stronger. We interpret this result as evidence of the crowding-out effect, as borrowers have to compete with government and monetary authorities for credit resources.

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APPENDICES

APPENDIX A. TABLES

Table 2. Datasets and Methods used in Interest Rate Pass-Through Studies

Sources	Sample	Transmission	Method
Saborowski and Weber (2013)	142 countries, unbalanced panel data over the sample period 2000m1:2011m12.	Central bank policy rates to retail lending rates.	Panel interaction VAR
Leroy and Lucotte (2016)	Sample of 11 euro area countries over the period 2003m1:2011m12.	MMR to harmonized bank lending rates to households and firms.	Single equation ECM, panel interaction ECM, panel interaction VAR
Gigineishvili (2011)	70 countries including low-income, emerging, and developed economies. Monthly data, 2005m12:2010m3.	From three-month treasury bill rates to one- to two-year corporate loans in domestic currency.	ARDL, Cross-sectional regression
Mojon (2000)	6 largest countries in the euro area (Belgium, Germany, Spain, France, Italy and the Netherlands). Annual averages over the periods 1979-82, 1982-88, 1988-92 and 1992-98.	From MMR to 25 credit rates and 17 deposit rates.	ECM, Panel regression
Gregor and Melecký (2018)	Czech Republic, 2004m1:2017m11.	From CNB policy rate to four lending rates: the consumer loan rate, mortgage loan rate, small corporate loan rate, and large corporate loan rate.	ARDL with interaction terms
Cottarelli and Kourelis (1994)	31 industrial and developing countries. Monthly data from the 1980s to 1993.	From MMR to the lending rate	Distributed lag regression, Cross-sectional regressions
Sørensen and Werner (2006)	10 countries, 1999m1:2004m6	Speed of transmission from market interest rates to 4 series of lending rates (loans to households for consumption, loans to households for house purchase, short-term loans to non-financial corporations, and long-term loans to non-financial corporations) and 3 series of deposit rates (current account deposits, time deposits, and savings deposits.	ECM by DSUR
Leuvensteijn et al (2008)	8 euro area countries. 1992–2004	From three-month MMR or government bond yields to bank loans interest rates	Panel ECM
Stanisławska (2015)	Poland, bank-level data, 2005m1 – 2013m7	From MMR with maturity of 1 month and 3 months to deposits of households and firms as well as loans granted to households and firms	Panel ECM

Table 3. Potential Determinants to Interest Rate Pass-Through Analyzed in the Literature

Sources	Factors	Variable	Impact on transmission	Empirical findings
Saborowski and Weber (2013)	Regulatory quality	World Bank regulatory quality index.	A weak regulatory environment creates uncertainty in the financial system and leads to a deformalization of financial transactions and a higher cost of financial intermediation. As a result, bank rates become less sensitive to changes in the policy rate.	Significant and sizable negative influence on pass-through.
Saborowski and Weber (2013)	Financial dollarization	Share of foreign currency loans in total loans	The cost of foreign currency funding is linked to external factors that are mostly outside the control of the central bank. To the extent that financial market participants can arbitrage between domestic and foreign currency instruments, the policy rate can thus only partially control market interest rates on domestic currency instruments.	Significant and sizable negative influence on pass-through.
Cottarelli and Kourelis (1994), Gigineishvili (2011), Saborowski and Weber (2013), Leroy and Lucotte (2016)	Financial development	Private sector credit and deposits as a share of GDP, Market capitalization to GDP ratio, Total assets and liabilities, Per capita GDP, The ratio between broad money and GDP (M2/GDP), The ratio between broad and narrow money	More variety in investment opportunities leads to increased competition between financial products. Market interest rates – including on wholesale markets – are thus more responsive to policy rate changes because profit margins are constrained.	Significant and large influence on the effectiveness of interest rate transmission.
Sørensen and Werner (2006), Gigineishvili (2011), Saborowski and Weber (2013), Stanisławska (2015)	Liquidity ratio	Share of liquid assets in total assets and short-term liabilities.	Countries with low excess liquidity have higher pass-through. Excess liquidity reflects differences in risk perceptions or a more conservative business model. It is also related to the lack of investment opportunities. In excessively liquid markets, when all banks are structurally on the same side of the market, interbank trading in short-term funds dries up, and interest rates fail to reflect the true marginal cost of financial resources. Naturally, the retail pricing of loans becomes less responsive to MMR and the connection between the two weakens.	Low excess liquidity enforces pass-through.
Cottarelli and Kourelis (1994), Mojon (2000), Sørensen and Werner (2006), Leuvensteijn et al (2008), Saborowski and Weber (2013), Leroy and Lucotte (2016), regor and Melecký (2018)	Competition	Banking sector concentration (Herfindahl index computed over asset shares of individual commercial banks), The banking sector's average return on equity, The standard deviation of NPLs across banks, Lerner Index of market power, The index of deregulation measures taken by European countries between 1980 and 1995,	In countries with a low concentration of the banking sector, long-run pass-through is higher. When banks have substantial market power, policy rate changes may translate into movements in spreads rather than market rates.	Banking competition reinforces the transmission of monetary policy. Banks tend to price their loans more in accordance with the market in countries where competitive pressures are stronger. Stronger loan market competition also means larger bank spreads (implying lower bank interest rates) on current accounts and time deposits. This would suggest that the competitive pressure is heavier in the loan market

Table 3 (continued). Potential Determinants to Interest Rate Pass-Through Analyzed in the Literature

Sources	Factors	Variable	Impact on transmission	Empirical findings
		Market share of the largest five banks and the number of bank branches per 100,000 inhabitants, Market power (RoE), Boone indicator		than in the deposit markets, so banks compensate for the reduction in their loan market income by lowering their deposit rates.
Sørensen and Werner (2006), Gigineishvili (2011), Saborowski and Weber (2013), Stanisławska (2015), Leroy and Lucotte (2016).	Asset quality	Share of non-performing in total loans, Aggregate measure of distances to default of listed banks by country, Gross of provisions.	Banks with weak balance sheets may react to an expansive monetary policy stance by shoring up liquidity rather than extending credit at lower rates. A change in the policy rate may thus have only a limited impact on market rates. Moreover, banks have to comply with regulatory requirements, implying that their capacity to expand lending depends, for instance, on their capital adequacy. However, the ratio of provisions to gross income is often negatively correlated with concentration ratios. Hence, this might imply that banks in a more competitive environment on average take on more problematic loans (leading to higher provisions), which might explain the positive effect on the pass-through.	Results are mixed. The majority of studies indicate that countries/banks with low NPLs have a long-term pass-through that is higher than that of countries/ banks with high NPLs.
Gigineishvili (2011), Saborowski and Weber (2013)	Exchange rate regime	Rigidity of exchange rate regimes from classification by Reinhart and Rogoff (2004)	The central bank's control over market rates is likely to be tighter when policy rates are set as part of a transparent and rules-based framework that is largely independent of other influences such as fiscal and exchange rate policy. A lack of exchange rate flexibility may signal that the policy rate is not set with the primary purpose of steering an intermediate target of monetary policy such as market interest rates or commercial bank reserves.	Countries with rather rigid exchange rate regimes have a long-run pass-through lower than those with flexible rates.
Cottarelli and Kourelis (1994), Mojon (2000), Gigineishvili (2011), Saborowski and Weber (2013), Leroy and Lucotte (2016)	Inflation	Inflation rate	Higher inflation ratios lead to more frequent price changes, thus making it more likely that policy rate changes impact market rates in a timely fashion.	Results are mixed. The majority of studies indicate that inflation increases pass-through.
Mojon (2000); Gigineishvili (2011); Leroy and Lucotte (2016)	Business cycle, Deposits supply, Loans demand	Industrial production index, The average real growth rate of credit and deposit volumes for retail markets, Average real growth rate of GDP or residential or non-residential investment, Gross national saving ratio, House prices.	An increase (decrease) of industrial production would encourage banks to modify the allocation of their portfolios towards riskier (low-risk) projects. However, since the perceived credit risk of borrowers is pro-cyclical, a reverse effect would also be possible. GDP and credit growth also can have a negative effect on the speed of adjustment. An increase in loan demand/ deposit supply allows banks to reduce the speed of interest rate adjustment, although the results are not unambiguous.	Decrease of pass-through during a crisis and in low-income economies. The volume of credit and real demand both tend to lower the pass-through to credit rates when interest rates are falling, while their impact is not significant when interest rates are rising. This is partially consistent with the ability of banks to preserve their interest rate margin on credit when they face stronger credit demand.

Table 3 (continued). Potential Determinants to Interest Rate Pass-Through Analyzed in the Literature

Sources	Factors	Variable	Impact on transmission	Empirical findings
				When rates increase, higher saving ratios seem to allow banks to adjust deposit rates faster than when the rates decrease, while higher GDP growth has the opposite effect.
Leroy and Lucotte (2016)	Macro-financial stance	Stock price Index; Spread between swaps 6-month Euribor and 10-year government bond rates; Spread between specific government bond rate and the EONIA.	A higher stock price index increases the pass-through and opposite effects for the country risk premium because of the marginal cost of bank funding.	Positive effect of stock price index on pass-through. Country risk premium alters the pass-through.
Cottarelli and Kourelis (1994), Mojon (2000), Gigineishvili (2011), Leroy and Lucotte (2016)	Markets volatility	MMR volatility; Size of the “random component” in the MMR series.	MMR volatility is expected to have a negative effect on bank interest pass-through. Theory suggests that monetary transmission will be more important whether the bank is confident that the change is permanent, and not temporary.	The negative impact of the MMR volatility on pass-through.
Sørensen and Werner (2006), Gigineishvili (2011)	Bank capitalization	Capital to total assets and capital to risk-weighted assets.	Excess capital at banks may act as a buffer against market fluctuations and would hence be expected to show a negative relation with the speed and strength of adjustment.	Negative effect on the speed of pass-through
Gigineishvili (2011)	Profitability	Returns on equity and assets; Net interest margin.	High profitability in the banking sector, which is often a reflection of inadequate competition and market power, weakens pass-through. In an uncompetitive environment, banks can charge higher premiums and deviate from marginal cost pricing. As a result, lending rates become less elastic to changes in the costs of funds.	Negative effect on pass-through
Mojon (2000), Gigineishvili (2011)	Costs structure	Overhead costs to total assets	Large overheads could be structural in nature, related to obstructive regulatory and legal frameworks, undeveloped financial infrastructure, and information asymmetry. These may include excessive costs originating from burdensome registration requirements, prolonged court litigation, legal obstacles in seizing and liquidating collateral, difficulties in assessing the creditworthiness of borrowers and the value of collateral, and so forth. To cover such costs, banks would have to maintain higher interest margins. To preserve these margins, an increase in MMR is likely to induce stronger pass-through to lending rates.	The coefficient for overhead costs is positive and statistically significant, implying that overhead costs contribute to the strength of pass-through.
		Ratios of banks’ staff costs to banks’ gross income.	If banks set their interest rates by adding a margin over their costs, one can expect the pass-through to reflect the impact of changes in the MMR on the total costs of the bank. A priori, a higher share of operating costs in total costs should imply a smaller pass-through.	The higher the staff costs, the smaller the impact of monetary policy shocks on bank credit rates.

Table 3 (continued). Potential Determinants to Interest Rate Pass-Through Analyzed in the Literature

Sources	Factors	Variable	Impact on transmission	Empirical findings
Mojon (2000), Sørensen and Werner (2006)	Income structure	Ratios of banks' non-interest income to banks' gross income.	A higher share of non-interest income to total gross income seems to speed up banks' rate adjustment. Banks that are relatively less dependent on interest-related income adjust their interest rates more quickly to a change in the market rate, perhaps to capture market shares in a competitive environment. It may be expected that a bank with a highly diversified portfolio of activities (i.e. banks that do not only rely on traditional banking activities such as granting loans and taking deposits, e.g. measured by the share of non-interest income) may be less sensitive to movements in market rates, which would imply a more sluggish pass-through. At the same time, it cannot be ruled out that in a highly competitive environment, very diversified banks may be able to exploit this by offering more attractive rates to conquer market shares, implying a speedier pass-through.	Results are mixed.
Cottarelli and Kourelis (1994), Mojon (2000)	Competition from direct finance	Size of the market for short-term negotiable financial instruments issued by enterprises and other agents, both measured in relation to each country's GDP; The ratio of commercial paper and total short-term securities to GDP.	The existence of a market for short-term instruments issued by enterprises (commercial paper and bankers' acceptances) may be relevant because it increases the elasticity of the demand for bank loans. In this case, if banks do not adjust rapidly to changes in money market conditions, they may be disintermediated. The existence of a market for other short-term marketable instruments (mainly certificates of deposit (CDs), and Treasury bills) may also be important. The existence of these instruments increases the liquidity of enterprise and household portfolios, thus increasing the elasticity of demand for loans. Moreover, if banks raise a large share of their resources from the issuance of CDs, whose interest rates rapidly adjust to money market conditions, they will face large costs if they delay the adjustment of their lending rates.	The development of a market for short-term instruments enhances the flexibility of lending rates.
Cottarelli and Kourelis (1994)	Openness of an economy	The barriers to foreign competition.	Capital controls reduce competitive pressures on the banking system (arising from foreign financial markets) and result in higher lending rate stickiness.	Negative effect on pass-through.
Cottarelli and Kourelis (1994)	Banking system ownership	Number of public banks out of the five largest ones.	The relative inefficiency of public banks or the existence of "political constraints" on interest rate changes make lending rates stickier.	Lending rates appear to be stickier in publicly-owned banking systems. Privatizing a publicly owned banking system would substantially increase the flexibility of lending rates.

Table 3 (continued). Potential Determinants to Interest Rate Pass-Through Analyzed in the Literature

Sources	Factors	Variable	Impact on transmission	Empirical findings
Sørensen and Werner (2006)	Interest rate risk (maturity mismatch)	LT assets/total assets vs. LT liabilities/total liabilities	The higher the interest rate risk banks are exposed to, the more they need to hedge and through their hedging activities the more sensitive they are to changes in market rates. This would tend to imply a speedier pass-through. Alternatively, it may be argued that the interest rate risk is linked to the degree of capitalization in the sense that the profit (and hence capital accumulation) of banks having a relatively large maturity mismatch is more sensitive to changes in market rates, which could induce them to adjust their interest rates more slowly to compensate for this potential loss.	Negative effect on pass-through.
Stanisławska (2015), Sørensen and Werner (2006)	Structure of funding	Share of non-financial sector deposits in liabilities	Banks with a large and stable pool of deposit funding (e.g. measured by the share of deposits to total liabilities) would be expected to be less vulnerable to changes in market rates (as most of their funding is non-market based) thereby leading to a relatively slower speed of adjustment. The rigidity of funding costs depends mainly on pricing practices in the banking sector and on the extent to which the interest rate received or paid by banks is itself rigid. A bank that can rely on traditional deposits is more likely to have more rigid funding costs than a bank that funds itself mostly by issuing debt on the capital markets.	Negative effect on pass-through.

Table 4. Variables, Definitions, and Sources

Notation	Variable	Description	Level	Source
HH_TR, NFCL_TR	Long-run transmission to deposit (HH) and credit (NFCL) rates	Long–run coefficient of transmission estimated via some modification of ARDL (linear, nonlinear, TVP)	Economy, Banks	authors' calculations
HHD_R	HH deposit rates	Weighted average interest rates on term deposits of HHs in national currency	Economy, Banks	NBU
NFCL_R	NFC credit rates	Weighted average interest rates on credits to NFCs in national currency	Economy, Banks	NBU
UONIA	Interbank overnight rate	Ukrainian weighted average overnight interbank rate	Economy	NBU
HHD_SHR	Share of deposits	Share of term deposits of HHs in national currency in the current month	Banks	NBU
NFCL_SHR	Share of credits	Share of credits to NFCs in national currency in the current month	Banks	NBU
NPL_AGR	Share of non-performing loans	Non-performing loans, mln.hrn./ Total loans to residents and households, mln. hrn.	Banks	NBU
FU_CST_HH	Cost of funds acquired from HHs	Payments to HHs, mln.hrn. / Funds attracted from HHs, mln.hrn.	Banks	NBU
FU_CST_NFC	Cost of funds acquired from NFCLs	Payments to NFCs, mln.hrn. / Funds attracted from NFCs mln.hrn.	Banks	NBU
P_VK	Profit after taxation to equity capital ratio	Profit (loss) after tax, mln.hrn. / Total equity capital, mln.hrn.	Banks	NBU, Banks' balance sheet reports
INTREV_A	Net interest revenues to assets ratio	Net interest margin, mln.hrn. / Total assets, mln.hrn.	Banks	NBU, Banks' balance sheet reports
RES_A	Provisions to assets ratio	-1*(Total provisions, mln.hrn. / Total assets, mln.hrn.)	Banks	NBU, Banks' balance sheet reports
VK_LIAB	Equity capital to liabilities ratio	Total equity capital, mln.hrn. / Total liabilities, mln.hrn.	Banks	NBU, Banks' balance sheet reports
SHORTSEC_A	Short-term securities of the NBU to assets	Securities at amortized cost (including refinanced by NBU), mln.hrn. / Total assets, mln.hrn	Banks	NBU, Banks' balance sheet reports
OVDP_A	Government bonds to assets	IGLB refinanced by NBU, mln.hrn. / Total assets, mln.hrn. IGLB – domestic bonds denominated in national currency	Banks	NBU, Banks' balance sheet reports
LIQ_A	Share of liquid assets	Cash and cash equivalents, mln.hrn. / Total assets, mln.hrn	Banks	NBU, Banks' balance sheet reports
TERMDEP_LIAB	Share of term deposits in liabilities	(Amounts due to customers – demand deposits from legal entities – demand deposits from individuals), mln.hrn. / Total liabilities, mln.hrn.	Banks	NBU, Banks' balance sheet reports
SEC_LIAB	Share of securities in total liabilities	(Debt securities issued by the bank + Other funds raised), mln.hrn. / Total liabilities payroll costs – tax on payroll – other staff costs	Banks	NBU, Banks' balance sheet reports
INTREV_REV	Share of interest income	Interest income, mln.hrn. / Gross income, mln.hrn.	Banks	NBU, Banks' balance sheet reports
NADMEXP_EXP	Administrative expenses to gross expenses ratio	(Administrative and other operating expenses – payroll costs – tax on payroll – other staff costs), mln.hrn. / Gross expenditures, mln.hrn.	Banks	NBU, Banks' balance sheet reports
PERSEXP_EXP	Staff costs to gross expenses ratio	(Payroll costs + tax on payroll + other staff costs), mln.hrn. / Gross expenditures, mln. hrn.	Banks	NBU, Banks' balance sheet reports
INTEXP_EXP	Share of interest expenses	Interest expenses, mln.hrn. / Gross expenses, mln.hrn.	Banks	NBU, Banks' balance sheet reports
LIQ	Liquidity in the banking system	CDs on banks' balance sheets, mln.hrn. / Total liabilities of banks, mln.hrn.	Economy	NBU

Table 4 (continued). Variables, Definitions, and Sources

Notation	Variable	Description	Level	Source
FSI	Financial stress index	The Financial Stress Index (FSI) is an indicator representing the stress level in the financial sector of Ukraine. It fluctuates from 0 to 1, where 0 – total absence of stress and 1 is the highest level of stress.	Economy	NBU
HHI_DEP	Herfindahl-Hirschman index for deposit market	Index estimated as a sum of squared market shares of each bank in banking system. It demonstrates concentration of HH deposit market. The index fluctuates from 0 to 1, increase means higher market concentration.	Economy	NBU, authors' calculations
HHI_CRED	Herfindahl-Hirschman index for credit market	Index estimated as a sum of squared market shares of each bank in banking system. It demonstrates concentration of NFC credit market. The index fluctuates from 0 to 1, increase means higher market concentration.	Economy	NBU, authors' calculations
CPI	Inflation	Year-over-year CPI change, %	Economy	NBU
RDEP_GR	Real growth of deposits	Proxy for deposits supply. Year-over-year growth of HH deposits deflated by CPI.	Economy	NBU, authors' calculations
RCRED_GR	Real growth of credits	Proxy for credits demand. Year-over-year growth of NFC credits deflated by CPI.	Economy	NBU, authors' calculations
DC_100D_SHR	Long-term NBU's certificates of deposit (CDs)	The share of CDs with a maturity of more than one day in the total amount of CDs allocated to banks.	Economy	NBU
NORM_RES	Reserve requirement ratio for HH deposits on demand and current accounts	Effective reserve requirement ratio for demand deposits and deposits on current accounts of individuals.	Economy	NBU

Table 5. Descriptive Statistics of Variables

Variable	Mean	Median	Max.	Min.	SD	Obs.	Banks	Sample period
UONIA	13.68	15.76	23.01	5.08	5.97	72	Economy	2018m1–2023m12
NFCL_R	18.62	19.27	38.04	3.46	4.35	3905	55	2018m1–2023m12
HHD_R	11.56	12.21	30.37	0.03	3.59	1800	25	2018m1–2023m12
HH_TR	0.72	0.72	1.09	0.38	0.12	1800	25	2018m1–2023m12
NFCL_TR	1.14	1.14	1.94	0.45	0.20	3905	55	2018m1–2023m12
NFCL_SHR	0.02	0.00	0.44	0.00	0.05	3905	55	2018m1–2023m12
HHD_SHR	0.04	0.01	0.43	0.00	0.08	1800	25	2018m1–2023m12
P_VK	0.01	0.01	0.46	-1.23	0.05	3905	55	2018m1–2023m12
INTREV_A	0.01	0.00	0.04	-0.02	0.00	3905	55	2018m1–2023m12
NPL_AGR	0.20	0.15	0.85	0.00	0.18	3905	55	2018m1–2023m12
RES_A	0.07	0.05	0.47	0.00	0.08	3905	55	2018m1–2023m12
FU_CST_HH	0.05	0.05	0.34	0.00	0.03	3905	55	2018m1–2023m12
FU_CST_NFC	0.05	0.04	0.25	0.00	0.03	3905	55	2018m1–2023m12
VK_LIAB	0.35	0.17	15.48	0.01	0.75	3905	55	2018m1–2023m12
SHORTSEC_A	0.15	0.11	0.75	0.00	0.14	3905	55	2018m1–2023m12
OVDP_A	0.13	0.09	0.74	0.00	0.14	3905	55	2018m1–2023m12
LIQ_A	0.08	0.06	0.39	0.00	0.05	3905	55	2018m1–2023m12
TERMDEP_LIAB	0.35	0.34	0.87	0.00	0.19	3905	55	2018m1–2023m12
SEC_LIAB	0.02	0.00	0.42	0.00	0.07	3905	55	2018m1–2023m12
NADMEXP_EXP	0.23	0.22	0.88	-0.73	0.11	3905	55	2018m1–2023m12
PERSEXP_EXP	0.25	0.24	0.87	0.00	0.12	3905	55	2018m1–2023m12
INTREV_REV	0.63	0.66	1.63	-0.42	0.18	3905	55	2018m1–2023m12
INTEXP_EXP	0.30	0.28	0.83	0.00	0.15	3905	55	2018m1–2023m12
LIQ	0.06	0.04	0.19	0.01	0.04	108	Economy	2015m1–2023m12
FSI	0.14	0.04	0.84	0.00	0.18	108	Economy	2015m1–2023m12
HHI_CRED	0.16	0.17	0.22	0.08	0.03	108	Economy	2015m1–2023m12
HHI_DEP	0.22	0.22	0.23	0.18	0.01	108	Economy	2015m1–2023m12
CPI	16	11	61	2	0.14	108	Economy	2015m1–2023m12
RCRED_GR	-13	-9	10	-60	0.17	108	Economy	2015m1–2023m12
RDEP_GR	-11	-3	34	-78	0.24	108	Economy	2015m1–2023m12
DC_100D_SHR	0.64	0.74	0.93	0	0.28	108	Economy	2015m1–2023m12
NORM_RES	5.68	6.5	20	0	5.35	108	Economy	2015m1–2023m12

Table 6. Information on ARDL Models for Deposits*

Bank, NKB	Optimal Model	R^2	Test for serial correlation[11]	Test for heteroscedasticity[12]	F bonds test	1 – residuals are not serially correlated	1 – homoscedasticity of residuals	1 – long-run relationship identified at 10% probability
2	ARDL(1, 0)	0.97	0.85	0.16	15.77	1	1	1
6	ARDL(1, 0)	0.96	0.78	0.36	8.13	1	1	1
36	ARDL(1, 5)	0.87	0.02	0.00	3.49	0	0	0
46	ARDL(1, 0)	0.98	0.23	0.02	7.91	1	0	1
88	ARDL(3, 4)	0.80	0.32	0.34	1.75	1	1	0
115	ARDL(1, 1)	0.93	0.42	0.34	3.81	1	1	1
136	ARDL(2, 0)	0.54	0.16	0.65	6.99	1	1	1
274	ARDL(2, 1)	0.95	0.19	0.00	5.86	1	0	1
49	ARDL(1, 0)	0.89	0.30	0.32	12.35	1	1	1
62	ARDL(1, 1)	0.90	0.60	0.81	4.41	1	1	1
91	ARDL(3, 0)	0.76	0.30	0.11	8.09	1	1	1
96	ARDL(2, 0)	0.93	0.38	0.83	7.25	1	1	1
105	ARDL(2, 0)	0.94	0.38	0.00	8.53	1	0	1
106	ARDL(2, 0)	0.80	0.15	0.14	9.68	1	1	1
123	ARDL(1, 0)	0.89	0.04	0.01	3.09	0	0	0
142	ARDL(3, 0)	0.91	0.25	0.76	7.82	1	1	1
153	ARDL(2, 3)	0.85	0.14	0.01	10.44	1	0	1
171	ARDL(1, 0)	0.87	0.09	0.21	4.72	0	1	1
205	ARDL(1, 0)	0.87	0.44	0.11	7.06	1	1	1
242	ARDL(1, 0)	0.91	0.20	0.21	3.09	1	1	0
270	ARDL(1, 0)	0.89	0.67	0.17	11.85	1	1	1
272	ARDL(2, 6)	0.94	0.09	0.00	1.61	0	0	0
290	ARDL(3, 0)	0.62	0.01	0.86	6.78	0	1	1
296	ARDL(2, 1)	0.71	0.09	0.87	11.44	0	1	1
320	ARDL(1, 0)	0.85	0.28	0.73	5.87	1	1	1

*HAC covariance matrix estimator is used to address issues of heteroscedasticity and serial correlation in regressions

[11] Breusch-Godfrey Lagrange Multiplier test for serial correlation.
[12] Breusch-Pagan-Godfrey test for heteroscedasticity.

Table 7. Information on ARDL Models for Loans*

Bank code	Optimal Model	R^2	Test for serial correlation[13]	Test for heteroscedasticity[14]	F bonds test	1 – residuals are not serially correlated	1 – homoscedasticity of residuals	1 – long-run relationship identified
2	ARDL(3, 1)	0.94	0.20	0.99	23.65	1	1	1
6	ARDL(3, 0)	0.76	0.04	0.08	6.19	0	0	1
29	ARDL(1, 5)	0.69	0.28	0.00	15.13	1	0	1
36	ARDL(1, 0)	0.95	0.49	0.00	17.82	1	0	1
43	ARDL(4, 0)	0.84	0.01	0.03	4.14	0	0	1
46	ARDL(1, 0)	0.68	0.91	0.18	5.39	1	1	1
49	ARDL(2, 2)	0.81	0.30	0.00	14.39	1	0	1
62	ARDL(3, 0)	0.91	0.71	0.67	9.89	1	1	1
88	ARDL(1, 0)	0.98	0.67	0.06	24.05	1	0	1
91	ARDL(3, 0)	0.86	0.55	0.23	11.37	1	1	1
95	ARDL(2, 0)	0.51	0.00	0.50	5.74	0	1	1
96	ARDL(2, 6)	0.60	0.08	0.15	3.76	0	1	1
101	ARDL(2, 1)	0.76	0.02	0.00	4.21	0	0	1
105	ARDL(2, 0)	0.91	0.83	0.44	12.22	1	1	1
106	ARDL(3, 0)	0.81	0.83	0.00	9.24	1	0	1
113	ARDL(3, 0)	0.95	0.29	0.05	9.12	1	0	1
115	ARDL(2, 0)	0.86	0.37	0.00	7.22	1	0	1
123	ARDL(1, 4)	0.93	0.13	0.04	1.49	1	0	0
128	ARDL(3, 0)	0.55	0.17	0.72	4.28	1	1	1
133	ARDL(3, 0)	0.62	0.18	0.00	4.43	1	0	1
136	ARDL(1, 2)	0.96	0.20	0.14	9.19	1	1	1
143	ARDL(2, 0)	0.80	0.13	0.02	1.37	1	0	0
146	ARDL(2, 5)	0.93	0.28	0.18	4.82	1	1	1
153	ARDL(2, 0)	0.92	0.83	0.00	17.65	1	0	1
171	ARDL(2, 4)	0.96	0.04	0.00	8.69	0	0	1
205	ARDL(2, 5)	0.86	0.00	0.00	8.01	0	0	1
231	ARDL(2, 0)	0.58	0.01	0.62	5.20	0	1	1
240	ARDL(2, 0)	0.80	0.45	0.24	7.96	1	1	1
242	ARDL(3, 0)	0.16	0.73	0.02	6.23	1	0	1
251	ARDL(5, 0)	0.85	0.00	0.16	7.32	0	1	1
270	ARDL(2, 0)	0.62	0.71	0.01	5.00	1	0	1
272	ARDL(2, 0)	0.76	0.10	0.04	14.11	1	0	1
274	ARDL(3, 0)	0.91	0.73	0.25	12.66	1	1	1
286	ARDL(5, 6)	0.88	0.49	0.00	3.28	1	0	0
288	ARDL(3, 0)	0.74	0.87	0.05	1.09	1	0	0
295	ARDL(4, 4)	0.98	0.18	0.00	1.56	1	0	0
296	ARDL(5, 5)	0.95	0.62	0.00	3.67	1	0	1
297	ARDL(1, 1)	0.93	0.33	0.07	19.96	1	0	1
298	ARDL(3, 0)	0.96	0.40	0.00	19.49	1	0	1
305	ARDL(3, 0)	0.92	0.01	0.52	17.19	0	1	1
320	ARDL(3, 0)	0.72	0.18	0.03	12.31	1	0	1
331	ARDL(3, 0)	0.90	0.10	0.00	4.93	1	0	1
377	ARDL(4, 0)	0.63	0.18	0.00	6.33	1	0	1
381	ARDL(2, 0)	0.89	0.41	0.37	10.69	1	1	1

[13] Breusch-Godfrey Lagrange Multiplier test for serial correlation
[14] Breusch-Pagan-Godfrey test for heteroscedasticity.

Table 7 (continued). Information on ARDL Models for Loans*

Bank code	Optimal Model	R^2	Test for serial correlation[13]	Test for heteroscedasticity[14]	F bonds test	1 – residuals are not serially correlated	1 – homoscedasticity of residuals	1 – long-run relationship identified
386	ARDL(2, 2)	0.84	0.29	0.00	4.55	1	0	1
387	ARDL(2, 0)	0.61	0.01	0.44	5.46	0	1	1
389	ARDL(4, 0)	0.89	0.57	0.01	11.50	1	0	1
392	ARDL(1, 0)	0.44	0.34	0.42	29.56	1	1	1
394	ARDL(3, 0)	0.27	0.32	0.08	4.50	1	0	1
395	ARDL(3, 0)	0.41	0.25	0.52	3.58	1	1	1
407	ARDL(2, 2)	0.96	0.42	0.62	5.19	1	1	1
455	ARDL(2, 4)	0.91	0.06	0.88	3.66	0	1	1
634	ARDL(1, 0)	0.45	0.19	0.31	6.99	1	1	1
694	ARDL(1, 0)	0.75	0.00	0.10	7.98	0	1	1
774	ARDL(1, 0)	0.85	0.16	0.91	2.62	1	1	0

* HAC covariance matrix estimator is used to address issues of heteroscedasticity and serial correlation in regressions

Table 8. Panel Regression: Determinants of Transmission to Deposit Rates, (2018m1 – 2023m12)

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Bank-level variables	HHD_SHR	1.335	1.335	1.335**				1.89	1.89	1.89***
	P_VK	-0.001	-0.001	-0.001				-0.017	-0.017	-0.017
	INTREV_A	-2.132	-2.132	-2.132				-1.675	-1.675	-1.675
	NPL_AGR	-0.056	-0.056	-0.056**				-0.033	-0.033	-0.033
	RES_A	0.33*	0.33*	0.33***				0.359**	0.359**	0.359***
	FU_CST_HHD	-0.100	-0.100	-0.100				0.767*	0.767	0.767***
	FU_CST_NFC	-0.389	-0.389	-0.389**				-0.172	-0.172	-0.172
	VK_LIAB	-0.034	-0.034	-0.034				-0.010	-0.010	-0.010
	SHORTSEC_A	-0.033	-0.033	-0.033				-0.008	-0.008	-0.008
	LIQ_A	-0.059	-0.059	-0.059				0.028	0.028	0.028
	TERMDEP_LIAB	0.027	0.027	0.027				0.014	0.014	0.014
	NADMEXP_EXP	0.006	0.006	0.006				0.019	0.019	0.019
	PERSEXP_EXP	0.091	0.091	0.091***				0.071	0.071	0.071**
	INTEXP_EXP	0.014	0.014	0.014				0.032	0.032	0.032
	INTREV_REV	0.056*	0.056*	0.056***				0.031**	0.031*	0.031**
Macro variables	LIQ				-0.807***	-0.807***	-0.807***	-0.586***	-0.586***	-0.586***
	FSI				-0.086***	-0.086*	-0.086***	-0.083***	-0.083***	-0.083***
	HHI_DEP				1.261***	1.261***	1.261***	0.77**	0.77*	0.77***
	CPI				-0.623***	-0.623**	-0.623***	-0.605***	-0.605***	-0.605***
	RDEP_GR				-0.243***	-0.243*	-0.243***	-0.232***	-0.232***	-0.232***
	DC_100D_SHR				0.073***	0.073**	0.073***	0.043**	0.043*	0.043**
	NORM_RES				0.004***	0.004**	0.004***	0.003*	0.003*	0.003***
	Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Time FE	Yes	Yes	Yes	No	No	No	No	No	No
	Heteroscedasticity	One-way clusterization	Two-way clusterization	HAC	One-way clusterization	Two-way clusterization	HAC	One-way clusterization	Two-way clusterization	HAC
	Autocorrelation			HAC			HAC			HAC
	N	1,800	1,800	1,800	1,800	1,800	1,800	1,800	1,800	1,800
	Within R^2	0.735	0.891	0.147	0.633	0.849	0.633	0.696	0.875	0.696

* p<0.05, ** p<0.01, *** p<0.0

Table 9. Panel Regression: Determinants of Transmission to Credit Rates, (2018m1 – 2023m12)

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Bank-level variables	NFCL_SHR	0.162	0.162	0.162				0.654	0.654	0.654**
	P_VK	-0.039	-0.039	-0.039				-0.017	-0.017	-0.017
	INTREV_A	7.486**	7.486**	7.486***				4.426	4.426	4.426**
	NPL_AGR	-0.045	-0.045	-0.045				-0.089	-0.089	-0.0889**
	RES_A	0.401	0.401	0.401***				0.266	0.266	0.266**
	FU_CST_HHD	-0.023	-0.023	-0.023				-0.400	-0.400	-0.400*
	FU_CST_NFC	0.269	0.269	0.269				-0.254	-0.254	-0.254
	VK_LIAB	0.014*	0.014	0.014				0.006	0.006	0.006
	SHORTSEC_A	0.012	0.012	0.012				0.025	0.025	0.025
	OVDP_A	-0.010	-0.010	-0.010				0.056	0.056	0.0564*
	LIQ_A	0.200	0.200	0.200**				0.059	0.059	0.059
	TERMDEP_LIAB	-0.062	-0.062	-0.062*				-0.108	-0.108	-0.108***
	NADMEXP_EXP	0.004	0.004	0.004				-0.005	-0.005	-0.005
	PERSEXP_EXP	-0.007	-0.007	-0.007				0.011	0.011	0.011
	INTEXP_EXP	0.075	0.075	0.0753**				0.019	0.019	0.019
	INTREV_REV	-0.029	-0.029	-0.029				-0.014	-0.014	-0.014
Macro variables	LIQ				-0.242*	-0.242	-0.242***	-0.344*	-0.344*	-0.344***
	FSI				0.075***	0.075*	0.075**	0.047*	0.047*	0.047
	HHI_CRED				0.787**	0.787	0.787**	0.987*	0.987*	0.987***
	CPI				-0.150	-0.150	-0.150	-0.166	-0.166	-0.166
	RCRED_GR				0.256***	0.256**	0.256***	0.169**	0.169*	0.169**
	DC_100D_SHR				0.066***	0.066	0.066***	0.061***	0.061*	0.061***
	Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Time FE	Yes	Yes	Yes	No	No	No	No	No	No
	Heteroscedasticity	One-way clusterization	Two-way clusterization	HAC	One-way clusterization	Two-way clusterization	HAC	One-way clusterization	Two-way clusterization	HAC
	Autocorrelation			HAC			HAC			HAC
	N	3,960	3,960	3,960	3,960	3,960	3,960	3,960	3,960	3,960
	Within R^2	0.343	0.819	0.044	0.237	0.790	0.237	0.281	0.802	0.281

* p<0.05, ** p<0.01, *** p<0.001

Table 10. Panel Regression: Determinants of Transmission to Deposit Rates for Different Horizons, (2018m1 – 2023m12)

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Transmission horizon	3m		6m		9m		12m	
Bank-level variables	HHD_SHR	0.410	0.410***	0.860	0.860***	1.240	1.240***	1.450	1.450***
	P_VK	-0.010	-0.013*	-0.020	-0.020	-0.020	-0.020	-0.020	-0.020
	INTREV_A	-0.720	-0.720*	-1.200	-1.202*	-1.510	-1.513*	-1.710	-1.710*
	NPL_AGR	0.000	0.000	0.000	0.000	-0.010	-0.010	-0.020	-0.020
	RES_A	0.060	0.060**	0.120	0.120***	0.170*	0.170***	0.200*	0.200***
	FU_CST_HHD	0.120	0.115*	0.220	0.218*	0.300	0.300*	0.390	0.390**
	FU_CST_NFC	-0.050	-0.050	-0.100	-0.100	-0.140	-0.140	-0.170	-0.170
	VK_LIAB	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SHORTSEC_A	-0.020	-0.020*	-0.020	-0.020	-0.010	-0.010	-0.010	-0.010
	LIQ_A	0.050	0.050	0.080	0.080	0.090	0.090	0.090	0.090
	TERMDEP_LIAB	-0.020	-0.020	-0.020	-0.020	-0.020	-0.020	-0.010	-0.010
	NADMEXP_EXP	0.020	0.020**	0.020	0.020*	0.020	0.020*	0.020	0.020
	PERSEXP_EXP	0.010	0.010	0.020	0.020	0.030	0.030	0.040	0.040
	INTEXP_EXP	0.010	0.010	0.030	0.030	0.030	0.030	0.030	0.030
	INTREV_REV	0.000	0.000	0.000	0.000	0.010	0.010	0.010	0.010
Macro variables	LIQ	-0.300***	-0.300***	-0.500***	-0.500***	-0.540***	-0.540***	-0.580***	-0.580***
	FSI	-0.020*	-0.020*	-0.040*	-0.040**	-0.050**	-0.050**	-0.060**	-0.060**
	HHI_DEP	0.300*	0.300***	0.500*	0.500***	0.620**	0.620***	0.690**	0.690**
	CPI	-0.120	-0.120**	-0.250*	-0.250***	-0.350**	-0.350***	-0.420**	-0.420**
	RDEP_GR	-0.050	-0.050*	-0.100*	-0.100**	-0.130*	-0.130**	-0.160**	-0.160**
	DC_100D_SHR	0.020**	0.020***	0.035**	0.035***	0.042**	0.042***	0.045**	0.045**
	NORM_RES	0.001**	0.001***	0.002**	0.002***	0.002**	0.002***	0.002**	0.002**
	Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Time FE	No	No	No	No	No	No	No	No
	Heteroscedasticity	Two-way clusterization	HAC	Two-way clusterization	HAC	Two-way clusterization	HAC	Two-way clusterization	HAC
	Autocorrelation		HAC		HAC		HAC		HAC
	N	1,800	1,800	1,800	1,800	1,800	1,800	1,800	1,800
	Within R^2	0.990	0.700	0.960	0.710	0.940	0.710	0.920	0.710

* p<0.05, ** p<0.01, *** p<0.001

Table 11. Panel Regression: Determinants of Transmission to Credit Rates for Different Horizons, 2018m1 – 2023m12

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Transmission horizon	3m		6m		9m		12m	
Bank-level variables	NFCL_SHR	0.150	0.150**	0.270	0.270**	0.350	0.350***	0.400	0.400***
	P_VK	0.000	0.000	-0.010	-0.010	-0.010	-0.010	-0.010	-0.010
	INTREV_A	0.240	0.240	0.700	0.700	1.460	1.460*	2.080	2.080**
	NPL_AGR	-0.010	-0.010	-0.010	-0.010	-0.020	-0.020*	-0.030	-0.030*
	RES_A	0.000	0.000	0.020	0.020	0.030	0.030	0.050	0.050
	FU_CST_HHD	-0.010	-0.010	0.020	0.020	0.020	0.020	0.000	0.000
	FU_CST_NFC	0.060	0.060**	0.040	0.040	-0.010	-0.010	-0.060	-0.060
	VK_LIAB	0.004***	0.004**	0.006**	0.006*	0.006*	0.006*	0.010	0.010
	SHORTSEC_A	-0.010	-0.010**	-0.020	-0.020*	-0.020	-0.020	-0.020	-0.020
	OVDP_A	0.010	0.010**	0.030	0.030***	0.040	0.040***	0.040	0.050***
	LIQ_A	0.010	0.010	0.020	0.020	0.020	0.020	0.030	0.030
	TERMDEP_LIAB	-0.030*	-0.030*	-0.050*	-0.050***	-0.050	-0.050***	-0.060	-0.060
	NADMEXP_EXP	-0.010	-0.010	-0.010	-0.010	-0.010	-0.010	-0.010	-0.010
	PERSEXP_EXP	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	INTEXP_EXP	0.010	0.010**	0.010	0.010	0.010	0.010	0.020	0.020
	INTREV_REV	0.000	0.000	0.000	0.000	-0.010	-0.010	-0.010	-0.010
Macro variables	LIQ	-0.080***	-0.080***	-0.130**	-0.130***	-0.17**	-0.170***	-0.190**	-0.190***
	FSI	0.000	0.000	0.000	0.000	0.010	0.010	0.010*	0.010
	HHI_CRED	0.150***	0.150***	0.270**	0.270***	0.370**	0.370***	0.460**	0.460***
	CPI	0.002	0.002	-0.010	-0.010	-0.020	-0.020	-0.030	-0.030
	RCRED_GR	0.026***	0.026**	0.048**	0.048**	0.068**	0.068**	0.084**	0.084**
	DC_100D_SHR	0.007***	0.007**	0.012**	0.012**	0.018**	0.018**	0.023*	0.023**
	Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Time FE	No	No	No	No	No	No	No	No
	Heteroscedasticity	Two-way clusterization	HAC	Two-way clusterization	HAC	Two-way clusterization	HAC	Two-way clusterization	HAC
	Autocorrelation		HAC		HAC		HAC		HAC
	N	3,960	3,960	3,960	3,960	3,960	3,960	3,960	3,960
	Within R^2	0.997	0.293	0.992	0.303	0.983	0.303	0.973	0.302

* p<0.05, ** p<0.01, *** p<0.001

Table 12. Alternative Specifications of Regressions for Long-Run Transmission to Deposit Rates, 2018m1–2023m12

		(1)	(2)	(3)	(4)	(5)	(6)
Bank-level variables	HHD_SHR	2.050	2.050	2.048***	1.700	1.700	1.699***
	P_VK	-0.020	-0.020	-0.020	-0.020	-0.020	-0.020
	INTREV_A	-1.620	-1.620	-1.620	-1.470	-1.470	-1.470
	NPL_AGR	-0.020	-0.020	-0.020	-0.040	-0.040	-0.043*
	RES_A	0.353**	0.353**	0.353***	0.346**	0.346**	0.346***
	FU_CST_HHD	1.037*	1.037*	1.037***	0.540	0.540	0.536**
	FU_CST_NFC	-0.230	-0.230	-0.230	-0.230	-0.230	-0.230
	VK_LIAB	0.020	0.020	0.020	-0.020	-0.020	-0.020
	SHORTSEC_A	-0.090	-0.090	-0.086**	-0.020	-0.020	-0.020
	LIQ_A	-0.060	-0.060	-0.060	-0.020	-0.020	-0.020
	TERMDEP_LIAB	0.040	0.040	0.040	0.020	0.020	0.020
	NADMEXP_EXP	0.010	0.010	0.010	0.010	0.010	0.010
	PERSEXP_EXP	0.050	0.050	0.050	0.080	0.080	0.076**
	INTEXP_EXP	0.030	0.030	0.030	0.030	0.030	0.030
	INTREV_REV	0.027*	0.027*	0.027*	0.029*	0.029*	0.029**
Macro variables	LIQ				-0.731***	-0.731***	-0.731***
	FSI	-0.107***	-0.107**	-0.107***	-0.077***	-0.077**	-0.077***
	HHI_DEP	0.220	0.220	0.220	0.02	0.020	0.020
	CPI	-1.020***	-1.020***	-1.020***	-1.260***	-1.260***	-1.260***
	CPI^2				2.624**	2.624**	2.624***
	RDEP_GR	-0.502***	-0.502***	-0.502***	-0.250***	-0.250***	-0.250***
	DC_100D_SHR	0.059***	0.059**	0.059***	0.049**	0.049**	0.049***
	NORM_RES	0.004**	0.004**	0.004***	0.005**	0.005**	0.005***
	Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
	Time FE	No	No	No	No	No	No
	Heteroscedasticity	One-way clusterization	Two-way clusterization	HAC	One-way clusterization	Two-way clusterization	HAC
	Autocorrelation			HAC			HAC
	N	1,800	1,800	1,800	1,800	1,800	1,800
	Within R^2	0.671	0.864	0.671	0.701	0.876	0.701

* p<0.05, ** p<0.01, *** p<0.001

Table 13. Alternative Specifications of Regressions for Long-Run Transmission to Credit Rates, 2018m1–2023m12

		(1)	(2)	(3)	(4)	(5)	(6)
Bank-level variables	NFCL_SHR	0.540	0.540	0.542*	0.600	0.600	0.600*
	P_VK	-0.020	-0.020	-0.020	-0.020	-0.020	-0.020
	INTREV_A	4.700	4.700	4.695**	4.980	4.980	4.970**
	NPL_AGR	-0.100	-0.1000	-0.102***	-0.080	-0.080	-0.080**
	RES_A	0.290	0.290	0.287***	0.280	0.280	0.280**
	FU_CST_HHD	-0.310	-0.310	-0.310	-0.340	-0.340	-0.335*
	FU_CST_NFC	-0.220	-0.220	-0.220	-0.170	-0.170	-0.170
	VK_LIAB	0.010	0.010	0.010	0.010	0.010	0.010
	SHORTSEC_A	-0.010	-0.010	-0.010	0.020	0.020	0.020
	OVDP_A	0.050	0.050	0.050	0.060	0.060	0.060*
	LIQ_A	0.000	0.000	0.000	0.090	0.090	0.090
	TERMDEP_LIAB	-0.100	-0.100	-0.103***	-0.100	-0.100	-0.100**
	NADMEXP_EXP	0.000	0.000	0.000	0.000	0.000	0.000
	PERSEXP_EXP	0.020	0.020	0.020	0.010	0.010	0.010
	INTEXP_EXP	0.010	0.010	0.010	0.0300	0.0300	0.030
	INTREV_REV	-0.020	-0.020	-0.020	-0.02	-0.02	-0.020
Macro variables	LIQ				-0.494***	-0.494**	-0.494***
	FSI	0.046*	0.050	0.050	0.052**	0.052*	0.0521*
	HHI_CRED	1.439**	1.439*	1.439***	-0.010	-0.010	-0.010
	CPI	0.000	0.000	0.000	-1.097***	-1.097**	-1.097***
	CPI^2				2.788**	2.788**	2.788***
	RCRED_GR	0.314**	0.314**	0.314***	0.080	0.080	0.080
	DC_100D_SHR	0.081***	0.081*	0.081***	0.078***	0.078**	0.078***
	Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
	Time FE	No	No	No	No	No	No
	Heteroscedasticity	One-way clusterization	Two-way clusterization	HAC	One-way clusterization	Two-way clusterization	HAC
	Autocorrelation			HAC			HAC
	N	3,960	3,960	3,960	3,960	3,960	3,960
	Within R^2	0.273	0.800	0.273	0.289	0.804	0.289

* p<0.05, ** p<0.01, *** p<0.001

Table 14. Transmission to Deposit Rates vs Transmission to Credit Rates, 2018m1 – 2023m12

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Transmission horizon	3m		6m		9m		12m		LR	
Bank-level variables	HHD_SHR	0.330	0.330**	0.740	0.740***	1.090	1.090***	1.280	1.280***	1.690	1.690***
	P_VK	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	INTREV_A	-0.220	-0.220	-0.650	-0.650	-0.980	-0.980	-1.160	-1.160	-0.800	-0.800
	NPL_AGR	0.020	0.020*	0.020	0.020	0.010	0.010	0.000	0.000	-0.020	-0.020
	RES_A	0.020	0.020	0.060	0.060	0.090	0.090*	0.120	0.120**	0.210	0.210**
	FU_CST_HH	0.110	0.110	0.220	0.220*	0.350	0.350**	0.490	0.490**	1.100**	1.100***
	FU_CST_NFCL	-0.040	-0.040	-0.050	-0.050	-0.040	-0.040	-0.050	-0.050	0.000	0.000
	VK_LIAB	-0.040*	-0.040***	-0.060	-0.060***	-0.070	-0.070***	-0.080	-0.070***	-0.120*	-0.120***
	SHORTSEC_A	-0.030	-0.030**	-0.030	-0.030	-0.020	-0.020	-0.010	-0.010	-0.010	-0.010
	LIQ_A	0.050	0.050*	0.100	0.100*	0.130	0.130*	0.140	0.140*	0.120	0.120
	TERMDEP_LIAB	-0.040	-0.040***	-0.050	-0.050**	-0.060	-0.060**	-0.060	-0.060*	-0.060	-0.060
	NADMEXP_EXP	0.015*	0.015**	0.020	0.020*	0.020	0.020	0.020	0.020	0.010	0.010
	PERSEXP_EXP	0.010	0.010	0.020	0.020	0.030	0.030*	0.040	0.040*	0.080	0.080***
	NFCL_TR_3M	0.400*	0.400***								
	NFCL_TR_6M			0.280	0.280***						
	NFCL_TR_9M					0.190	0.190***				
	NFCL_TR_12M							0.150	0.150***		
	NFCL_TR									0.070	0.070***
Macro variables	LIQ	-0.280***	-0.280***	-0.470***	-0.470***	-0.600***	-0.600***	-0.650***	-0.650***	-0.720***	-0.720***
	FSI	-0.020*	-0.020**	-0.040*	-0.040**	-0.050*	-0.050**	-0.060*	-0.060***	-0.080**	-0.080***
	HHI_DEP	0.300*	0.300***	0.530**	0.530***	0.680**	0.680***	0.770**	0.770***	0.930**	0.930***
	CPI	-0.110	-0.110**	-0.220*	-0.220**	-0.310*	-0.310***	-0.360*	-0.360***	-0.490*	-0.490***
	RDEP_GR	-0.050	-0.050*	-0.090*	-0.090**	-0.120*	-0.120**	-0.150*	-0.150**	-0.210**	-0.210**
	DC_100D_SHR	0.020***	0.020***	0.037***	0.037***	0.050***	0.050***	0.050***	0.050***	0.060***	0.060***
	NORM_RES	0.001***	0.001***	0.002**	0.002***	0.003**	0.003***	0.003**	0.003***	0.003**	0.003***
	Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Time FE	No	No	No	No	No	No	No	No	No	No
	Heteroscedasticity	Two-way clusterization	HAC	Two-way clusterization	HAC	Two-way clusterization	HAC	Two-way clusterization	HAC	Two-way clusterization	HAC
	Autocorrelation		HAC		HAC		HAC		HAC		HAC
	N	1,656	1,656	1,656	1,656	1,656	1,656	1,656	1,656	1,656	1,656
	Within R^2	0.989	0.771	0.967	0.754	0.947	0.747	0.928	0.746	0.887	0.728

* p<0.05, ** p<0.01, *** p<0.001

Table 15. Transmission to Credit Rates vs Transmission to Deposit Rates, 2018m1 – 2023m12

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Transmission horizon	3m		6m		9m		12m		LR	
Bank-level variables	NFCL_SHR	0.220*	0.220***	0.300	0.300***	0.310	0.310**	0.320	0.320**	0.170	0.170
	P_VK	0.003	0.003	0.004	0.004	-0.010	-0.010	-0.010	-0.010	-0.010	-0.010
	INTREV_A	0.190	0.190	0.870	0.870	1.890*	1.890	2.640*	2.640*	5.140*	5.140*
	NPL_AGR	-0.050	-0.050***	-0.087*	-0.087***	-0.130*	-0.130***	-0.160*	-0.160***	-0.370**	-0.370***
	RES_A	0.020	0.020	0.050	0.050	0.090	0.090	0.120	0.120	0.290	0.290*
	FU_CST_HH	-0.110	-0.110*	-0.060	-0.060	-0.020	-0.020	-0.010	-0.010	0.040	0.040
	FU_CST_NFCL	0.150	0.150***	0.230	0.230***	0.210	0.210*	0.170	0.170	-0.090	-0.090
	VK_LIAB	0.049*	0.049***	0.050	0.050***	0.050	0.050*	0.050	0.050	0.080	0.080
	SHORTSEC_A	0.010	0.010	-0.010	-0.010	-0.030	-0.030	-0.040	-0.040	-0.020	-0.020
	OVDP_A	0.040	0.040***	0.070	0.070***	0.080	0.080**	0.080	0.080*	0.030	0.030
	LIQ_A	-0.050	-0.050*	-0.090	-0.090*	-0.140	-0.140*	-0.170	-0.170*	-0.340	-0.340*
	TERMDEP_LIAB	-0.010	-0.010	-0.020	-0.020	-0.030	-0.030	-0.030	-0.030	-0.010	-0.010
	NADMEXP_EXP	-0.010	-0.010*	-0.020	-0.020	-0.020	-0.020	-0.020	-0.020	-0.030	-0.030
	PERSEXP_EXP	0.020	0.020**	0.040	0.040**	0.050	0.050**	0.070	0.070**	0.120	0.120**
	HHD_TR_3M	0.270*	0.270***								
	HHD_TR_6M			0.200*	0.200***						
	HHD_TR_9M					0.150	0.150***				
	HHD_TR_12M							0.130	0.130**		
	HHD_TR									0.100	0.100
Macro variables	LIQ	-0.010	-0.010	-0.030	-0.030	-0.050	-0.050	-0.060	-0.060	-0.0700	-0.070
	FSI	0.010	0.010	0.010	0.010	0.020	0.020	0.020	0.020	0.05	0.050
	HHI_CRED	0.130	0.130*	0.250	0.250**	0.360	0.360*	0.440	0.440*	0.520	0.520
	CPI	0.030	0.030	0.030	0.030	0.030	0.030	0.020	0.020	-0.080	-0.080
	RCRED_GR	0.048**	0.048***	0.084**	0.084***	0.100**	0.100**	0.120**	0.120**	0.180	0.180*
	DC_100D_SHR	0.007***	0.007*	0.016***	0.016*	0.024***	0.024*	0.030***	0.030*	0.055**	0.055*
	Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Time FE	No	No	No	No	No	No	No	No	No	No
	Heteroscedasticity	Two-way clusterization	HAC	Two-way clusterization	HAC	Two-way clusterization	HAC	Two-way clusterization	HAC	Two-way clusterization	HAC
	Autocorrelation		HAC		HAC		HAC		HAC		HAC
	N	1,656	1,656	1,656	1,656	1,656	1,656	1,656	1,656	1,656	1,656
	Within R^2	0.998	0.492	0.991	0.455	0.977	0.434	0.96	0.422	0.839	0.375

* p<0.05, ** p<0.01, *** p<0.001

Table 16. Determinants of Transmission to Deposit Rates for Different Horizons, 2018m1 – 2023m12, (two largest banks excluded)

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Transmission horizon	3m		6m		9m		12m		LR	
Bank-level variables	HHD_SHR	0.280	0.282*	0.640	0.638*	0.950	0.947**	1.040	1.043*	0.760	0.760
	P_VK	-0.020	-0.019**	-0.030	-0.028**	-0.030	-0.031*	-0.030	-0.031*	-0.030	-0.030
	INTREV_A	-0.750	-0.753*	-1.240	-1.239*	-1.540	-1.542*	-1.720	-1.717*	-1.530	-1.530
	NPL_AGR	0.000	0.000	-0.010	-0.010	-0.010	-0.010	-0.020	-0.020	-0.030	-0.030
	RES_A	0.108*	0.108***	0.197*	0.197***	0.257**	0.257***	0.300**	0.300***	0.400**	0.400***
	FU_CST_HH	0.010	0.010	0.040	0.040	0.070	0.070	0.130	0.130	0.390	0.392*
	FU_CST_NFCL	-0.060	-0.060	-0.120	-0.120	-0.160	-0.160*	-0.180	-0.181*	-0.100	-0.100
	VK_LIAB	0.010	0.010	0.010	0.010	0.020	0.020	0.020	0.020	0.020	0.020
	SHORTSEC_A	-0.030	-0.027**	-0.030	-0.030	-0.020	-0.020	-0.020	-0.020	-0.030	-0.030
	LIQ_A	0.020	0.020	0.020	0.020	0.020	0.020	0.010	0.010	-0.080	-0.080
	TERMDEP_LIAB	0.000	0.000	0.010	0.010	0.020	0.020	0.020	0.020	0.030	0.030
	NADMEXP_EXP	0.010	0.013*	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020
	PERSEXP_EXP	-0.005	-0.005	-0.010	-0.010	-0.010	-0.010	-0.010	-0.010	0.030	0.030
	INTEXP_EXP	0.036*	0.036***	0.061*	0.061***	0.072*	0.072***	0.080*	0.080***	0.070	0.070**
	INTREV_REV	-0.000	-0.000	0.002	0.002	0.005	0.005	0.008	0.008	0.025*	0.025*
Macro variables	LIQ	-0.260***	-0.260***	-0.400***	-0.400***	-0.470***	-0.470***	-0.500***	-0.500***	-0.480***	-0.480***
	FSI	-0.020	-0.020*	-0.033*	-0.033*	-0.044*	-0.044**	-0.050*	-0.050**	-0.070**	-0.070***
	HHI_DEP	-2.940***	-2.940***	-5.120***	-5.120***	-6.530***	-6.530***	-7.280***	-7.280***	-8.330***	-8.330***
	CPI	-0.170**	-0.170***	-0.340***	-0.340***	-0.470***	-0.470***	-0.550***	-0.550***	-0.790***	-0.790***
	RDEP_GR	-0.080**	-0.080***	-0.160***	-0.160***	-0.200***	-0.200***	-0.250***	-0.250***	-0.340***	-0.340***
	DC_100D_SHR	0.002	0.002	-0.002	-0.002	-0.010	-0.010	-0.010	-0.010	-0.010	-0.010
	NORM_RES	0.001**	0.001***	0.002**	0.002***	0.002**	0.002***	0.003**	0.003***	0.003*	0.003***
	Banks FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Time FE	No	No	No	No	No	No	No	No	No	No
	Heteroscedasticity	Two-way clusterization	HAC	Two-way clusterization	HAC	Two-way clusterization	HAC	Two-way clusterization	HAC	Two-way clusterization	HAC
	Autocorrelation		HAC		HAC		HAC		HAC		HAC
	N	1,656	1,656	1,656	1,656	1,656	1,656	1,656	1,656	1,656	1,656
	Within R^2	0.987	0.747	0.959	0.749	0.936	0.754	0.916	0.758	0.901	0.75

* p<0.05, ** p<0.01, *** p<0.001

Table 17. Determinants of Transmission to Deposit Rates for Different Horizons, 2018m1 – 2023m12, (nonlinear effects of market concentration)

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Transmission horizon	3m		6m		9m		12m		LR	
Bank-level variables	HHD_SHR	0.340	0.342**	0.750	0.751***	1.110	1.114***	1.320	1.317***	1.730	1.733***
	HHD_SHR_inter	0.010	0.010	0.010	0.010	0.010	0.010	0.020	0.020	0.050	0.050
	P_VK	-0.010	-0.010	-0.010	-0.010	-0.010	-0.010	-0.010	-0.010	-0.010	-0.010
	INTREV_A	-0.760	-0.760*	-1.270	-1.270*	-1.590	-1.590*	-1.800	-1.800*	-1.760	-1.760
	NPL_AGR	0.000	0.000	-0.010	-0.010	-0.020	-0.020	-0.020	-0.020	-0.040	-0.040
	RES_A	0.050	0.050**	0.110	0.110***	0.161*	0.161***	0.199*	0.199***	0.350**	0.350***
	FU_CST_HH	0.040	0.040	0.100	0.100	0.170	0.170	0.250	0.250	0.620	0.620**
	FU_CST_NFCL	-0.050	-0.050	-0.110	-0.110	-0.150	-0.150	-0.170	-0.170*	-0.170	-0.170
	VK_LIAB	-0.002	-0.002	-0.005	-0.005	-0.010	-0.010	-0.010	-0.010	-0.010	-0.010
	SHORTSEC_A	-0.020	-0.020*	-0.020	-0.020	-0.020	-0.020	-0.010	-0.010	-0.010	-0.010
	LIQ_A	0.040	0.040	0.070	0.070	0.080	0.080	0.080	0.080	0.010	0.010
	TERMDEP_LIAB	-0.020	-0.020*	-0.020	-0.020	-0.020	-0.020	-0.010	-0.010	0.010	0.010
	NADMEXP_EXP	0.010	0.010*	0.020	0.020*	0.020	0.020	0.020	0.020	0.010	0.010
	PERSEXP_EXP	0.020	0.020*	0.030	0.030*	0.040	0.040*	0.040	0.040*	0.080	0.080**
	INTEXP_EXP	0.010	0.010	0.020	0.020	0.020	0.020	0.030	0.030	0.030	0.030
	INTREV_REV	0.002	0.002	0.005	0.005	0.010	0.010	0.010	0.010	0.031**	0.031**
Macro variables	LIQ	-0.290***	-0.290***	-0.440***	-0.440***	-0.530***	-0.530***	-0.570***	-0.570***	-0.560***	-0.560***
	FSI	-0.030**	-0.030***	-0.050***	-0.050***	-0.070***	-0.070***	-0.080***	-0.080***	-0.100***	-0.100***
	HHI_DEP	0.390**	0.390***	0.610**	0.610***	0.720**	0.720***	0.780**	0.780***	0.750*	0.750***
	HHI_DEP_inter	0.021*	0.021***	0.035*	0.035***	0.044*	0.044***	0.047*	0.047***	0.047*	0.047***
	CPI	-0.120	-0.120**	-0.200*	-0.250***	-0.350**	-0.350***	-0.400**	-0.400***	-0.590**	-0.590***
	RDEP_GR	-0.040	-0.040	-0.090	-0.090*	-0.121*	-0.121**	-0.145*	-0.145**	-0.216**	-0.216**
	DC_100D_SHR	0.018**	0.018***	0.027**	0.027***	0.032*	0.032***	0.034*	0.034***	0.032*	0.032*
	NORM_RES	0.001**	0.001***	0.002**	0.002***	0.002*	0.002***	0.002*	0.002***	0.003*	0.003**
	Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Time FE	No	No	No	No	No	No	No	No	No	No
	Heteroscedasticity	Two-way clusterization	HAC	Two-way clusterization	HAC	Two-way clusterization	HAC	Two-way clusterization	HAC	Two-way clusterization	HAC
	Autocorrelation		HAC		HAC		HAC		HAC		HAC
	N	1,800	1,800	1,800	1,800	1,800	1,800	1,800	1,800	1,800	1,800
	Within R^2	0.987	0.715	0.963	0.716	0.943	0.72	0.922	0.723	0.877	0.701

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Table 18. Determinants of Transmission to Credit Rates for Different Horizons, 2018m1 – 2023m12 (nonlinear effects of market concentration)

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Transmission horizon	3m		6m		9m		12m		LR	
Bank-level variables	NFCL_SHR	0.170	0.173**	0.300	0.301***	0.390	0.386***	0.450	0.451***	0.760	0.756**
	NFCL_SHR_inter	-0.010	-0.010	-0.020	-0.020	-0.030	-0.030	-0.030	-0.030	-0.060	-0.060
	P_VK	0.000	0.000	-0.010	-0.010	-0.010	-0.010	-0.010	-0.010	-0.020	-0.020
	INTREV_A	0.240	0.240	0.710	0.710	1.470	1.470*	2.090	2.090**	4.470	4.470**
	NPL_AGR	-0.010	-0.010	-0.010	-0.010	-0.020	-0.020*	-0.030	-0.027*	-0.090	-0.090**
	RES_A	0.000	0.000	0.020	0.020	0.030	0.030	0.050	0.050	0.270	0.266**
	FU_CST_HH	-0.010	-0.010	0.020	0.020	0.020	0.020	0.000	0.000	-0.400	-0.396*
	FU_CST_NFCL	0.060	0.060**	0.040	0.040	-0.010	-0.010	-0.060	-0.060	-0.250	-0.250
	VK_LIAB	0.004***	0.004**	0.006**	0.006*	0.007*	0.007*	0.010	0.010	0.010	0.010
	SHORTSEC_A	-0.010	-0.010**	-0.020	-0.018*	-0.020	-0.020	-0.020	-0.020	0.030	0.030
	OVDP_A	0.010	0.010**	0.030	0.030***	0.040	0.040***	0.050	0.050***	0.060	0.057*
	LIQ_A	0.010	0.010	0.020	0.020	0.020	0.020	0.030	0.030	0.060	0.060
	TERMDEP_LIAB	-0.030*	-0.030***	-0.050*	-0.050***	-0.050	-0.050***	-0.060	-0.060***	-0.110	-0.100***
	NADMEXP_EXP	-0.010	-0.010	-0.010	-0.010	-0.010	-0.010	-0.010	-0.010	0.000	0.000
	PERSEXP_EXP	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.010	0.010
	INTEXP_EXP	0.010	0.011**	0.010	0.010	0.010	0.010	0.020	0.020	0.020	0.020
	INTREV_REV	-0.003	-0.003	-0.005	-0.005	-0.010	-0.010	-0.010	-0.010	-0.010	-0.010
Macro variables	LIQ_5	-0.090***	-0.090***	-0.140**	-0.140***	-0.170**	-0.170***	-0.200**	-0.200***	-0.300*	-0.300***
	FSI	-0.000	-0.000	0.004	0.004	0.010	0.010	0.010	0.010	0.050*	0.050
	HHI_CRED	0.156**	0.156***	0.268**	0.268***	0.376**	0.376***	0.467**	0.467***	1.020*	1.020***
	HHI_CRED_inter	0.002	0.002	0.002	0.002	0.001	0.001	-0.000	-0.000	-0.010	-0.010
	CPI	0.002	0.002	-0.010	-0.010	-0.020	-0.020	-0.030	-0.030	-0.170	-0.170
	RCRED_GR	0.026***	0.026**	0.048**	0.048**	0.068**	0.068**	0.084**	0.084**	0.170*	0.170**
	DC_100D_SHR	0.007***	0.007**	0.012**	0.012**	0.018**	0.018**	0.023**	0.023**	0.061*	0.060***
	Banks FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Time FE	No	No	No	No	No	No	No	No	No	No
	Heteroscedasticity	Two-way clusterization	HAC	Two-way clusterization	HAC	Two-way clusterization	HAC	Two-way clusterization	HAC	Two-way clusterization	HAC
	Autocorrelation		HAC		HAC		HAC		HAC		HAC
	N	3,960	3,960	3,960	3,960	3,960	3,960	3,960	3,960	3,960	3,960
	Within R^2	0.997	0.293	0.992	0.303	0.983	0.303	0.973	0.302	0.802	0.281

* p<0.05, ** p<0.01, *** p<0.001

Table 19. Determinants of Transmission to Deposit Rates, 2015m1 – 2023m12

	(1)	(2)	(3)	(4)
	LR			
LIQ_5	-1.055***	-1.057***	-1.055***	-1.057***
FSI	0.104*	0.020	0.104***	0.020
HHI_DEP	1.572***	1.487***	1.572***	1.487***
RDEP_GR	0.090	-0.020	0.090	-0.020
DC_100D_SHR	0.126***	0.077***	0.126***	0.077***
NORM_RES	0.000	0.000	0.000	0.002***
CPI	0.080	-0.437*	0.080	-0.437***
CPI^2		0.724**		0.724***
Bank FE	Yes	Yes	Yes	Yes
Time FE	No	No	No	No
Heteroscedasticity	Two-way clusterization	Two-way clusterization	HAC	HAC
Autocorrelation			HAC	HAC
N	2,659	2,659	2,659	2,659
Within R^2	0.71	0.72	0.36	0.37

* p<0.05, ** p<0.01, *** p<0.001

Table 20. Determinants of Transmission to Credit Rates, 2015m1 – 2023m12

	(1)	(2)	(3)	(4)
	LR			
LIQ_5	-0.297	-0.327*	-0.297***	-0.327***
FSI	0.112***	0.037	0.112***	0.037
HHI_CRED	0.813***	0.599**	0.813***	0.599***
RCRED_GR	0.092*	0.125**	0.093***	0.125***
DC_100D_SHR	0.084***	0.042	0.084***	0.042**
CPI	-0.059	-0.424**	-0.059	-0.424***
CPI^2		0.759***		0.759***
Banks FE	Yes	Yes	Yes	Yes
Time FE	No	No	No	No
Heteroscedasticity	Two-way clusterization	Two-way clusterization	HAC	HAC
Autocorrelation			HAC	HAC
N	5,807	5,807	5,807	5,807
Within R^2	0.726	0.729	0.147	0.156

* p<0.05, ** p<0.01, *** p<0.001

APPENDIX B. FIGURES

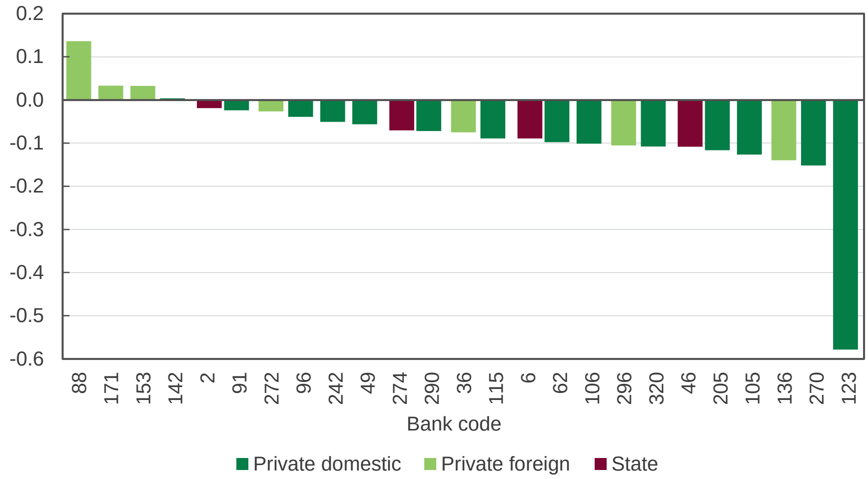


Figure 7. Asymmetry of Transmission to Deposit Rates (a negative sign means the response to a decrease in the market rate is stronger)

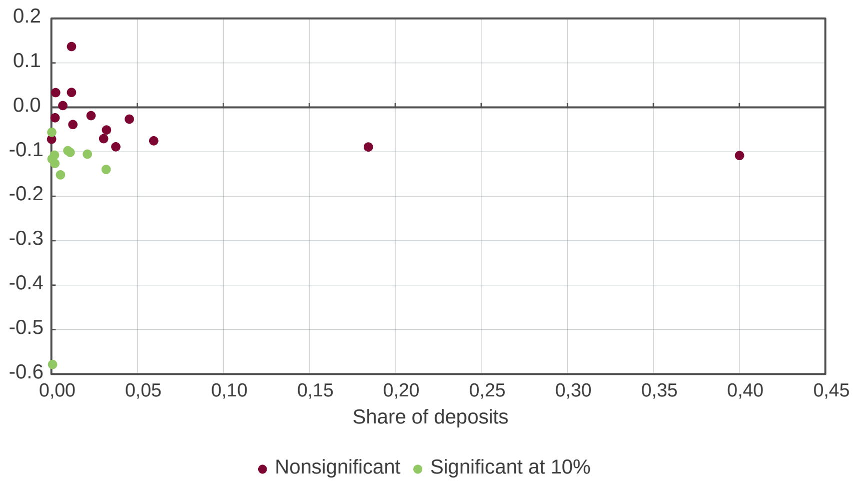


Figure 8. Pass-Through Asymmetry for Deposits and Share of Deposits

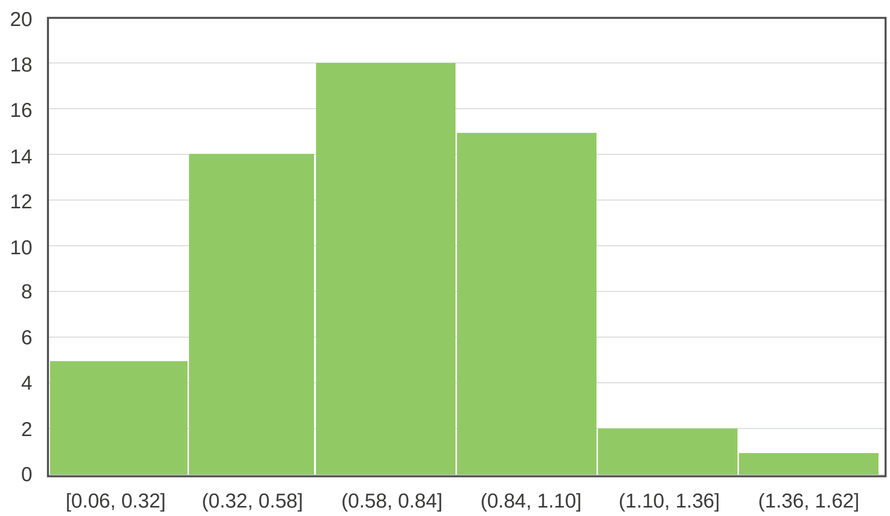


Figure 9. Histogram Plot of the Long-Run Pass-Through for NFC Loans

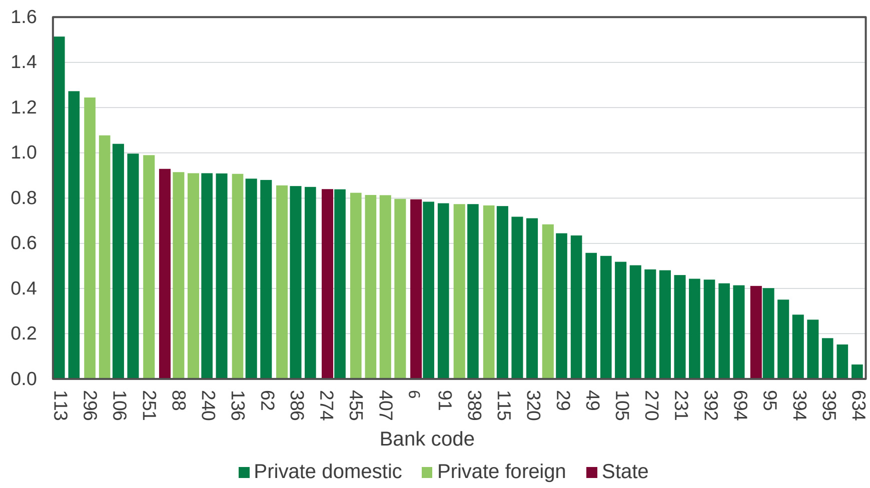


Figure 10. Long-Run Pass-Through for NFC Loans

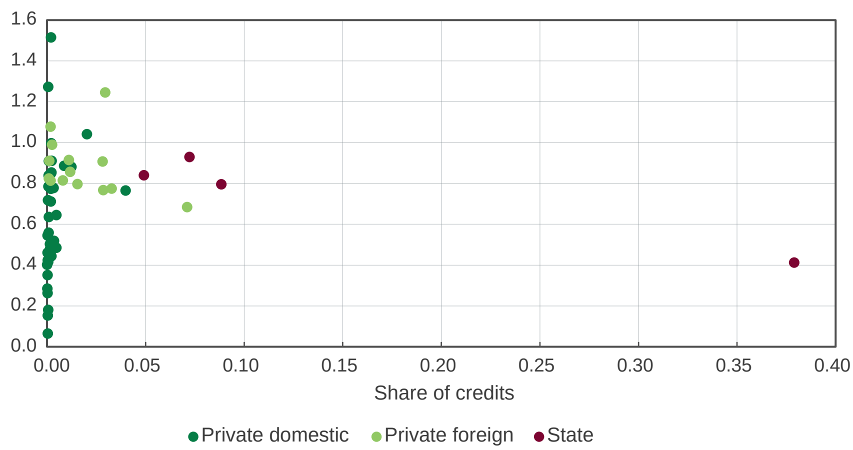


Figure 11. Long-Run Pass-Through for NFC Loans and Share of NFC Loans

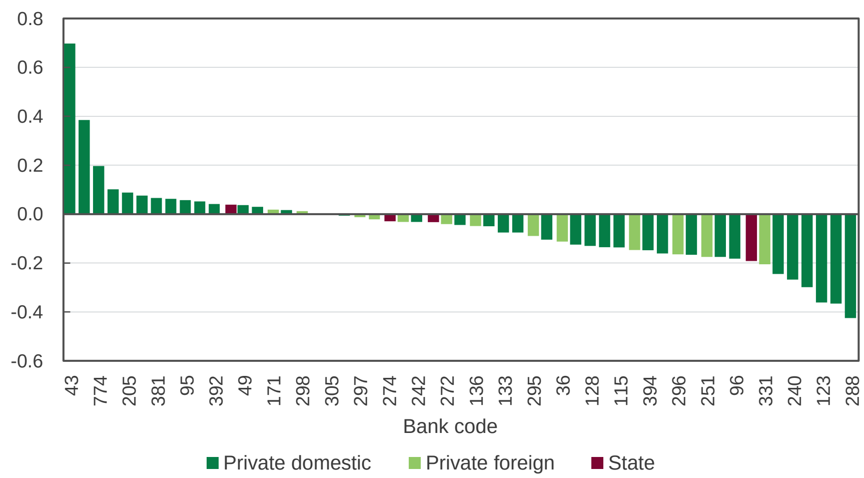


Figure 12. Asymmetry of Transmission to Credit Rates (a negative sign means the response to a decrease in the market rate is stronger), transmission asymmetry, bank code

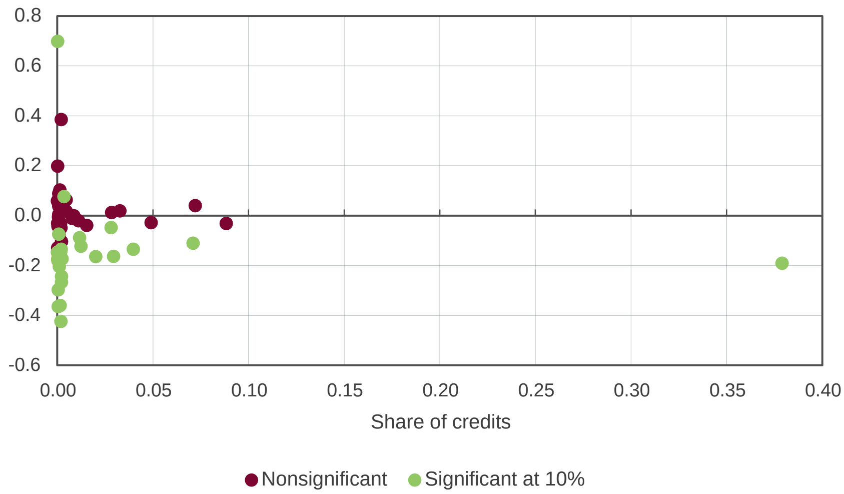
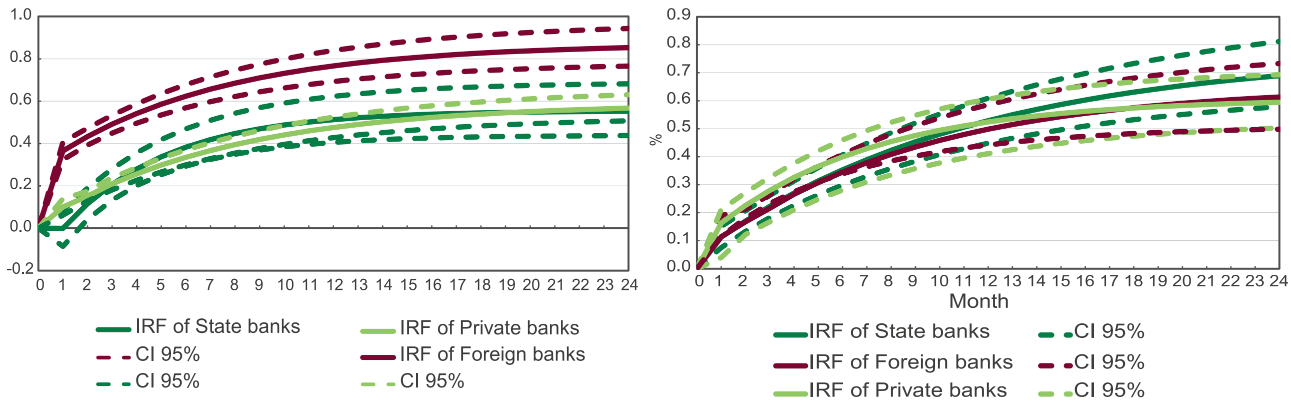


Figure 13. Long-Run Pass-Through for NFC Loans and Share of Loans



A) Credit rate

B) Deposit rates

Figure 14. Impulse Response Functions for State, Foreign, and Domestic Private Banks, %, month

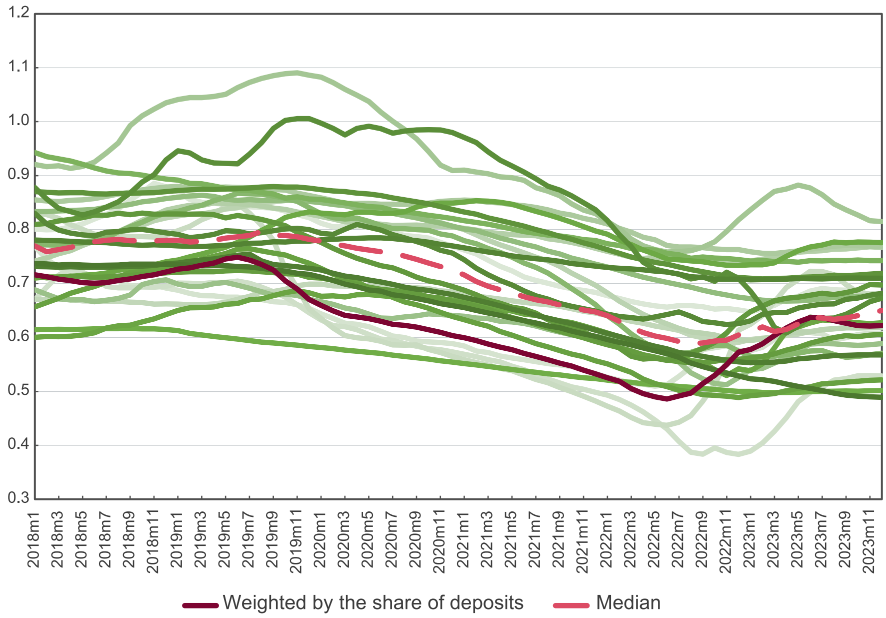


Figure 15. Time Variant Pass-Through for Deposit Rates, long-run[15]

[15] Lines of different green tones correspond to separate banks.

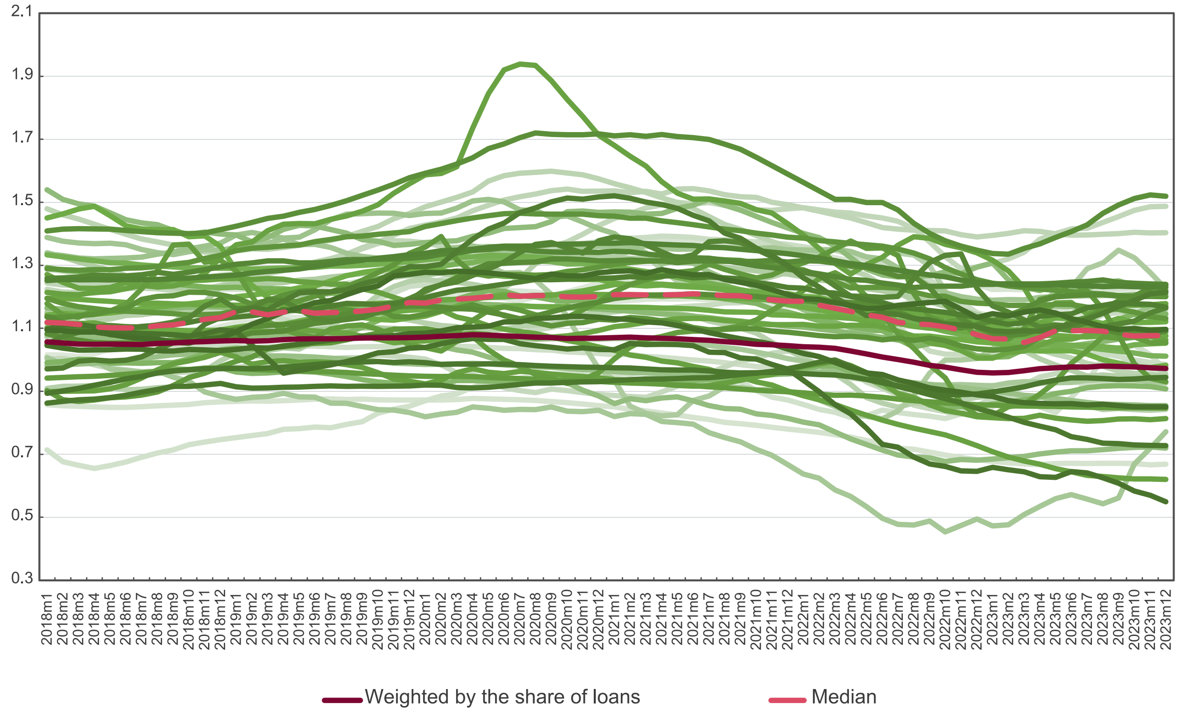


Figure 16. Time Variant Pass-Through for NFC Loan Rates, long-run

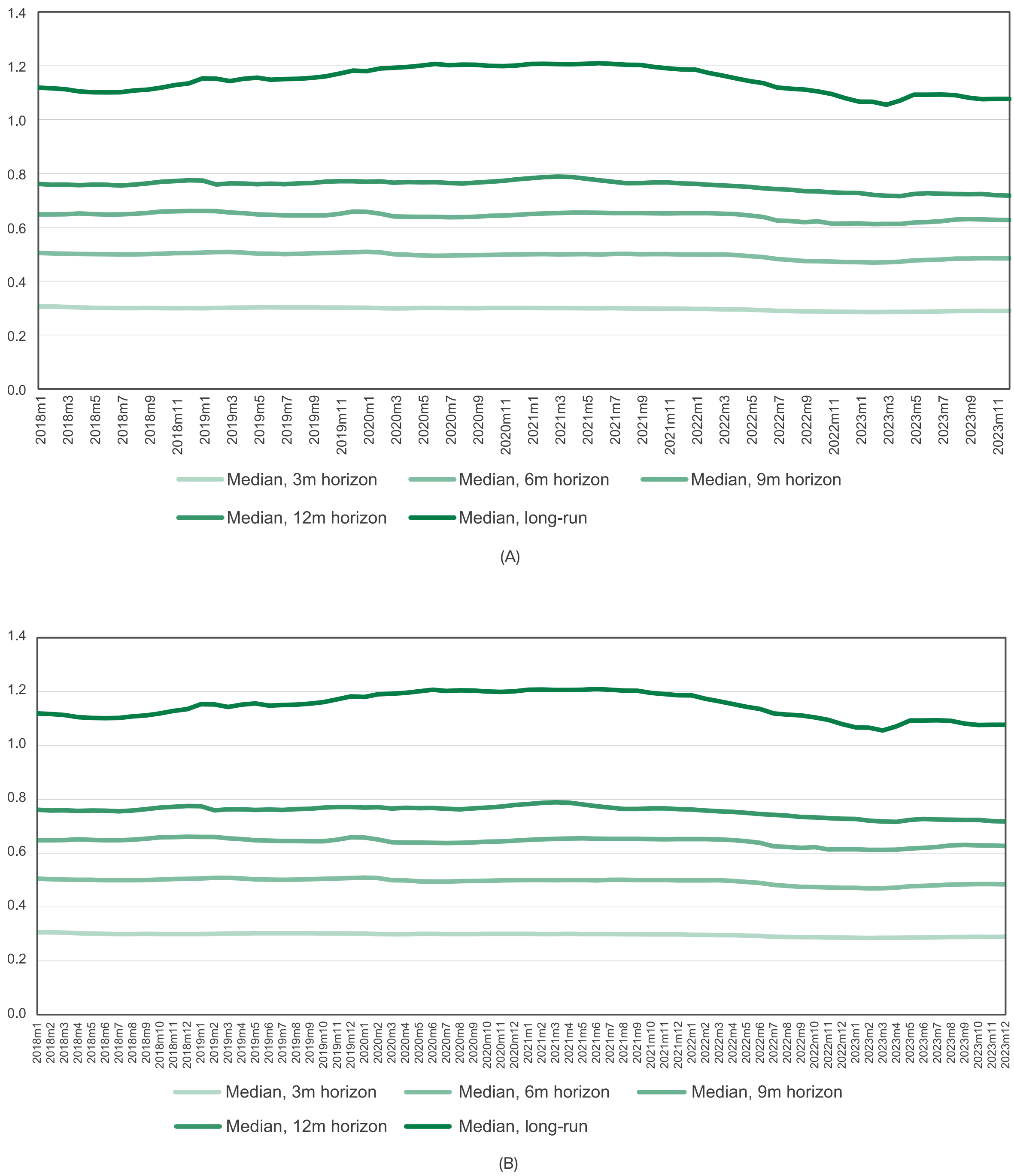


Figure 17. Time-Varying Pass-Through for (A) Deposit Rates and (B) Credit Rates on Different Horizons

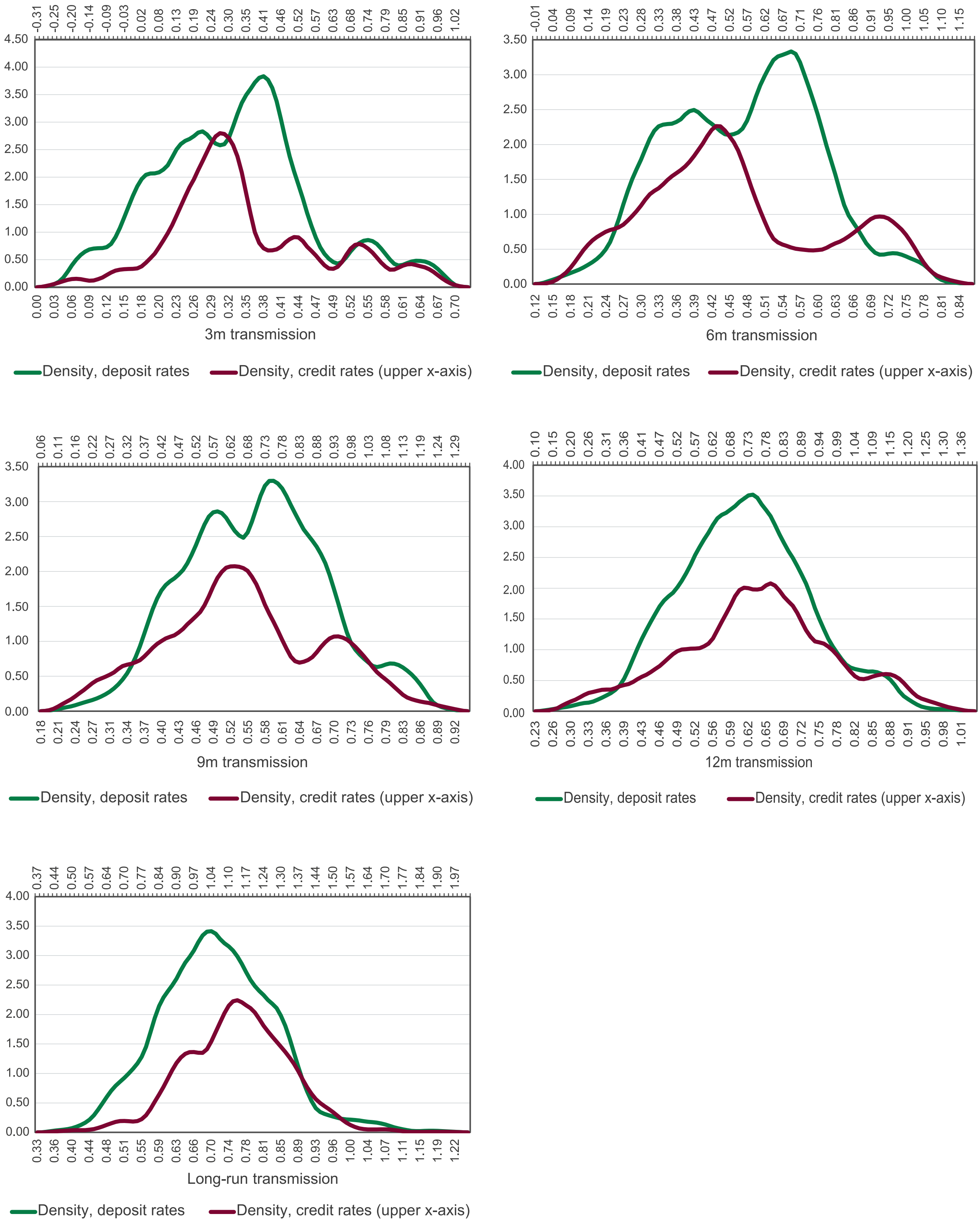


Figure 18. Kernel Densities of Pass-Through Strength on Different Horizons

A) B)

Figure 19. Time-Varying Transmission Strength of the Banks that Changed Ownership Status, (A) – deposit rates, (B) – credit rates

Note: Dots on the plots mark months when ownership status has been changed. The median is estimated for the subsample excluding banks with ownership changes. Confidence intervals were estimated as +/- 1.96*s.e.

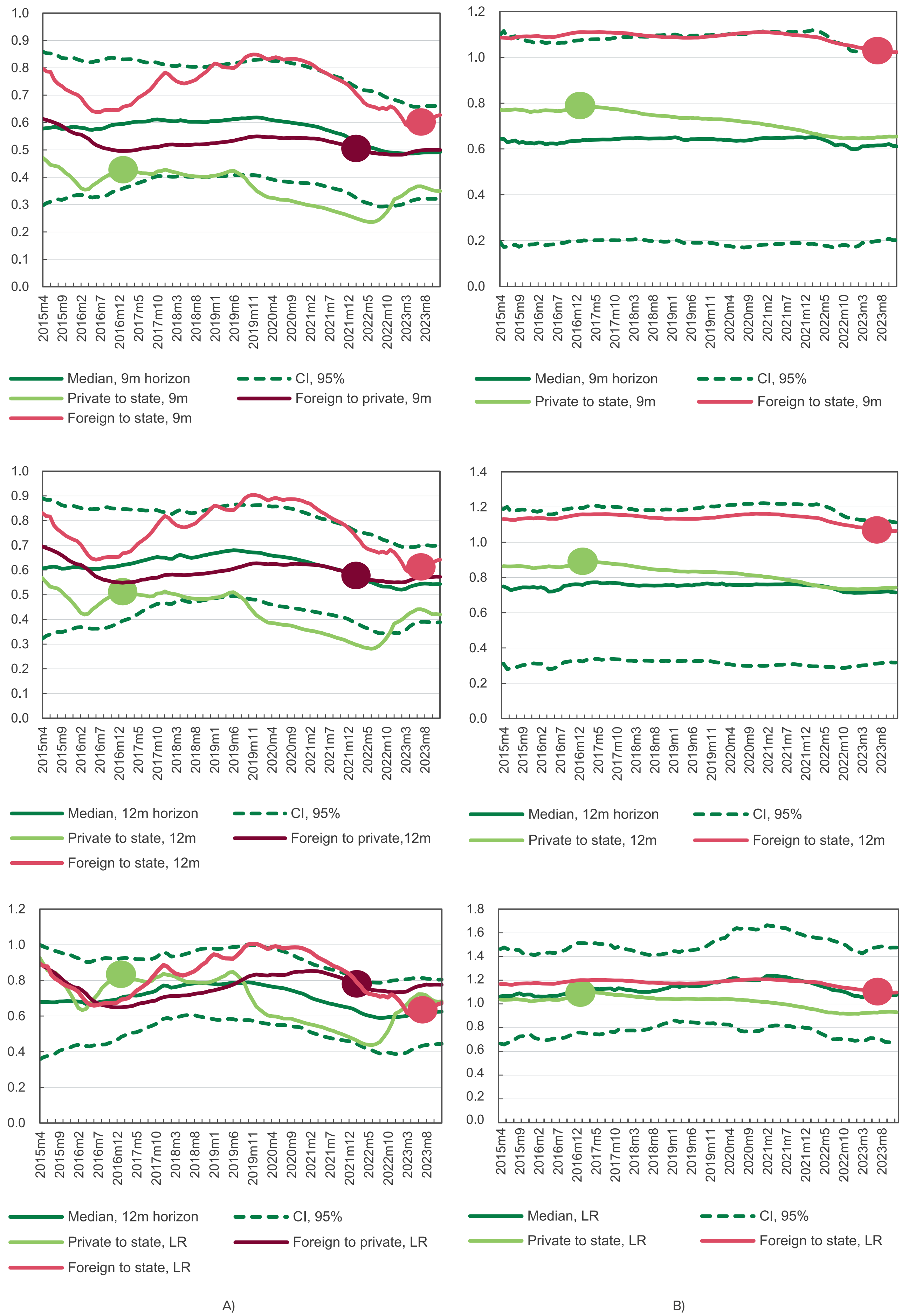


Figure 19 (continued). Time-Varying Transmission Strength of the Banks that Changed Ownership Status, (A) – deposit rates, (B) – credit rates

Figure 20. Transmission to Deposit Rates: Parameters of Baseline Specification for Different Groups of Banks

Figure 21. Transmission to Credit Rates: Parameters of Baseline Specification for Different Groups of Banks