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Can central banks be heard over the sound of gunfire?

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Abstract

In this study, we examined the effectiveness of central bank communications during times of significant adverse shocks. Specifically, we examined how the National Bank of Ukraine (NBU) regulated foreign exchange (FX) markets during the Russo-Ukrainian War in 2022. Data collected from both the black and authorized FX markets suggested that the content of the NBU's announcements significantly impacted FX market agents. Announcements aimed at maintaining a fixed (floating) FX rate prompted an increase (decrease) in the black market premium in cash transactions. Moreover, the NBU's announcements influenced the sale side of foreign currency more than any other aspect, an area where the black market FX traders held near monopolistic power.

JEL CLASSIFICATION
D83, E44, E58, F31

1 | INTRODUCTION

Central bank communications are one of the most important policy tools by which a central bank supports its objectives and manages public expectations (Woodford, 2001). An established and simple method used to evaluate the effectiveness of central bank communications is to examine the reaction of the economy and

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financial markets to developments within central banks. For instance, Rosa (2011) has investigated the effect of the Federal Reserve's decisions and statements made in relation to U.S. stock market indices and found that the latter can have a greater impact. Moreover, Gorodnichenko et al. (2023) and Hayo and Zahner (2023) have demonstrated that sentiment conveyed in central bank announcements, and even the voice of the speaker, can influence financial markets. However, most previous studies conducted on central bank communications have focused on Western Economies that typically operate in low-volatility environments. By extension, we take a step further by examining the reactions to central bank announcements during a full-scale war, one of the most severe shocks that any country can face.

During times of significant exogenous shocks to the economy, assessing the impact and effectiveness of central bank communications becomes increasingly challenging. Hayo and Neuenkirch (2015) and Vayid (2013) have investigated the role of central bank communications during a subprime crisis. Cieslak and Schrimpf (2019) and Égert and Kočenda (2014) find that the nonmonetary policy announcements related to economic growth and financial risks significantly drive the stock market during periods of financial crisis. Beyond that, Unsal and Garbers (2021) have studied the effects of the COVID-19 pandemic on world economies and found that it forced central banks to resort to using extraordinary, unconventional measures such as quantitative easing, foreign exchange (FX) intervention, and even direct lending to major corporations. However, while all of these studies have examined significant economic shocks, none of those shocks have had as severe an impact on the economy and financial markets as a military conflict that has led to massive economic destruction. This study aims to fill that gap by examining the effectiveness of central bank communications under extreme stress, specifically in the case of Ukraine during the Russo-Ukrainian War. While researchers typically examine stock market reactions to central bank communications, we choose not to do so due to the underdeveloped stock market in Ukraine. Instead, this paper investigates the responses of the black market for foreign currency in Ukraine to announcements released by the National Bank of Ukraine (NBU) in 2022.

The Ukrainian black FX market provides an ideal laboratory for exploring our primary research question. The interplay of the dollarization of the economy, a fixed exchange rate, and initially negative expectations about the prospect of the Russo-Ukrainian War decreased the demand for UAH relative to USD. The consequence was a downward pressure on its exchange rate, which fuelled the black market for USD. As a result, for many individuals, exchanging USD for UAH using the NBU's official rate lost its appeal. The mirror transaction, that is, purchasing foreign currency for Ukrainian hryvnia from an authorized agent, became next to impossible when commercial institutions were no longer willing to part with their foreign reserves at below market-clearing prices. In response, as individuals sought more favorable exchange rates for their USD holdings, a black market for foreign currencies emerged. Thus, anyone wanting to convert their cash holdings of USD into UAH would receive a more favorable exchange rate than the official rate. In addition to this, the black market offered a rare possibility to purchase foreign currency for UAH, albeit at a significant markup. Those markups constitute the black market FX premium, which we use as the main response variable in our analysis.

A black market premium (BMP) is not a phenomenon unique to Ukraine (Fardmanesh and Douglas, 2008). In the literature, it refers to the percentage difference in exchange rates between the official exchange rate set by the authorities and the rate at which foreign currency can be obtained through the black market (Bahmani-Oskooee, 2002). The existence of a BMP often signifies restrictions on the availability of FX, as individuals may be willing to pay a premium to obtain access to foreign currencies via unofficial channels (Fishelson, 1988). Several factors have been identified as contributing to the emergence of BMPs, including a currency control policy and FX restrictions. For example, Fardmanesh and Douglas (2008) have shown that FX controls and expansionary monetary policy exert a positive effect on BMPs. Similarly, Cerra (2016) found that a capital control policy can create a shortage in the supply of foreign currency and drive up its price on the black market. In addition to this, Acharyya (2001) has examined the link between exchange rate policies and BMPs through the income effect and export quality channels and has shown that they work in opposite directions.

To calculate the BMP, we take advantage of the unique situation in Ukraine that resulted in the coexistence of three different UAH-USD exchange rates and, as a result, three datasets. The first is the official interbank exchange rate, which is directly set by the NBU and was fixed on February 24, 2022.[1] The second source consists of buy and sell quotes from 35 authorized banks and 49 non-bank financial organizations.[2] These institutions have an NBU-issued license to trade foreign currencies using cash transactions. The third resource consists of the median daily black market buy and sell quotes in 23 Ukrainian cities. Consequently, we measure the BMP on the agent–city–day level as being the difference between agent prices and the black market price medians in the same city in which the agent is located.

Our chief explanatory variable is constructed based on the FX-related announcements issued by the NBU, a type of news source widely used as a measure of central bank communications. For instance, Cieslak and Schrimpf (2019) used the news released by the central bank as a proxy for the central bank communications. There are multiple advantages to taking such an approach. First, official announcements published by the NBU offer an accessible, open resource in which policy actions and news are updated in real time. Second, the standardized announcements archive allows for the measurement of the communication sentiment in consistent ways, thereby providing a systematic structure for analyzing and understanding how central bank communications can affect the black market. We, thus, downloaded the NBU's FX-related announcements and used ChatGPT to quantify the sentiment (content) embedded in the textual announcements.[3] Using ChatGPT, we analyzed the announcements and constructed a continuous index, ranging from −1 to +1, that characterizes the announcements as being either more float- or more fixed-intended.

Our results suggest that central bank communications remain an effective tool, even in times of heightened distress. In particular, they indicate that the FX market closely follows the NBU's announcements, and these have a notable effect on its sell-side quotes and the BMP. For example, by the end of a week, the movement of the BMP for the “sell” quotes in response to a “fix-intended” announcement is 1.8 percentage points, but only 1.3 percentage points for the “buy” side. Furthermore, the “buy” side's response appears to be delayed relative to the “sell” side's response. This may be because, during the war, when the official exchange rate has been lower than the market-clearing equilibrium, the black market has been the sole option for parties seeking to buy USD. Moreover, there is evidence that the content of “fix-intended” announcements exert a greater influence on the FX market than any content indicating a “float” sentiment. This evidence may indicate that the market views “fix-intended” announcements as being more credible and, thus, responds to them more strongly. Indeed, because the NBU has not returned to the floating exchange rate system since the beginning of the war, all fix-intended announcements have been backed up by the NBU's actions: that is, continuing to maintain the fixed exchange rate.

Our paper also makes important contributions across several other dimensions. For one, it discusses the consequences of central bank regulation on the FX market and highlights some of its successes and failures. It is an established fact that central bank communications transmitted via channels such as interviews and announcements, as well as policy actions, can trigger significant market movements (Pescatori, 2018; Ranaldo & Rossi, 2010). However, whether a central bank announcement actually drives the market in the intended direction is rarely examined. Additionally, this paper expands the literature on the consequences of war, one notable economic outcome of which is the BMP (Fishelson, 1988; Pinto, 1991; Schiumerini & Steinberg, 2020). Although the existing literature describes the connection between the black market and macro-level information, such as political corruption, inflation and economic sanctions, it typically examines professional actors (Cerra, 2019; Zamani et al., 2021). Whether or not non-professionals, members of the general public as well as

[1]Since then, the NBU has adjusted the UAH/USD rate only once on July 21, 2022.

[2]Throughout this paper, when we identify the side of the market as being “buy” or “sell”, we are taking the agency's perspective, not the perspective of the private individual seeking to exchange currency.

[3]As a robustness check, we repeat the analysis using a more traditional textual analysis method, similar to Baker et al. (2016).

underground dealers, respond to central bank communications has been an open question. Last, the paper contributes to the literature on analyzing central bank communications (Bianchi et al., 2022; Hayo & Neuenkirch, 2015). To our knowledge, this is the first study to use artificial intelligence (i.e., Chat-GPT) to analyze and classify central bank announcements. Moreover, we examine the case of a developing country during a war, whereas the existing literature has typically used dictionary-based models (Brzeszczynski et al., 2017; Fiser & Horvath, 2010; Gardner et al., 2022) or has employed large pre-trained language models (LLMs) (Doh et al., 2020; Gorodnichenko et al., 2023) to quantify the sentiment of central bank communications, almost always with a focus on the developed economies in times of peace.

The remainder of this paper is organized as follows. Section 2 provides a detailed discussion of the data used in this study. Section 3 outlines our empirical methodology, while Sections 4 and 5 present our findings. Section 6 offers a range of robustness checks to support our results. Finally, in Section 7, we conclude the article by discussing the policy implications of our findings.

2 | DATA

We collected data from three sources: bank. gov. ua, finance. ua, and minfin. ua over the period from February 24, 2022 to December 10, 2022. Those data include (1) public announcements from bank. gov. ua, released by the NBU; (2) authorized market data from finance. ua, which include all sell and buy quotes from 84 agents in 20 Ukrainian cities; and (3) black market data from minfin. ua, which contain information about daily median sell and buy quotes in 23 major Ukrainian cities.

2.1 | Central bank communication data

Whether the exchange rate of UAH should remain as the fixed regime or return to floating was discussed in the media throughout the entire year of 2022. The NBU played a consistently active role in these discussions. To gain an understanding of the central bank's position and the ways in which the bank communicated its position to the markets, we collected the NBU's public announcements from its official website (bank. gov. ua). From the website, we downloaded 220 individual announcements and selected those focused on FX-related policies. At that point, we labeled the announcements containing words such as “FX market”, “foreign currency”, “foreign residence”, “abroad payment”, “FX account”, “FX transaction” and “exchange rate” as being FX announcements. As a result, we ended up with 33 policy announcements related to FX. The dates and titles of the announcements are listed in Table A1. An example of such an announcement is the NBU publication titled “NBU Allows Banks to Sell FX Cash to People, Clarifies Rules for Loan Repayment by Banks to Nonresidents”, published on April 14, 2022. Central bank communications, as one piece of the puzzle, are our primary policy variable. The other is the FX data on the UAH-USD exchange rate, and the BMP in particular, which acts as our primary response variable.

2.2 | Foreign exchange data and black market premium

In terms of the FX market, several different nominal exchange rates co-exist in Ukraine on any given date in any given location: the official interbank FX rate set by the NBU, the exchange rate provided by numerous authorized financial institutions with prices partly regulated by the NBU, and the exchange rate provided by black market traders and which is, thus, not regulated by anyone. The last two serve the general public and regularly perform cash transactions, for instance, by exchanging USD for UAH. For that reason, they are in direct competition with each other. However, whereas authorized financial institutions (e.g., banks and currency exchange shops) must currently set their prices within only 10 percent of the NBU's prices, black market traders are free of this requirement.

Data on daily quotes from authorized actors came from www.finance.ua, which allows financial institutions authorized by the NBU to list their sell and buy prices on the FX currency platform.[4] The website contains buy and sell quotes provided by 84 authorized agents in 20 Ukrainian cities. We should note that the NBU allows, not only banks, but also non-bank financial institutions (e.g., currency exchange shops) to participate in the FX market. In the data set, nearly half of those authorized agents are non-bank financial institutions. Consequently, we constructed the authorized market data set containing the price quotes for USD at the agent–city–day level. Table 1 presents the descriptive statistics for the exchange rates. The average buying price in the authorized market was 36.60 UAH per 1 USD. By contrast, the selling price of 1 USD was approximately 37.53 UAH. Unsurprisingly, the authorized rates exceeded the NBU's official rates by approximately 10%.

The black market data were collected from www.minfin.ua,[5] which allows noninstitutional traders to post advertisements containing offers to privately buy or sell USD. The quotes listed on the website are not authorized by the currency authority, and all transactions between sellers and buyers are not traced or recorded by the website. As the black market is completely unregulated, the black market quotes could reflect the market-clearing UAH/USD exchange rate in Ukraine. We collected the archived historical median buy and sell quotes for USD for each day in 23 Ukraine cities from that website. As shown in Table 1, the average median buying price in the black market was 37.66 UAH, while the selling price was 38.03 UAH. Unsurprisingly, both prices exceeded those of their authorized market counterparts. Figure 1 plots the time series for the three FX rates that have existed in Ukraine since February 24, 2022. There is almost no gap (i.e., BMPs) between the authorized market rate and the black market rate before 24 February, the day when the Russo-Ukrainian war began and when the NBU decided to end the float. This suggests that while the black FX market existed before the war, its size and effects were minimal. Since then, the black market rate has increased dramatically. By contrast, the authorized market rate remained close to the interbank rate due to the NBU's price limitation restriction. That regulation was partly lifted on April 14, 2022 when the NBU allowed authorized agents to trade foreign currencies for prices within 10% of the official rate. As a result, the authorized and black market rates converged in late May 2022 and remained so until the NBU devalued the official hryvnia by 25% on July 21, 2022. Both rates increased again and peaked in mid-September at around 43 UAH to one USD. Following this, both authorized and black market prices relaxed and remained at approximately 40 UAH throughout the rest of 2022.

3 | METHODOLOGY

3.1 | Calculating the announcement sentiment index (S_t)

Central bank communications are not directly perceptible. Therefore, an important question for empirical analyses examining the role of central bank communications in financial markets is how to quantify the information communicated. In terms of exchange rates, there are two directions that an FX announcement can signal: to impose (or maintain) a fixed FX rate for hryvnia; or to return to the floating FX rate. To classify them as one or the other in the case of Ukraine, we employ an advanced machine learning tool, ChatGPT, to read, evaluate, and quantify the sentiments.[6] To this end, we split each announcement into paragraphs, created a

[4]Founded in 2000, finance.ua is one of the leading comprehensive financial media outlets in Ukraine. Aiming to build a “financial online supermarket” for Ukrainian citizens, finance.ua provides financial news, financial advice, currency exchange rates, and personal credit ratings.

[5]Since being founded in 2008, minfin.ua has been providing economic news, advice, and posts reviews of financial institutions. Registered users are allowed to use its forum and posting boards.

[6]We also used a dictionary-based method to classify the announcements as “fix” and “float”-intended. Those results are discussed in Section 6.2.

TABLE 1 Descriptive statistics of FX markets between February 20, 2022 and December 20, 2022. The *NBU Exchange Rate (Official Rate)* is the official USD/UAH exchange rate set by the National Bank of Ukraine. The *Authorized Market Rate (Buy, Sell, Midpoint)* represent the buy, sell, and midpoint quotes in the authorized market, respectively. The *Black Market Rate (Buy, Sell, Midpoint)* represent the the buy, sell, and midpoint quotes in the black market, respectively. *Black Market Premium (Sell, Buy)* is the black market premium, calculated as the difference between the black market and authorized rates.

	Mean	Std. Dev.	p25	p50	p75	Obs
NBU Exchange Rate						
Official Rate	32.936	3.663	29.255	36.569	36.569	301
Authorized Market Rate						
Buy	36.603	4.012	34.000	38.000	40.000	14,308
Sell	37.534	3.961	35.360	39.700	40.700	14,308
Midpoint	37.068	3.959	34.750	39.000	40.325	14,308
Black Market Rate						
Buy	37.660	3.559	35.250	39.600	40.550	14,308
Sell	38.031	3.369	35.500	39.850	40.700	14,308
Midpoint	37.847	3.446	35.325	39.700	40.615	14,308
Black Market Premium						
Buy Premium	3.138	4.131	0.568	1.489	3.927	14,308
Sell Premium	1.596	4.580	−0.495	0.049	1.566	14,308

conversation in ChatGPT and asked whether a particular paragraph of the announcement would make the exchange rate of hryvnia more fixed, more flexible, or neither.[7] ChatGPT selected one of those three answers. We then aggregated Chat GPT's per-paragraph AI responses at the announcement level to obtain the fix/float announcement sentiment index S_t as:

$$S_t = 100 \times \frac{\sum \overline{paras_t} - \sum \widetilde{paras_t}}{\sum \overline{paras_t} + \sum \widetilde{paras_t}} \tag{1}$$

in that equation, *paras* is the number of "Fixed"-tagged paragraphs in the announcement, while *paras* is the number of "Float"-tagged paragraphs in the announcement on date t. The result is a continuous index that ranges from −1 (i.e., float exchange rate sentiment) to +1 (i.e., fixed exchange rate sentiment). During the period sampled, the NBU made 220 announcements, 33 of which were FX-related announcements. Of these, ChatGPT identified 13 "fix", 14 "float", and six "no-direction" announcements. For example, on February 24, 2022, the NBU issued a statement titled "NBU Makes Changes to Resolution No. 18 on the Operation of the Banking System under Martial Law Dated 24 February 2022." ChatGPT's verdict suggested that this announcement contains 5 "Fix" paragraphs and 0 "Float" paragraphs; this resulted in a sentiment index, S, equal to +1, which signals a strong "Fix" intent.

[7]In our analysis, we used the November 30, 2022 version of ChatGPT that was trained using pre-2022 data and was therefore not "aware" of the war. It also could not analyze the subsequent market response to the NBU's announcements or account for policies adopted at a future date, t + h, while evaluating the sentiment of communication released at time t. In a sense, ChatGPT produced a fair assessment of the text, just as a live human being would in real time.

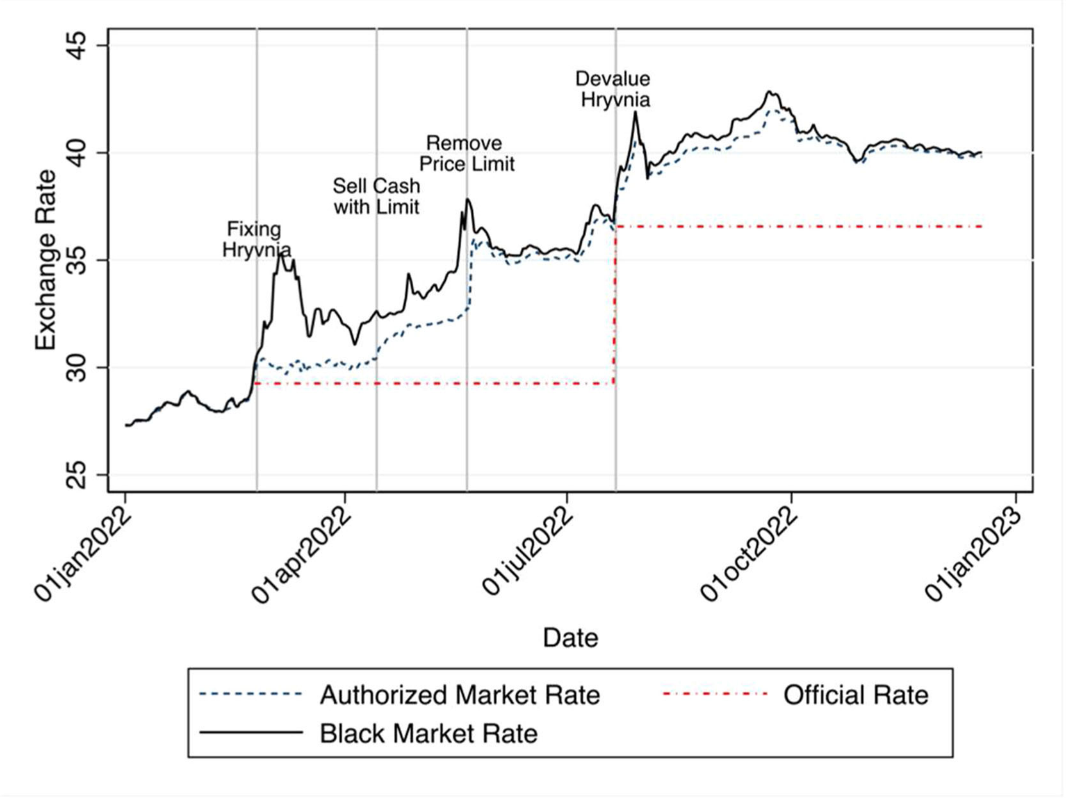

FIGURE 1 Evolution of three exchange rates in Ukraine throughout 2022. The solid line represents the black market midpoint for selling and buying prices. The dashed line represents the authorized market buy and sell midpoints. The dash-dotted line represents the official rate regulated by the NBU since 24 February 2022. The Y-axis represents the FX exchange rate (i.e., UAH-USD), while the X-axis represents the date. The grey vertical lines represent four direct FX interventions by the NBU. [Color figure can be viewed at wileyonlinelibrary.com]

3.2 | Calculating the black market premium ($BMP_{ic,t}$)

We calculated the BMP for sell and buy sides separately. Due to data availability, the black market data in our sample was the median dealers' prices in cities. Therefore, we used the percentage difference between the authorized agent quotes and black market medians in the same city to proxy the BMP, as follows:

$$BMP_{ic,t} = 100 \times \frac{P^{BM}_{c,t} - P^{A}_{ic,t}}{P^{A}_{ic,t}} \tag{2}$$

in which i represents the agent's ID, c is the city, and t is the date. $P^{BM}_{c,t}$ represents the buy (or sell) median price on the black market in the same city, c, where agent i located, while $P^{A}_{ic,t}$ represents the buy (or sell) quote provided by agent i in city c on date t. Figure 2 shows the evolution of the BMP for both sell and buy sides of the market, as well as the history of selected fix- and float-intended announcements. Having defined both the dependent and independent variables, we were able to proceed to establishing the econometric specification.

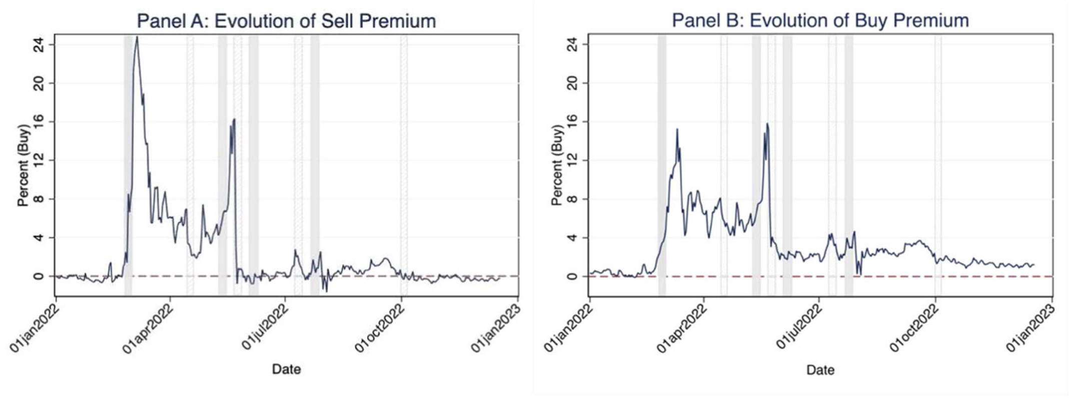

FIGURE 2 Evolution of the black market premium (BMP) on the sell (Panel A) and buy (Panel B) sides. The BMP is defined as the percentage difference between the authorized agent quotes and black market median exchange rates in the same city. The Y-axis represents the BMP, while the X-axis represents the date. The grey solid bars represent the one-week periods at the beginning of which the fix-sentiment announcements were released, whereas the patterned grey bars represent the one-week periods at the beginning of which the float-sentiment announcements were released. Only a few select announcements are shown in the figure. [Color figure can be viewed at wileyonlinelibrary.com]

3.3 | Econometric specification

To estimate the effect that central bank announcements had on the FX market and, in particular, on the BMP, we estimate the following model:

$$BMP^{BS}_{ic,t+j} = \beta S_t + \gamma X_{it} + \alpha_i + \eta_c + \delta_t + \epsilon_{ic,t} \tag{3}$$

in which the dependent variable, $BMP^{B,S}_{ic,t+j}$, is the black market buy (B) or sell (S) premium for agent i in city c on date $t+j$, which is calculated using Equation 2. The time-shift index $j \in [-2, -1, ..., 7]$ is measured in days.

The premium was explained by our primary independent variable, which was the sentiment of the central bank announcement, S_t, calculated according to Equation 1. In Equation 2, the sentiment S_t is positive if the announcement on time t suggests that the NBU is favoring the fixed exchange rate, and is negative if it points to the possibility of returning to a floating exchange rate. By contrast, it equals 0 on the dates when no FX-related announcements were made by the NBU. The first two possible values for j (i.e., −2 and −1) correspond to the leads of S_t. If the model is specified correctly and there is no leakage of information, then those values should not affect the BMP, thereby resulting in β being insignificant. By contrast, the positive values of j allow us to estimate how quickly the black market responds to news, which are the announcements released by the NBU. The sentiment S_t, was expected to be positively related to the BMP for both the sell and buy sides. Put differently, announcements intended to signal that the hryvnia exchange rate will remain fixed were expected to increase the BMP.

The vector of controls, X_{it}, contains market characteristics that previous research has shown to affect the BMP. To capture the market momentum, we controlled for the average buy and sell prices of USD in the authorized market. To account for the size and competitiveness of the local markets, we also controlled for the number of authorized FX traders in each city.

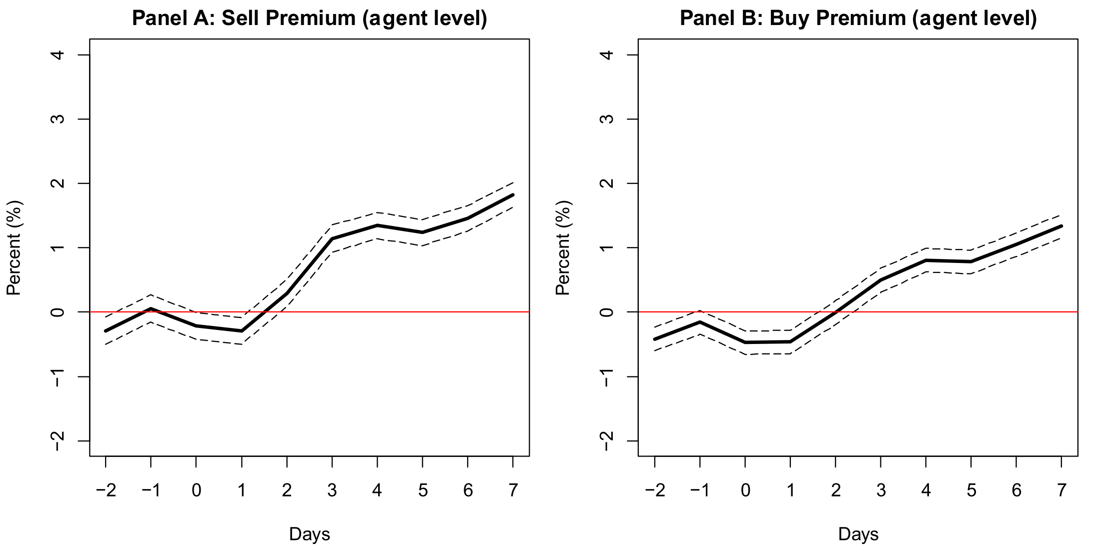

FIGURE 3 Evolution of the sentiment response coefficient for the sell (Panel A) and buy (Panel B) sides. This figure shows the results of estimating the sentiment coefficient β from Equation 3 for the time shift j varying between 2-days before and 7-days after the announcement. The Y-axis is the BMP response, while the X-axis is the time shift parameter, j. The dashed lines show the 95% confidence interval. [Color figure can be viewed at wileyonlinelibrary.com]

Our model also includes agent α_i, and city η_c as fixed effects that control for time-invariant characteristics, and monthly and weekday time effects δ_t to account for the general macroeconomic situation and the weekend effect.

4 | RESULTS

4.1 | Baseline specification

The evolution results for the sentiment coefficient, β, from Equation 3 as a function of j are plotted in Figure 3.[8] The time shift parameter j varies from −2 (i.e., 2 days before) to +7 (i.e., a week after) the date of announcement. The numerical estimates for all other coefficients appear in Table 2.[9]

4.1.1 | The role of communication

Figure 3 clarifies that, regardless of whether the buy or sell sides are examined, the “fixed” NBU announcements were positively related to the BMP. Starting with 2 days following the announcement ($j = 2$), the response was

[8]The Ukrainian FX market has two main foreign currencies, USD and EUR, both of which are traded in the authorized market and black market. The baseline estimation focuses on USD because the exchange rate for hryvnia is anchored to USD. The results of estimating Equations (3) and (5) using the EUR-based BMP are qualitatively and quantitatively similar and are available upon request.

[9]The results where Equation 2 is estimated over the sample that excludes 1 week before and after July 21, 2022 (the only time the NBU took action and devalued the UAH) are virtually the same and are available upon request.

TABLE 2 Results of estimating Equation (3) for different lag length values of parameter *j* for the sell (Panel A) and buy (Panel B) sides of the market. The dependent variable is the sell and buy BMP in Panels A and B, respectively. *Fix Sentiment* is the central bank announcements' sentiment, calculated according to Equation (1). *No. of Dealers* is the number of authorized FX traders in each city. *Average Sell/Buy* are the average buy and sell prices of USD in the authorized market in each city.

Time Lag *j*	−2	−1	0	1	2	3	4	5	6	7
Panel A: The sell side of the market										
Fix Sentiment	−0.288**	0.056	−0.217*	−0.289**	0.294**	1.143***	1.343***	1.236***	1.458***	1.822***
	(0.007)	(0.604)	(0.040)	(0.006)	(0.006)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
No. of Dealers	0.007	0.000	−0.005	0.007	0.004	−0.013	−0.007	−0.014	−0.024**	−0.014
	(0.376)	(0.978)	(0.524)	(0.412)	(0.618)	(0.107)	(0.362)	(0.073)	(0.002)	(0.062)
Average Sell	−0.247***	−0.500***	−0.739***	−0.817***	−0.836***	−0.884***	−0.863***	−0.846***	−0.840***	−0.781***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R-Square	0.519	0.517	0.520	0.530	0.533	0.542	0.540	0.543	0.554	0.574
Sample size	12,757	13,035	13,665	13,018	12,731	12,643	12,582	12,545	12,665	12,853
Panel B: The buy side of the market										
Fix Sentiment	−0.416***	−0.159	−0.474***	−0.465***	−0.008	0.495***	0.808***	0.780***	1.049***	1.334***
	(0.000)	(0.095)	(0.000)	(0.000)	(0.934)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
No. of Dealer	−0.008	0.004	0.014*	0.016*	0.002	−0.016*	−0.018*	−0.030***	−0.041***	−0.037***
	(0.278)	(0.552)	(0.042)	(0.020)	(0.726)	(0.026)	(0.012)	(0.000)	(0.000)	(0.000)
Average Buy	−0.053	−0.310***	−0.606***	−0.702***	−0.759***	−0.859***	−0.899***	−0.917***	−0.946***	−0.974***
	(0.061)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R-Square	0.552	0.547	0.552	0.562	0.563	0.567	0.570	0.569	0.567	0.570
Sample size	12,763	13,042	13,674	13,023	12,736	12,647	12,588	12,552	12,672	12,861

positive and was, in general, statistically significant. Thus, if the NBU issued a fix-intended FX announcement, then the black market raised prices, and the BMP increased. Likewise, it dropped them in response to a float-intended announcement. The response built up over time and after 7 days, if we use the sell-side as an example, increased to approximately 1.8 percentage points following a strong fix-intended FX announcement (i.e., when sentiment S switches from 0 to +1), while remaining statistically significant. It is worth noting that the changes in the BMP before the announcement release date (for $j = -2$ or -1) were generally weak and insignificant, as expected.

When the impact response between Panels A and B of Figure 3 is compared, it appears that the NBU's fix-intended announcements have a somewhat larger effect on the BMP for the sell side of the market, than on the buy side.[10] Compared with the buy side, the sell-side response was of a greater magnitude, was faster to act (the sell-side BMP started to increase on the second day), and continued to increase with time for at least seven more days. For the buy side, on the other hand, it took 3 days for the premium to respond and become positive, and the size of the announcement effect on the buy-side BMP was smaller.

The finding that the sell side responded more strongly than the buy side was expected. Although the NBU allows private individuals to purchase USD from authorized institutions that sell USD, the agents' supply of cash holdings of USD is generally very limited. Anecdotal evidence suggests that, in 2022, it was next to impossible to purchase foreign currency in the authorized market. The fact that the average sell price for USD in the authorized market was less than the average buy price in the black market (Table 1) supports the evidence. Thus, the black market remained the only viable option for parties seeking to purchase foreign currency and, thus, gained significant market power. By contrast, all authorized institutions were ready to purchase foreign currency from the public. Although the black market did and generally does offer more competitive rates, it is not the only option available. For this reason, it is natural to expect the black market sell quotes to be more elastic and to respond more aggressively to the news than the buy quotes.

4.1.2 | The role of FX market indicators

When it comes to the FX market-related controls $X_{c,t}$, the signs of the estimated coefficients are as expected and reflect the effect of competition on prices (Table 2). The number of authorized dealers in the market, *No. of Dealers*, was negatively related to the BMP for the buy side at long horizons, but insignificant for the sell side, regardless of the horizon. The buy-side result is consistent with findings in the existing literature (Elbadawi, 1997). Quantitatively, it implies that for the days immediately following the announcement, ten extra buy quotes in a particular city were associated with a decrease of 0.3 to 0.4 percentage points in the BMP. Considering the average number of agents in a city was approximately 30 and the average BMP for both sides is 1.32%, this effect was not trivial. When it comes to the market momentum, both *Average Buy* and *Average Sell* variables are negatively related to the BMP, which is a common result evidenced in the literature (Subrahmanyam, 2018). This finding suggests that the high market momentum in the authorized market could significantly mitigate the BMP.

4.2 | Asymmetrical specification

The baseline specification in Equation 3 has one potential drawback: it does not allow the BMP response to change in magnitude, regardless of whether the NBU announces that it is planning to further extend the fixed rate regime or is considering returning to a floating exchange rate. If the market considers the former announcements to be more credible than the latter, then it may respond to them more aggressively, and vice versa. To account for this

[10]Those differences were even more pronounced when the dictionary approach, and not ChatGPT, was used to to characterize the announcements, as discussed in Section 6.2.

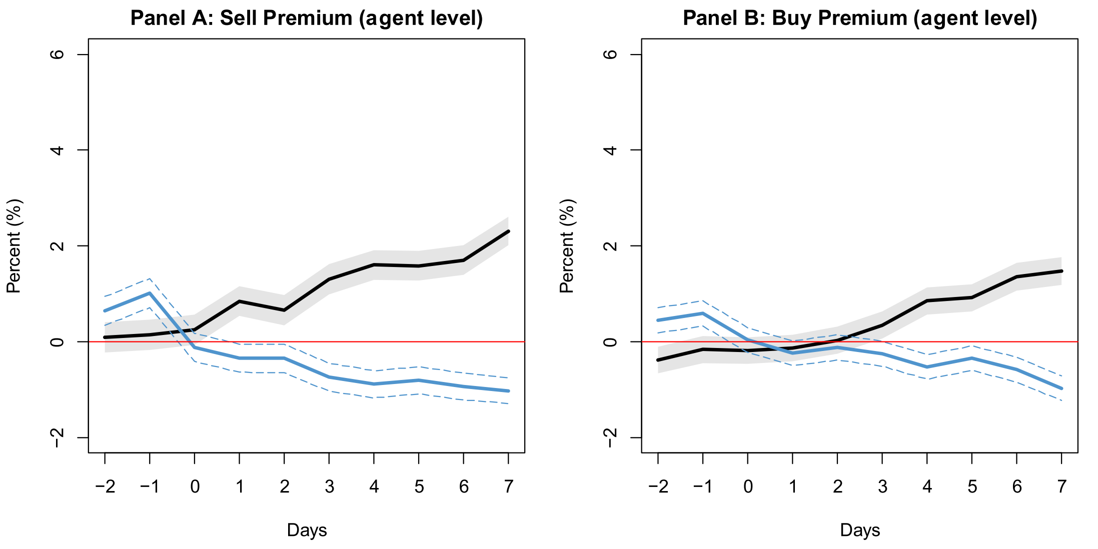

FIGURE 4 Evolution of the "fix" and "float" sentiment response coefficients for the sell (Panel A) and buy (Panel B) sides. The figure shows the results of estimating the sentiment coefficient β from Equation 5 for the time shift parameter j, which varies between 2-days before and 7-days after the announcement. The Y-axis is the BMP response, while the X-axis is the time shift parameter, j. The dashed lines, as well as shaded lines show the 95% confidence interval. The solid black line represents the coefficients for the "fix" sentiment $\bar{S}$, whereas the solid-blue line represents the coefficients for the "float" sentiment $\tilde{S}$. [Color figure can be viewed at wileyonlinelibrary.com]

possibility, we split the sentiment variable, S, into those observations expressing the fixed sentiment $\bar{S}$ and those expressing the float $\tilde{S}$ sentiments as follows:

$$\begin{aligned} \bar{S} &= |S| \times I(S > 0) \\ \tilde{S} &= |S| \times I(S < 0) \end{aligned} \tag{4}$$

in which $I(\cdot)$ is a true-false indicator variable. Unlike in the previous case, both "fix" and "float" announcements resulted in a positive value of the corresponding index. The next step was adding them to the equation and producing an estimation:

$$BMP^{B,S}_{ic,t} = \bar{\beta}\,\bar{S}_{t-j} + \tilde{\beta}\tilde{S}_{t-j} + \gamma\,X_{it} + \alpha_i + \eta_c + \delta_t + \epsilon_{ic,t} \tag{5}$$

Figure 4 shows the evolution of the coefficients $\bar{\beta}$ and $\tilde{\beta}$ associated with the "fix"-related announcements ($\bar{S}$), as well as the "float"-related announcements ($\tilde{S}$) for the sell (Panel A) and buy (Panel B) sides of the market.[11] We found the market response to fix-sentiment to be stronger than the reaction to float-intended announcements, regardless of the side of the market. For instance, for the sell side, the BMP response to a "fix" announcement increased the BMP by approximately 2.2 percent points over the following week, whereas the response to a "float" sentiment is only 1.4 percentage points over the same horizon. This finding suggests that market participants were more sensitive to the news intended to maintain or strengthen the fixed exchange rate of hryvnia, than to announcements related to returning to a

[11] The estimates for the rest of the coefficients are available in Table A2.

floating exchange rate. One reason could be that they considered the former to be more credible given the circumstances. The speed and timing of the effects, however, were almost identical for the two types of announcements.

4.3 | Subsample analysis

To gain additional insights, we also conducted a subsample analysis in which we split the data set along one of its dimensions that had not been directly taken into account by our existing econometric specification. First, as authorized market agents include both banks and non-bank financial institutions, we investigated the differences, if any, between them. We did this by estimating Equation 3 separately over the sample of bank and non-bank financial institutions. Specifically, Figure A1 shows that banks responded faster and more strongly to NBU's announcements, an effect observed for both the sell- and buy-side of the market. This trend likely indicates the lower level of expertise of currency exchange shops compared with banks.

Second, as 75% of the agents in our sample were located in the Ukrainian capital, Kyiv, differences may exist between agents residing in Kyiv, and those based in other parts of Ukraine. Thus, we estimated our model separately for the Kyiv and non-Kyiv samples. The results are presented in Figure A2. When we compared the estimates of the slope coefficients between Panels A and B and between Panels C and D, we observed that the fix-intended NBU announcements created a larger BMP among agents based outside Kyiv. This outcome was expected, since Kyiv, as the capital of Ukraine, is one of the most competitive markets in the country. This trend can be expected to hold even when we consider the informal black market. The more semi-legal buyers and sellers that operate in that market, the lower the markups that traders on the black market use when selling USD to the public.

Last, we expected the BMP to be higher in frontline cities where there is an urgency to sell and buy USD, while at the same time those doing so are faced with high search costs. Thus, we re-estimated Model (3) by adding an interaction term to capture the interaction between sentiment S_t and the $Frontline_{c,t}$ city indicator, which equals 1 if city c is the fighting ground on day t, and 0 otherwise. For instance, the index was 1 for Kharkiv during the "Battle of Kharkiv," a military engagement that took place in and around the city from February 24 to May 14, 2022. Those results appear in Table 3 and show that the interaction term was positive and highly significant for the "sell" side of the market. For some horizons, the BMP's response to NBU announcements for front-line cities exceeded their values for rear-echelon cities by a factor of four. Indeed, people are willing to pay a significant BMP to convert UAH into USD when there is a real possibility that their city could be seized and that Ukrainian currency may consequently lose value. Another reason for this is that, in frontline cities, many authorized agents could be in the process of evacuating from the war zone, and are thus not serving customers. This leaves the black market as the only seller and buyer of USD.

5 | PRICE DISPERSION RESULTS

Our analysis described above used agent-level data, with multiple authorized agents operating in a single city. Collapsing the data by city can give us an opportunity to explore other aspects of our data set. Specifically, since we have data on multiple quotes from the authorized agents within each city, we can study how dispersion, rather than the level, of prices changes in response to NBU announcements.

Price dispersion refers to the degree to which prices vary across different sellers or locations (Lach, 2002). It occurs when different sellers offer different prices for the same commodity within a particular market place. In our case, it is the US dollar. Price dispersion is a common phenomenon in many markets, including the insurance market (Hun Seog, 2002), mortgage market (Bhutta et al., 2020), and energy market (Noel & Qiang, 2019). The authorized FX market in Ukraine also experiences this phenomenon.

TABLE 3 Results of estimating Equation (3) for the frontline and non-frontline cities and for different lag length values of the parameter *j* for the sell (Panel A) and buy (Panel B) sides of the market. The dependent variable is the sell and buy BMP in Panels A and B, respectively. *Frontline* is a city indicator, which equals 1 if city *c* is the fighting ground on day *t*, and 0 otherwise. *Fix Sentiment* is the central bank announcements' sentiment, calculated according to Equation (1). *No. of Dealers* is the number of authorized FX traders in each city. *Average Sell/Buy* are the average buy and sell prices of USD in the authorized market in each city.

Time Lag *j*	−2	−1	0	1	2	3	4	5	6	7
Panel A: The sell side of the market										
Fix Sentiment	−0.289**	−0.048	−0.352**	−0.386***	0.196	0.963***	1.156***	1.108***	1.325***	1.739***
	(0.009)	(0.671)	(0.001)	(0.000)	(0.077)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Fix Sentiment × Frontline	0.015	1.341***	1.680***	1.385***	1.577***	3.073***	3.058***	2.316***	2.326***	1.327***
	(0.969)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
No. of Dealers	0.007	0.002	−0.002	0.008	0.006	−0.010	−0.004	−0.012	−0.022**	−0.012
	(0.376)	(0.764)	(0.768)	(0.313)	(0.488)	(0.219)	(0.616)	(0.121)	(0.004)	(0.097)
Average Sell	−0.247***	−0.501***	−0.740***	−0.817***	−0.836***	−0.885***	−0.863***	−0.846***	−0.841***	−0.781***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R-Square	0.519	0.518	0.521	0.531	0.534	0.544	0.543	0.544	0.555	0.575
Sample size	12,757	13,035	13,665	13,018	12,731	12,643	12,582	12,545	12,665	12,853
Panel B: The buy side of the market										
Fix Sentiment	−0.311**	−0.037	−0.376***	−0.394***	0.042	0.507***	0.833***	0.740***	1.001***	1.286***
	(0.001)	(0.709)	(0.000)	(0.000)	(0.667)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

TABLE 3 (Continued)

Time Lag *j*	−2	−1	0	1	2	3	4	5	6	7
Fix Sentiment × Frontline	−1.369***	−1.568***	−1.228***	−1.006**	−0.798*	−0.202	−0.407	0.724	0.851*	0.749*
	(0.000)	(0.000)	(0.000)	(0.003)	(0.031)	(0.599)	(0.266)	(0.065)	(0.029)	(0.038)
No. of Dealer	−0.010	0.002	0.012	0.015*	0.002	−0.016*	−0.018**	−0.029***	−0.040***	−0.036***
	(0.158)	(0.822)	(0.082)	(0.030)	(0.812)	(0.025)	(0.010)	(0.000)	(0.000)	(0.000)
Average Buy	−0.051	−0.308***	−0.604***	−0.702***	−0.759***	−0.859***	−0.899***	−0.918***	−0.947***	−0.975***
	(0.071)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R-Square	0.553	0.547	0.553	0.562	0.563	0.567	0.570	0.569	0.567	0.570
Sample size	12,763	13,042	13,674	13,023	12,736	12,647	12,588	12,552	12,672	12,861

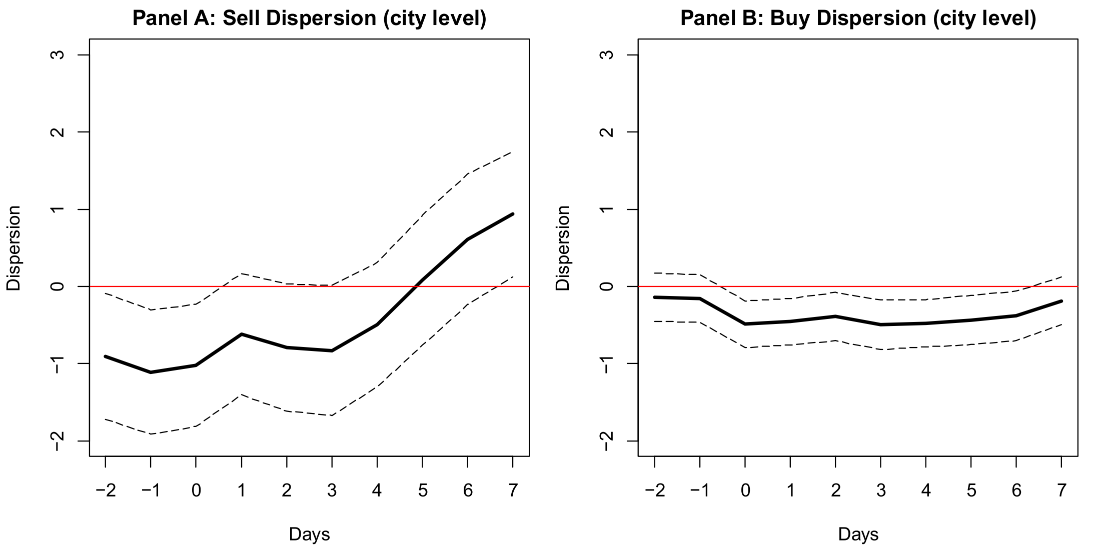

FIGURE 5 Evolution of the sentiment response coefficient for the sell (Panel A) and buy (Panel B) sides when the dependent variable is *Price Dispersion*. *Price Dispersion* is defined as being the coefficient of variation of buy (sell) prices of authorized agents, within a city on a given day. This figure shows the results of estimating the sentiment coefficient β from Equation 3 with the dependent variable being *Price Dispersion*, for the time shift index *j* varying between 2-days before and 7-days after the announcement. The Y-axis is the price dispersion response, while the X-axis is the time shift parameter *j*. The dashed lines show the 95% confidence interval. [Color figure can be viewed at wileyonlinelibrary.com]

We, therefore, re-estimate Equation 3 while replacing the black market premium (BMP) with price dispersion as the dependent variable. Following Zhao (2006), we calculate dispersion as being the coefficient of variation of buy (sell) prices of authorized agents, within a city on a given day. The results are shown in Figure 5. It can be seen from Figure 5 that there is no significant short-term effect of an announcement on the dispersion of prices, regardless of the side of the market. However, we do find that eventually, a fix-intended announcement increases the sell price dispersion (Panel A). The point estimate of the effect is 0.94. Since the within-city average dispersion of selling prices for USD is 2, this impact is considerable. It means that within a week after the announcement, the dispersion of prices increases by around 50%. One may interpret this finding as being a fix-intended announcement leading to a more "fixed" hryvnia, which further limits the availability of foreign currency in the authorized market and increases the associated search costs. It could also mean that the professional authorized agents (banks) change their prices more often and/or faster than nonprofessional authorized agents (i.e., currency exchange shops), thus contributing to within-city price dispersion. We do not find a similar effect for the buy-side of the market.

6 | ROBUSTNESS CHECKS

Although our results remained consistent despite various specifications and setups, there are three possible elements for which we had not accounted that could have led to spurious results. First, the factor of "luck" and the choice of our particular sample could have made results appear to be significant, regardless of all other factors. Second, our results could have been driven by the choice of our primary independent variable: ChatGPT's assessment of the NBU announcements. Third, our relatively strong results could have been an artifact of the estimation method. We address all three of these concerns in the following sections.

6.1 | Placebo experiment

To ensure that we did not obtain spurious results due to the sample selection, we estimated a placebo model. To that end, we replaced the BMP in 2022 in Equation 3 with its values on the same calendar dates exactly 1 year prior in 2021. All variables and controls on the right-hand-side remained as they were before, that is, corresponding to values from 2022.

The results, shown in Figure A3, aligned with our expectations in that the impact response was statistically insignificant regardless of the horizon, *j*. Both the sell side and buy side's BMP are not affected by the announcement proxies of the following year (Panels A and B). These results suggest that the significant results of our study were not likely to have been driven by particular seasonal factors.

6.2 | Dictionary-based announcement classification

In the baseline estimation, we used ChatGPT to identify whether an announcement shows a "fix" or "float" sentiment. In this robustness check, we instead followed Neuhierl and Weber (2019) who used the "search and count" approach to label a text's sentiment as being either "fix" or "float". First, we created a dictionary that contains the list of words that signal an intention to "fix" or "float". Words with the "fix" intent include "cease", "prohibit", "limit", "suspend", "ban", whereas words with the "float" intent included "ease", "allow", "lift", "simplify", "relieve", "permit" and "simplified." Next, we used the complete dictionary, shown in Table A1, to count the number of occurrences of "fix" and "float" words in the announcement as a means of calculating the fix/float announcement sentiment S_t, as follows:

$$S_t = 100 \times \frac{\sum \overline{words_t} - \sum \widetilde{words_t}}{\sum \overline{words_t} + \sum \widetilde{words_t}} \tag{6}$$

in which, *words* is the number of "fix" words in the announcement on the date *t*, and *words* is the number of "float" words. The result is a continuous index ranging from −1 (i.e., float exchange rate sentiment) to +1 (i.e., fixed exchange rate sentiment). For example, on May 25, 2022, the NBU issued a statement titled "NBU to Retain Current Fixed Exchange Rate" which, per the analysis, had six "fix" words and two "float" words. This results in the sentiment index *S* being equal to +0.5, which indicates a moderate to strong "fix" intent. To allow for a comparison of the sentiment index values obtained from using the dictionary method with those produced by ChatGPT, we created Table A3. The correlation between the two measures was 0.7439, which was significant at 99%.

The estimation results for Equation 5 using the dictionary-based sentiment measure are presented in Figure 6. They show that all of our major conclusions remained intact, and our results appear to be robust in relation to the choice of sentiment measure. Moreover, with the dictionary-based index being used instead of the ChatGPT-based index, we found highly significant differences between the "fix" and "float" announcement responses, including that the former was much stronger quantitatively and occured several days ahead of the latter.

6.3 | Event analysis

Although we have used a regression analysis to conduct an estimation, which combined the dates of FX-related announcements, non-FX related announcements, as well as dates with no NBU announcements at all, heterogeneity could have existed between the announcement and non-announcement dates, as well as between the behavior of the agents on those days. To address this risk, we focused only on the dates when the NBU made any kind of announcements in 2022. There were 220 such days. Next, using the event analysis apparatus, we compared the FX market response to the "fix" (n = 13), "float" (n = 14), and "no-direction" (n = 193) announcements.

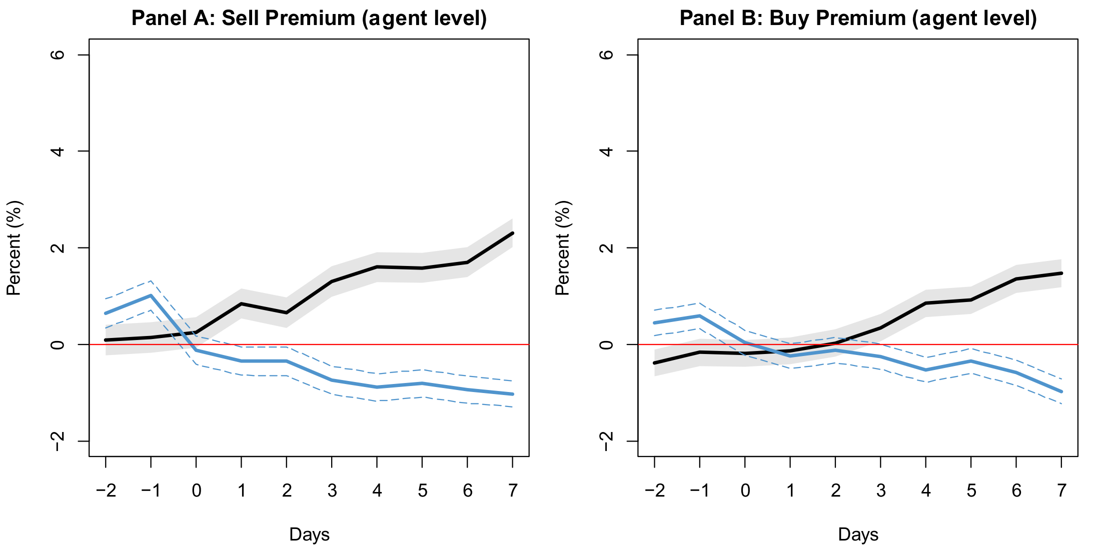

FIGURE 6 Evolution of the textual-based sentiment response coefficient for the sell and buy sides. The figure shows the results of estimating the sentiment coefficient, β, from Equation 5 for the time shift parameter, j, varying between 2-days before and 7-days after the announcement. The Y-axis represents the BMP response, while the X-axis, represents the time shift parameter, j. The dashed and shaded lines represent the 95% confidence interval. [Color figure can be viewed at wileyonlinelibrary.com]

TABLE 4 Summary statistics and event analysis results of abnormal BMP response to central bank announcements. *Abnormal BMP* is defined as the difference between the black market premium at j days after an announcement and the baseline BMP. Columns (1)-(3) represent the average *Abnormal BMPs* for "fix", "float", and "no-direction" FX announcements. Column (4) represents the p-value for the ANOVA test; the null hypothesis is that the three mean abnormal BMPs are equal to each other.

	Average abnormal BMPs			ANOVA
	Fix ($S_t > 0$)	Float ($S_t < 0$)	No-directionannouncements ($S_t = 0$)	p-value
Time shift factor j	(1)	(2)	(3)	(4)
Panel A: Sell side				
$j = 0$	0.775	−0.919	0.024	0.00
$j = 1$	1.21	−1.823	0.101	0.00
$j = 2$	1.775	−3.444	0.315	0.00
$j = 3$	3.694	−1.295	0.114	0.00
Panel B: Buy side				
$j = 0$	0.369	−0.667	−0.022	0.00
$j = 1$	0.121	−1.355	0.017	0.00
$j = 2$	0.694	−2.715	0.161	0.00
$j = 3$	1.171	−0.897	0.108	0.00
Events	13	14	193	
Sample size	446	572	6,697	

Regardless of the nature of an announcement occurring at time t, we defined (future) abnormal BMP as the difference between the black market premium at $t+j$ and the baseline BMP. The latter was calculated as the 3-day average BMP directly before the announcement:

$$Abnormal\ BMP_{t+j} = BMP_{t+j} - \frac{1}{3}\sum_{k=1}^{3} BMP_{t-k} \tag{7}$$

The average abnormal BMPs following the NBU's "fix", "float", and "no-direction" announcements are presented in Table 4. As expected, regardless of the side of the market, the abnormal premium was positive for the "fix-intended" announcements and negative for the "float-intended" ones. For the "no-direction" announcements, it was close to 0. All of these findings agree with our regression-based results. Moreover, it appears that the quantitative response (i.e., the largest deviation from the baseline) occurred most often on the second day after the announcement; after that, the markets started to adjust. Last, the three responses clearly differed from each other, regardless of the value of j or the side of the market. An ANOVA test rejected the equal means hypothesis at all meaningful levels of significance.

7 | CONCLUSIONS

Central bank announcements are crucial for communicating policy decisions and ensuring the stability of an economy's financial system. They gain heightened importance during periods of substantial disruption, such as financial crises and natural disasters. In those instances, the credibility of the central bank is put to the test, and it becomes imperative for the bank to take swift, effective action to stabilize the economy. However, there is a noticeable lack of evidence regarding the effectiveness of central bank communications during full-scale wars and other significant shocks. To address this gap, this study investigated the connection between the communication efforts of the NBU and the FX market following the full–scale Russian invasion of Ukraine in 2022. Although researchers have examined stock market reactions to central bank communications, we were not able to follow in their footsteps in this study because of the underdeveloped stock market in Ukraine. Thus, in the context of Ukraine, we focused on the FX market, which is an instant indicator of the financial market reaction to announcements released by the central bank. To gather data for the study, we collected FX buy and sell quotes from both authorized agents and regional black markets. Using this data, we calculated the BMP as being the difference between the former and the latter. Central bank announcements were downloaded from the NBU's website and were then, using ChatGPT, classified into having either "fixed" or "float" sentiments.

Our findings suggest that central bank communications continue to be a powerful tool, even in times of heightened distress. We observed that the FX market closely tracked the NBU's announcements, with a pronounced impact on its sell-side quotes and the BMP. For instance, by the end of a week, in response to a "fix" announcement, the BMP for "sell" quotes increased by 1.8 percentage points, but increased by only 1.3 percentage points for "buy" quotes. Moreover, the response on the "buy" side appeared to be delayed compared with the "sell" side's response, possibly because, during wartime, when the official exchange rate is lower than the market equilibrium, the black market becomes the preferred option for those parties seeking to buy USD. Furthermore, there is evidence that the content of "fix" announcements exerts a greater influence on the FX market than "float"-sentiment content. This likelihood suggests that the market perceives "fix" announcements as being more credible and, consequently, responds more vigorously. Indeed, since the start of the Russo-Ukrainian War, the NBU has consistently maintained a fixed exchange rate.

Our findings add valuable insights to the literature in multiple ways. Firstly, they underscore the importance of the sentiment conveyed in central bank announcements, particularly by revealing that a well-phrased announcement, even without stimulating immediate action and even if released during highly volatile times, can still have nontrivial effects in the market. For instance, "fix-intended" announcements issued by NBU, even without any changes to the exchange rate regime, resulted in an increase in the BMP, whereas float-intended announcements led to a reduction of the premium. Second, we demonstrate that the public appears to attribute varying levels of credibility to different types of announcements. For example, "fix-intended" FX announcements tended to exert a more pronounced influence in the market than "float-intended" announcements. Last, we have shown that, contrary to anecdotal evidence, both the general public and noninstitutional entities pay heed to central banks. This includes semi-legal black market traders and authorized small currency exchange shops, all of whom adjust their prices in response to the relevant announcements released by the NBU.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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