War Intensity and Currency Market Responses: Evidence from Daily Air Alerts and Foreign Exchange Behavior in Ukraine

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Abstract

This paper investigates the real-time impact of war intensity on currency market behavior using a novel, high-frequency dataset from Ukraine following the 2022 full-scale Russian invasion. A daily, non-textual index of war intensity is constructed based on the duration of official air raid alerts. The analysis proceeds on two levels. At the national level, a distributed-lag time-series model is used to examine the effect of alert intensity on the net sale of foreign currency by the National Bank of Ukraine (NBU), controlling for exchange rate policy and capital control regulations. At the regional level, a two-way fixed effects panel model studies how localized alert exposure affects public demand for currency, proxied by Google search volume. The findings reveal a dual-channel response: the regional analysis shows that higher alert intensity significantly increases public search interest for foreign currency, confirming a strong *precautionary motive*. Crucially, this effect is driven entirely by Ukrainian-language searches, as Russian-language searches show a negative correlation, likely reflecting war-induced population displacement and social linguistic shifts. Conversely, the national transaction data reveals a *liquidity effect*, where, after controlling for policy, a spike in alerts leads to households becoming net sellers of foreign currency, likely to cover immediate local-currency expenses. These results provide granular evidence of the complex and sometimes contradictory financial pressures that direct physical threats place on a wartime population. Importantly, neither dataset captures informal ('black market') transactions, which may also have shaped behavior.

1 Introduction

The economic and financial consequences of geopolitical conflict are a central and enduring theme in economic research. Major conflicts can induce macroeconomic instability by triggering precautionary behaviors, deterring investment, and generating extreme volatility in financial markets (Caldara and Iacoviello, 2022). Foreign exchange (FX) markets are often the primary conduits through which these shocks are transmitted, given their high liquidity and sensitivity to investor sentiment. Understanding these high-frequency responses during wartime is thus crucial for assessing economic resilience and the transmission of geopolitical shocks. The full-scale Russian invasion of Ukraine on February 24, 2022, provides a tragic but analytically unique natural experiment. The conflict led to widespread disruptions and panic-driven household reactions, including a well-documented flight to the safety of hard currencies. A central feature of daily life in wartime Ukraine is the system of government-issued air raid alerts, which signal imminent missile or drone attacks. These alerts serve as a real-time, objective, and geographically granular proxy for the population's direct exposure to physical danger, offering a rare opportunity to study economic behavior under extreme stress (Constantinescu et al., 2022).

This thesis seeks to answer the following research question: **How does daily war intensity, as measured by regional air alerts, affect foreign currency market behavior in Ukraine at both the national and regional levels?** This question is addressed through a dual-level analysis. At the national level, the analysis examines whether heightened war intensity causes measurable shifts in the net volume of foreign currency transacted by the public, as reflected in official data. At the regional level, the study investigates whether populations in more heavily targeted oblasts exhibit a stronger "flight-to-safety" impulse, as proxied by their online search activity for foreign currency. By disaggregating this search data by language (Ukrainian and Russian), the analysis further explores how the war's profound demographic and social impacts are reflected in these digital footprints.

While this dual-level framework leverages the best available official and online data sources, it is important to acknowledge that the analysis does not capture activity on the informal or "black" currency market, which emerged under wartime conditions. During the full scale invasion, the suspension of official FX trading, capital controls, and limits on withdrawals created fertile ground for parallel exchange markets. Estimates indicate that the spread between unofficial and official exchange rates—i.e., the black-market premium—reached levels as high as 28%, suggesting that a substantial share of household currency demand may have been directed through these unobserved channels (Centre for Economic Policy Research, 2024; Banque de France, 2024).

To empirically address this question, this paper makes three primary contributions to overcome key challenges in measurement and identification. First, it addresses a core **measurement challenge** by constructing a novel, high-frequency measure of war intensity. While standard Geopolitical Risk (GPR) literature relies on monthly, text-based indices (Caldara and Iacoviello, 2022), this study contributes a daily, non-textual index based on the duration of official air raid alerts. This provides a direct proxy for the physical threat perceived by the population. The profound geographic heterogeneity of this threat is visualized in Figure 1, which starkly illustrates the disparity in war exposure across Ukraine and highlights the key source of variation used for the regional analysis.

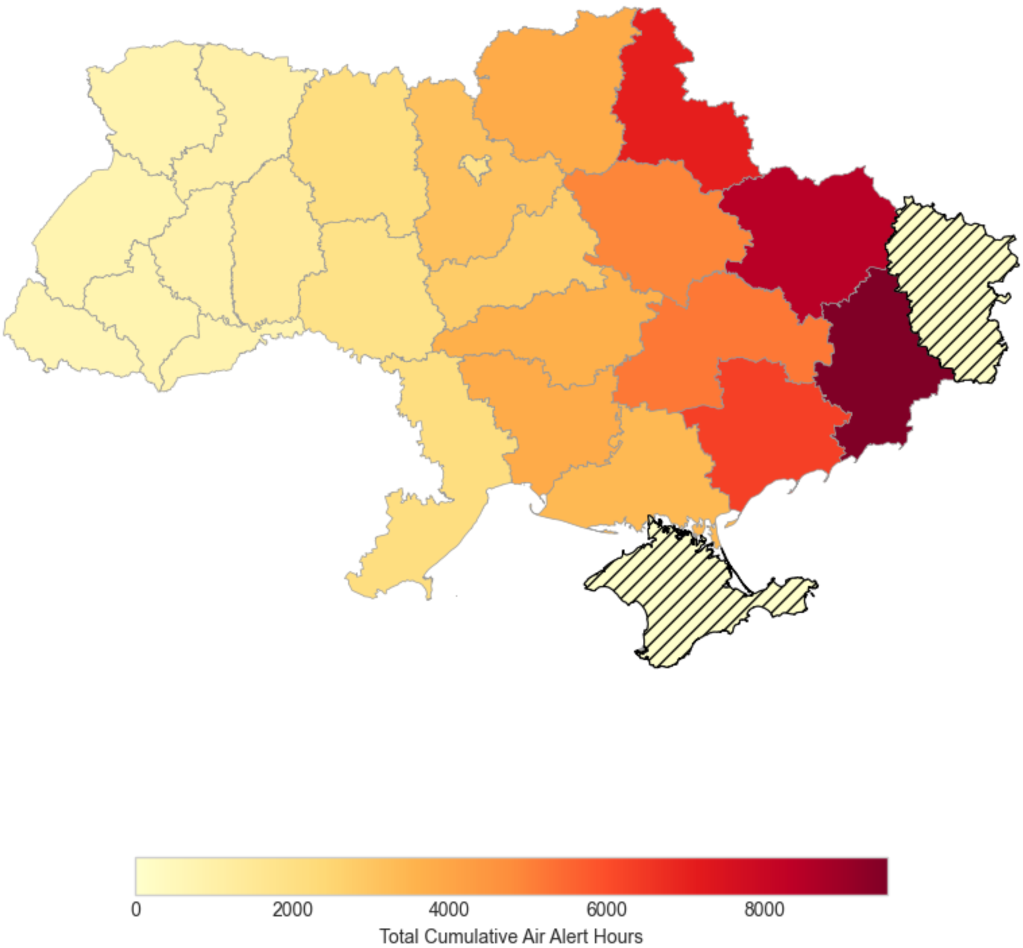

Figure 1: Total Cumulative Air Alert Duration by Oblast

Notes: The map displays the total cumulative duration of air raid alerts (in hours) for each Ukrainian oblast from February 24, 2022, to the end of the sample period. The color scale indicates intensity, with darker red representing a higher cumulative duration of alerts. The hatching pattern indicates territories that were fully occupied by Russia for the majority of the analysis period (Crimea and Luhansk Oblast) and for which alert data is either unavailable or represents a constant state of threat rather than specific, time-bound events.
Source: Author's calculations based on official and volunteer alert data.

The second contribution solves a critical **identification challenge** at the national level: isolating the war's impact from the effects of concurrent government policies. The full-scale invasion prompted a profound structural break in currency markets and triggered stringent capital controls by the National Bank of Ukraine (NBU). The sheer magnitude of this shock is made explicit in Figure 2. The figure plots daily net FX sales and shows how market dynamics over 2022–2025 were tightly intertwined with NBU interventions and phased liberalization.

At the start of the invasion, martial law and a fixed exchange rate regime froze most household FX purchases, producing the sharp discontinuity in late February 2022. By March and April, limited channels for selling foreign cash were reintroduced, creating volatile but low volumes as households converted existing savings for urgent needs. In July 2022, the NBU devalued the hryvnia by 25% and allowed controlled non-cash FX purchases linked to deposits, which marked the beginning of a moderate upward trend. Through late 2022, volumes remained subdued, but early 2023 brought renewed growth as some prohibitions were lifted, pent-up demand from 2022 entered the market, and households increasingly sought FX as a savings hedge under stabilized expectations. A major surge occurred in August 2023, when individuals gained access to online FX purchases (up to 50,000 UAH/month) and higher deposit-related limits, followed by the decisive step of May 2024, when remaining restrictions were lifted. This timeline explains the structural shifts visible in Figure 2, linking each turning point in the trend to concrete policy decisions and macroeconomic conditions.

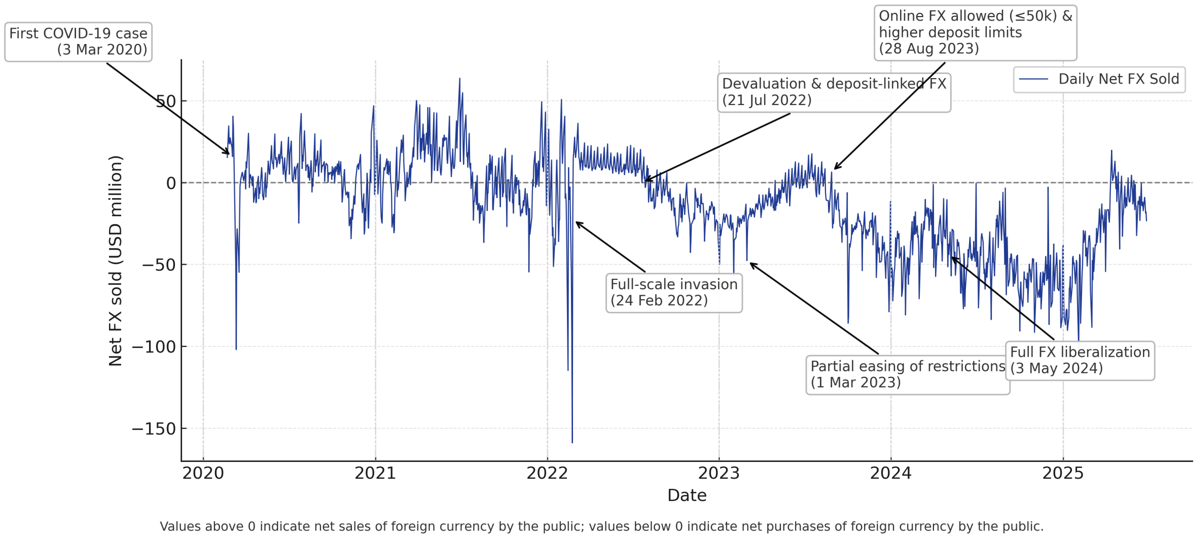

Figure 2: Raw Daily Net FX Sold to Individuals (USD million)

Notes: The dashed horizontal line marks zero. Values above zero indicate net sales of foreign currency by the public, while values below zero indicate net purchases of foreign currency by the public. The dynamics highlight how the invasion shock, subsequent easing, and eventual liberalization shaped household FX flows.

Source: National Bank of Ukraine; author's calculations.

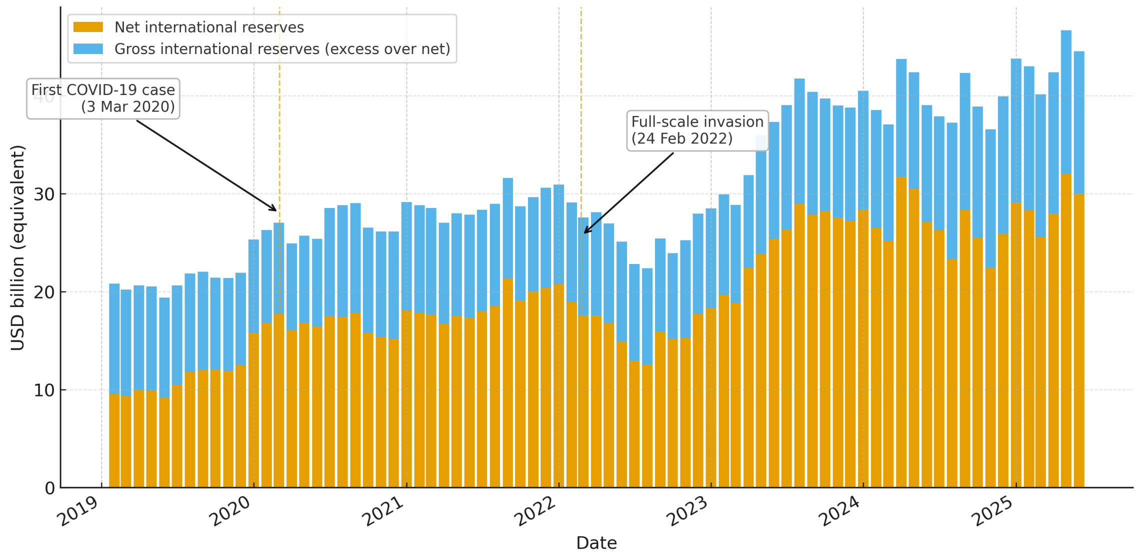

Figure 3: Dynamics of International Reserves (USD billion, gross and net)

Notes: Monthly international reserves (gross and net) for Ukraine over the sample period. Bars illustrate the joint evolution of the reserve buffer alongside FX-market policies.
Source: National Bank of Ukraine; author's rendering from official data.

The evolution of **international reserves** in Figure 3 reinforces this interpretation and provides economic grounding for the FX dynamics. Reserves declined in the first half of 2022 as the NBU supplied foreign currency to stabilize the financial system and finance critical external needs under martial law. In balance-of-payments terms, reserves acted as a *buffer stock* offsetting wartime outflows at a time when household FX purchases were still heavily restricted; this also helps explain the temporary early-war spikes in official net sales, which partly reflected policy-driven support operations rather than unconstrained public demand. From late 2022 into 2023, substantial external financing inflows (alongside the fixed exchange-rate anchor) facilitated a recovery of reserves even as the NBU gradually reopened legal channels for household FX transactions. Since mid-2023, reserves have been broadly stable at elevated levels: increased household access to FX (visible in rising net sales) has been balanced by continued official inflows and calibrated intervention, indicating a new policy equilibrium consistent with the classic "impossible trinity" intuition—exchange-rate stability and monetary autonomy were maintained by combining capital controls with external financing.

The third contribution of this paper is to uncover the **behavioral mechanisms** driving the aggregate market outcomes. Since official transaction data is not available at a sub-national level, the analysis employs a regional panel data approach. Following the seminal work on investor attention by Da et al. (2011), this study uses Google's Search Volume Index (SVI) as a proxy for public interest in foreign currency. By constructing a weekly panel dataset for all 24 Ukrainian oblasts and employing a two-way fixed effects (TWFE) model, the analysis isolates the effect of local alert intensity while controlling for all unobserved regional and time-specific factors. This part of the strategy provides a direct test of the behavioral response to perceived threats.

The findings from this dual analysis are consistent and robust. The national-level results reveal a complex dynamic. Once NBU policy and the exchange rate are controlled for, a statistically significant "liquidity effect" emerges: an increase in air alert duration is associated with the public becoming a net **seller** of foreign currency. This suggests that during times of acute crisis, households may be forced to liquidate their hard currency savings to cover immediate, hryvnia-denominated expenses. This effect is short-lived, decaying after four days. The R-squared of the full model is approximately 0.60, indicating that war intensity and policy controls together explain a majority of the variation in daily FX flows.

The regional-level analysis provides strong evidence for a countervailing "precautionary motive" that drives public attention. The two-way fixed effects model shows that a higher weekly duration of air alerts in a specific oblast leads to a statistically significant increase in Google search volume for terms related to buying foreign currency in that same region. This demonstrates that while actual transactions may be constrained by policy and liquidity needs, the underlying behavioral impulse in response to a direct threat is a flight-to-safety desire. The divergence between the national transaction data and the regional attention data paints a rich picture of economic decision-making under duress.

These results are highly relevant for policymakers managing economies in conflict. They show that while capital controls and a fixed exchange rate can prevent a currency collapse, they do not eliminate the underlying public anxiety. The simultaneous presence of a "liquidity effect" (selling FX for immediate needs) and a "precautionary motive" (wanting to buy FX for safety) suggests that central bank policy should consider not only broad restrictions but also mechanisms to provide targeted local currency liquidity to households under acute stress.

This research contributes to three primary strands of literature. First, it offers a methodological innovation to the field of **geopolitical risk (GPR) measurement**. The standard GPR index from Caldara and Iacoviello (2022) and its subsequent adaptations (Bondarenko et al., 2024) rely on the frequency of war-related terms in major newspapers. While foundational, this approach captures media narratives at a relatively low (monthly) frequency. This thesis advances the field by constructing and validating a high-frequency (daily), non-textual, and geospatially granular measure of conflict intensity using air alert data. This provides a direct proxy for the physical threat perceived by the population, bypassing potential media biases and enabling a more immediate analysis of events on the ground.

Second, this thesis extends the literature on **investor and consumer attention**. The foundational work of Da et al. (2011) established that Google's Search Volume Index

(SVI) is a direct and powerful proxy for retail investor attention, with predictive power for stock returns and trading volume. Subsequent research, such as Khalfaoui et al. (2023), has applied this concept to the Russia-Ukraine conflict, linking public attention for war-related terms to volatility in cryptocurrency and equity markets. This study contributes by exploring a new domain—the demand for safe-haven currency by a general population in a warzone. Furthermore, it provides a cleaner identification strategy than is typical in the attention literature by linking a localized, objective measure of physical threat (regional alerts) directly to a behavioral attention metric (regional search), thereby isolating a specific risk-attention-behavior channel.

Finally, this paper contributes to the field of **conflict economics** by applying **high-frequency data and methods** to analyze real-time behavior. Recent studies, such as the "Warcast Index" by Constantinescu et al. (2022), have pioneered the use of unconventional data sources—including Google Trends, Twitter, and nightlight intensity—to nowcast aggregate economic activity in Ukraine when official statistics are unavailable. This thesis complements that important work by focusing not on overall economic output, but on quantifying a specific **behavioral financial response** to conflict. By examining the flight-to-safety impulse in currency markets, this research provides micro-level evidence that helps explain the macroeconomic phenomena documented by others.

The remainder of the thesis proceeds as follows. Chapter 2 details the data, institutional background, and empirical methodology. Chapter 3 presents the national- and regional-level results, including robustness and heterogeneity analyses. Chapter 4 discusses policy implications for exchange-rate management and capital-account liberalization in wartime, and concludes with directions for future research.

2 Data and Methodology

The empirical analysis in this paper proceeds in two parts: a national-level time-series analysis and a regional-level panel analysis. This section details the data sources, variable construction, and the specific econometric models employed to identify the causal relationship between war intensity and foreign exchange market behavior. The empirical analysis relies on a unique combination of datasets to measure war intensity, market behavior, and policy, with each source chosen to provide high-frequency, granular information for the period following the full-scale invasion on February 24, 2022.

2.1 Data Sources and Variable Construction

The primary independent variable, a proxy for **War Intensity**, is constructed from air raid alert data. In Ukraine, an air raid alert is an official civil defense warning issued by regional military administrations to signal an imminent threat of aerial attack. The duration of these alerts functions as a direct and salient proxy for both the immediate level of perceived physical danger and the intensity of war-induced economic disruption. This study constructs a comprehensive alert dataset from two distinct sources, as archived in a public repository. For the initial phase of the war (*February 24 to March 14, 2022*), the analysis uses a dataset compiled by volunteers. From *March 15, 2022, onward*, the analysis switches to the official, systematically recorded dataset. For this study, two permanent, non-terminating alerts (in Luhansk Oblast since April 2022 and Crimea since December 2022) are excluded from the main analysis as they represent a constant state of threat rather than a specific, time-bound shock. All alert timestamps are converted to the Europe/Kyiv timezone. From this raw data, two key variables are generated: a daily national index of total alert duration (*Alert Hours*), and a regional panel dataset of weekly alert duration and frequency (*Alert Count*) for each oblast.

The primary dependent variable for the national-level analysis is the daily **Net Sale of Foreign Exchange (FX)**, sourced directly from the National Bank of Ukraine (NBU). While the NBU publishes data on four transaction components (purchases and sales of both cash and non-cash currency), this study focuses on the aggregated Net Sale figure for several reasons. First, it is the most comprehensive measure of the overall market direction. It captures the balance of supply and demand from the household sector, reflecting whether individuals as a group are net buyers or sellers. Second, a negative value for net sales serves as a direct and intuitive proxy for a "flight-to-safety" impulse. Third, using the net figure mitigates measurement noise from specific behavioral shifts, such as a temporary preference for physical cash over electronic transactions, providing a more robust measure of overall market pressure.

For the regional-level analysis, where a direct measure of FX transactions is unavailable, this study constructs a proxy for public attention and currency demand using **Google Trends**. The use of search query data as a direct, real-time measure of public attention is a well-established methodology in the finance and economics literature. The foundational work by Da et al. (2011) demonstrated that the Google Search Volume Index (SVI) for stock tickers is a powerful proxy for retail investor attention and can predict short-term trading activity and price pressure. This approach has since been widely adopted to measure sentiment and economic activity, particularly in contexts where official data is lagging or unavailable. For instance, recent studies on the current conflict have used Google Trends to measure everything from geopolitical risk perceptions to the impact of war-related attention on cryptocurrency markets (Bondarenko et al., 2024; Khalfaoui et al., 2023).

To validate the representativeness of this measure, it is important to note the dominance of Google in Ukraine's search engine market. As shown in Figure 4, Google accounts for more than 90% of search activity during the sample period (Feb 2022 – June 2025), with Yandex and Bing together representing less than 10% and all other providers below

1%. This overwhelming dominance reinforces the validity of using Google Trends as a reliable proxy for public attention in Ukraine.

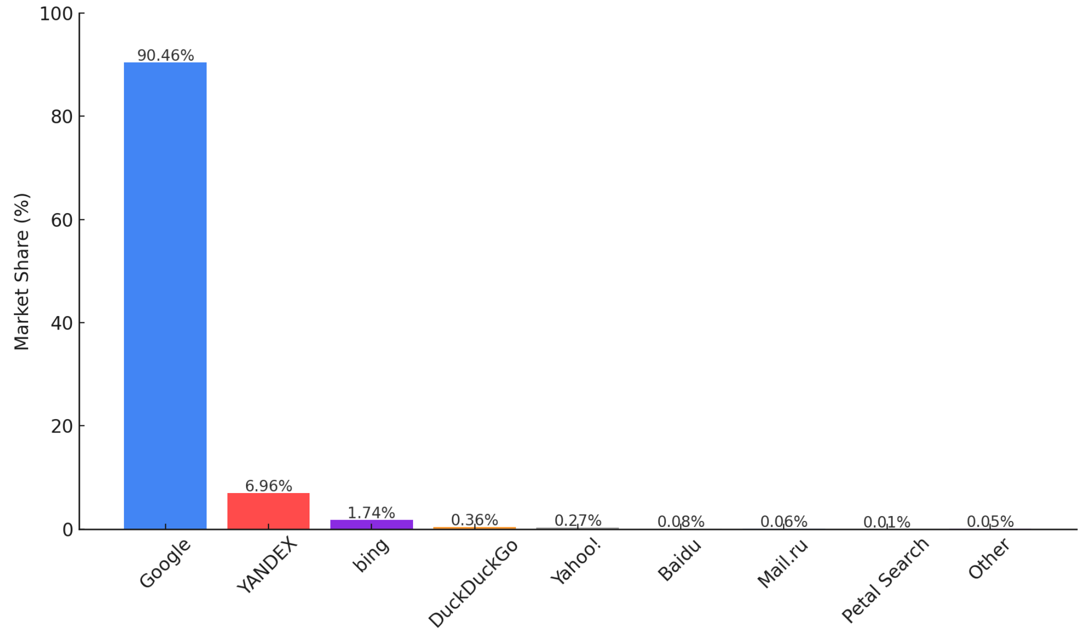

Figure 4: Search Engine Market Share in Ukraine (Feb 2022 – June 2025)
Notes: Google accounts for 90.5% of searches in Ukraine during this period, followed by Yandex (7.0%) and Bing (1.7%). Other search engines (DuckDuckGo, Yahoo, Baidu, Mail.ru, Petal Search, and others) collectively represent less than 1%.
Source: StatCounter Global Stats.

Following this literature, this study collects weekly SVI data for a set of specific, transactional search terms: "buy dollar" and "buy euro," in both Ukrainian («купити долар», «купити євро») and Russian («купить доллар», «купить евро»). Using these precise, action-oriented terms, rather than broader concepts like "war" or "economy," allows for a more direct measurement of the public's active interest in acquiring foreign currency. Collecting these terms in both Ukrainian and Russian enables a nuanced analysis of behavioral responses across linguistic groups and provides a window into the war's heterogeneous social and demographic impacts. For this panel analysis, the regions of Crimea and Sevastopol are excluded due to the unavailability of reliable and time-varying alert and search data for the analysis period.

A key challenge with using Google Trends data is its internal normalization, where search interest is scaled from 0 to 100 relative to the peak within the selected time frame and geography. To gather regional data for the entire period, this study employs a meticulous manual data collection process. For each week from February 2022 to the present, the regional breakdown for all of Ukraine ('geo=UA') was downloaded. A critical implication of this weekly download process is that *each week's data is scaled independently*. The "100" score in one week represents the peak search interest **for that week only** and is not directly comparable to the "100" score from another week. This data-generating process effectively removes any nationwide time-series trend from the raw data, as any common shock that raises search interest across all of Ukraine in a given week will be absorbed into that week's normalization. This study directly addresses this crucial data feature through the use of a *two-way fixed effects model*. As will be detailed in the next subsection, the inclusion of *time (week) fixed effects* in the panel regression perfectly and non-parametrically controls for this week-by-week rescaling. By doing so, the model identifies the effect of war intensity purely from the cross-sectional variation within each week—that is, whether regions with abnormally high air alerts in a given week also show abnormally high search interest relative to other regions in that same week.

Finally, two key control variables are constructed for the national-level model. First, the daily official **USD/UAH Exchange Rate** is included to account for price effects. As shown in Figure 5, the exchange rate was held at a fixed peg by the NBU for the first five months of the invasion before a significant one-time devaluation in July 2022. This structural break necessitates its inclusion as a control variable. Second, to isolate the impact of war intensity from concurrent policy shifts, a novel **NBU FX Regulation Index** was manually constructed for this study. This index is designed to quantify the stringency of capital controls imposed on individuals' foreign exchange transactions over time.

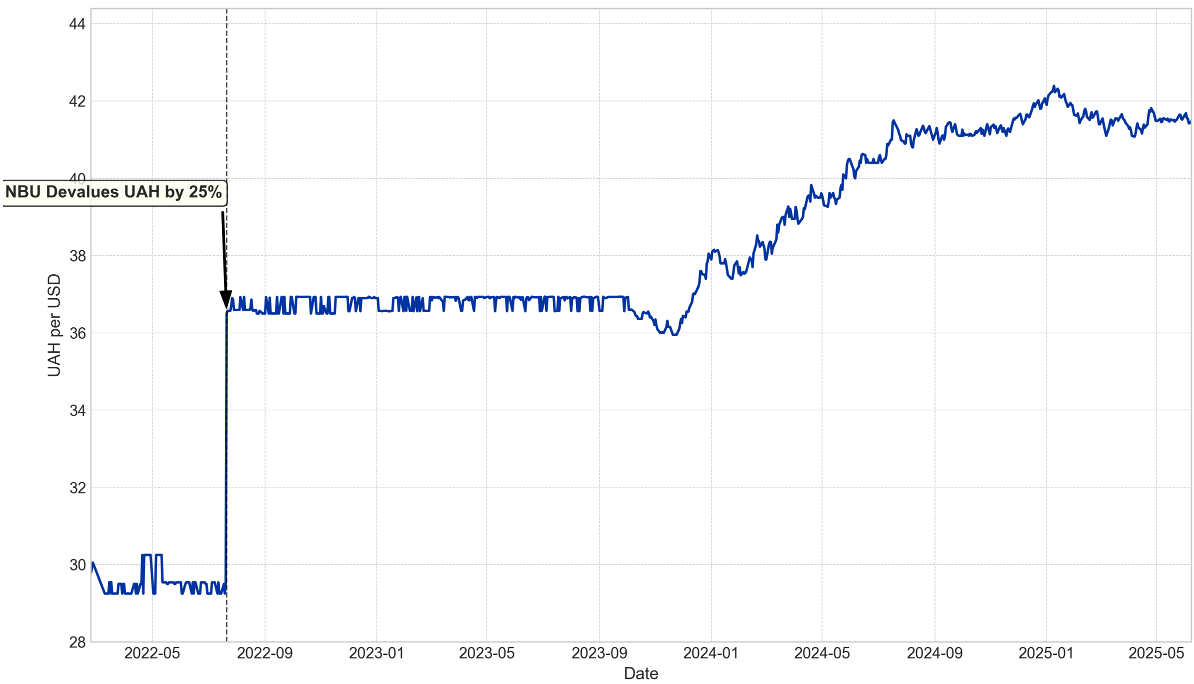

Figure 5: Official USD/UAH Exchange Rate (2022-2025)
Notes: The figure shows the daily official exchange rate set by the National Bank of Ukraine. The dashed line marks the NBU's decision on July 21, 2022, to devalue the hryvnia by 25% from 29.25 to 36.57 UAH per USD.

The construction of the index is based on a systematic review of NBU Board Resolution No. 18, enacted on February 24, 2022, and its subsequent amendments (National Bank of Ukraine, 2022). Each major policy change affecting the ability of individuals to buy or sell foreign currency was identified and categorized as either a "tightening" or "easing" of the FX regime. A numerical score was assigned to each event to reflect its relative impact. The index begins at a baseline value of 10 on February 24, 2022, representing the initial state of maximum restrictions where the FX market was effectively frozen for individuals. The index value decreases with each easing measure and increases with each tightening measure, creating a daily time-series that proxies for the intensity of policy-induced market friction. The key events and their corresponding score changes are detailed in Table 1.

To provide a comprehensive answer to the research question, the empirical analysis is structured in two distinct parts: a national-level time-series analysis and a regional-level panel analysis. This dual approach allows the study to first establish the aggregate, market-level relationship between war intensity and currency transactions, and then to investigate the underlying micro-foundations of this relationship using disaggregated behavioral data. The primary identification challenge across both models is to isolate the causal impact of war intensity from a wide range of potential confounding factors, including concurrent policy changes, broader macroeconomic trends, and unobserved sources of heterogeneity across regions. Each econometric model is therefore chosen specifically to address these challenges at its respective level of analysis.

2.2 Econometric Models and Identification Strategy

The empirical analysis is structured around two distinct econometric models, each chosen to address the identification challenges at its respective level of analysis.

2.2.1 National-Level Model: Distributed Lag Time-Series

At the national level, the goal is to estimate the dynamic impact of nationwide war intensity on the official foreign exchange market. Behavioral and market responses to shocks are rarely instantaneous; they often unfold over several days as information disseminates and individuals react. To capture these delayed effects, a **distributed-lag time-series model** is employed. This class of models is standard for estimating dynamic causal effects in macroeconomics and finance (Hamilton, 1994). The full specification is:

$$NetFXSold_t = \alpha + \sum_{i=0}^{p} \beta_i \cdot AlertHours_{t-i} + \delta' X_t + \epsilon_t \tag{1}$$

where $NetFXSold_t$ is the net volume of foreign currency sold by the NBU on day t. The key explanatory variables are the contemporaneous and lagged values of nationwide air

Table 1: Construction of the NBU FX Regulation Index

Date	**Resolution / Event**	**Key Change Affecting Individuals**	**Interpretation**	**Score Change**
2022-02-24	N° 18	Martial law begins. FX market is essentially frozen for individuals. Fixed exchange rate is introduced.	Maximum Restriction (Baseline)	+10 (Start)
2022-07-21	N° 154	NBU devalues UAH by 25%. Allows individuals to buy **non-cash** FX for 3-month deposits (up to 50k UAH/month).	First significant easing.	-2
2022-10-01	N° 154 (effective)	Limit for payments abroad with UAH cards reduced from 100k to 30k UAH/month.	Tightening.	+1
2023-08-29	N° 104	Allows buying **non-cash** FX online up to 50k UAH/month without conditions. Increases deposit limit to 200k UAH/month.	Major Easing.	-3
2023-12-01	NBU Policy Shift	NBU abandons the fixed exchange rate for a "managed flexibility" regime.	Fundamental Easing.	-3
2024-05-03	N° 56	Lifts **all remaining restrictions** on the sale of foreign currency to the public.	Full Liberalization.	-3

Notes: The index quantifies the strictness of NBU regulations on individuals' FX transactions. A higher score indicates a more restrictive regime. The index starts at 10 and cumulatively adjusts based on the score changes listed.

alert hours, $AlertHours_{t-i}$, up to lag p. The vector X_t contains crucial control variables: the official USD/UAH_t exchange rate and the newly constructed NBU_Index_t, which proxies for the stringency of capital controls. The term α is the model intercept, and ϵ_t is the error term, capturing all other unobserved factors.

A key parameter choice in this model is the lag length, p. An excessively short lag structure could suffer from omitted variable bias, while an excessively long one could introduce noise and reduce statistical power. To address this, the optimal lag length is determined empirically by estimating a series of models and selecting the specification that minimizes the Akaike Information Criterion (AIC), a standard approach for model selection (Akaike, 1974). Furthermore, daily financial time-series data are known to exhibit strong persistence and conditional heteroscedasticity. Preliminary analysis confirms this with a low Durbin-Watson statistic. To ensure the validity of statistical inference under these conditions, all specifications are estimated using Newey-West Heteroscedasticity and Autocorrelation Consistent (HAC) standard errors, a robust estimation technique common in financial econometrics (Newey and West, 1987).

2.2.2 Regional-Level Model: Two-Way Fixed Effects Panel

While the time-series model can identify aggregate effects, it cannot leverage the rich geographical variation in war intensity across Ukraine. The regional-level analysis addresses this by employing a **Two-Way Fixed Effects (TWFE)** panel model, which is a powerful tool for causal inference with panel data (Wooldridge, 2010). For this analysis, the daily alert and search data are aggregated to a weekly frequency. This choice is made to mitigate the high level of noise and data sparsity often present in *daily* regional-level Google Trends data, thereby providing a more stable and meaningful signal of public attention over time. The TWFE model is specified as:

$$SVI_{i,t} = \beta_1 \cdot AlertIntensity_{i,t} + \mu_i + \lambda_t + \epsilon_{i,t} \tag{2}$$

where i denotes the region (oblast) and t denotes the week. The dependent variable, $SVI_{i,t}$, is the Google Search Volume Index. The key independent variable, $AlertIntensity_{i,t}$, is the total duration (or, for robustness, the count) of air alerts in region i during week t.

The TWFE specification is crucial for identification as it isolates the effect of interest from major sources of confounding variation. The term μ_i represents *region fixed effects*, which control for all time-invariant differences between regions that could affect both war intensity and currency demand. This includes factors such as baseline wealth, demographics, historical attitudes towards currency substitution, industrial structure, and proximity to the front lines. By including μ_i, the model effectively compares each region only to itself over time.

The term λ_t represents *time fixed effects*, which absorb all common shocks that affect all regions in a given week. This is particularly important for two reasons. First, it controls for any nationwide events, such as major presidential addresses, significant battlefield news, or NBU policy changes that apply universally. Second, it non-parametrically controls for the week-by-week rescaling inherent in the downloaded Google Trends data, a critical feature of the data construction process. By differencing out both time-invariant regional characteristics and common time shocks, this identification strategy ensures that the coefficient of interest, β_1, is estimated from the variation in local alert intensity *within* a specific region over time, net of any aggregate trends. This approach is robust to many forms of omitted variable bias. To account for potential serial correlation of errors within a given region over time, standard errors are robust and clustered at the region level.

3 Descriptive Statistics

This section provides an overview of the key variables used in both the national-level and regional-level analyses. It begins with a clear definition of each variable, followed by a detailed summary of their statistical properties and visualizations of their evolution over time and distribution across regions. This exploration highlights the core sources of variation that underpin the subsequent econometric analysis.

Table 2: Variable Definitions

Variable	**Definition**
National-Level Variables (Daily)	
Net FX Sold	Net sale of foreign currency by the NBU to individuals, in millions of USD. A negative value indicates that public purchases exceed public sales.
Alert Hours	Total nationwide duration of all air raid alerts on a given day, in hours. This is the primary measure of war intensity.
USD/UAH	Official daily exchange rate of the Ukrainian Hryvnia to the U.S. Dollar, as set by the NBU.
NBU Restriction Index	A manually constructed index (0 to 10) quantifying the stringency of NBU capital controls on individual FX transactions. A higher value indicates more restrictions.
Regional-Level Variables (Weekly)	
Google Trends Score (SVI)	Weekly Google Search Volume Index (0-100) for currency-related keywords, at the oblast level. This serves as a proxy for public attention and currency demand.
Alert Hours	Total duration of all air raid alerts in a specific oblast during a given week, in hours.
Alert Count	Total number of distinct air raid alert events in a specific oblast during a given week. Used as a robustness check for war intensity.

3.1 National-Level Summary

The national-level analysis focuses on a daily time series spanning from February 2022 through June 2025. Table 3 reports the summary statistics for the key variables used in the final time-series regression model, which includes 845 daily observations. The primary independent variable, *Alert Hours*, averages approximately 66 hours per day nationwide. However, this mean value masks significant volatility; the standard deviation is large (40.94 hours), and the range is extreme, from a minimum of just over 2 hours on the quietest days to a maximum of over 280 hours during periods of intense, coordinated attacks. This substantial time-series variation is crucial for identifying the effects of war intensity.

The main dependent variable, *Net FX Sold*, has a mean of -24.99 million USD. The negative sign confirms the prevailing market dynamic over the period: on average, the Ukrainian public was a net buyer of foreign currency, absorbing nearly $25 million per day from the banking system. The large standard deviation ($24.80 million) and wide range (from a net sale of $24.3 million to a net purchase of $101.9 million) indicate a highly volatile market. The control variables also exhibit significant variation. The official *USD/UAH* exchange rate averaged 37.63, reflecting the NBU's policy of maintaining a stable, albeit adjusted, peg for much of the period. The *NBU Restriction Index*, which is re-centered for the analysis, shows that the policy environment was far from static, moving across its full potential range.

Table 3: Descriptive Statistics for National-Level Variables

Variable	Mean	Std. Dev.	Min	Max	N
Net FX Sold (USD mil)	-24.99	24.80	-101.90	24.30	845
Alert Hours (Daily)	65.83	40.94	2.14	280.60	845
USD/UAH Exchange Rate	37.63	3.51	29.25	42.39	845
NBU Restriction Index	-5.01	4.11	-10.00	0.00	845

Notes: Statistics are calculated based on the final regression sample of 845 daily observations. The statistics for 'Alert Hours' reflect the contemporaneous value (t); statistics for the lagged variables are nearly identical.

Figure 6 plots the total daily air alert duration over time. The lighter red line shows the raw daily data, which exhibits significant volatility. To better illustrate the underlying trend in war intensity, a 14-day rolling average is shown as a solid dark red line. The time series reveals several distinct phases of the conflict: an initial period of high but erratic intensity following the invasion, a relative lull during the summer of 2022, and a sharp, sustained escalation beginning in the autumn of 2022, corresponding to Russia's systematic attacks on Ukraine's energy infrastructure. This substantial time-series variation, with both high- and low-intensity periods, provides the empirical leverage needed for the econometric analysis.

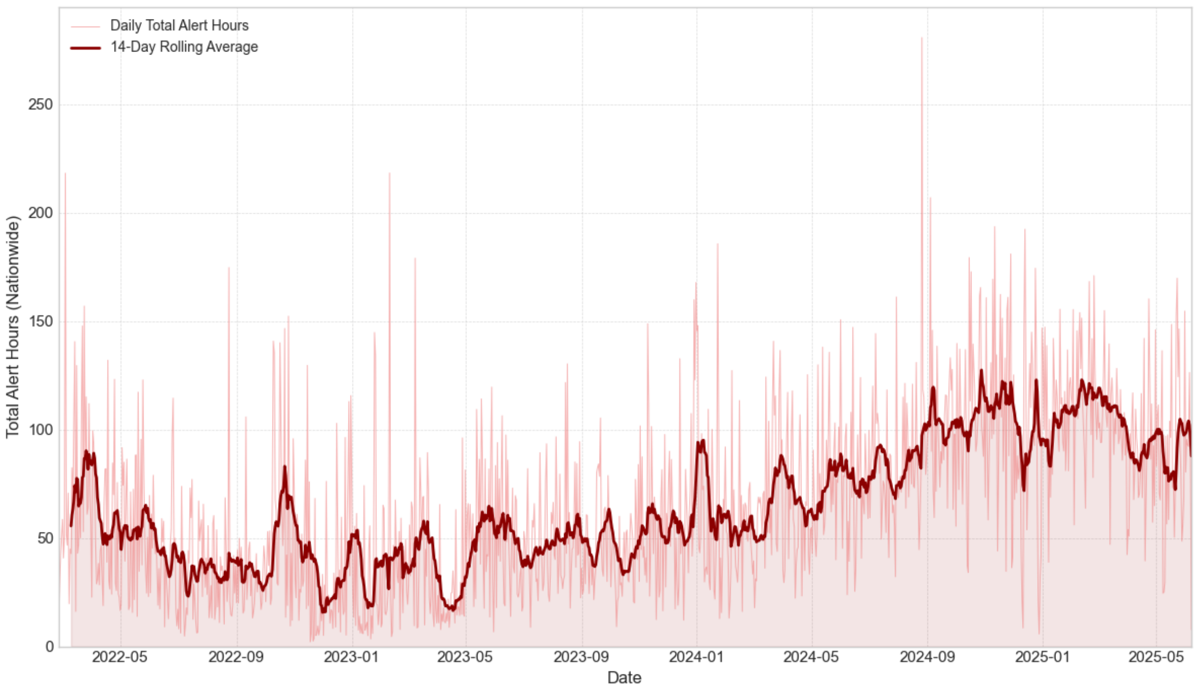

Figure 6: National Daily Air Alert Duration Over Time

Notes: The figure shows the total nationwide duration of air alerts in hours. The light red line represents the raw daily total. The dark red line is a 14-day centered rolling average, added to illustrate the underlying trend in war intensity.

Source: Author's calculations based on official and volunteer alert data.

Figure 7 shows the corresponding net sales of foreign currency. The 14-day rolling average reveals a clear structural shift around July 2022, when the NBU significantly devalued the hryvnia and began to ease FX restrictions. This policy change triggered a sustained period of large net purchases by the public (indicated by negative values), which gradually tapered off as the exchange rate stabilized and new regulations took hold in 2023. This visual evidence underscores the importance of controlling for NBU policy in the regression models to avoid spurious correlations.

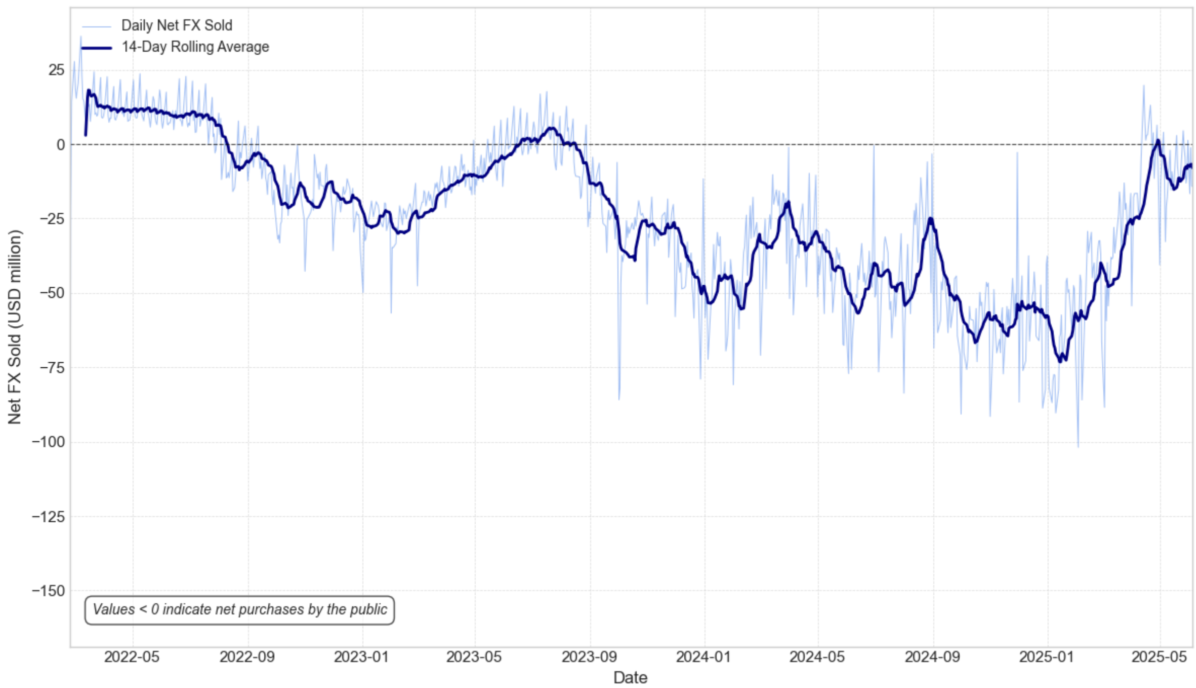

Figure 7: NBU Net Sale of Currency to Individuals

Notes: The figure shows the daily net sale of foreign currency by the banking system to the public, in millions of USD. The light blue line is the raw daily data, while the dark blue line is a 14-day centered rolling average. Values below the dashed zero-line indicate that public purchases exceeded sales (net demand for FX).
Source: National Bank of Ukraine.

3.2 Regional-Level Summary

The regional analysis utilizes a weekly panel dataset covering 24 Ukrainian oblasts. Table 4 presents the summary statistics for the key variables. The mean weekly alert duration per region is approximately 29 hours. However, the standard deviation (68.16) is more than double the mean, and the maximum value exceeds 1000 hours, indicating that some regions experienced weeks of near-constant threat. This confirms the presence of extreme heterogeneity in war exposure across regions. The *Google Trends Score* is heavily skewed, with a median of zero and a mean of 11.11. This is a typical feature of SVI data, suggesting that search interest for these specific terms is often below Google's reporting threshold but spikes during periods of high salience, providing the variation needed for the analysis.

Table 4: Descriptive Statistics for Regional Panel Data

Variable	Mean	Std. Dev.	Min	Max
Google Trends Score (SVI)	11.11	26.97	0.0	100.0
Weekly Alert Hours	29.18	68.16	0.0	1024.42

Notes: Statistics are based on a panel of 24 regions over 173 weeks, for a total of 17,150 region-week observations.

Figure 8 provides a clear visualization of the regional heterogeneity in war exposure by plotting the distribution of weekly alert hours for each oblast. The boxplot starkly illustrates the geographic nature of the conflict. Regions in the east and south, such as **Donetsk Oblast**, exhibit not only a very high median alert duration but also an extremely wide distribution, with numerous outlier weeks indicating periods of intense, sustained attacks. In contrast, western oblasts like **Lviv Oblast** and **Zakarpats'ka oblast** show distributions tightly clustered around zero, with much lower medians and shorter whiskers, signifying a significantly lower level of direct, weekly threat. The plot also reveals that even within relatively safer areas, there is a right-skewed distribution with occasional outlier weeks of high alert activity. This substantial cross-sectional and time-series variation in war exposure across regions is the primary source of identification in the two-way fixed effects panel model, as it allows for a robust comparison of how different levels of threat affect behavior while holding nationwide conditions constant.

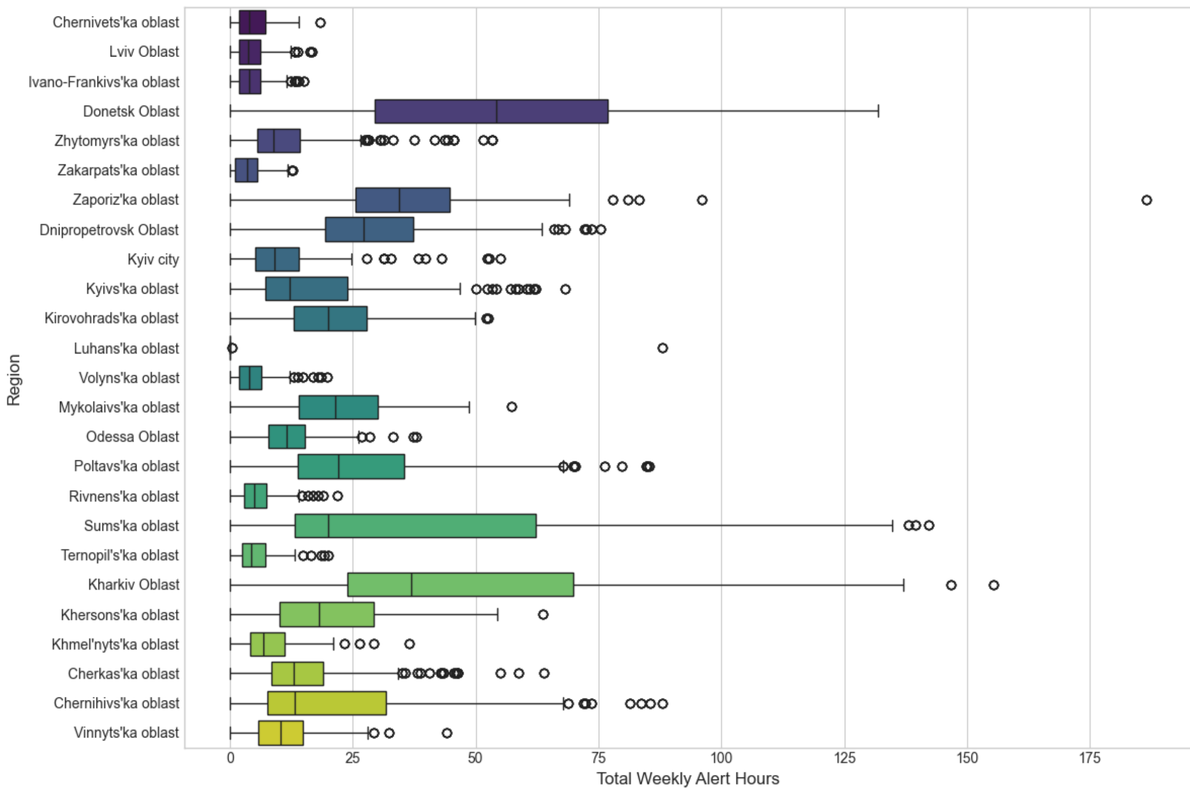

Figure 8: Distribution of Weekly Air Alert Hours by Region

Notes: Each box represents the interquartile range (IQR) of weekly alert hours for a given oblast. The line inside the box is the median. Whiskers extend to 1.5 times the IQR, and points beyond are shown as outliers.

Source: Author's calculations based on official and volunteer alert data.

4 Empirical Findings and Interpretation

This section presents the empirical results of the study. It begins with the national-level time-series analysis, which establishes the aggregate relationship between war intensity and foreign currency market dynamics. Following this, the regional-level panel analysis explores the behavioral underpinnings of these aggregate trends.

4.1 National Time-Series Analysis

The national-level analysis examines the daily relationship between the nationwide total of air alert hours and the net volume of foreign currency sold to the public by the NBU. The analysis progresses methodologically through three specifications to build a robust understanding of the market's response to war intensity. The key results from this progression are summarized in Table 5.

4.1.1 The Initial Correlation (Baseline Model)

The analysis begins with a simple OLS regression of net FX sales on the contemporaneous value of the alert index, presented in Column (1) of Table 5. The coefficient for *Total Alert Hours (t)* is **-0.186** and highly significant ($p < 0.001$). This initial, naive result suggests a "flight-to-safety" behavior, where a one-hour increase in nationwide air alerts is associated with an additional $186,000 in net FX purchases by the public. However, this simple model is likely misspecified due to significant omitted variable bias and dynamic effects, explaining only 9.3% of the variation in FX sales.

4.1.2 Diagnosing the Full Model (The Multicollinearity Problem)

To obtain a more accurate estimate, the analysis moves to a full dynamic specification, presented in Column (2) of Table 5. This model is theoretically superior, as it includes seven daily lags of the alert variable as well as continuous controls for the official exchange rate and the NBU Regulation Index, with standard errors corrected for autocorrelation (Newey-West HAC). While the inclusion of these controls dramatically improves the model's fit (R-squared rises to 0.541), a formal diagnostic assessment reveals a severe multicollinearity problem that renders its coefficients unreliable.

Before interpreting the model, a check for multicollinearity was performed. A correlation matrix revealed a strong negative correlation of **-0.827** between the *USD/UAH Rate* and the *NBU Restriction Index*. To formally quantify this, a Variance Inflation Factor (VIF) analysis was conducted. The VIF score for the *NBU Restriction Index* was **5.14**, exceeding the common threshold of 5 for problematic multicollinearity. This statistical issue manifests directly in the regression output: the coefficient on the *NBU Restriction Index* is positive (3.146) and highly significant, which is economically counter-intuitive as it implies that stricter regulations lead to *more* net FX purchases. These diagnostics confirm that the model in Column (2) cannot reliably disentangle the individual effects of the exchange rate and the restriction index.

4.1.3 The Robust Solution (Preferred Model)

To resolve the diagnosed multicollinearity, the analysis proceeds to the preferred specification shown in Column (3) of Table 5. An intermediate step (detailed in the Appendix) revealed that simply replacing the continuous restriction index with policy period dummies while retaining the USD/UAH variable exacerbated the multicollinearity, with VIF scores reaching as high as 131. This indicates that the effect of the exchange rate is almost entirely subsumed by the distinct policy regimes.

Therefore, the final, preferred model removes the redundant USD/UAH variable and includes only the alert lags and the policy period dummies. This specification successfully resolves the methodological issues; a final VIF analysis confirms that all scores are now well below the critical threshold of 5, validating the model's stability. The results from this robust specification are therefore clear and interpretable.

First, the coefficient on contemporaneous alert hours, *Total Alert Hours (t)*, is **positive and statistically significant (0.033, $p < 0.05$)**, solidifying the **"liquidity effect"** hypothesis. This indicates that after controlling for the prevailing policy regime, on days with higher war intensity, the public on aggregate becomes a net *seller* of foreign currency. To assess the economic significance of this finding, we can evaluate the impact of a one-standard-deviation shock. Given a standard deviation of 40.94 hours for daily alerts, a one-standard-deviation increase in war intensity is associated with an additional **$1.35 million** in net foreign currency sales by the public. While statistically significant, this magnitude is economically modest, representing just 5.4% of a standard deviation in daily net FX flows.

However, the importance of this finding lies in its context. The estimated effect of policy liberalization, by contrast, can shift the market by over **$54 million** per day (the coefficient for the final "Substantial Liberalization" period). The fact that the model can detect this subtle, but persistent, liquidity-driven behavior on top of these powerful policy shocks is a key contribution. It suggests that while policy dictates the overall market regime, direct physical threats impose real, measurable financial pressures on households at the margin, forcing them to liquidate safe-haven assets to meet immediate local-currency needs. The discovery of this "signal within the noise" provides granular evidence of a specific financial coping mechanism during wartime.

While the data do not allow for a direct test of the specific uses of funds, several plausible and non-mutually exclusive channels can explain this urgent need for local-currency liquidity. First, direct physical damage to property from missile or drone strikes necessitates immediate, unplanned expenses for repairs, such as replacing broken windows or patching roofs, which require cash or local digital payments. Second, heightened alerts can disrupt local supply chains and instill a sense of urgency, leading to precautionary stockpiling of essential goods like non-perishable food, medicine, and fuel—all of which are purchased in hryvnia. Finally, the threat of damage to critical infrastructure, including power grids and communication networks, may increase the perceived risk of electronic payment system failures. This could prompt households to increase their holdings of physical cash for transactional security, a need met by liquidating a portion of their most accessible foreign currency savings. These channels collectively illustrate how a direct physical threat translates into an urgent, micro-level demand for local currency that can temporarily outweigh the strategic desire to hold safe-haven assets.

Table 5: The Impact of Air Alerts on Net FX Sales (Time-Series Analysis)

VARIABLES	(1) Baseline OLS	(2) Main Model (HAC)	(3) Preferred Model (HAC)
Total Alert Hours (t)	-0.186***	0.044**	0.033**
	(0.022)	(0.017)	(0.017)
Total Alert Hours (t-1)		0.009	-0.002
		(0.014)	(0.013)
Total Alert Hours (t-2)		0.013	0.004
		(0.015)	(0.015)
Total Alert Hours (t-3)		-0.002	-0.011
		(0.016)	(0.015)
Total Alert Hours (t-4)		0.021	0.009
		(0.014)	(0.014)
Total Alert Hours (t-5)		-0.008	-0.017
		(0.014)	(0.014)
Total Alert Hours (t-6)		-0.018	-0.028**
		(0.014)	(0.014)
Total Alert Hours (t-7)		-0.001	-0.012
		(0.017)	(0.016)
USD/UAH Rate		-2.070***	
		(0.409)	
NBU Restriction Index		3.146***	
		(0.571)	
Policy: Period 2 (Easing)			-17.088***
			(2.420)
Policy: Period 3 (Tightening)			-24.558***
			(2.107)
Policy: Period 4 (Major Easing)			-38.546***
			(2.727)
Policy: Period 5 (Managed Flex)			-50.121***
			(2.926)
Policy: Period 6 (Full Lib)			-54.043***
			(4.213)
Constant	-11.959***	64.830***	12.446***
	(1.500)	(14.417)	(3.100)
Observations	864	845	845
R-squared	0.093	0.541	0.583
Controls (Policy/FX)	No	Yes	Dummies
HAC Errors	No	Yes	Yes

Notes: The dependent variable is the daily Net Sale of Foreign Currency (in USD millions). Standard errors are in parentheses. Models (2) and (3) include 7 lags of 'Alert Hours'. Model (1) is a simple OLS. Model (2) is the full specification with the NBU index and exchange rate, estimated with Newey-West HAC standard errors. Model (3) is the preferred specification, replacing the collinear continuous controls with policy period dummies. *** p<0.01, ** p<0.05, * p<0.1.

4.2 Regional-Level Panel Analysis

While the national-level analysis provides a clear picture of the aggregate market response, it cannot distinguish between regional variations in threat perception and behavior. To delve deeper into the micro-foundations of currency demand during the conflict, this study employs a panel data approach. This allows for the examination of how localized war intensity affects a behavioral proxy for currency demand within each of Ukraine's oblasts. The data is aggregated to a weekly frequency for this analysis.

A key feature of the manually collected Google Trends data is that each week's search scores are normalized independently. This means that a score of 100 in one week is not comparable to a score of 100 in another, as it only reflects the peak search interest *within that specific weekly timeframe*. This data-generating process effectively removes any common nationwide trends from the SVI data. Consequently, the only appropriate econometric specification is a **Two-Way Fixed Effects (TWFE) model**, as the inclusion of time (week) fixed effects is essential to control for this week-by-week rescaling. The entity (region) fixed effects are likewise necessary to account for time-invariant differences across oblasts. Therefore, all results presented in this section are from the TWFE model.

4.2.1 Baseline TWFE Regression Results: A Tale of Two Languages

The main regional-level results, presented in Table 6, reveal a striking and informative divergence in the public's search behavior that depends on language. While the Ukrainian-language search term for "buy dollar" («купити долар») confirms the precautionary motive, the Russian-language equivalent shows the opposite effect.

Specifically, for the Ukrainian-language query, the coefficient for weekly alert hours is **positive and statistically significant (0.0586, p $<$ 0.01)**. This finding provides strong evidence for the "precautionary motive" hypothesis: a direct, localized threat measurably increases public attention towards acquiring safe-haven currency. In stark contrast, the coefficient for the Russian-language term («купить доллар») is **negative and statistically significant (-0.2271, p $<$ 0.01)**.

This divergence does not imply that Russian-speaking individuals have a lower desire for dollars when threats increase. Rather, it suggests that the two search terms now represent distinct populations whose behavior and circumstances are shaped by the war's demographic and social consequences. This counter-intuitive result can be explained by three interconnected factors.

First, the most powerful explanation is likely **war-induced population displacement**. As shown in the alert intensity maps (Figure 1) and distributions (Figure 8), the highest concentration of air alerts is in the eastern and southern oblasts, which historically had the largest shares of Russian speakers. Intense, sustained bombing in these regions has prompted mass evacuations. Therefore, a higher alert duration in an area like Donetsk or Kharkiv oblast is directly correlated with a smaller population remaining to conduct searches in any language. The negative coefficient for the Russian term likely captures this tragic demographic footprint of the war, as the population that would have searched in Russian has been forced to flee.

Second, this effect is compounded by a well-documented societal **linguistic shift**. Since the full-scale invasion, many Ukrainians who were previously bilingual have consciously switched to using the Ukrainian language as an expression of national identity and resistance. In moments of heightened threat, even a habitual Russian speaker might substitute Ukrainian for financial searches, channeling attention towards the Ukrainian query and away from its Russian counterpart.

Finally, for those remaining in occupied territories or active frontline areas, their **divergent economic realities** make searches for buying dollars through the official Ukrainian financial system irrelevant. These populations are severed from the national banking system, and their economic concerns are fundamentally different, centered on survival, barter, or navigating an occupation currency.

Therefore, the analysis strongly suggests that «купити долар» is the most salient and representative search query for the precautionary motive among the population integrated into the Ukrainian financial system. The negative result for the Russian equivalent is not a behavioral contradiction but rather a powerful statistical artifact of war-induced displacement and societal change, rendering it an unreliable proxy for this specific financial impulse.

Table 6: Two-Way Fixed Effects (TWFE) Panel Regression Results

	Dependent Variable: Google Trends Score			
Search Term	'buy dollar' (Ukr)	'buy dollar' (Rus)	'buy euro' (Ukr)	'buy euro' (Rus)
Weekly Alert Hours	**0.0586***** (0.0224)	**-0.2271***** **(0.0829)**	-0.0103 (0.0138)	-0.1117** (0.0458)
Observations	4,200	4,300	4,325	4,325
Entity & Time Effects	Yes	Yes	Yes	Yes

Notes: The table displays the coefficient for weekly alert hours from the preferred Two-Way Fixed Effects model. Robust standard errors, clustered by region, are in parentheses. *** $p<0.01$, ** $p<0.05$.

4.2.2 Robustness Checks

To ensure the stability and validity of the baseline findings, a series of robustness checks were performed.

Levels vs. First-Differences. To ensure the finding is robust, an alternative specification was estimated to test whether public attention is driven by the week-over-week *change* in alert intensity, rather than its absolute *level*. This alternative model regressed the Google Search Volume Index on the first-difference of weekly alert hours ($\Delta \text{AlertHours}_{i,t} = \text{AlertHours}_{i,t} - \text{AlertHours}_{i,t-1}$) using the same two-way fixed effects specification. This tests whether public attention responds more to the 'shock' of a change in threat rather than the 'level' of threat. The results from this alternative specification showed a coefficient that was both counter-intuitive (negative) and statistically insignificant (p = 0.051). This provides strong evidence that public attention is not driven by the salience of weekly changes in war intensity. In contrast, the primary model using the absolute level of alert hours yields a stable, positive, and highly significant coefficient. Therefore, the level specification was retained as the methodologically and theoretically superior model.

Alert Count vs. Duration. A potential concern is that the *frequency* of alerts may not be the best measure of perceived threat. An alternative hypothesis is that the number of times people must interrupt their lives is a more salient driver of anxiety. To test this, the TWFE model was re-estimated using the weekly count of distinct alert events as the independent variable. As shown in Table 7, the coefficient for the primary search term remains positive and statistically significant (0.0918, p = 0.0120). This confirms that the main finding is robust to the choice of threat metric.

Table 7: Robustness Check: Alert Count vs. Alert Duration (TWFE)

	Dependent Variable: Google Trends Score	
Search Term	(1) *'buy dollar'* (Ukr)	(2) *'buy dollar'* (Rus)
Weekly Alert Count	0.0918**	-0.2971**
	(0.0365)	(0.1321)
Observations	4,200	4,300
Entity & Time Effects	Yes	Yes

Notes: The table displays the results of the TWFE model using weekly alert count as the independent variable. Robust standard errors are in parentheses. ** p<0.05.

Logarithmic Specification. To account for the highly skewed distributions of the data, a final robustness check was performed using a log-log specification. This model estimates the elasticity between war intensity and public attention. The results confirm the core finding: the coefficient on log-transformed alert hours was positive and statistically significant at the 5% level (coefficient = 0.071, p = 0.046). This result can be interpreted as an elasticity: a 1% increase in weekly alert hours is associated with an approximate 0.071% increase in the search volume index for "buy dollar." This confirms the stability and reliability of the main conclusions.

4.2.3 Placebo Tests and Further Research

While the TWFE model provides a strong basis for causal inference, further tests could bolster the findings. A potential placebo test would involve running the same regression with non-threatening search terms (e.g., "weather," "recipes"). A null result from such a test would provide stronger evidence that the observed effect is specific to financial anxiety. Additionally, one could use leads of the alert variable to test for pre-trends. The absence of a significant coefficient on future alerts would support the claim that search interest does not systematically rise *before* an alert, but rather responds directly *to* it. While these tests are beyond the scope of this current analysis, they represent important avenues for future research.

5 Conclusion

This thesis set out to investigate how the daily intensity of war influences foreign exchange market behavior in Ukraine. By leveraging a novel, high-frequency measure of physical threat—daily air raid alerts—this research provides a clear answer: the population's financial response to heightened war intensity is a complex interplay between a **precautionary motive** to secure wealth and an immediate **liquidity need** to cover expenses. These two forces, operating simultaneously, are clearly visible when analyzing the market at different levels.

The regional-level analysis, which uses Google search data as a proxy for public attention, robustly demonstrates the precautionary motive. In oblasts experiencing more intense or prolonged air alerts, public search interest for terms like "buy dollar" increases significantly. This finding, identified using a methodologically robust two-way fixed effects model that controls for all unobserved regional and time-specific factors, confirms that the underlying behavioral impulse in response to direct danger is a flight to the safety of foreign currency. The result is stable across multiple specifications, holding for both alert duration and frequency, and is confirmed in a log-log model.

In contrast, the national-level analysis of official NBU transaction data reveals the binding constraints of policy and real-world needs. The preferred time-series model, which diagnoses and resolves a severe multicollinearity issue by controlling for NBU policy with regime-based dummies, shows that on days with higher alert intensity, the public on aggregate becomes a net **seller** of foreign currency. This liquidity effect suggests that the urgent need for local currency—likely to cover emergency costs such as immediate repairs to damaged property, the stockpiling of essential goods amidst supply uncertainty, or securing temporary relocation—can override the desire to hoard safe-haven assets. The divergence between the observed behavioral intent (in searches) and the actual market outcome (in transactions) is a key finding of this thesis, painting a nuanced picture of economic decision-making under extreme duress.

These findings have important implications. For policymakers, they highlight that managing a currency during wartime requires addressing both public anxiety and acute liquidity shortages. For the academic literature, this study makes three contributions. It introduces a novel, non-textual measure of war intensity that complements existing news-based GPR indices. It extends the investor attention literature to a new domain, linking an objective physical threat to a financial behavior proxy with a clean identification strategy. Finally, it provides granular, high-frequency evidence for the field of conflict economics, documenting the specific financial coping mechanisms of households during a war.

The analysis is, however, subject to certain limitations that open avenues for future research. The primary limitation is the reliance on proxies; official transaction data is not available at the regional level, and Google Trends data measures attention, not action. The striking divergence between the results for Ukrainian and Russian-language search terms provides a key insight: in a conflict zone, online data acts not only as a proxy for economic behavior but also as a sensor for profound demographic shocks, such as mass population displacement. This finding underscores a critical consideration for future research using high-frequency digital data in crisis settings. Furthermore, neither dataset captures activity on the informal or "black" currency market, which was likely significant. Future work could address this by incorporating data on the black-market exchange rate premium to provide a more complete view of currency pressures. Such an analysis could reveal whether the official and informal markets react in unison or if households substitute one for the other in response to direct threats and evolving regulations. Another valuable extension would be to explore further regional heterogeneity, for instance, by examining whether the presence of internally displaced persons (IDPs) or pre-war levels of dollarization amplify the observed effects. Ultimately, this thesis provides strong evidence that the daily rhythm of war echoes directly in the financial decisions of a nation's citizens, underscoring that a population's confidence in its own currency is a critical component of economic resilience in times of conflict.

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A Appendix: Additional Tables and Figures

A.1 Full Descriptive Statistics for National-Level Time Series

Table 8 provides the complete descriptive statistics for all continuous variables used in the national-level time-series regression models, including contemporaneous and lagged values of the *Alert Hours* variable.

Table 8: Full Descriptive Statistics for National-Level Regression Sample

Statistic	Alert Hours (t)	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7	Net FX Sold
count	857.00	857.00	857.00	857.00	857.00	857.00	857.00	857.00	857.00
mean	65.95	65.88	66.03	65.98	65.92	65.80	65.78	65.73	-24.60
std	41.02	40.97	41.29	41.28	41.28	41.17	41.17	41.21	24.87
min	2.14	2.14	2.14	2.14	2.14	2.14	2.14	2.14	-101.90
25%	34.08	34.08	34.08	34.08	34.08	34.08	34.08	34.04	-43.14
50%	58.94	58.94	58.94	58.88	58.48	58.48	58.48	58.48	-22.24
75%	93.37	93.36	93.37	93.37	93.36	92.59	92.59	92.59	-6.08
max	280.60	280.60	280.60	280.60	280.60	280.60	280.60	280.60	24.30
skew	0.82	0.83	0.86	0.86	0.87	0.87	0.87	0.87	-0.34
kurtosis	0.72	0.74	0.83	0.84	0.84	0.87	0.87	0.86	-0.48

Notes: Statistics are calculated for the 857 daily observations used in the final regression models that include 7 lags. *Net FX Sold* is measured in millions of USD.

A.2 Diagnostic Checks for National-Level Model

To justify the choice of the preferred time-series specification (Model 3 in Table 5), several diagnostic checks for multicollinearity were performed on the full model that included both continuous control variables (Model 2).

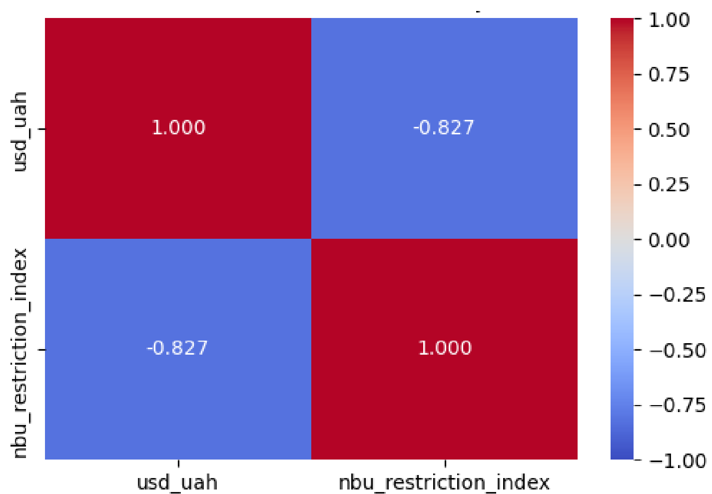

Figure 9: Correlation Between Continuous Policy Control Variables
Notes: The figure shows a strong negative correlation of -0.827 between the USD/UAH exchange rate and the NBU Restriction Index, indicating a high degree of collinearity.

The high correlation between the policy controls, shown in Figure 9, is formally tested using the Variance Inflation Factor (VIF). Table 9 presents the VIF scores for the two main specifications. In the problematic model (Panel A), the score for the *NBU Restriction Index* is **5.14**, exceeding the common threshold of 5 for problematic multicollinearity. In the preferred model (Panel B), all variables are well below this critical threshold, confirming that the specification successfully resolves the multicollinearity issue.

Table 9: VIF Diagnostics for National-Level Models

(a) Problematic Model (Model 2)		**(b) Preferred Model (Model 3)**	
Variable	VIF	Variable	VIF
const	319.35	const	20.94
Alert Hours (t)	1.53	Alert Hours (t)	1.56
Alert Hours (t-1)	1.57	Alert Hours (t-1)	1.59
Alert Hours (t-2)	1.53	Alert Hours (t-2)	1.56
Alert Hours (t-3)	1.53	Alert Hours (t-3)	1.56
Alert Hours (t-4)	1.51	Alert Hours (t-4)	1.53
Alert Hours (t-5)	1.54	Alert Hours (t-5)	1.56
Alert Hours (t-6)	1.55	Alert Hours (t-6)	1.57
Alert Hours (t-7)	1.49	Alert Hours (t-7)	1.51
USD/UAH Rate	3.20	Policy Period 2	1.56
NBU Restriction Index	**5.14**	Policy Period 3	2.59
		Policy Period 4	1.59
		Policy Period 5	1.95
		Policy Period 6	4.40

Notes: The table displays the Variance Inflation Factor (VIF) scores for the variables in the full specification with continuous controls (Panel A) and the preferred specification with policy period dummies (Panel B). A VIF score above 5 typically indicates problematic multicollinearity.

A.3 Full Panel Model Comparison Results

The following tables present the results from four different panel model specifications (Pooled OLS, Region FE, Time FE, and Two-Way Fixed Effects) for each of the four primary search terms. This comparison justifies the selection of the Two-Way Fixed Effects (TWFE) model as the preferred specification for the regional analysis. The instability of the *Weekly Alert Hours* coefficient across the simpler models highlights the severe omitted variable bias that is only resolved by the inclusion of both region and time fixed effects.

Table 10: Model Comparison for SVI on "Buy Dollar" Search Terms

	Dependent Variable: SVI for *'buy dollar'* (Ukr)				Dependent Variable: SVI for *'buy dollar'* (Rus)			
VARIABLES	(1) OLS	(2) Region FE	(3) Time FE	(4) TWFE	(5) OLS	(6) Region FE	(7) Time FE	(8) TWFE
Weekly Alert Hours	-0.178	-0.007	-0.175	**0.059*** **	0.091	-0.348***	0.220**	**-0.227*** **
	(0.105)	(0.013)	(0.121)	**(0.022)**	(0.099)	(0.085)	(0.106)	**(0.083)**
Constant	10.385*	7.366***	10.338*	6.196***	14.387***	22.222***	12.090***	20.069***
	(5.363)	(0.227)	(5.709)	(0.396)	(3.983)	(1.524)	(3.593)	(1.481)
Observations	4,200	4,200	4,200	4,200	4,300	4,300	4,300	4,300
R-squared (within)	-0.033	0.000	-0.032	-0.005	-0.029	0.049	-0.081	0.043
Region Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes
Time Fixed Effects	No	No	Yes	Yes	No	No	Yes	Yes

Notes: The table presents results from four panel model specifications. The dependent variable is the weekly Google Trends Score. Robust standard errors, clustered by region, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 11: Model Comparison for SVI on ”Buy Euro” Search Terms

	Dependent Variable: SVI for *’buy euro’* (Ukr)				Dependent Variable: SVI for *’buy euro’* (Rus)			
VARIABLES	(9) OLS	(10) Region FE	(11) Time FE	(12) TWFE	(13) OLS	(14) Region FE	(15) Time FE	(16) TWFE
Weekly Alert Hours	-0.136	-0.013	-0.155	**-0.010**	0.150	-0.162***	0.224*	**-0.112****
	(0.084)	(0.008)	(0.096)	**(0.014)**	(0.121)	(0.052)	(0.136)	**(0.046)**
Constant	8.331*	6.124***	8.669*	6.082***	12.527***	18.099***	11.199**	17.196***
	(4.317)	(0.144)	(4.583)	(0.247)	(4.385)	(0.920)	(4.401)	(0.819)
Observations	4,325	4,325	4,325	4,325	4,325	4,325	4,325	4,325
R-squared (within)	-0.015	0.000	-0.020	0.000	-0.039	0.015	-0.068	0.013
Region Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes
Time Fixed Effects	No	No	Yes	Yes	No	No	Yes	Yes

Notes: The table presents results from four panel model specifications. The dependent variable is the weekly Google Trends Score. Robust standard errors, clustered by region, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

A.4 Additional Robustness Checks for Regional Analysis

This section contains the detailed output from the robustness checks discussed in the main text of the Regional-Level Analysis. These checks confirm the stability and validity of the baseline findings.

Table 12: Robustness Check: Levels vs. First-Differences

VARIABLES	(1) Level (Baseline)	(2) First-Difference
Weekly Alert Hours (Level)	**0.0586***** **(0.0224)**	
Weekly Alert Variation (Change)		-0.0589* (0.0302)
Constant	6.196*** (0.3960)	7.230*** (0.0047)
Observations	4,200	4,175
R-squared (within)	-0.0049	-0.0002
Entity & Time Effects	Yes	Yes

Notes: The table compares the baseline TWFE model using the level of weekly alert hours to an alternative specification using the week-over-week change. The dependent variable is the SVI for *'buy dollar'* (Ukr). Robust standard errors, clustered by region, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 13: Robustness Check: Correlation of Linguistic Term Residuals

	Residuals (*'buy dollar'* (Ukr))	Residuals (*'buy dollar'* (Rus))
Residuals for *'buy dollar'* (Ukr)	1.000	
Residuals for *'buy dollar'* (Rus)	-0.013	1.000

Notes: The table shows the correlation between the residuals of the TWFE models for the Ukrainian and Russian language search terms for "buy dollar." The near-zero correlation suggests the unobserved drivers of search behavior are distinct across the linguistic groups.

Table 14: Robustness Check: Log-Log Specification

VARIABLES	(1) Log(SVI Score)
Log(Weekly Alert Hours + 1)	**0.0712****
	(0.0356)
Constant	0.2579***
	(0.0844)
Observations	4,200
R-squared (within)	-0.0051
Entity & Time Effects	Yes

Notes: The table shows the results of the log-log TWFE model for the search term *'buy dollar'* (Ukr). The coefficient on the log-transformed alert hours can be interpreted as an elasticity. Robust standard errors, clustered by region, are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.