Political Uncertainty and Credit Risk: The Role of Event Markets in Forecasting Ukraine's Sovereign Spreads

Mary Becker* — The University of Akron

Zachary McGurk† — Canisius University

May 29, 2025

Abstract

This study examines the role of prediction market data in forecasting Ukrainian sovereign bond spreads. Specifically, we use information contained in Polymarket event contracts to train an artificial neural network to predict changes in spread and improve forecast accuracy, particularly for 10-year bonds spreads. Because Polymarket contracts cover events from across the globe, we can capture real-time geopolitical uncertainty free of the filtration necessary for textual based analysis. The contribution of the paper is to show that a measure of geopolitical risk can be gathered from prediction market data, and show its usefulness in highly complex situations.

JEL Codes: G12,G14,D72,F34,H63
Keywords: Ukraine, Sovereign Bond Spreads, Geopolitical Risk, Polymarket, Out-of-sample Forecasting

1 Introduction

In August 2024 international bond holders of Ukrainian debt agreed to a 37% cut on the par of their holdings (Jones (2024)). The write down, which was required by the IMF, was considered a necessary step for financial stability and was brought on by Russia's full-scale invasion of Ukraine launched February 24, 2022. The restructuring reduced the country's external debt by more than $8.5 billion and came as the moratorium on debt payments -

*Department of Finance, College of Business, The University of Akron, Akron, OH. Phone: (216) 288-6280, Email: mbecker@uakron.edu

†Department of Economics and Finance, Wehle School of Business, Canisius University, 2001 Main St, Buffalo, NY 14208. Phone: (716) 888-2786, Email: mcgurkz@canisius.edu

granted to Ukraine in the summer of 2022 - was expiring (Fenbert and news desk (2024).[1] Besides debt relief, the restructuring provided a credible signal that the private sector was supportive of Ukraine's efforts to restore stability and fund its continued defense against Russia, as more than 97% of holders of Ukraine's existing bonds participated in the exchange offer (Jones (2024)).

Current global developments combined with the ongoing war and the precedent of debt restructuring lead us to believe that Ukraine's ability to meet its debt obligations is closely tied Ukraine's overall geopolitical risk. Given this dynamic, Economic Policy Uncertainty (EPU) from sources around the globe are likely prominent factors in the pricing of Ukrainian debt. In this study, we create a novel and expansive measure of EPU using pricing information found on the event contract market website, Polymarket.com(Polymarket), and determine if it provides information useful in forecasting Ukrainian bond spreads.

The impact of political uncertainty on financial markets is well documented (Huang et al. (2015); Li et al. (2018)), and increases in political uncertainty are associated with higher sovereign bond spreads (Subramaniam (2022)). EPU is not directly observable, and past research has relied on elections and political cycles (Brogaard et al. (2019); Li et al. (2018); McQueen and Roley (1993)) to indicate uncertainty and shocks, while another stream of literature has used textual searches to measure EPU (Wang et al. (2019),Baker et al. (2016)).[2] Follow up research in this area has led to the development of multiple indices for different countries (see Ghirelli et al. (2019), Arbatli Saxegaard et al. (2022), and Cho and Kim (2023) for examples).

We argue traditional measures of EPU are inadequate for understanding the role of political uncertainty within the highly complex situation of Ukraine. A better approach lies in examining event markets. This approach allows for an impartial measure of uncertainty without a priori expectations. Further, use of event markets will enable us to examine EPU independently from dictionaries and translations that are necessary for textual based searches. Because Ukraine is dependent on foreign support for its continued defense and ultimate rebuilding, an appropriate measure of EPU will necessarily measure current defense efforts along with global events and uncertainty. Using event markets allows us to take a global perspective where the market provides the information without filtration by journal-

[1] This was the second such restructuring in a decade, the first coming after the 2014 Russian invasion of Crimea.

[2] See Dai and Zhang (2019) for a review.

ists or researchers.

Polymarket is the world's largest event betting marketplace and covers a wide array of political, economic and specific Russo-Ukrainian War events.[3] In addition to advantages mentioned above, EPU determined from event markets is more timely than textual searches. Markets available on Polymarket are based on events that play out over a predetermined time period, and prices and returns are based on users' ex-ante expectations. Further, events outside of the country of interest can be accounted for and properly weighted without the judgment of a researcher. In essence, when using Polymarket information, the data guide the importance of each event. While investors outside of France, United States, United Kingdom and a few other restricted areas may participate in Polymarket, rational investors with local knowledge may help correct any mispricing.[4]

To capture the impact on EPU on Ukrainian bond spreads, we train a neural network to analyze the daily spread between Ukrainian sovereign debt and equivalent US Treasury securities using lag pricing data from 149 unique event contracts on Polymarket. Data ranges from September 3, 2024 to February 12, 2025. Events pricing utilized can be categorized as political events outside of Russia and Ukraine, political events in Russia and Ukraine, and events pertaining to the progress of the war. Table 1 provides a list of all events utilized.[5]

We conduct out-of-sample forecasting analysis using the Clark-West test (Clark and West (2007) to determine the added forecastability of our measure. Results show that a model using our estimate improves upon the mean model and models containing financial factors, especially for longer-term bonds. These findings suggest that event markets contain valuable information regarding the pricing of Ukrainian credit risk, and we believe this methodology can be fruitful for researchers wishing to determining EPU in a broad variety of cases.

[3]Examples of Polymarket markets include election winners, whether or not a ceasefire will be declared, and Federal Reserve decisions.

[4]Polymarket has been accused of allowing US residents of trading on the market. See https://www.reuters.com/markets/us/us-criminal-civil-authorities-probing-polymarket-source-says-2024-11-14/

[5]Note some events contain multiple contracts references outcomes outside of "Yes" or "No."

2 Literature

Our paper adds to a growing body of literature examining the role of politics, world events, and political sentiment in financial markets (Aboody et al. (2018); Dai and Zhang (2019)). Financial economics theory suggests that a relationship exists between asset returns and political and macroeconomic uncertainty. For example, the model developed by Pástor and Veronesi (2013) suggests political shocks are orthogonal to economic shocks and that EPU commands a risk premium. Further, the premium is larger in weaker economic conditions. Political outcomes influence asset prices by way of investors' beliefs about possible future economic conditions created by political decisions.

Prior research has worked to refine and improve EPU measurement. Early work by Tetlock (2007) suggests that financial markets are sensitive to information from news reports. He shows that more negative words in a popular *Wall Street Journal* column predicts daily stock returns. Garcia (2013) builds on this work and finds that this relationship is strongest for times of macroeconomic hardship, in particular during recessions. Looking at a broader set of sources, Baker et al. (2016) create an index of EPU based on the frequency of terms related to uncertainty in articles in 10 leading US newspapers (BBC metric). They find that political uncertainty is associated with greater stock price volatility and reduced investment. The declines in stock returns from uncertainty shocks are thought to be the result of broader macroeconomic consequences such as delayed or increased cautiousness of investment (Bloom (2009); Gholipour (2019); Bloom et al. (2007); Baker et al. (2016)).

Subsequent work has focused on developing indices, similar to the BBC metric, that are textual and country-specific. For example Ghirelli et al. (2019) create a Spanish EPU index by searching a larger set of Spanish-relevant national newspapers, and restricting articles relevant to Spain (although a wider search does not change their results). Other examples, not a comprehensive list, come from Japan (Arbatli Saxegaard et al. (2022)), Korea (Cho and Kim (2023)), and Turkey (Kilic and Balli (2024)).

Past literature has specifically explored the relationship between news and bond spreads. For example, Liu (2014) finds that European bond spreads are related to sovereign credit risk using a textual dictionary and Beetsma et al. (2013) find a domestic and international effect of "Eurointelligence newsflash" news variables on bond spreads. In an investigation of Italian bond spreads, Consoli et al. (2022) find that economic news within a neural network is related to bond spread.

Evidence that political uncertainty in one country can spillover to asset prices in another comes from work by Brogaard et al. (2019) which shows that uncertainty as measured by the US Election cycle leads to a fall in stock returns in non-US countries. Their testing suggests that the fall in stock prices is due to an increase in investors' risk aversion. Apergis et al. (2023) shows that higher partisanship in the US is related to lower bank lending activities in the UK, and Gavriilidis et al. (2023) find evidence of herding by institutional investors during politically uncertain times.

Our study contributes to the literature in a few ways. First, we provide a novel measure of EPU that does not require reading news or social media. Second, we avoid the limitations of textual search, namely an inability to measure the progress of the war and global political events. Third, we provide additional evidence of the relationship between EPU and sovereign bond spreads in highly complex times.

3 Data and Empirical Methods

3.1 Data

3.1.1 Uranian Sovereign Credit Spread

On August 30th 2024, Ukraine refinanced and reissued its foreign currency denominated debt. The new debt was issued in USD with terms five, ten, and eleven years, maturing in 2029, 2034, and 2035. We focus our analysis on the five year and ten year debt with coupon payments of 175 bps. The spread between the Ukrainian Sovereign bond yields and the equivalent US Treasury Security yield are obtained from Bloomberg. We conducted an Augmented Dickey Fuller test to determine evidence of a unit root, as we were unable to reject the null hypothesis. We calculated the change in spread as such: $\Delta CS_{it} = CS_{it} - CS_{it-1}$. CS represents the spread and i represents the specific term, either $5y$ or $10y$.

3.1.2 Financial Prediction Set

We follow Riedel et al. (2013) and obtain the standard risk proxy measures. As Ukraine is located in Europe but debt is issued in USD, we look at both US and European measures. These include implied market volatility, measured by the change CBOE VIX (ΔVIX) and currency risk measured by the return from the USD to EUR exchange rate ($R_{USD/EUR}$).

Equity market risk is measured by the daily returns of the S&P 500 (R_{US}), and STOXX Europe 600 (R_{EUR}). Yield curve risk is accounted for by the difference between the yield on the 2Y and 10Y benchmark for the US Treasuries ($Yield_{US}$) and German Bonds ($Yield_{DE}$). We also obtain the return from the ICE BofA Commodity Index eXtra CLA Index (R_{Oil}), a crude oil index. As Ukraine's main export is seed oils and other grain, we also include the return from the World Agricultural Commodity Index (R_{Ag}).[6]

As the National Bank of Ukraine employs capital controls, information in currency and domestic equity markets are not likely to accurately reflect risk. Therefore we proxy for domestic equity risk by obtaining the returns from a value weighted index of Ukrainian firms which have equities traded in foreign markets (R_{UA}). These include six firms with shares trading in PLN on the Warsaw Stock Exchange and two firms trading on the London Stock Exchange in USD and GBP.[7] Table 2 shows a list of all variables utilized, a definition, and source.

3.1.3 Polymarket Event Markets

We gather data from the prediction event marketplace, Polymarket. Prediction markets are those where participants purchase contracts based on future events, specifically buying yes or no assets that will pay out \$1 (\$0) if the event concludes with that outcome (the opposite outcome). Because we are interested in political events that affect Ukrainian bond risk, we gather political market data for events in Ukraine, the US, Russia, China, and former Soviet Republics. Market examples used include "Will Ukraine join NATO in 2024?" and "Will Putin meet with Trump in the first 100 days?"

Residents in the US, France, UK, and a few other locations are bared from trading through only an IP location check. However, while Polymarket's terms of service states that utilizing a VPN to bypass location requirements is forbidden, circumventing this restriction is possible.[8]

Polymarket offers several advantages as a prediction marketplace for this study. First, there are no limits to the number of contracts sold in any specific market nor are there restrictions on how much can be held by one investor. Second, markets are suggested by market participants and can cover a wide array of topics or issues. This leads to a third advantage, which is that markets cover a variety of geopolitical events happening all over the world.[9]

[6] See USDA - Ukraine Agricultural Production and Trade.
[7] Weighting is done by average market capitalization in PLN in 2023.
[8] See: Polymarket TOS.
[9] This allows for more macabre event markets to be actively trade. For example, "Will Russia use a

In the context of this study, Polymarket has active contracts concerning the progression of the Russo-Ukranian War as well as numerous other markets connected to political outcomes across Europe. Markets are short or long term. For example, some markets may cover long term political events, such as the US presidential election, while new events can appear and settle within the month, potentially adding new information.

We argue that information gleaned from Polymarket auctions may be more reflective of EPU versus other information sources. Specifically, rational local investors may readily account for relevant information due to a superior understanding of the culture, language, and political climate, whereas outside investors may depend on filtered information. For example, Kim et al. (2023) and Ferreira et al. (2017) find evidence that local investors perform better and have an information advantage. While a bias may, at times, exist due to users differing from the population at large, changes in prices should reflect correct movement in expectations, ultimately pressuring markets to be correctly priced. This assertion fits well with the long literature that has found that domestic investors outperform foreign investors (Coval and Moskowitz, 1999; Choe et al., 2005; Agarwal et al., 2009).

We gather all Polymarket contracts settled and still being traded based on geopolitical events occurring in every country in Europe, the former Soviet Republics, US, and China. We drop any asset where the number of days traded is less than 25, yielding 270 separate assets. We then remove the least liquid assets (zero variance in price) and those not trading for at least 30 days after the Ukrainian bond issuance of August 30th, 2024, yielding 120 assets in 52 separate markets.[10] Table 1 lists all markets, their associated country, and the total value of all contracts in the market. The volume runs the gambit from as little as \$15,000 for "New Netherlands election called in 2024" to \$3.6 billion for "Presidential Election Winner 2024(US)"

3.2 Empirical Methods

3.2.1 Neural Network Approach for Financial Modeling

As Polymarket event contracts are on average only traded for 48 days, contracts are introduced and removed throughout the sample period. By definition, a non-linear relationship exists between individual contracts and ΔCS, as contracts provide no information before they are introduced and after they expire. To effectively model this non-linearity, we employ an artificial neural network, which can capture the complex nature of financial time series. Alternative dimension reduction techniques and machine learning methods would be

nuclear weapon in 2024?" or "Which country will have a higher COVID-19 case count?"

[10] Generally, each market has a yes and no asset, but some markets, such as "UK election called by...?" has multiple dates and each date has a yes and no asset.

inappropriate. Standard methods like principle component analysis, dynamic factor models, and LASSO assume linearity and by definition this relationship should be non-linear. Other methods like long short term networks and gradient boosting machines often require longer time series for stable estimation. Given the nature of our data, an artificial neural network provides a feasible approach for obtaining information from event market prices.

We employ methods widely used in finance machine learning literature (see discussion and methods (Gu et al., 2020)). Similar methods have been utilized in other forecasting settings for yield spreads in the case for Europe (Belly et al., 2023) and Italy specifically (Consoli et al., 2022).

An augmented Dickey Fuller test was conducted on all assets and the difference was taken for those assets found to have evidence of a unit root.[11]. We then employ a Kalman filter and impute missing observations for dates that are missing and available for ΔCS_{it}.[12]

We use Multi-Layer Perceptron to model the relationship between the lagged event contract prices and ΔCS_i. This is estimated for both the ten year and five year spread. Our model is consists of an input layer (contract prices), two hidden layers, and an output layer (ΔCS_i).[13] At the input layer, we use min-max normalization to scale all predictors. In the hidden layers, we use rectified linear activation functions, allowing our estimation to capture both potential linear and non-linear relationships. The model is trained using stochastic gradient descent with the Adam optimization algorithm, allowing for learning rates to have dynamic adjustment. The model is optimized using the Mean Squared Error loss. Eighty percent of the data was used for training and the remaining twenty percent for validation. As a result, we can obtain a prediction of ΔCS_i using only information on Polymarket.

As our primary goal is to determine if the event contracts contain any forecasting information that would be useful in practical application, we estimate the neural network once using the first sixty percent of the observations and then re-estimate after each forecast has been realized, updating information. This is done to limit look ahead bias. In our in-sample results, this is minimized and for our out-of-sample results it is eliminated. We label the predict value of ΔCS_i using the artificial neural network $\widehat{\Delta CS}_{NN,i}$.

Figure 2 and Figure 3 show a graphical representation of the event contracts connections between each other and the target variables, ΔCS for the five year and ten year bonds, respectively.[14] Only the top 27 nodes by weight with the target are shown, with interconnection between event contracts only shown if their weight was greater than 0.3. This was

[11] These results can be provided upon request

[12] In most cases, this yields a value of zero for imputed observations.

[13] We utilize two layers as it can capture potential higher-order interactions between event contracts but limits potential of overfitting in deeper networks.

[14] These show the graphs on the last estimation.

done to improve readability. The first two letters on any node label represent the market's country of interest, and to potentially too a second country. LG refers to the legislature elections or decisions and LD refers to the countries leader election or decisions. The last couple of letters refer mostly to specific candidates in elections. For example, $UA.RU.CF$, refers to the contract "Russia x Ukraine Ceasefire in 2024?" Further, $RO.LD.CG10$ refers to the asset "Romania Presidential Election Margin of Victory?" - Călin Georgescu by over 10.

In both graphical nodes, we see that potential leadership changes in Ireland, the dissolution of the Bundestag, and the first-round elections in Romania are interconnected and closely related to ΔCS. This may reflect shifting political dynamics in Europe more broadly. Legislators in Romania, Ireland, and Germany were governing as coalitions, potentially moderating policy toward Ukraine. As a skeptic of aid to Ukraine, George Simion ($RO.LD.R1.S$) and his expected performance in the first round of the Romanian election may be indicative of this trend.

Surprisingly, very few actual military events in the Russo-Ukraine War appear to be directly linked to yield spreads. The recapture of Sudzha by Russia and Ukraine's defense of Kursk seem to be exceptions. Both events relate to the newest front of the war, Ukraine's incursion into Russian territory in August 2024. While there has been movement in other regions over the past year, the war is generally viewed as a stalemate. Ukraine's ability to maintain this stalemate is believed to be tied to the continuation of weapons and aid from the West. This may explain why outcomes in European elections are more closely related to yield spreads than battlefield developments.

Figure 4 shows a graph of estimated Ukrainian yield spread $\widehat{\Delta CS}_{NN,i}$ and actual yield spread (ΔCS_i) over the sample. To improve readability, we have scaled $\widehat{\Delta CS}_{NN,i}$ by the standard deviation of actual ΔCS_i. Our predictor seems to do a relatively good job in estimating the overall trend and movement of ΔCS_i. Although does poorly in predicting large changes which are likely due to events that were unpredictable by information found on Polymarket. For example, the largest gain in spread occurred on November 19th, this may correspond to Putin escalating nuclear tensions by signing a degree that allows Russia to attack a non-nuclear power if they are being aided by a nuclear power. While the largest fall occurred on Febuary 5th, possibly due President Trump announcement of Tariffs on Canada and Mexico.[15]

[15]While multiple Polymarket contracts addressed tariffs on Canada and Mexico, they were excluded due to insufficient trading days.

3.3 Forecasting Methods

Our goal in this forecasting exercise is to determine the marginal gain in forecast accuracy from models containing our $\widehat{\Delta CS}_{NN,i}$. We employee both in-sample and out-of-sample forecasting techniques to determine if the latent EPU information found on Polymarket event contracts is a useful predictor.

We estimate several one step ahead forecasting models utilizing both our $\widehat{\Delta CS}_{NN,i}$ and other measures of risk. All models take the form of:

$$\Delta CS_{i,t+1} = \mu + \gamma_1 \widehat{\Delta CS}_{NN,i,t} + X_t \Gamma + \epsilon_{i,s,t+1} \tag{1}$$

All models are estimated utilizing OLS and X_t represents the predictor set for that individual model. In all models X_t includes the change in the CBOE VIX index, ΔVIX, the log return on the USD-EUR exchange rate, $R_{USD/EUR}$, the log return on and oil index, R_{Oil}, the log return on a world agricultural commodity index R_{Ag}, and the log return of a value weighted index of Ukrainian stocks, R_{UA}. Additional variables specific to US or European markets include the 10- to 2-year difference on US Treasuries ($Yield_{US}$) and German bunds ($Yield_{DE}$), and returns on the S&P500 (R_{US}), and Europe 600 (R_{EUR}) indices. Table 2 gives variable definitions and sources.

The model containing the US risk factors is called *US Model*, the model containing the European risk factors is called *EUR Model*. The model containing all factors is *All Model*. For in-sample analysis, we also include $\Delta CS_{i,t}$ to determine if our measure is simply picking up a potential autoregressive structure of $\Delta CS_{i,t+1}$. While for out-of-sample analysis,we include a model only including $\widehat{\Delta CS}_{NN,i}$ as the only predictor.

As in-sample methods utilize all observations in estimation, we freely admit our in-sample analysis will suffer from some level of look-ahead bias. We do try to limit this as discussed in Section 3.2.1. We argue that due to the increasing use of Polymarket over the last year and the reissue of Ukrainian bonds in August 2024, this issue cannot be avoided while conducting in-sample analysis. Further we believe this would have some value as longer sample size lead to more precise parameter estimates.

For out-of-sample analysis we utilize a recursive estimation method starting with sixty nine in-sample observation (P) to estimate parameters and the remaining observations were used to forecast (R).[16] Resulting in P/R ratio of approximately 1.5.[17] As this matches the artificial neural network, our out-of-sample forecast does not suffer from look-ahead bias, it fully represents only information available a day before the yields were realized.

All out-of-sample forecasts are compared against to a baseline model of the historic mean. Further *US Model*, *EUR Model*, *All Model* are also compared against a model removing only our $\widehat{\Delta CS}_{NN,i}$. These are by definition nested model comparisons the standard Diebold and Mariano test (Diebold and Mariano, 2002) would be inappropriate. As such, we use the Clark-West Adjusted MSFE test (CW test) to determine forecast accuracy as developed in Clark and West (2007).

The CW test statistic (CW stat) is calculated as follows:

$$CW = \frac{1}{T-S}\sum_{t=S}^{T}\left[(e_{\text{null},t+1})^2 - (e_{\text{alt},t+1})^2 + (f_{\text{null},t+1} - f_{\text{alt},t+1})^2\right] \tag{2}$$

where $e_{\text{null},t+1} = y_{t+1} - \bar{y}_{t+1}$, the forecast error for the baseline (null) model. $e_{\text{alt},t+1} = y_{t+1} - \hat{y}_{t+1}$ represents the Forecast error from the comparison (alternative) model. $f_{\text{null},t+1}$ and $f_{\text{alt},t+1}$ are the out-of-sample forecasts from the benchmark and comparison models. Finally, $T - S$ represents the number of out-of-sample observations. CW represents the average gain (loss) of forecast accuracy, as it is simply an adjusted difference in MSFE between the two models. CW is then utilized to obtain CW stat, as described below:

$$CW \text{ stat} = \frac{\sqrt{T-S}\cdot CW}{\sqrt{\text{AVAR}(CW)}} \tag{3}$$

$avar(CW)$ is the estimated asyomtotic variance of the CW.

In the CW test, the null hypothesis is that the CW statistic equals zero and the alternative is that the CW statistic is greater than zero. Intuitively, if the baseline and comparison model were equally predictive, then the difference in MSFE between the baseline model and the comparison model would be zero. If the comparison model performs better than the baseline model, the CW stat would be positive, as the MSFE from the baseline model would be larger. The mean model is utilized as the baseline model for all other models.

[16] Fixed and Rolling estimation methods were also estimated with similar results. These results are omitted for brevity.

[17] P/R ratio will differ between models due to differences in trading days between US and European Markets.

4 Results

4.1 In-sample Evaluation

In order to test the reliability of the predicted spread, we first produce an in-sample evaluation and OLS to estimate the one-day change in the Ukrainian to US spread on the 5-year bond (columns 1 to 4) or the 10-year bond (columns 5-10), $\Delta CS_{i,t+1}$. Results are given in Table 3. All models are estimated for the change in spread on day $t+1$. All models include the change in spread at time $t=1$. The independent variable of interest, $\widehat{\Delta CS}_{NN,i}$, is the predicted change in bond spread based on the neural network model described in Section 3.2.1.

The in-sample evaluation includes prediction variables as described in Section 3.3 and we provide results for three specifications, the *US Model* in columns (2) and (6), the *EUR Model* in columns (3) and (7) and the *All Model* in columns (4) and (8). The coefficient on the predicted change in spread, $\widehat{\Delta CS}_{NN,i}$, is significantly related to change in spread for all specifications. Indicating risk information found on event markets are leading spreads. It is also important to note that while these results are strong, the inherent look-ahead bias in the estimation of $\widehat{\Delta CS}_{NN,i}$ limits conclusions in-sample to it is likely a useful predictor that warrants further investigation. The ΔVIX is negatively related to the Ukrainian bond spread, possibly detecting a declining yield in US bonds when investors seek safety, in the *US Model* and *All Model*. Results in columns (6) and (8) suggest that there is a negative relationship between the return on the agricultural index and spread for the 10-year bond only. Considering that Ukraine's top exports are agricultural, increasing returns on this index may provide investors with a higher level of confidence that the country will be able to make future debt payments.

For all specifications, the coefficient on the R_{UA} is positive and significant, possibly indicating that investors view Ukrainian stocks and bonds as complementary investments. A negative coefficient on the R_{US} variable suggests that the Ukrainian bond spread moves inversely with US stock returns. This is not unexpected as investors may seek alternative investments when US stock prices are high.

4.2 Out-of-Sample Evaluation

All out-of-sample forecasts are compared against a baseline model of the historic mean. Further *US Model*, *EUR Model*, *All Model* are also compared against a model removing only our $\widehat{\Delta CS}_{NN,i}$.[18] Table 4 presents the results from the Clark West test. The first column details the spread (5-*year* or 10-*year*), the second column the comparison model, and the third column the baseline model. Note by definition, the baseline model is nested within the comparison model. The fourth column shows the CW representing the difference in the adjusted MSFE between the two models. This metric can be interpreted by how much the model improves over the baseline model. The fifth column is the estimated asymptomatic variance of the CW measure. Finally, the sixth column is the *p-value* associated with the CW test.

Our results demonstrate EPU information transmitted through Polymarket event contracts are useful in predicting the future movement in Ukrainian risk premium. Additionally these results corroborate the in-sample resuts found above. For both spreads, $\widehat{\Delta CS}_{NN}$ *Only* produces statistically significantly more accurate forecasts compared to the *Mean* model, at the five percent level. $\widehat{\Delta CS}_{NN}$ *Only* model produces the largest reduction in MSFE for the five year spread and a similar reduction as the models which contain additional financial factors for the ten year spread. While this model is more parsimonious than other specifications, the $\widehat{\Delta CS}_{NN}$ measure is potentially picking up information regarding financial markets movements not connected to EPU. Intuitively, this transmission could happen within event markets in the following way: if economic conditions are improving (degrading) candidates/parties representing the status quo election chances' may also improve (degrade). As such we compare forecasts from the *US Model*, *EUR Model* and *All Model* against the *Mean* model. All of these models produce statistically significant forecasts compared to the *Mean* model. The strongest results are found for *US Model* and *All Model* which are significant at the one percent level. This potentially indicates that beyond EPU, US markets are providing more forecasting information.

Results suggest that the addition of $\widehat{\Delta CS}_{NN}$ does not necessarily improve forecasts over the financial factors for the five year spread. Improvement here is only seen in comparison to the *EUR Model w/o* ΔCS_{NN} where the inclusion of $\widehat{\Delta CS}_{NN}$ produces a marginally statistically significant increase of forecast accuracy at the 10 percent level. This result is contrast to the ten year spread where the inclusion of $\widehat{\Delta CS}_{NN}$ produces at least marginally

[18]Other models were estimated using alternative lags of ΔCS and results are still similar.

statistically significant forecasts for all three financial factor only models. $EUR\ Model$ and $All\ Model$ are significant at the five percent level. These results still indicate that useful information is being found $\widehat{\Delta CS}_{NN}$ over the standard financial factors.

The difference in these results could be simply due to the short time series and noisiness of financial data at the one day time horizon, as the models without $\widehat{\Delta CS}_{NN}$ produce insignificantly more accurate forecasts for the five year spread compared to the $Mean$ model. Further, $US\ Model$, $EUR\ Model$ and $All\ Model$ are only marginally significant against the $Mean$ model, possibly indicating that these financial predictors are weak predictors by themselves. Alternative explanations could be the EPU risk which is being captured by $\widehat{\Delta CS}_{NN}$ is being priced heavier in the long term. In other words, political events today may effect Ukraine's ability to rebuild, improve institutions, or attract future foreign investment, ultimately determining the country's ability to repay debt obligations in the longer term. Due to the structure of international organizations like NATO and the EU, smaller nations have over-sized power to influence policy. World Bank Group (2024) notes the importance of EU aid and attempts towards integration in the rebuilding of Ukraine; political shifts in even smaller EU countries could hinder these efforts.

Results presented here are important to policymakers in Ukraine and suggest that efforts to limit EPU risk may lead to better terms from lenders. Serious efforts to curtail corruption may better convince investors and foreign political leaders that funds will be used appropriately and help in reconstruction. Odarchenko and Poznii (2024) note that Ukrainian institutions need to address the problem of corruption, although increased efforts in this area by President Zelensky have had some success. Expanding these efforts would likely reduce the cost of Ukrainian debt.

5 Conclusion

In this study, we show how information found on political and economic event contract markets are useful in forecasting Ukrainian sovereign spreads. Using lagged pricing data from 149 US and European politics event contracts on Polymarket, we train an artificial neural network to predict changes in Ukrainian sovereign spreads. We then apply out-of-sample forecasting techniques to determine the marginal gain in forecasting accuracy from our metric. We find evidence our predictor is able to improve forecast accuracy compared to baseline models of the historic mean and only financial factors. Gains in accuracy are stronger for the ten year spread compared to the five year, potentially indicating EPU is a more important factor for pricing risk in Ukraine in the long run.

A potential explanation is that current US and European policies, such as military aid, financial assistance, or EU market integration, may impact its ability to service longer term debt. These results suggest that Ukraine policymakers looking to reduce borrowing costs should engage in policies, like corruption reduction measures, which aim to limit EPU risk. Our study is timely, as Ukraine reissued debt while Polymarket usage increased significantly, reflecting the numerous elections and political events in Europe and the United States. We demonstrate that readily-available unbiased data is a significant predictor of bond spreads, by way of a measure of uncertainty. Importantly, our novel approach has shown success in forecasting bond spreads where the guaranteeing country is engaged in war. The traditional macroeconomic factors, which not entirely irrelevant, pale in importance to global political factors.

It is worthwhile to consider other extensions of this approach. We believe this methodology can be fruitful for researchers determining EPU in a broad variety of cases. As new markets can be created during any crisis for any reason, market expectations surrounding any event are revealed. For example, the ability to forecast spreads for developing nations and those engaged in crises would benefit from this technique. Furthermore, future research may uncover relationships between event markets and asset pricing, where valuations are influenced by a range of geopolitical events and risks.

Finally, to address the specific case of Ukraine, we suggest that if the current momentum of Ukraine-skeptical political parties in the West continues, future Ukrainian debt issuance may become more costly, potentially constraining its ability to conduct the war effectively. News reports suggest that continued trading of Ukrainian bonds is driven in large part by ceasefire talks (George and Jones (2025)). Additionally, support for Ukraine by the United States and European allies is not guaranteed (George and Jones (2025)). For example, the reelection of Donald Trump in the United States in November 2024, and the relatively strong showing of the AfD party in the February 2025 German Bundstag election suggests growing support of political parties and leaders who are critical of involvement in Ukraine.[19]

The invasion of Ukraine on February 24, 2022 by Vladimir Putin's Russia has wrought

[19] Both Donald Trump and the leaders of the AfD would at the minimum be considered pushing for less intervention. See https://www.dw.com/en/russias-best-friends-in-germany-afd-and-bsw/a-70072663 and https://www.donaldjtrump.com/platform

dire consequences for the country including loss of life, poverty, food shortages, and daily trauma for millions of people (Kilfoyle (2023)). The future of the country is highly uncertain. The ability to continue fighting the war, and ultimate reconstruction, depends on the political support of international forces. While the economic consequences of the war, and in particular bond spreads, fail to capture the human toll of an armed invasion, this study is a step in the direction of understanding the long-term effects of the Russo-Ukrainian war.

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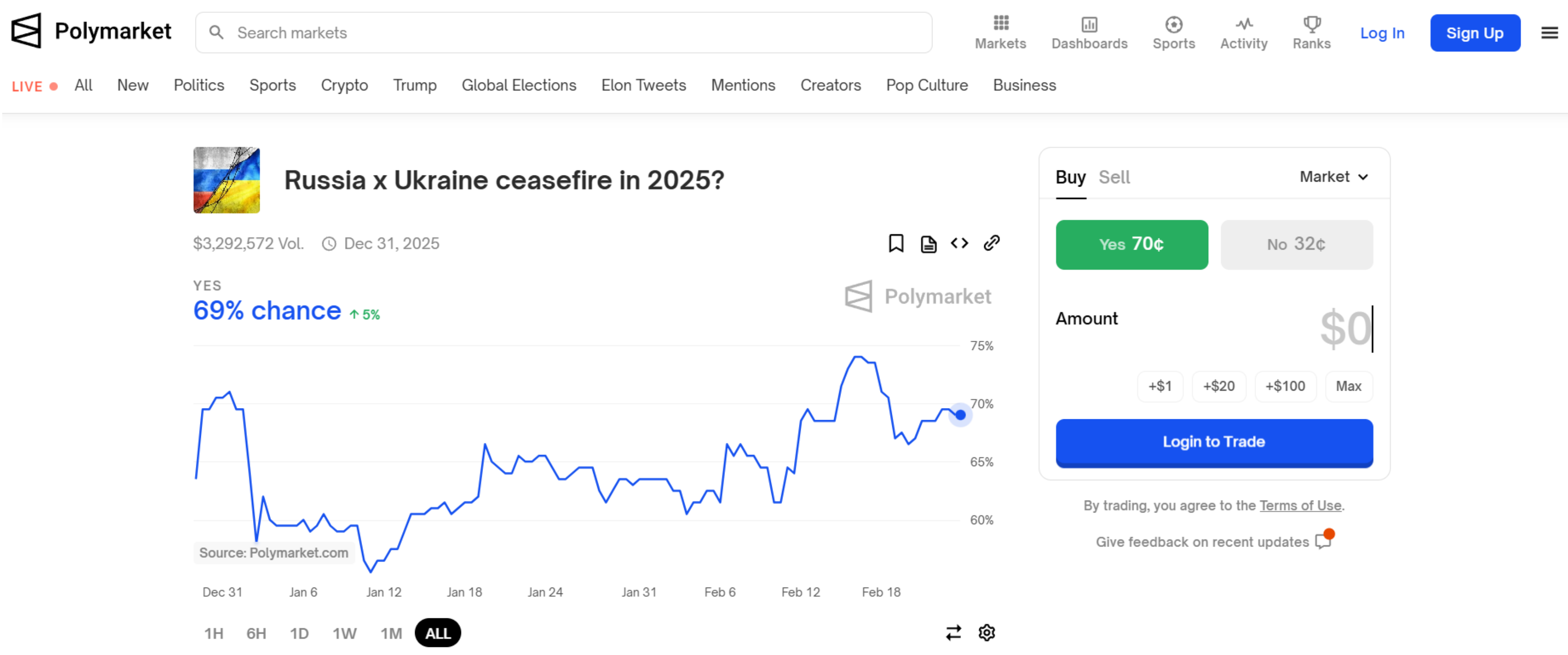
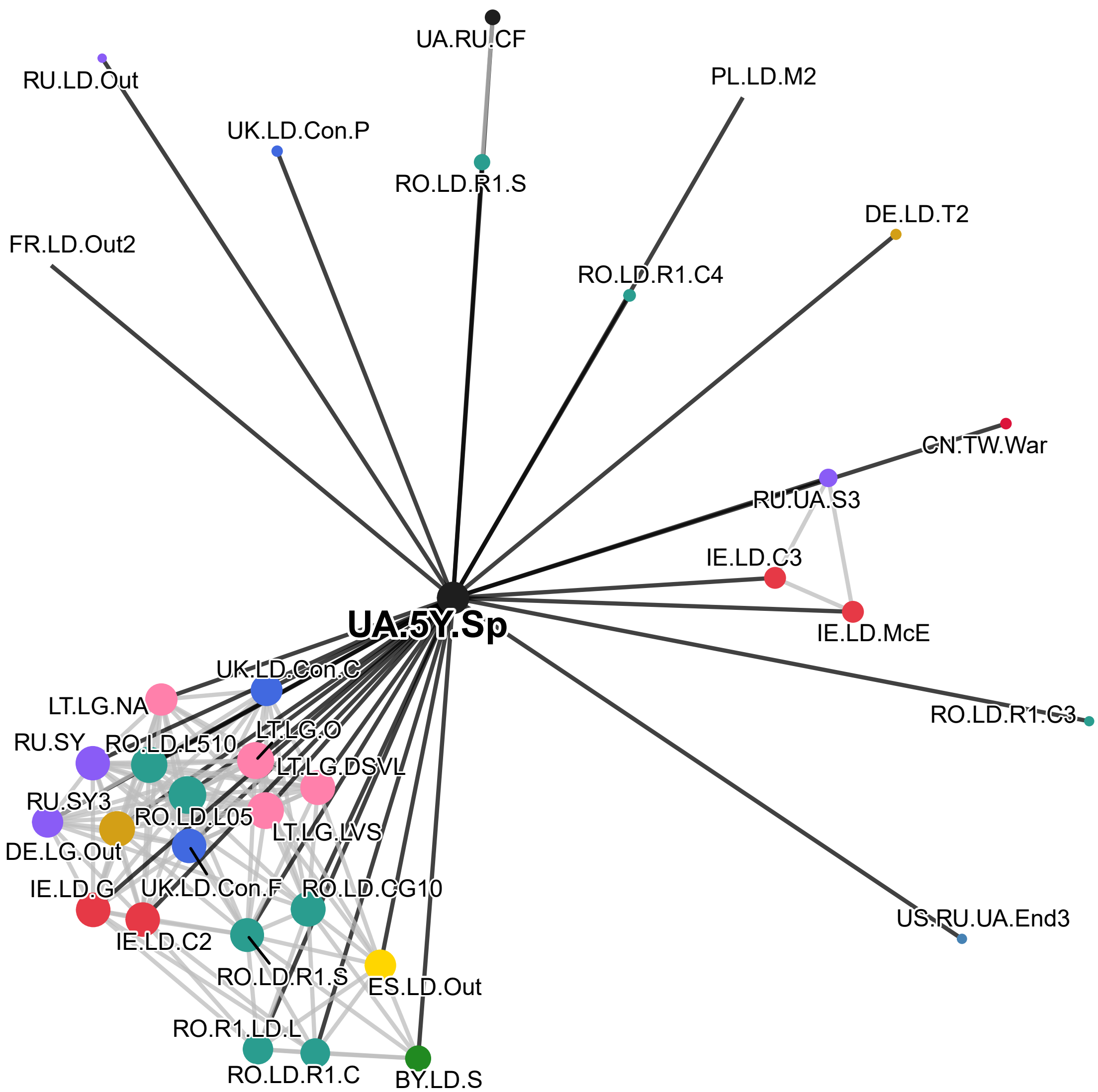
Figure 1: Example Market on Polymarket



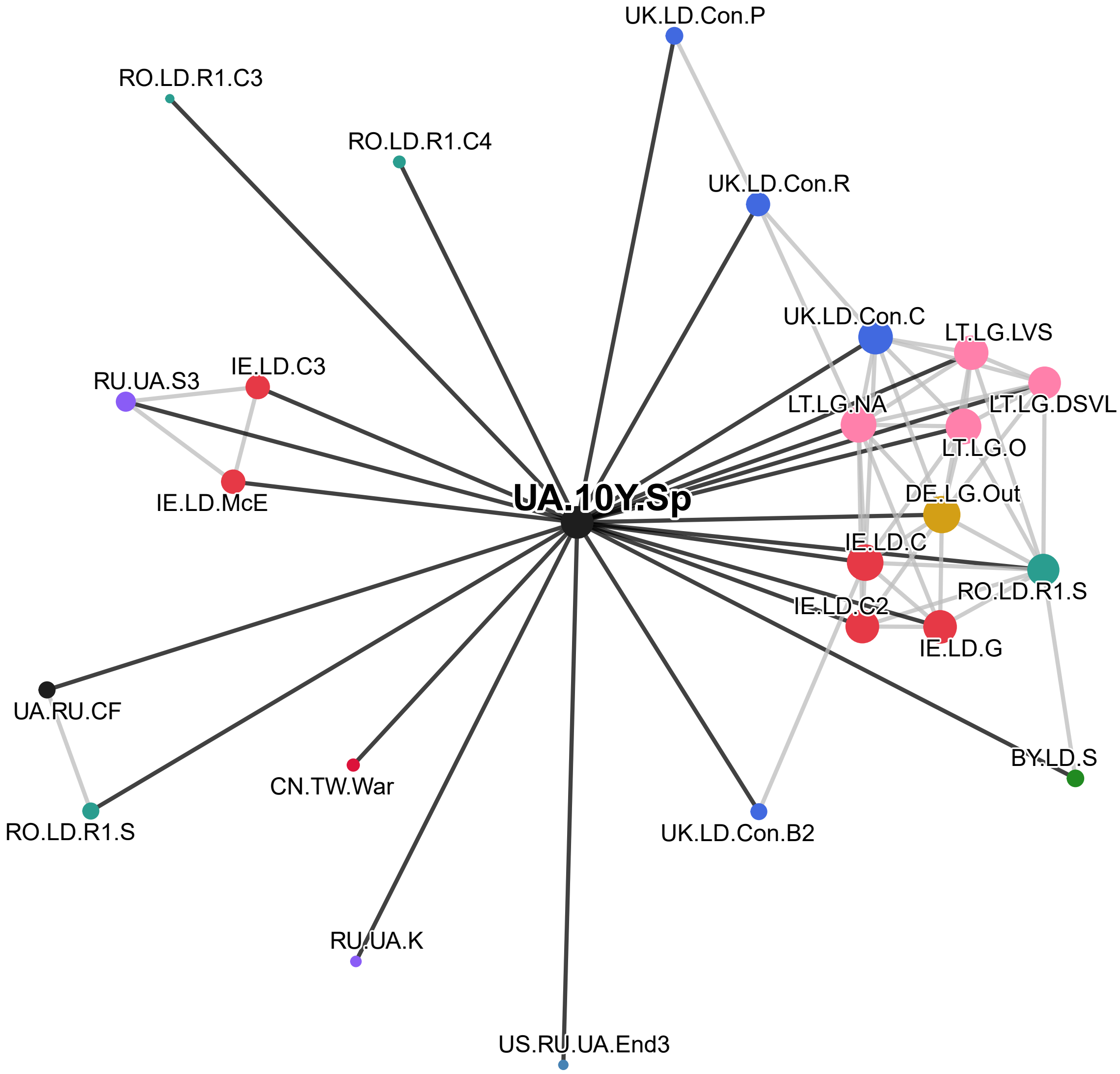
Note: Figure 1 shows an example market on Polymarket. Information given is the name of the market (”Russia x Uraine ceasefire in 2025?”), volume ($3,292,572), latest day the market will conclude (Dec 31, 2025), and the current price ($0.70). A time series graph of how the ”Yes” asset has evolved over the contract. Data is able to be downloaded from the start of the market until the conclusion of the contract from the minute to day level.

Figure 2: Polymarket Event Contract Connections to the Ukrainian-US five year bond spread



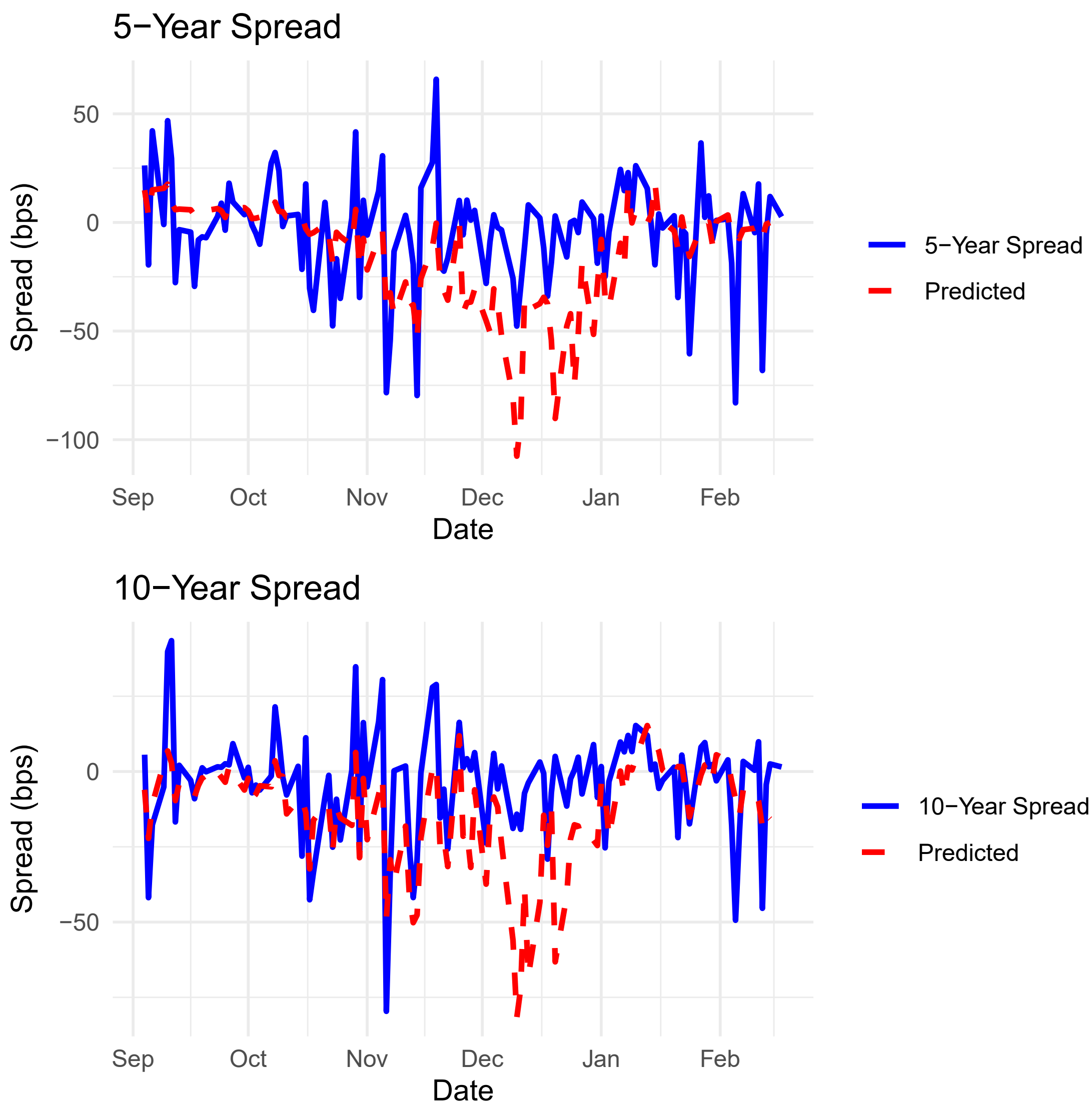
Note: Figure 2 shows a graphical representation of the top 33 Polymarket event contract connections between each other and the Ukrainian-US five year bond spread (target), for the last estimation. Interconnections between event contracts are shown if the weight is greater than 0.3. Node labels consist of the market's country or countries of interest and events and events. Country key: UA=Ukraine, BY=Belarus, CN=China, HR=Croatia, FR=France, DE=Germany, IE=Ireland, LT=Lithuania, NL=Netherlands, RO=Romania, PL=Poland, RU=Russia, US=United States. Event key: LG=legislature elections LD=leader election or decisions. Other codes point to the specific event.

Figure 3: Polymarket Event Contract Connections to the Ukrainian-US ten year bond spread



Note: Figure 3 shows a graphical representation of the top 24 Polymarket event contract connections between each other and the Ukrainian-US ten year bond spread (target), for the last estimation. Interconnections between event contracts are shown if the weight is greater than 0.3. Node labels consist of the market's country or countries of interest and events and events. Country key: UA=Ukraine, BY=Belarus, CN=China, HR=Croatia, FR=France, DE=Germany, IE=Ireland, LT=Lithuania, NL=Netherlands, RO=Romania, PL=Poland, RU=Russia, US=United States. Event key: LG=legislature elections LD=leader election or decisions. Other codes point to the specific event.

Figure 4: Overtime



Note: Figure 4 shows the actual (blue solid line) ΔCS_i and predicted (red dashed line) $\widehat{\Delta CS}_{NN,i}$ change in the Ukrainian to US bond spread in basis points for the 5-year (upper panel) and 10-year bond (lower panel). Predicted spread is developed using a neural network based on Polymarket event contracts, and is scaled by the standard deviation of actual ΔCS_i to increase readability. Sample period is from September 3, 2024 to February 12, 2025.

Table 1: Polymarket Markets

Country	Question	Volume
Belarus	Belarus Presidential Election	$7,470,877
China	Will China invade Taiwan in 2024?	$5,672,418
Germany	German Bundestag dissolved in 2024?	$1,175,398
Germany	Next Chancellor of Germany?	$22,427,008
Germany	Scholz out as chancellor of Germany in 2024?	$627,421
Germany	Germany Parliamentary Election Winner	$134,150,975
Spain	Sánchez resigns as PM of Spain before March?	$39,303
France	Michel Barnier out as prime minister of France in 2024?	$630,014
France	Macron out as president of France in 2024?	$206,359
Croatia	Croatia Presidential Election	$5,061,742
Ireland	Next Prime Minister of Ireland	$13,618,947
Lithuania	Which party wins the most seats in Lithuanian Election?	$244,135
NATO	NATO article 5 before March?	$606,185
Netherlands	New Netherlands election called in 2024?	$15,227
Netherlands	Will Schoof resign as Netherlands PM in 2024?	$22,875
Poland	Poland Presidential Election	$35,018,416
Romania	Georgescu banned from Romania election?	$177,938
Romania	Which candidates will advance in Romanian Election 1st round?	$1,246,428
Romania	Romania Presidential Election 1st round winner?	$540,282
Romania	Romania Presidential Election Margin of Victory?	$658,022
Russia	Will Russia abandon Syrian naval base before April?	$2,071,825
Russia	Russian nuke in space in 2024?	$49,805
Russia	Will Russia use a nuclear weapon in 2024?	$2,363,771
Russia	Putin out as President of Russia in 2025?	$259,308
Russia	Will Putin remain President of Russia through 2024?	$2,187,634
Russia	Will Putin remain President of Russia through June?	$126,014
Russia	Assad leaves Russia before 2026?	$22,468
Russia	Will Russia pull out of Syria before April 2025?	$574,546
Russo-Ukrainian War	Will Russia capture Chasiv Yar before December?	$1,103,397
Russo-Ukrainian War	Will Russia capture Pokrovsk in 2024?	$1,180,652
Russo-Ukrainian War	Crimean bridge hit before 2025?	$93,402
Russo-Ukrainian War	Will Ukraine hold Kursk through 2024?	$2,602,340
Russo-Ukrainian War	Will Russia capture Kurakhove before December?	$2,298,871
Russo-Ukrainian War	Will Ukraine hold Kursk through October 31?	$2,109,992
Russo-Ukrainian War	Ukraine hits Moscow before 2025?	$231,677
Russo-Ukrainian War	Will Russia capture Pokrovsk in 2024?	$1,180,652
Russo-Ukrainian War	Will Russia capture Siversk before December?	$217,337
Russo-Ukrainian War	Will Russia recapture Sudzha before December?	$609,295
Russo-Ukrainian War	Russia x Ukraine Ceasefire in 2024?	$3,514,408
Russo-Ukrainian War	Russia x Ukraine ceasefire in 2025?	$3,293,113

Continued on next page

Table 1 continued

Country	Question	Volume
Ukraine	Ukraine election scheduled in 2024?	$177,780
Ukraine	Ukraine joins NATO in 2025?	$30,527
Ukraine	Will Ukraine join NATO in 2024?	$2,220,103
United Kingdom	UK civil war in 2024?	$422,061
United Kingdom	UK election called before 2025?	$78,304
United Kingdom	UK election called by...?	$47,745
United Kingdom	Next UK leader of the Conservatives?	$8,661,395
United Kingdom	Starmer out as UK prime minister in 2024?	$1,268,434
United States	Presidential Election Winner 2024	$3,686,335,059
United States	Will Putin meet with Trump in first 100 days?	$3,853,129
United States	Trump ends Ukraine war before inauguration?	$5,108,187
United States	Trump ends Ukraine war in first 90 days?	$18,696,446

Note: Table 1 shows the Polymarket markets used in our investigation. Column 1 gives the country within which the market event is taking place, column 2 gives the question the market is based on, and column 3 gives the total volume transacted on the market from market inception until February 12, 2025. There are 52 separate markets yielding 120 total assets.

Table 2: Description of Variables

Variable	Definition	Source
ΔCS	The spread between Ukrainian sovereign bond yields and comparable US Treasury yields, either 5 year or 10 year, reflecting Ukraine's country risk premium and market perceptions of default risk.	Bloomberg
ΔVIX	The change in the CBOE Volatility Index measures implied volatility in the S&P 500 index	Bloomberg
$R_{\text{USD/EUR}}$	The log of the return on the exchange rate between the Euro and USD	Bloomberg
R_{Oil}	The log return on the ICE BofA Commodity Index eXtra CLA Index, which primarily tracks crude oil prices.	Bloomberg
R_{Ag}	The log return on the World Agricultural Commodity Index, which tracks a broad basket of globally traded agricultural commodities, including wheat, corn, and soybeans.	Bloomberg
R_{UA}	The log return of a value-weighted portfolio consisting of eight Ukrainian firms with publicly traded equities. Six of these firms trade on the Warsaw Stock Exchange (PLN), while two are listed on the London Stock Exchange (GBP and USD).	Bloomberg
$Yield_{DE}$	The German yield spread, calculated as the difference between 2-year and 10-year German bund yields.	Bundesbank
$Yield_{US}$	The US yield spread, calculated as the difference between 2-year and 10-year US Treasury bond yields.	US Treasury
R_{EUR}	The return on the STOXX Europe 600 index.	S&P Capital IQ
R_{US}	The return on the S&P 500 index.	S&P Capital IQ

Table 2 details all variables beyond Polymarket event contract pricing used in this study. The first column details the variable name, the second a brief definition, and finally the data source.

Table 3: In-sample Evaluation

	Dependent variable:							
	$\Delta CS_{5\text{-}year,t+1}$				$\Delta CS_{10\text{-}year,t+1}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta CS_{i,t}$	0.025	0.100	0.020	0.067	0.051	0.173	0.113	0.189
	(0.069)	(0.077)	(0.087)	(0.088)	(0.082)	(0.106)	(0.103)	(0.119)
$\widehat{\Delta CS}_{NN,i}$	2.044***	1.992***	2.299***	2.160***	3.193***	3.112***	3.203***	3.081***
	(0.547)	(0.591)	(0.554)	(0.604)	(0.909)	(1.046)	(0.934)	(1.064)
ΔVIX		−86.853***	2.055	−92.414**		−53.822**	10.804	−54.926**
		(32.142)	(27.520)	(37.023)		(25.710)	(20.769)	(27.491)
$R_{\text{USD/EUR}}$		129.89	213.99	252.27		197.84	79.648	204.24
		(611.82)	(633.67)	(634.99)		(396.19)	(398.24)	(382.61)
R_{Oil}		−21.917	−33.655	−40.549		−7.078	−36.675	−15.687
		(119.26)	(118.01)	(127.81)		(72.057)	(77.689)	(75.695)
R_{Ag}		−225.84	−210.25	−227.07		−242.51**	−138.53	−246.28**
		(227.59)	(177.52)	(234.43)		(119.90)	(119.93)	(121.55)
R_{UA}		2.255**	1.858*	1.967*		2.067***	1.714**	1.992**
		(1.084)	(1.115)	(1.084)		(0.777)	(0.843)	(0.792)
R_{US}		−1,171.8**		−1,254.4**		−868.55**		−909.60**
		(462.33)		(545.70)		(342.89)		(364.95)
$Yield_{US}$		−85.389		−69.580		35.287		34.502
		(67.837)		(68.632)		(38.376)		(40.425)
$Yield_{DE}$			−106.20	−119.00*			36.375	15.836
			(70.140)	(66.190)			(49.397)	(50.935)
R_{EUR}			−46.887	278.25			−110.64	149.42
			(279.92)	(294.16)			(233.02)	(214.87)
Constant	1.111	1.446	0.506	1.818	2.743	3.388	1.989	3.172
	(2.610)	(2.839)	(2.724)	(2.913)	(2.001)	(2.367)	(2.147)	(2.484)
Obs	117	103	110	100	117	103	110	100
Adj R^2	0.119	0.142	0.124	0.152	0.233	0.270	0.237	0.256

Note: Table 3 depicts in-sample evaluation where the dependent variable is Ukrainian to US spread on the 5-year (columns 1-4) or 10-year bond (columns 5-8), $\Delta CS_{i,t+1}$. Independent variables include the prior day's change in spread, $\Delta CS_{i,t}$, the predicted change in bond spread based on a neural network, $\widehat{\Delta CS}_{NN,i}$, a measure of volatility (ΔVIX), the return in the USD-Euro exchange rate ($R_{USD/EUR}$), returns on indices tracking oil (R_{Oil}) and agricultural commodity prices (R_{Ag}), returns on Ukrainian (R_{UA}), US (R_{US}), and Eurpoean stocks (R_{EUR}), and yield curve metrics for the US ($Yield_{US}$) and Germany ($Yield_{DE}$) Variables are defined in Table 2. Newey-West standard errors are shown in parenthesis. *p<0.1; **p<0.05; ***p<0.01

Table 4: Out-of-Sample Forecast Evaluation

Spread	Model	Baseline Model	CW	AVAR(CW)	*p-value*
5 *year*	$\widehat{\Delta CS}_{NN}$ *Only*	*Mean*	197	$651,643$	0.043
5 *year*	*US Model*	*Mean*	170	$513,211$	0.083
5 *year*	*EUR Model*	*Mean*	136	$408,318$	0.086
5 *year*	*All Model*	*Mean*	150	$297,105$	0.062
5 *year*	*US Model w/o* ΔCS_{NN}	*Mean*	122	$393,734$	0.128
5 *year*	*EUR Model w/o* ΔCS_{NN}	*Mean*	6	$187,879$	0.464
5 *year*	*All Model w/o* ΔCS_{NN}	*Mean*	135	$536,474$	0.153
5 *year*	*US Model*	*US Model w/o* ΔCS_{NN}	39	$186,999$	0.298
5 *year*	*EUR Model*	*EUR Model w/o* ΔCS_{NN}	111	$202,119$	0.057
5 *year*	*All Model*	*All Model w/o* ΔCS_{NN}	113	$377,425$	0.152
10 *year*	$\widehat{\Delta CS}_{NN}$ *Only*	*Mean*	100	$102,567$	0.015
10 *year*	*US Model*	*Mean*	118	$59,458$	0.002
10 *year*	*EUR Model*	*Mean*	91	$92,468$	0.028
10 *year*	*All Model*	*Mean*	113	$57,987$	0.005
10 *year*	*US Model w/o* ΔCS_{NN}	*Mean*	91	$62,753$	0.017
10 *year*	*EUR Model w/o* ΔCS_{NN}	*Mean*	19	$53,611$	0.300
10 *year*	*All Model w/o* ΔCS_{NN}	*Mean*	66	$61,156$	0.070
10 *year*	*US Model*	*US Model w/o* ΔCS_{NN}	134	$316,243$	0.081
10 *year*	*EUR Model*	*EUR Model w/o* ΔCS_{NN}	111	$111,423$	0.017
10 *year*	*All Model*	*All Model w/o* ΔCS_{NN}	139	$167,026$	0.029

Note: Table 4 presents the results from the Clark West test. The first column details the spread (5-*year* or 10-*year*), the second column the comparison model, and the third column the Baseline model. Note by definition, the baseline model is nested within the comparison model. The fourth column shows the CW representing the difference in the adjusted MSFE between the two models. The fifth column is the estimated asyomtopic variance of the CW measure. Finally, the sixth column is the *p-value* associated with the CW test.