Final Project
Projections of Aid to Ukraine

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Introduction

Since February 2022, Ukraine has been fighting a defensive war against Russia with the support of a coalition of countries. As of June 2024, the North Atlantic Treaty Organization (NATO) partners and some non-NATO members have contributed equipment and funds worth an estimated 147,090,397,201 EUR to Ukraine's defence. Figure 1 shows the evolution of this cumulative aid. This figure includes military assistance, such as weapons, equipment and funding; financial aid, loans and grants to support the government's budget; and humanitarian assistance to public programs and non-governmental organizations (NGOs) that alleviate the suffering caused by Russia's unprovoked invasion.

However, the incoming administration may affect this trend. During the campaign trail, the vice presidential candidate and other officials have occasionally expressed that they intend to stop supporting Ukraine.[1] Donald Trump's victory in the presidential elections of November 2024 have heightened uncertainty on the future of the war in Ukraine. In anticipation, the current Secretary of State has recently vowed that "every dollar we have at our disposal will be pushed out the door between now and Jan. 20." [2] For military officials and humanitarian workers on the ground, estimating how much assistance they will receive is critical to plan operations and manage resources in the coming months.

Figures 1 and 2 present two central aspects of foreign aid to Ukraine. First, the US is the single largest contributor of aid to Ukraine, and has allocated more aid to Ukraine then all European countries together. The second, is that some countries have exhibited a larger willingness to support Ukraine than others. When scaled by GDP, the group of Denmark, Estonia, Finland, Latvia, Lithuania, and Sweden stand out in their support to Ukraine. After this group of Baltic Sea States, the remaining European countries have contributed more than the US when scaled by GDP. Putting these two insights together raises the question of how much a reduction in US aid could affect total aid, given that other countries have exhibited a higher willingness to support Ukraine. This project will test various regression models to make such predictions and estimate the cost of a discontinuation in US aid to Ukraine's defense.

[1] Politico (2024, October) *J.D. Vance's views on Ukraine.* Retrieved from `https://www.politico.eu/article/jd-vance-europe-russia-ukraine-donald-trump-kyiv-vp-pick-policy-us-elections-ohio-aid-war/`

[2] Bohannon (2024, November) *Biden administration will send every dollar possible to Ukraine.* Forbes. Retrieved from: `https://www.forbes.com/sites/mollybohannon/2024/11/13/biden-administration-will-send-every-dollar-possible-to-ukraine-before-trumps-presidency/`

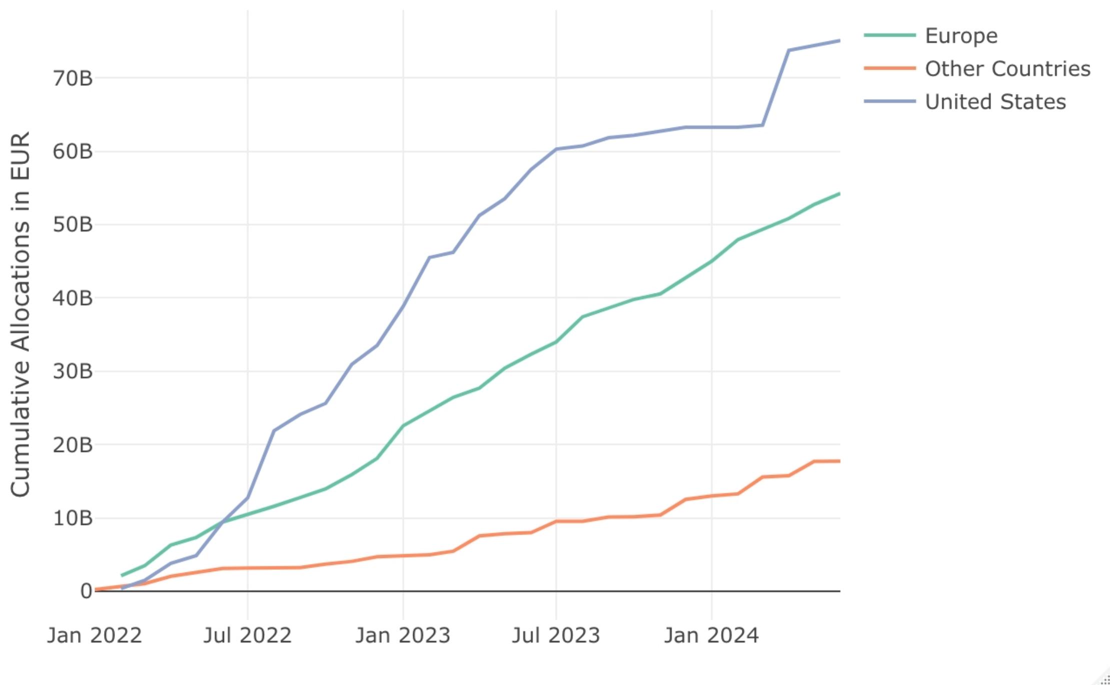

Figure 1: Cumulative aid to Ukraine

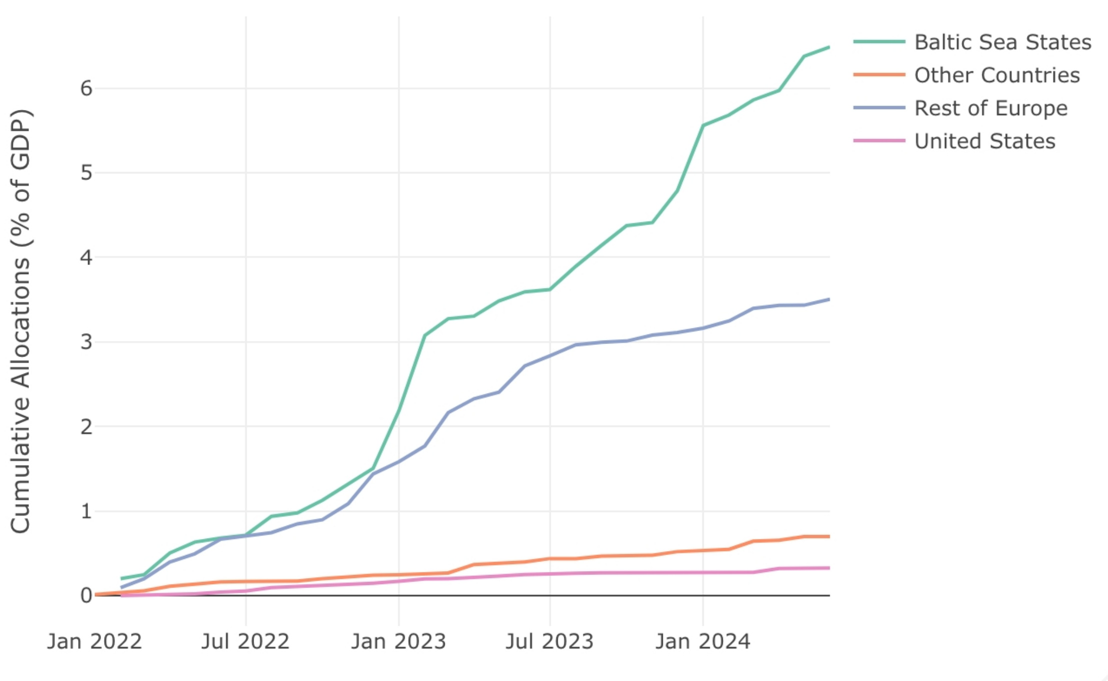

Figure 2: Cumulative aid to Ukraine relative to GDP

Data

The data was made available by the Ukraine Support Tracker (UST) at the Kiel Institute for the World Economy (IfW).[3] The UST conducts open-source data collection on official, bilateral aid to Ukraine. Their dataset contains 3737 allocations or commitments of aid to Ukraine by 41 countries and three international institutions from January 2022 to June 2024. An 'allocation' refers to an official act at the administrative level of government, such as a ministerial budget. A 'commitment' instead is an act of high-level political support, such as a memorandum of understanding between Ukraine and the head of state of a donor country.[4]

Each entry in the UST dataset corresponds to one of these acts and reports its characteristics in great detail. These include the donor country, the announcement date, several estimates for its monetary value, the type of aid, and the expected delivery date, among others. These entries are placed into three broad types: humanitarian, financial, and military, according to their intended purpose.

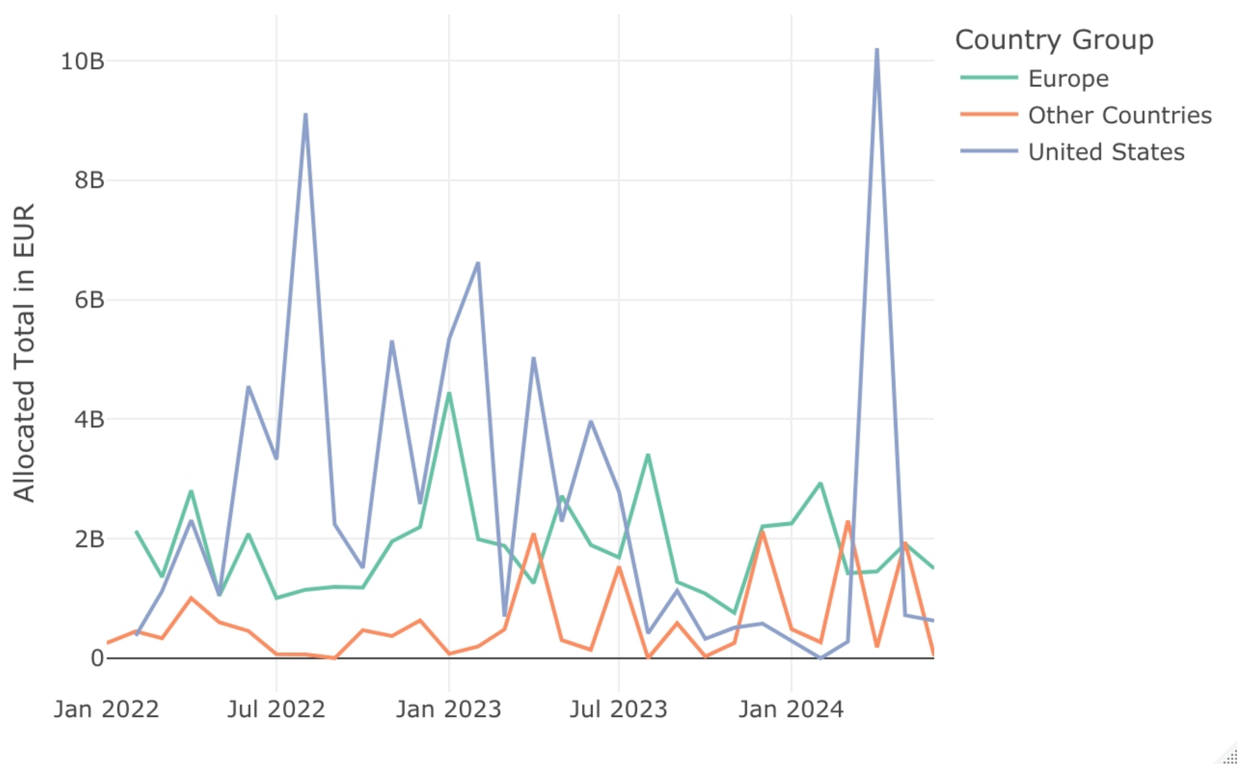

Figure 3: Monthly aid to Ukraine

This analysis focused on the 'Allocated Total in EUR (redistributed)' estimate for the value of aid for two reasons. First, allocations are a better approximation of delivered aid than

[3]Kiel Institute for the World Economy. (2024, August). *Ukraine Support Tracker Data*. Retrieved from https://www.ifw-kiel.de/publications/ukraine-support-tracker-data-20758/

[4]Kiel Institute for the World Economy. (2024, August). *The Ukraine Support Tracker: Which countries help Ukraine and how?*. Retrieved from https://www.ifw-kiel.de/publications/the-ukraine-support-tracker-which-countries-help-ukraine-and-how-20852/

commitments, which mostly signal political support. Second, this value accounts for aid delivered by several EU institutions, which is 'redistributed' to member states according to their ownership share or contribution to the budget of the relevant organization. Figure 3 shows a marked decrease in allocations from the US between August 2023 and April 2024, when gridlock in the US Congress prevented the approval of new funding for aid to Ukraine. While lower, allocations of aid from Europe and other countries seem to be more stable series.

Cleaning and Preparation

Since the UST database has a high degree of granularity, the first task was to select the columns of interest. These include 'Countries,' 'Allocated Total in EUR (redistributed),' 'ID' (a serial identification number), 'Announcement Date' and 'Allocated Total in EUR (redistributed).' The data was filtered further to exclude commitments and allocations by the European Investment Bank, the European Union and the European Peace Facility. These institutions were excluded to prevent double counting since the estimate of choice accounts for these allocations. The result is a short version of the dataset with allocations of aid attributed to the 41 nation-states tracked by the UST.

Next, creating a new column containing the month and year of each entry was necessary. Of the new 'Month Year' column values, 7.4 per cent are "unclear", "undisclosed", or entries that were updated retroactively. While these allocations do not have an official announcement date, they are ordered with a serial number that indicates the order in which they entered the dataset. Using this, we assign allocations with an unknown date to the date of the closest allocation from the same country. To this end, we arrange data by country and ID number and perform first a backward fill and then a forward fill. We label the remaining 3.2 per cent of the missing values as 'Unknown;' these correspond to small allocations from countries with single entries.

Following, the value of entries from the same month, year, country, and type of aid were aggregated to create a continuous time series. This operation produced invalid values in the column with the value of allocations for countries with no allocations for a particular month and year combination. It is fitting to substitute them with zero because the UST did not record any aid from these countries during those periods. Having aggregated allocations on their date, we then aggregated them again according to the type of aid to prepare for making projections.

Feature Engineering

To produce the predictor matrix (X), we filtered allocations by country and aid type and then merged these results into a unique dataset. This process was repeated for all countries, and the outputs were consolidated into a single data frame in which the columns represent the monthly allocations by country and aid type. The final database contains the three types of aid for each of the 41 tracked countries, and 30 rows, one for each month from January 2022 until June 2024.

This database with 123 features by 30 rows served as the predictor matrix (X) for the outcome of interest, total monthly aid to Ukraine. The outcome variable was calculated by aggregating allocations from all countries and types of aid for each month, and placed into a vector (y). Moreover, since the objective is to predict aid in the following month, the predictor variables (X) and the outcome variable (y) were shifted so that the variables for a month are aligned with the outcome of the following period.

As can be seen in Figure 1, there can be a large difference between the value of allocations from large and small countries. Since some of the models that we will evaluate, such as LASSO, Ridge and kNN are sensitive to the scale of variables, allocation values were scaled by country GDP. Each predictor variable was divided by the 2023 GDP of the corresponding country, and the outcome (y) was divided by the added 2023 GDP of the 41 countries. This normalization was done to prevent variables with large magnitudes (such as allocations from the US) from disproportionately influencing projections.

Since the database contains aid data from January 2022 to June 2024, it will serve to make a prediction for total aid allocated in July 2024. Next, we will find an estimate for the cost to Ukraine from expected changes in the aid from the US from July 2024 to June 2025. To introduce this shock, we will assume that all countries repeated their aid trends from the past 11 month into the following 11 months. In the predictor matrix (X), this is tantamount to extending the last 11 rows to reach June 2025. This will constitute our baseline scenario which reflects the status quo projection of international aid to Ukraine.

To introduce a potential shock in the aid from the US, we will consider a plausible scenario in which the Trump Administration drops completely in the months following January 2025. In addition, we will suppose that the Biden Administration fully allocates all aid committed to Ukraine in the months preceding the change in government. Since the Ukraine Security Supplemental Appropriations Act of April 2024,[5] there remain 26 billion EUR in unallocated commitments as of June 2024. We distribute these evenly across aid types and the last months of the Biden Administration. To project aid under this scenario, we replaced the series corresponding to humanitarian, financial and military aid from the US with the expected allocations under the Biden Administration on the first five rows of the predictor matrix (X), and for the expected allocations under the Trump administration, a series of zeros, on the last six rows of the predictor matrix (X).

[5] Congress.gov. (n.d.). *H.R.8035 - Ukraine Security Supplemental Appropriations Act.* Retrieved November 29, 2024, from `https://www.congress.gov/bill/118th-congress/house-bill/8035`

Methodology

Next, we compared a comprehensive range of regression models and evaluated them based on the accuracy of their predictions. Since we intend to make predictions that minimize the error to the actual value, the comparative statistic of interest was the square root of the mean square error (RMSE). Moreover, we are also interested in estimating the cost to Ukraine of a change in US aid. Thus, we identified the model with the lowest RMSE, which also assigns some importance to US humanitarian, financial, and military aid features.

The eight models were trained on a subset of the data. Eighty per cent of the rows were separated for training models, and the remaining 20 per cent was kept for testing. We calculated the RMSE between the predictions of each model and the actual values in the testing data to evaluate each model on unseen data. Since we want the model to make predictions for periods outside of the dataset, it must perform well on unseen data, not just training data.

We began with a simple linear regression model, to which we compared more sophisticated models with the expectation that they could deliver increasing improvements in the accuracy of their estimates. Then, we considered the penalized linear regression techniques LASSO, Ridge, and Elastic Net. For these models, cross-validation was used to find the optimal penalty term (lambda) so that each model balances bias and variance. After linear models, we explored non-linear models to capture more complex relationships in the data. First, we used k-nearest Neighbors (kNN) to predict total aid. We tested a series of values of k and calculated the associated Mean Squared Error (MSE) to determine the optimal k. The model was then fitted with k, and predictions were generated. Second, we tried a regression tree model, generated predictions, and extracted the importance of variables from their impact on splits.

Model	RMSE
Regression Tree	1.834080e-05
Boosting	1.968782e-05
Reduced Random Forest	2.499569e-05
Random Forest	2.521986e-05
KNN	2.626096e-05
Elastic Net	2.815974e-05
LASSO	3.092027e-05
Tuned Boosting	3.117680e-05
Ridge	3.626194e-05
Linear regression	1.762120e-04

Table 1: Models ranked on RMSE

Building on decision trees, we implemented Random Forest to improve accuracy. The code performed a grid search to optimize the number of trees and the number of features considered at each split. After identifying the optimal parameters, the final model was trained on the training data and evaluated on the test set. Seeking to improve the model's performance, we tried a reduced version of the Random Forest in which we kept features with

Model	Humanitarian	Financial	Military
Regression Tree	0.00	0.00	0.00
Random Forest	0.14	0.97	0.07
Boosting	0.69	0.00	0.41
Tuned Boosting	1.90	4.03	0.17

Table 2: Variable importance of US features across models.

positive importance. Finally, we tried sequentially Boosting a series of trees, each correcting the errors of the previous ones. The initial model was set with default parameters, while subsequent tuning tested values of learning rate, tree depth, and number of trees to optimize performance. We used cross-validation to identify the best parameter settings and used them in the final model to generate predictions.

These eight models offer a wide range of approaches to prediction from which we selected the best fit for projecting aid to Ukraine. Table 1 shows that the Regression Tree was the model that minimized RMSE. This suggests that there may be a non-linear relationship between past and future aid to Ukraine and that the combination of certain features may be important to affect the predicted variable. The regression tree may account for these by splitting the data based on combinations of features by country or aid type. Then, the Regression Tree model offered the most accurate prediction of foreign aid to Ukraine. Using this model on the last row of the predictor variables (X), we predict 3,680,795,370 EUR of total aid allocated to Ukraine for July 2024.

However, note from Table 2 that the Regression Tree model did not assign any importance to the variables associated with the US. This poses a problem since we expect the best predictive model to account for Ukraine's single largest donor to some extent. In addition, we needed a model to generate meaningful predictions in the scenario of a change in US aid. Tables 1 and 2, show that Random Forests was the model with the lowest RMSE that assigned some value to all three of the US features. For this model, the grid search found 200 trees and 31 features considered at each split to be optimal. This suggest that the relationship between the predictors and total aid to Ukraine is sufficiently complex to require multiple trees and that many predictors contribute meaningfully, possibly due to the the varying importance of countries and aid types in shaping the overall allocation patterns.

Results

We used this Random Forests model to generate predictions in the scenario in which the Trump Administration decreases all allocations to zero and all other countries followed the same trends as in the previous months. The projected trend of total aid allocations under this scenario is plotted in Figure 4. If the Trump Administration stopped aid to Ukraine, we expect total aid allocations to remain below average until March 2025.

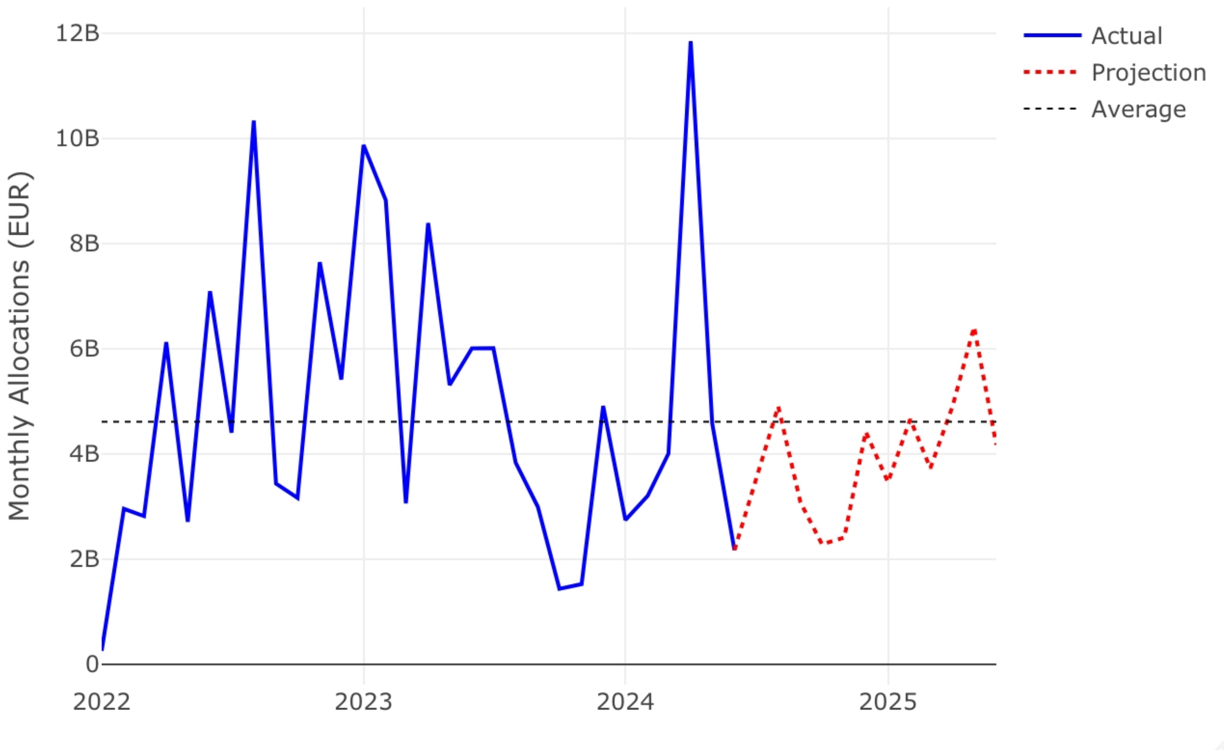

Figure 4: Monthly aid to Ukraine from all Donors (Actual And Projection)

Next, we compared the projection done under the scenario of a Trump-induced shock to the most accurate projection without a shock. We use the Regression Tree model from before to make predictions for the status quo scenario in which all countries, including the US, maintained their trends from preceding months into July 2024 and until June 2025. Figure 5 plots the evolution of cumulative aid under this scenario against the previous scenario of a shock induced by the Trump Administration. This comparison indicates that cumulative aid would diverge from its normal evolution if there was a Trump induced shock. By June 2025, we would expect this divergence to have costed Ukraine 3,519,366,494 EUR in foreign aid relative to the status quo projection.

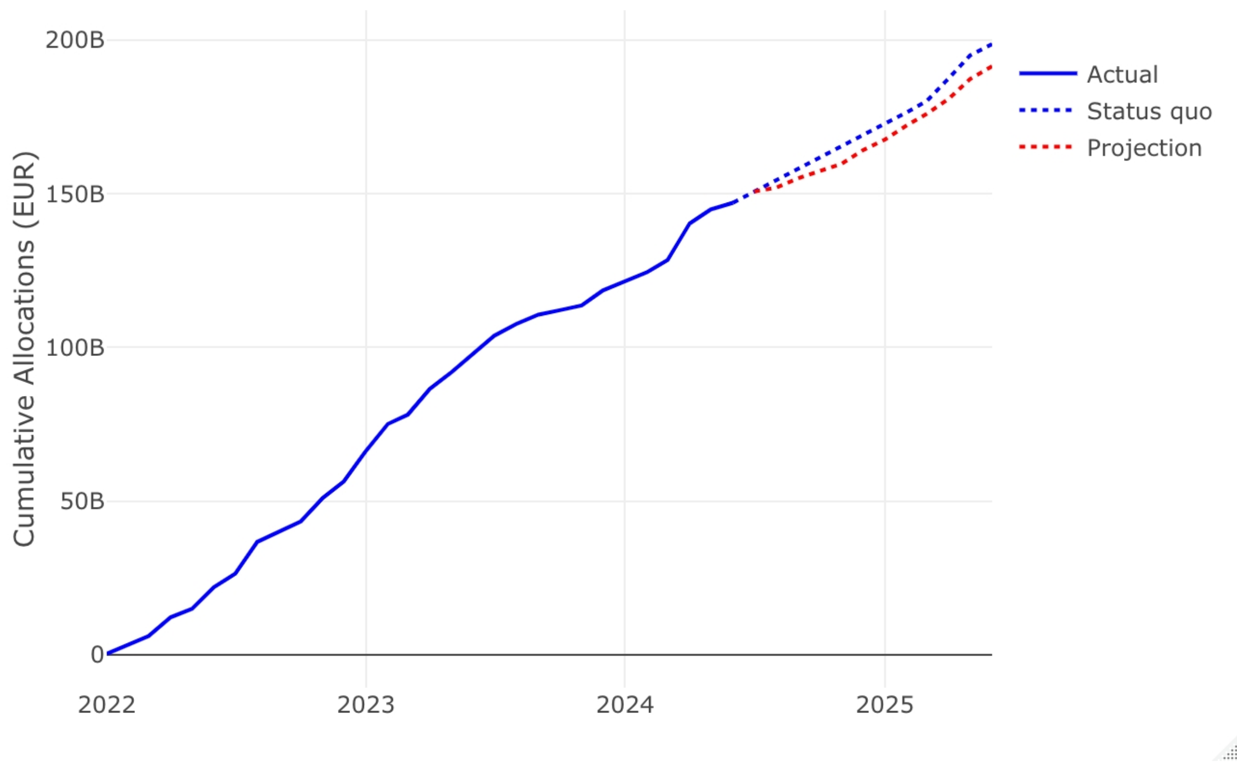

Figure 5: Cumulative aid to Ukraine from all Donors (Actual and Projection)

In all likelihood, this was an overestimate of the costs to Ukraine since it did not account for the expected change in allocations of the Biden Administration preceding the Trump inauguration. Using the Random Forests model, we created projections for the following scenarios. First, we assume that the Biden Administration fully allocates committed aid to Ukraine until January 2025, after which the Trump administration halts all aid allocations. The second is a baseline scenario using the Random Forests model, in which all countries repeat their trends from the previous eleven months. Table 3 shows the predictions for these scenarios and presents the absolute difference and the percentage change between the projected scenario and the baseline.

Table 3 presents a more realistic prediction of the cost to Ukraine than our previous estimate. Notice that in the months in which the Biden Administration is expected to ramp up aid allocations, there tends to be an increase in the total aid to Ukraine relative to the baseline scenario. After January 2025, when the Trump Administration is expected to stop allocations, there is either a decrease or no difference between total aid in the projection and baseline scenarios. Figure 6 plots the difference between the Baseline and Projection scenarios in percentage change.

Month.Year	Baseline	Projection	Difference	Change(%)
2024-08	4,904,053,417	4,897,286,884	-6,766,533	-0.14
2024-09	3,078,347,144	3,477,491,557	399,144,413	12.97
2024-10	2,282,263,848	2,619,602,838	337,338,990	14.78
2024-11	2,409,468,246	2,880,526,803	471,058,557	19.55
2024-12	4,422,058,961	4,715,052,548	292,993,588	6.63
2025-01	3,567,978,699	3,462,957,405	-105,021,294	-2.94
2025-02	4,659,707,073	4,659,707,073	0	0.00
2025-03	3,727,669,858	3,727,669,858	0	0.00
2025-04	4,905,998,549	4,905,998,549	0	0.00
2025-05	6,465,790,527	6,415,692,137	-50,098,389	-0.77
2025-06	4,251,230,880	4,173,946,185	-77,284,695	-1.82

Table 3: Scenarios of Monthly Aid to Ukraine from all Donors in EUR.

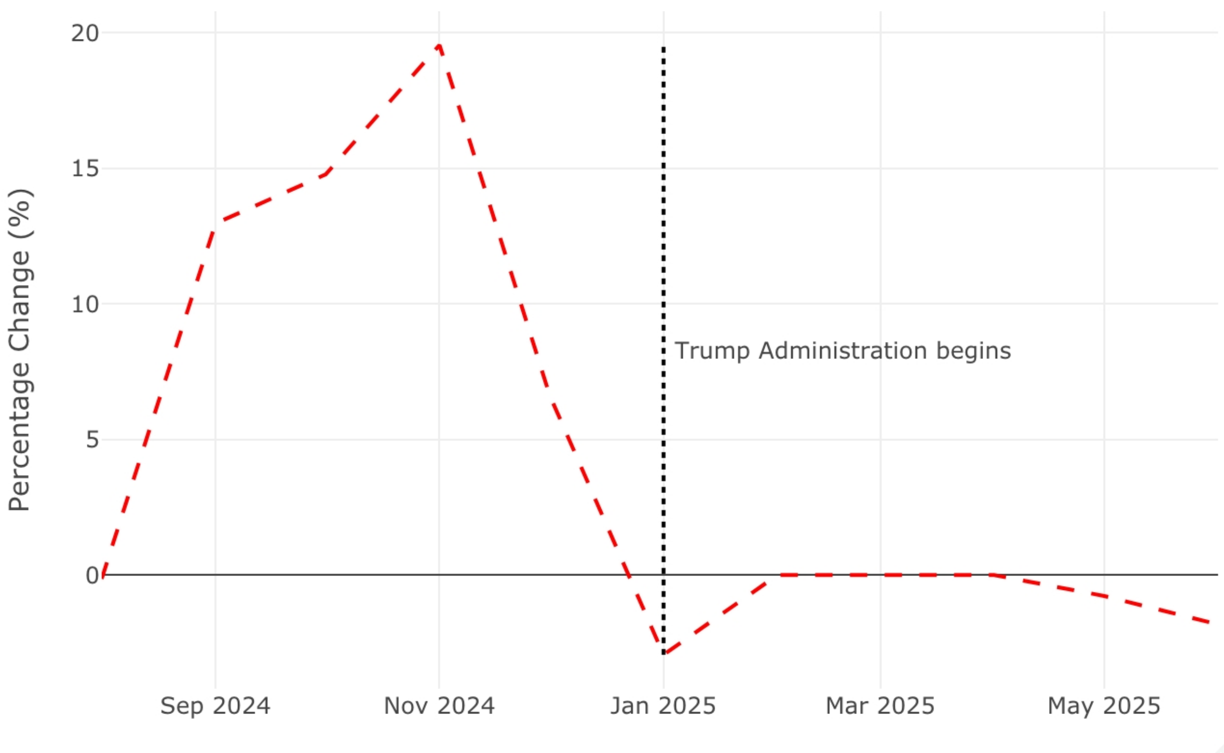

Figure 6: Difference between Baseline and Projection Scenarios of Monthly Aid to Ukraine

From the 'Difference' column in Table 3, we expect Ukraine to receive 1,261,364,637 EUR more under the shock scenario than in the baseline projection until June 2025. This suggests that the Biden Administration could offset the projected reduction in total aid to Ukraine by fully allocating commitments before January 2025. Nevertheless, if the US policy of zero aid continued beyond June 2025, the difference with the baseline prediction would become negative despite the Biden Administration increasing aid allocations in its last months.