Bachelor's thesis

NTNU
Norwegian University of Science and Technology
Faculty of Economics and Management
Department of Economics

Hanh-Chan Vo
Jesper Grøttumsbråten
Selena Schwenke

Reliance on Russian Fossil Fuels and Wartime Aid to Ukraine

SØK2013 Bachelor Thesis In Economics Spring 2023

Bachelor's thesis in Economics
Supervisor: Doriane Mignon
May 2023

NTNU
Norwegian University of Science and Technology

Hanh-Chan Vo
Jesper Grøttumsbråten
Selena Schwenke

Reliance on Russian Fossil Fuels and Wartime Aid to Ukraine

SØK2013 Bachelor Thesis In Economics Spring 2023

Bachelor's thesis in Economics
Supervisor: Doriane Mignon
May 2023

Norwegian University of Science and Technology
Faculty of Economics and Management
Department of Economics

NTNU
Norwegian University of
Science and Technology

Abstract

Using data from IEA and the Kiel Institute, this thesis statistically examines the relationship between imports of Russian fossil fuels before the outbreak of war and aid given to Ukraine since the start of the invasion. We utilize the ordinary least square (OLS) method to estimate this relationship and control for several relevant variables. We find no statistically significant relationship between the level of fuel dependence on Russia and the amount of support sent. This could be due to the large number of factors at play and the difficulty in measuring complex political variables, which is further compounded by the lack of data available on the subject.

Table of contents

1. Introduction

On the 24th of February 2022, Russia invaded Ukraine. Marking a watershed moment in European and world politics, governments from all over the world condemned the attack. Several countries including the United Kingdom and the United States quickly decided to denounce the invasion. EU leaders came together to oppose Russia's actions, support Ukraine with ammunition and sanction both the Russian state and affiliated actors (Council of the European Union, 2023).

Through their actions, the western world took a stance against this new war on European soil. Yet despite the outflow of support, many pointed out that the continent at the center of this struggle, Europe, had a fuel reliance on Russia – and that this could prove to be a major hurdle to effectively helping Ukraine defend itself (Surwillo & Slakaityte, 2022, p.1-2). Citizens of some EU countries consider all major sectors of their society to be at risk - and a majority of the EU's population considers energy security to be especially vulnerable (Krastev & Leonard, 2022, p.10). Compounding this, a consequence of the war and the resulting sanctions is massive shocks in world energy markets that threaten to severely reduce growth and undermine post-pandemic recovery (OECD, 2022).

2022 would not be the first time Russia had used energy exports as political leverage, with similar occurrences at the outbreak of unrest in eastern Ukraine in 2014 (The Guardian, 2014). Evidently, there are then potential conflicts of interest when governments are faced with what may seem like a choice between European solidarity and the economic prosperity of their citizens. What matters the most for governments in difficult situations like the one they currently find themselves in? How do we meaningfully assess the myriad of different factors at play in such a complicated conflict? While we are limited by the relatively short time frame since the beginning of the conflict, this thesis attempts to contribute to the debate by statistically examining the relationship between aid-giving and reliance on Russian fossil fuels. Our research question is thus:

"Does increased reliance on energy resources from the Russian Federation decrease aid commitments to Ukraine?"

We will examine how energy reliance on the Russian Federation affects the economic and political calculations done by governments deciding to send aid to Ukraine. We accomplish this by analyzing data from 34 countries that have sent material or financial support to Ukraine. Our thesis will start by introducing earlier work relevant to the topic, before elaborating on the utilized econometric methods and presenting our results. Lastly, we will discuss our findings and what, if anything, we can learn from them.

2. Theory and Earlier Work

2.1 General Incentives for Foreign Aid

Of interest to our thesis is both the general framework for aid motivations, as well as the specific reasons for differing types of support. We will discuss some of the relevant incentives for donors to give aid in general, and how it can benefit both donors and recipients with focus on commercial self interest and political considerations.

It is relevant to start out by mentioning the fact that we are dealing with an aid recipient embroiled in an armed conflict, as it may have an effect on the motivations of donors. The literature emphasizes that the role of conflict as a determinant of aid flows is difficult to determine, yet that many of the same factors are as relevant as in peace-time aid (Balla & Reinhardt, 2008, p.2580-2581). Thus, the general principles and motivations for aid that we will outline in this section will be valid in the case of Ukraine.

According to the article *Aid Allocation: comparing donors' behaviors,* the reason why donors give aid is mainly because of self-interest motives, especially concerning bilateral (government-to-government) aid (Berthélemy, 2006, p.9). Closely connected to this self-interest, as shown by the database the article uses, there is a clear connection with trade and aid (Berthélemy, 2006, p.9). Donors would be more likely to give aid to a recipient that aligns with their commercial interests. The database also shows that the allocation of bilateral aid motives are rather more egoistic than altruistic. The results the article found was that trade partners of donors receive the most aid (Berthélemy, 2006, p 14). In addition, the analyses of the article *Instrumental Philanthropy: Trade and the Allocation of Foreign Aid* provide further support that aid allocation is significantly influenced by bilateral trade (Breunig et al., 2010, p.744). Foreign aid can make the business climate more favorable to the donor country as well as protecting existing investments (Breuning et al., 2010, p.738). The end product of this reasoning is that governments focus aid on recipients to which they have good trade connections, as it will benefit domestic business interests (Breunig et al., 2010, p.739). This provides a clear benefit for countries giving aid to Ukraine, in that it could strengthen business ties and stimulate commercial activity to the benefit of the donor.

The literature considers that donors provide aid to recipients who are like-minded or are political allies (Berthélemy, 2006, p.6). One central work on this topic is provided to us by Hans Morgenthau. Morgenthau notes that certain national interests cannot be secured by military power or traditional diplomacy alone (Morgenthau, 1962, p.301). To fill the gap, foreign aid may be utilized. The author separates foreign aid into several categories, and especially relevant to our thesis is humanitarian and military foreign aid. While humanitarian aid is mostly non-political, the context in which it is provided can give it a political function (Morgenthau, 1962, p.301). In our context, this would imply that humanitarian aid such as medicine sent to Ukraine could be argued to possess political undertones. Exploring rationales for military aid, the author points out that foreign aid has historically been used as an instrument of foreign policy to strengthen alliances and divide tasks between alliance members (Morgenthau, 1962, p.303). Yet this function is not only limited to formal alliance members; military aid can also be given to nations that are not committed to an alliance in an official sense, in order to give political advantages to both countries (Morgenthau, 1962, p.303).

There are several measurements that show coinciding interests between Ukraine and both NATO and Europe. Ukraine has had security ties with NATO since the 1990s, and that cooperation has intensified over the years (NATO, 2023). Additionally, NATO and EU members Poland and Germany are Ukraines 2nd and 4th largest trading partners, respectively (Statista, 2023). Collectively, these indicators show that many western countries have political and commercial interests in Ukraine, providing them with a base for commercial and political benefits from the support they send.

2.2 The benefits of foreign aid - Popular Engagement and Security

It is not possible to detach the current conflict between Ukraine and Russia from the fact that it is located on the European continent. Countries in the proximity of Ukraine may have a vested interest in the conflict, and their populace may develop a deeper interest in the war

(Braunig et al., 2010, p.741). Complementing this, Jacobs & Page use median voter theory to suggest that policymakers respond to public opinion on issues when shaping their political platforms (Jacobs & Page, 2005, p.109). Evidence suggests that on both a nationwide and a local level, the political stance of the general population does affect policies and actions by ruling parties (Jacobs & Page, 2005, p.109). With this framework in mind, it could be meaningful to examine some of the broader European attitudes to the conflict between Russia and Ukraine and how it might affect decision-makers.

In early 2022, before the start of the invasion, a think-tank called The European Council on Foreign Relations (from now on referred to as "ECFR") conducted a survey of several European countries in order to gauge their opinions on the brewing conflict between Ukraine and Russia. With a survey representing two-thirds of the European Union's population, the ECFR finds several indications that the conflict in Ukraine engages and matters to Europeans generally (Krastev & Leonard, 2022, p.14). More than half of the respondents held the opinion that the conflict in Ukraine mattered for Europe as a whole (Krastev & Leonard, 2022, p.4). Yet despite this general agreement, attitudes differed on who it was that should step up to the challenge. The EU and NATO are considered by most to be likely candidates, and interestingly the least common answer is the respondents own country (Krastev & Leonard, 2022, p.6). Poland is a notable exception here, as 65% of Poles believe their country should defend Ukraine if Russia were to invade (Krastev & Leonard, 2022, p.8). Several countries clearly see Ukrainian security as intertwined with their own security. Aiding Ukraine can thus be seen as a benefit to the donor country, as it can shore up its own security concerns and additionally appease domestic voters.

2.3 The Costs of Giving Aid

The direct cost of giving aid is the monetary value of the aid being sent. Trucks, guns, ammunition and first-aid kits all cost money, and will often need to be replaced in their country of origin. Additionally, this cost may vary with the proximity of the donor, as a donor close to Ukraine will have an easier time delivering such items (Braunig et al., 2010, p.741). Central to our thesis are also potential indirect costs. Fuel dependence is not an immediate monetary cost, but having a large amount of fuel imports from Russia may matter to your policy choices. More specifically, we propose that Russia uses its energy exports as a deliberate tool of foreign policy, by reducing outflows or cutting of gas supplies entirely. In turn, potential supporters of Ukraine have to factor this cost into their foreign policy calculus. If their imports are high, the potential costs are also high. Support for this view can be found in the literature, and one such work is written by Marc Ozawa and Ion Iftimie.

The authors point out that Russia under Vladimir Putin has a goal of becoming a great power, and one of the main tools by which it will accomplish this is by utilizing its vast array of natural resources (Ozawa & Iftimie, 2020, p.13-14). Russia is a world-leading producer and the single largest exporter of natural gas (Ozawa & Iftimie, 2020, p.17). This has led to natural gas being a centerpiece of Russian strategy to increase its standing generally and influence European politics specifically (Ozawa & Iftimie, 2020, p.16-17). The authors make this point clear:

Through the use of resource nationalism, Russia has managed to become an energy super-state, a geopolitical model that allows Russia to use its natural resources (and in particular its natural gas reserves) as strategic assets and political tools in its foreign relations and negotiations with many European and NATO countries. (Ozawa & Iftimie, 2020, p.16-17).

The authors further point out that Russia uses natural gas as an economic tool to pursue broader strategic geopolitical objectives. By blending economic threats and incentives, Russian state actors attempt to influence the policy of countries to align with Russian strategic objectives (Ozawa & Iftimie, 2020, p.19). This is especially true for its usage of natural gas and the dependence relationships it creates (Ozawa & Infitimie, 2020, p.19).

With this in mind, it seems reasonable to assume that Russia does consciously use its energy resources to affect policy in the states that it trades with. This strategy becomes especially important when one notes that European countries import a large share of their energy resources from Russia (IEA 2022). European countries also account for a large part of the donors that are captured in our dataset, making the focusing of Russian efforts on EU countries especially relevant. The risk of Russia restricting access to energy resources can thus be seen as a potential cost for donor countries. Such costs could manifest as industrial slowdown, reduced trade and higher levels of unemployment (De Bella et al., 2022, s.24-25). These costs will have to be weighted against the benefits that may stem from commercial ties and security concerns, as previously mentioned. Due to this tradeoff, we would expect a negative relationship between reliance on Russian fossil fuels and support given to Ukraine.

3. Methods

3.1 Ordinary Least Squares (OLS) method

We start with the simple linear regression (SLR) model with one independent variable:

$$(3.1)\ y = \beta_0 + \beta_1 x + u$$

In equation (3.1) we denote y as the dependent variable and x as the independent variable. The equation tells us how the independent variable relates to the dependent variable, assuming a linear relationship. The variable u is a representation of other factors than x that affect y. This is called the error term. We see that when the error term is constant the change in y is given by the change in x multiplied by β_1. We therefore call β_1 the slope parameter. We also have the intercept parameter β_0 which is a constant parameter. This tells us the level of y when the x and u is equal to zero (Woolridge, 2020, p.20-21).

We now want to estimate the parameters β_0 and β_1. We will then use a sample of the population with sample size n. Then we have for each observation (i) in the sample:

(3.2) $y_i = \beta_0 + \beta_1 x_i + u_i,\ \ i = 1,2, \dots, n$

From all the observations in the sample we try to estimate the population regression function. We assume that the average value of u in the population is zero and thus the expected value of u is zero:

(3.3) $E(u) = 0$

We also assume that u is uncorrelated with x:

(3.4) $E(x) = E(u)$

From this we get the implication that the covariance between x and u is zero:

(3.5) Cov(x,u)=E(xu)=0

We can now rewrite equation (3.3) with equation (3.1):

(3.6) $E(y - \beta_0 - \beta_1 x) = 0$

We can do the same with equation (3.5):

(3.7) $E[x(y - \beta_0 - \beta_1 x)] = 0$

Equation (3.6) and (3.7) is for the whole population and now we can rewrite them for the sample:

(3.8) $\sum_{i=1}^{n} \left(y_i - \widehat{\beta_0} - \widehat{\beta_1} x_i\right) = 0$

(3.9) $\sum_{i=1}^{n} x_i\left(y_i - \widehat{\beta_0} - \widehat{\beta_1} x_i\right) = 0$

Equation (3.8) and (3.9) is the first order conditions for the OLS estimates and from these we can get the estimates of β_0 and β_1:

$$(3.10)\ \widehat{\beta_0} = \underline{y} - \widehat{\beta_1} x$$

$$(3.11)\ \widehat{\beta_1} = \frac{\sum_{i=1}^{n} (x_i - \underline{x})(y_i - \underline{y})}{\sum_{i=1}^{n} (x_i - \underline{x})^2}$$

Here $\underline{y}$ is the sample average of y and $\underline{x}$ is the sample average of x. For the values of $\widehat{\beta_0}$ and $\widehat{\beta_1}$ defined by (3.10) and (3.11) we now get a fitted value for y when $x = x_i$:

(3.12) $\hat{y}_i = \widehat{\beta_0} + \widehat{\beta_1} x_i$

We can now form the estimated OLS regression line:

$$(3.13)\ \hat{y} = \widehat{\beta_0} + \widehat{\beta_1} x$$

The residual for observation i ($\widehat{u_i}$) is the difference between the actual value of y_i and the fitted value ($\widehat{y_i}$). Mathematically we have:

(3.14) $\widehat{u_i} = y_i - \widehat{y_i} = y_i - \widehat{\beta_0} - \widehat{\beta_1} x_1$

If we have a sample of n observations, we will have n residuals. The sum of squared residuals will then be:

(3.15) $\sum_{i=1}^{n} \hat{u}_i^2 = \sum_{i=1}^{n} (y_i - \widehat{\beta_0} - \widehat{\beta_1} x_i)^2$

If we minimize the sum of squared residuals and choose $\widehat{\beta_0}$ and $\widehat{\beta_1}$based on this, we will get equations (3.10) and (3.11). We then see that the OLS estimation is the minimizing of the squared residuals (Woolridge, 2020, p.24-27).

Now we will define the total sum of squares (SST), the explained sum of squares (SSE) and the residual sum of squares (SSR):

(3.16) $SST = \sum_{i=1}^{n} (y_i - \underline{y})^2$

(3.17) $SSE = \sum_{i=1}^{n} \quad (\widehat{y_i} - \underline{y})^2$

(3.18) $SSR = \sum_{i=1}^{n} \quad \widehat{u_i}^2$

SST is the total sample variation of y, SSE is the sample variation in $\widehat{y_i}$ and SSR is the sample variation in $\widehat{u_i}$. The total variation of y (SST) can be explained by the sum of the explained variation (SSE) and the unexplained variation (SSR):

(3.19) SST=SSE+SSR

To measure how well the independent variable, x, explains the dependent variable, y, we will look at the Goodness-of-Fit. For this we need to calculate the R-squared. This is defined as:

(3.20) $R^2 = \frac{SSE}{SST} = 1 - \frac{SSR}{SST}$

We see that the R^2 is the ratio between the explained variation compared to the total variation. The R^2 will always be a number between 0 and 1. If R^2 is equal to 1 the OLS gives a perfect fit to the observed data. If the R^2 is close to 0, we know that very little of the total variation is captured by the explained variation from the OLS (Woolridge, 2020, p.34-35).

3.2 Multiple linear regression (MLR)

Up until now we have only looked at a SLR with only one independent variable. Now we can extend to a multiple linear regression (MLR) model with k independent variables. Then the population model can be written as:

(3.21) $y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \cdots + \beta_k x_k + u$

We try to find estimates for $\widehat{\beta_0}, \widehat{\beta_1}, \ldots, \widehat{\beta_k}$ so that we get the estimated OLS regression line:

(3.22) $\hat{y} = \widehat{\beta_0} + \widehat{\beta_1} x_1 + \widehat{\beta_2} x_2 + \ldots + \widehat{\beta_k} x_k$

The residual for observation i, is still defined as the difference between the actual value of y_i and the fitted value ($\widehat{y_i}$). For the case with k variables we have:

(3.23) $\widehat{u_i} = y_i - \widehat{y_i} = y_i - \widehat{\beta_0} - \widehat{\beta_1} x_1 - \cdots - \widehat{\beta_k} x_k$

The sum of squared residuals will then be:

(3.24) $\sum_{i=1}^{n} \quad \hat{u}_i^2 = \sum_{i=1}^{n} \quad (y_i - \widehat{\beta_0} - \widehat{\beta_1} x_{i1} - \cdots - \widehat{\beta_k} x_{ik})^2$

As with the simple regression analysis, the OLS estimates are chosen to minimize the sum of squared residuals. For k independent variables this will lead to k+1 linear equations to solve k+1 parameters $\widehat{\beta_0}, \widehat{\beta_1}, \ldots, \widehat{\beta_k}$:

$$\begin{aligned}
&\textstyle\sum_{i=1}^{n} \quad (y_i - \widehat{\beta_0} - \widehat{\beta_1} x_{i1} - \cdots - \widehat{\beta_k} x_{ik})^2 = 0 \\
&\textstyle\sum_{i=1}^{n} \quad x_{i1}(y_i - \widehat{\beta_0} - \widehat{\beta_1} x_{i1} - \cdots - \widehat{\beta_k} x_{ik})^2 = 0 \\
(3.25) \quad &\textstyle\sum_{i=1}^{n} \quad x_{i2}(y_i - \widehat{\beta_0} - \widehat{\beta_1} x_{i1} - \cdots - \widehat{\beta_k} x_{ik})^2 = 0 \\
&\ldots \\
&\textstyle\sum_{i=1}^{n} \quad x_{ik}(y_i - \widehat{\beta_0} - \widehat{\beta_1} x_{i1} - \cdots - \widehat{\beta_k} x_{ik})^2 = 0
\end{aligned}$$

Equations (3.25) gives us the OLS first order conditions. Solving these will give us an estimate of the OLS regression line (Woolridge, 2020, p.69). For the MLR the SST, SSE, SSR and R-squared is defined the same way as in the SLR (see equations 3.16, 3.17, 3.18, 3.20) (Woolridge, 2020, p.77).

3.3 Multiple linear regression (MLR)

For the MLR there are some assumptions (MLR.1-6) that needs to be met for the estimation of the parameters to be unbiased and for it to be possible to perform statistical inference (Woolrdige, 2020, p.117).

3.3.1 MLR.1 Linear assumptions

The first MLR assumption states that the model for the population should be linear in the parameters β_0, β_1,…, β_k. Thus, the population model can be written as equation (3.21).

3.3.2 MLR.2 Random sampling

The second MLR assumption states that the observations should be a random sample of n observations from the population.

3.3.3 MLR.3 No perfect collinearity

The third MLR assumption is that none of the independent variables in the sample are constant or have an exact linear relationship. Then the model will suffer from perfect collinearity (Woolridge, 2020, p.80).

3.3.4 MLR.4 Zero conditional mean

The MLR. assumption of zero conditional mean is given by the equation below:

(3.26) $E(x_1, x_1, \ldots, x_k) = 0$

This states that the expected value of the error term (u) is zero for any values of the independent variables. If MLR.4 holds we have exogenous explanatory variables. However, if x_j is correlated with the error term, then x_j is called an endogenous explanatory variable (Woolridge, 2020, p.82).

3.3.5 MLR.5 Homoscedasticity

The assumption of homoscedasticity states the following:

(3.27) $Var(x_1, x_1, \ldots, x_k) = \sigma^2$

This means that the variance of the error term, u, is the same for all values of the explanatory variables. If this condition fails, the model exhibits heteroscedasticity.

3.3.6 MLR.6 Normality

The assumption of normality states that the error term u is independent of the explanatory variables and is normally distributed with zero mean and variance σ^2: $u{\sim}Normal\ (0, \sigma^2)$

This assumption also assumes MLR.4 and MLR.5 and is therefore a stronger assumption than the previous assumptions we have made. From MLR.6 we have that:

(3.28) $E(x_1, x_1, \ldots, x_k) = E(u) = 0$

(3.29) $Var(x_1, x_1, \ldots, x_k) = Var(u) = \sigma^2$ (Woolridge, 2020, p. 118).

3.4 Hypothesis testing

We will perform hypothesis testing on our estimators to see if there is a significant association between our independent variables on our dependent variable or not. We will set up a null hypothesis that β_j, where j can refer to any of the k independent variables, has no significant association on the dependent variable. This can be expressed as:

(3.30) $H_0 : \beta_j = 0$

The alternative hypothesis will be that there is a significant association:

(3.31) $H_1: \beta_j \neq 0$

When testing about a single population parameter we will be using a t-statistic:

(3.32) $t = \frac{estimate - hypothesized\ value}{standard\ error} = \frac{\widehat{\beta_j} - a_j}{se(\widehat{\beta_j})} = {\sim}t_{n-k-1}$

Where $n - k - 1$ is the degrees of freedom and a_j is the hypothesized value of β_j. In our case, we have $a_j = 0$, and thus:

(3.33) $t = \frac{\widehat{\beta_J}}{se(\widehat{\beta_J})}$

This is a two-sided hypothesis test and the rejection rule is that the absolute value of the t-statistic for the estimated parameter is larger than the critical value, c:

(3.34) $|t_{\widehat{\beta_J}}| > c$

The critical value c is chosen to make the area in each tail of the t-distribution equal to $2 * \alpha$, where α is the significance level. If we reject H_0, we have that x_j is statistically significant on the specified significance level (Woolridge 2020, p.120-128). Using the econometric software STATA, we can compute a p-value to test the smallest significance level at which the null hypothesis would be rejected, given the observed t-statistic. The p-value is a probability between 0 and 1, and when testing for the null hypothesis as in equation (3.30), the p-value is given as:

(3.35) $P(|T|) > |t|$

In (3.35) T is a t distributed random variable with n-k-1 degrees of freedom and t is the calculated numerical value of the t-statistic. A smaller p-value is evidence against the null hypothesis. For a significance level, α, H_0 is rejected if p-value< α (Woolridge 2020, p.130-132).

4 Data

4.1 Dependent variable

To measure the bilateral aid to Ukraine we use data from the database *Ukraine support tracker* given by the Kiel Institute for the World Economy. For our analysis, we have used the 8th edition, which gives data on support to Ukraine from January 24th to November 20th, 2022. January 24th is the day several NATO countries put their troops on alert and the U.S. embassy started to evacuate its embassy staff in anticipation of the Russian invasion on February 24th. From this database, we found numbers for the cumulative bilateral commitments countries have given as support to Ukraine, as percentage of GDP. Here bilateral commitments are defined as commitments from one government to the Ukrainian government. In addition, the Ukraine support tracker report argues that the relevance of aid coming from the EU institutions has become so significant that it is insufficient to focus only on bilateral aid by itself. Therefore, they have added EU commitments to each of the country's bilateral commitments. The EU commitments have been assigned based on the member country`s relative contribution to the EU budget. This total sum has then been calculated as a percentage of GDP (Antezza et al, 2022, p.12). These combined numbers are what we have used as our dependent variable *totcomeu_gdp*. We chose to look at the commitments as a percentage of GDP to control for the size of the economy when measuring how much aid they have given. The list of countries we have data for from the Ukraine support tracker, and therefore is included in our analysis, are available upon request.

To see if reliance on fossil fuels gives an extra incentive to give aid, outside of loyalty to the EU, we will also run a restricted model with only the EU countries. Here we will omit the EU share from each of the countries aid, and only focus on bilateral aid. This gives us the independent variable: *totcom_gdp*.

In the "Ukraine support tracker" there is also data where the bilateral commitments are separated into three categories, financial, humanitarian and military. Military commitments include the values of weapons, military equipment and items donated to the Ukrainian army, in addition to financial assistance tied to military purposes. Humanitarian assistance is the value of aid supporting the civilian population, mainly food, medicines and relief items. Financial assistance refers to grants, loans, guarantees and swap-lines (Antezza et al, 2022, p.5). In our further analysis, we will also consider that the effect of Russian fossil fuels might influence different types of aid differently. We will therefore extend our analysis to also include different types of bilateral aid. For humanitarian assistance as a percentage of GDP we have the variable *humcom_gdp*. To generate *humcom_gdp*, we have used the following formula:

(4.1) humcom_gdp= $\frac{Humanitarian\ assitance\ (in\ billion\ euros)}{GDP\ 2021\ (in\ billion\ euros)} * 100\%$

The variable *fincom_gdp* measures the financial commitments as a percentage of GDP. We have generated this in a similar way:

(4.2) fincom_gdp=$\frac{Financial\ assitance\ (in\ billion\ euros)}{GDP\ 2021\ (in\ billion\ euros)} * 100\%$

We have defined a variable *milcom_gdp* for the military commitments as percentage of GDP of the given country. This is calculated by:

(4.3) milcom_gdp=$\frac{Military\ assitance\ (in\ billion\ euros)}{GDP\ 2021\ (in\ billion\ euros)} * 100\%$

Now we have our independent variables and will present the descriptive statistics in table 1. To present the percentage distribution of the variables we have histograms for each of the variables. This is shown in figure 1-5.

Table 1: Shows descriptive statistics for the dependent variables.

Variable	**Mean**	**Standard deviation**	**Min**	**Max**	**Number of observations**
totcomeu_gdp	0.350	0.271	0.008	1.317	34
totcom_gdp	0.174	0.248	0.004	1.097	34
milcom_gdp	0.123	0.236	0	1.080	34
humcom_gdp	0.023	0.030	0	0.131	34
fincom_gdp	0.028	0.043	0	0.169	34

Figure 1: totcomeu_gdp

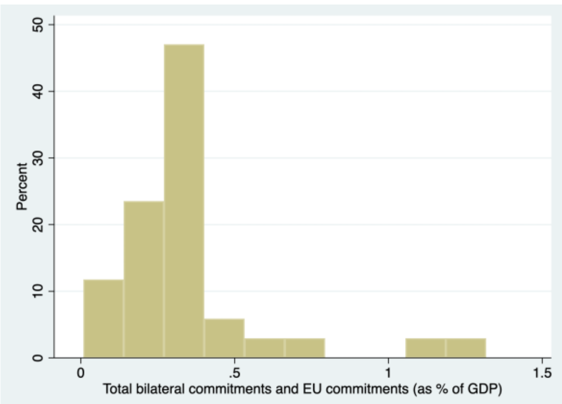


Figure 2: totcom_gdp

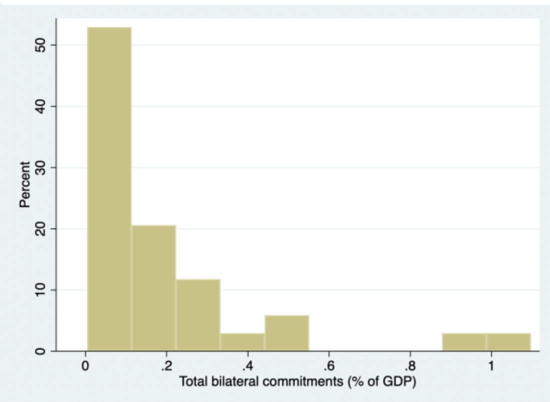


Figure 3: milcom_gdp

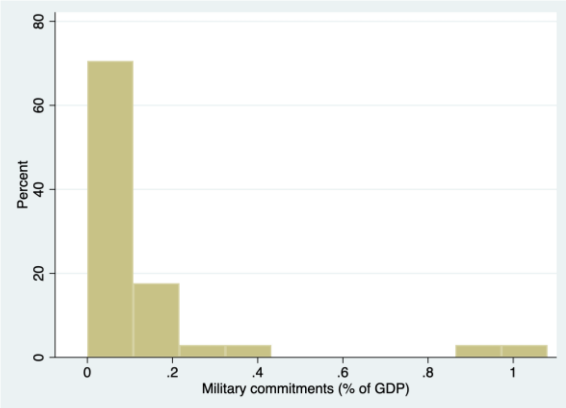


Figure 4: humcom_gdp

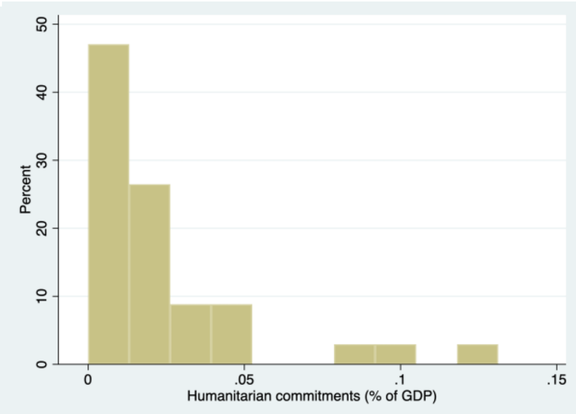
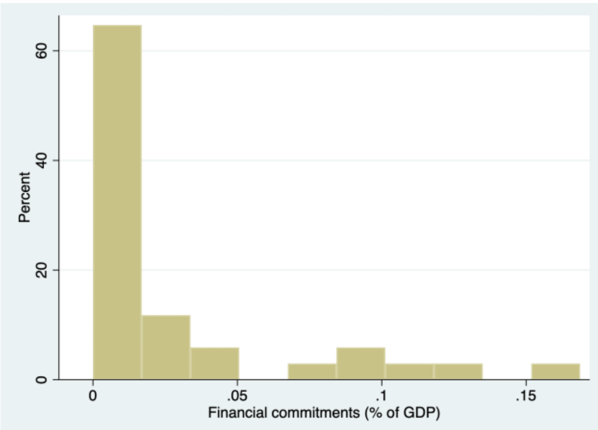


Figure 5: fincom_gdp



First, we look at our main dependent variable *totcomeu_gdp*. From table 1, we see that we have 34 observations with a mean of 0.350. From figure 1 we see that more than half of the countries have given less than 0.5% of GDP. A few countries have given significantly more, up to 1.317% of GDP. This variation around the mean, together with the low number of observations, explains the high standard deviation of 0.271.

For *totcom_gdp*, we see from table 1 that we have 34 observations with a mean of 0.174. From figure 2 we see that more than half of the countries have given less than 0.2 % of GDP. A few countries have given significantly more, up to 1.097% of GDP. This variation around the mean, together with the low number of observations, explains the high standard deviation.

Now we look at table 1 for the different types of aid, *milcom_gdp*, *humcom_gdp* and *fincom_gdp*. We see that the military commitments make up much more of the bilateral commitments given with a mean of 0.123% of GDP and a maximum value 1.080% of GDP, compared to a mean of 0.023% and a maximum value of 0.030% of GDP for humanitarian commitments and a mean of 0.028% and a maximum value of 0.043% for financial commitments. From the histograms (figure 3, 4 and 5) we see that the percentage distribution of military, humanitarian and financial commitments have a similar shape with most of the countries giving in the lower range of the variable distribution and a few countries giving quite significantly more. We therefore see that for the low number of observations we have a high variation around the mean and therefore a high standard deviation for all the variables.

4.2 Interest variable

To measure the reliance on Russian fossil fuels, we use data from the data set *Reliance on Russian Fossil Fuels in OECD and EU countries* given by the IEA (International Energy Agency). From this we have our main independent variable *relfos2020.* This shows the ratio between the sum of imports of coal, oil and natural gas from Russia to the total energy supply (TES) for the OECD and EU countries in 2020. TES refers to the total energy commodity for the country and is measured as:

(4.4) $TES = production + imports - exports - international\ marine\ bunkers - international\ aviation\ bunkers\ \pm stock\ changes$

We then have our main independent variable given by:

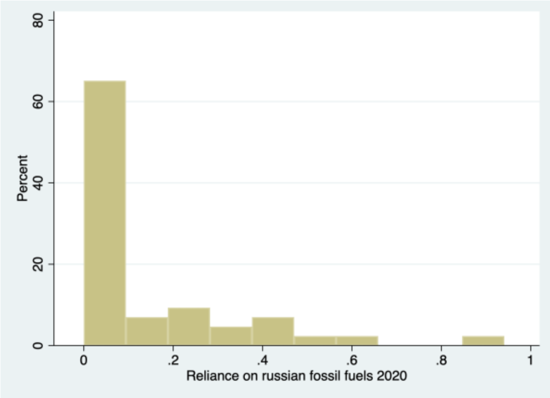
(4.5) $relfos2020 = \frac{(Coal\ imports + Oil\ imports + Natural\ gas\ imports)_{From\ Russia}}{TES}$ (IEA, 2022).

The data set gives information for 43 countries, but to do our analysis we will restrain these to match the countries in the Ukraine support tracker data set. Therefore, we only keep 34 observations.

Table 2: Shows descriptive statistics for the interest variable *relfos2020*.

Interest variable: relfos2020	
Mean	0.154
Standard deviation	0.202
Min	0
Max	0.941
Number of observations	34

Figure 6: relfos2020



From table 2 descriptive statistics, we have 34 observations with a mean of 0.154. Figure 6 shows the percentage distribution of *relfos2020* in a histogram. From figure 6, we see that more than 60% of the countries have a reliance on Russian fossil fuels that is between 0 and 20%. A few countries have a higher reliance, at different levels with 94,1% as the maximum value. We again see that the low number of observations and high variation around the mean, gives us a high standard deviation for the interest variable as well.

4.3 Control variables

Our dataset includes five control variables. These are military spending, bilateral trade with Ukraine, distance from Ukraine and two dummy variables for EU-membership and former eastern bloc countries. These variables are included to account for several effects that have the potential to affect our dataset. Military spending acts as an indicator of military strength, which in turn could affect resilience to foreign pressure (Odehnal & Neubauer, p.521). As a possible explanatory variable, we have thus included it to parcel out the effect that a country's military strength may have on its willingness to send aid to Ukraine. The military spending variable, *milspend21*, consists of one value per country, and is measured as a percentage of GDP. It is collected from the World Bank (World Bank, 2023). Bilateral trade is pointed out in much of the aid literature as a very common factor explaining how much aid is given to a country (Breunig et al., 2010, p.744). It is measured as the percentage of each country's trade that is conducted with Ukraine, both imports and exports, and is collected from the World Bank via the World Integrated Trade Solution (World Integrated Trade Solution, 2023).

Lastly, we have included two dummy variables and one variable for distance. Together, these are our variables that attempt to capture some of the geopolitical interests at play. The variable for distance, *distance*, has been calculated by measuring the distance between the closest points of each country to Ukraine (Geodatos, 2023). This variable is included to account for the relationship between proximity and the cost of aid-giving mentioned in our theory. In addition, it captures that political developments closer to a donor country are likely to be more consequential for said donor (Braunig et al., 2010, p.741). The first of the dummy variables, *eu*, is membership in the EU. This is due to the fact that the EU as an organization has decided to oppose the invasion of Ukraine, and many of its members are vocal about the Russian invasion (Council of the European Union, 2023). In addition, as pointed out in our theory, a large part of Russian natural gas strategies was centered on EU member countries. As a result, it will be prudent to add this variable for membership, as it may also capture some of the effect of said Russian pressure. The EU-membership variable is integrated into the dataset from the Ukraine support tracker and is sourced from there. The second dummy variable, *eastblock,* controls for former members of the soviet bloc. We included this variable due to the inherent political and cultural connections between previous members of the soviet political bloc (Das Kundu, 2007, p.50).

Table 3: Shows descriptive statistics for the control variables

Control variable	Mean	Standard deviation	Min	Max	Number of observations
milspend21	1.666	0.758	0.265	3.867	34
distance	2051	3366	0	15834	34
eu	0.758	0.435	0	1	34
tradeukraine	0.950	1.109	0.04	4.12	34
eastblock	0.235	0.431	0	1	34

4.4 The MLR assumptions for the data

To see if our model is unbiased under the MLR assumptions, we evaluate each one of them below for our main model:

totcomeu_gdp= $\beta_0 + \beta_1 relfos2020 + \beta_2 distance + \beta_3 eu + \beta_4 eastblock +$
$\beta_5 milspend21 + \beta_6 tradeukaine + u$

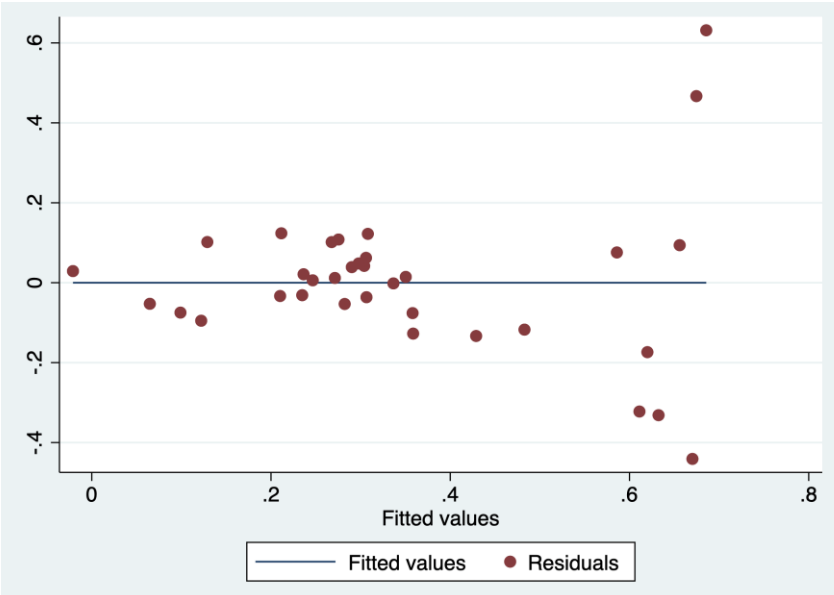
4.4.1 MLR.1 Linearity

If the MLR.1 assumption holds we have linearity in parameters and our linear regression model will take the form:

totcomeu_gdp= $\beta_0 + \beta_1 relfos2020 + \beta_2 distance + \beta_3 eu + \beta_4 eastblock + \beta_5 milspend21 + \beta_6 tradeukaine + u$

To see if the linearity assumption holds, we can plot the residuals against the values predicted by the model for *totcomeu_gdp*. This gives us the scatter plot shown in figure 7.

Figure 7



In figure 7, we have the fitted values on the x-axis and the residuals on the y-axis. Ideally, the residual dots should be scattered evenly along the horizontal fitted values line. Then we would have linearity. We see that we generally have a linear trend for the smaller values, but some variation for some of the higher values. As the residual plots move further away from the horizontal line for higher values, we could have a case of heteroscedasticity. We will look at this more closely under the section MLR.5 homoscedasticity. From this it seems that we might violate the linearity assumption. If this is the case, the independent variables do not have a linear relationship with the dependent variable and our linear model will not give the best estimations for predicting our data. We still choose to move on with the model but are careful about drawing conclusions based on the coefficients in our estimated model.

4.4.2 MLR.2 Random sampling

In our analysis, we are looking at the full population of the given countries and therefore do not need to pick a random sample from a larger population. Thus, the MLR.2 assumption of random sampling is not violated.

4.4.3 MLR.3 No perfect collinearity

To look at if we have perfect collinearity between any of our variables, we make a correlation matrix. Here the correlation between variables takes a value between -1 and 1 where 0 is an indication of no correlation, 1 means that the variables are perfectly positively correlated and -1 means that the variables are perfectly negatively correlated. The correlation matrix for the main model is presented in table 4.

Table 4

Pairwise correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) totcomeu_gdp	1.000						
(2) relfos2020	0.344*	1.000					
	(0.047)						
(3) eu	0.434*	0.382*	1.000				
	(0.010)	(0.026)					
(4) eastblock	0.606*	0.440*	0.308	1.000			
	(0.000)	(0.009)	(0.077)				
(5) distance	-0.432*	-0.325	-0.668*	-0.335*	1.000		
	(0.011)	(0.061)	(0.000)	(0.035)			
(6) milspend21	0.282	0.110	-0.062	0.147	0.008	1.000	
	(0.106)	(0.506)	(0.727)	(0.393)	(0.961)		
(7) tradeukraine	0.589*	0.653*	0.412*	0.830*	-0.423*	0.216	1.000
	(0.000)	(0.000)	(0.016)	(0.000)	(0.007)	(0.206)	

** shows significance at p<.05*

Here we see that none of the variables have a perfectly positive relationship (1) or a perfectly negative relationship (-1). However, there seems to be some correlation between some of the variables. We run a VIF test to see if we have a problem with collinearity. The results are shown in the column VIF test 1 in table 5.

Table 5

Variable	VIF test 1	VIF test 2	VIF test 3
tradeukraine	9.51	1.90	
eastblock	6.50		1.30
relfos2020	2.29	1.89	1.49
eu	2.00	1.99	1.98
distance	1.87	1.86	1.85
milspend21	1.15	1.15	1.15
Mean VIF	**3.89**	**1.76**	**1.55**

If we have a value of 1 from the VIF column, we see that there is no correlation between the variable and any other independent variables. If the VIF value for a variable is higher than 5, this indicates a problematic amount of collinearity between the variable and other explanatory variables (James et. al, 2017, p.101). From table 5, we see that this is the case for the variables *tradeukraine* and *eastblock* in VIF test 1. We therefore try to run a VIF test without eastblock. This is shown in table 5 as VIF test 2. Then we try to remove *tradeukraine*. This is shown under the column VIF test 3 in table 5.

We see that when running the VIF tests without any one of these two variables, we do not violate the assumption of multicollinearity. Therefore, it seems that *tradeukraine* and *eastblock* are highly correlated, which is also supported by the correlation matrix (table 4). As we included the *eastblock* variable to capture some of the loyalty and close ties between the former eastern bloc countries, it could indicate that some of these ties might be captured by a higher level of trade as well. When estimating the effect of an independent variable on the dependent variable, the coefficient tells us how much the increase in one unit of the independent variable will affect the dependent variable, holding all other variables constant. However, if the independent variables are correlated with each other and a change in one of them leads to a change in another, the estimated coefficients will not give us precise results of the effect of the individual variables.

To get a better model that does not violate the multicollinearity assumption we decide to omit one of the variables. When running the regression on only the independent variable, the interest variable and one control variable at the time, we see that there is a switch in the coefficient from positive to negative, when we have only *tradeukraine* as the control variable[1]. Therefore, it seems that *tradeukraine* is correlated with both the independent variable and the interest variable and omitting this variable can create an omitted value bias. From this we choose to keep this control variable and omit the *eastblock* variable. When running the VIF test for only the EU countries and omitting the eastern bloc countries, we see that we do not violate the MLR.3 for this model either[2].

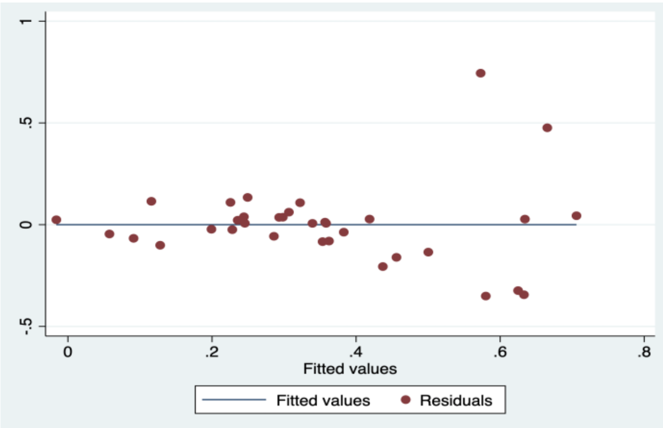
4.4.4 MLR.4 Zero conditional mean

For the zero conditional mean assumption to hold there should be no omitted factors that are correlated with any of the independent variables $x_1, x_2,\ldots, x_k$. This is a hard assumption to satisfy as there in any analysis will be variables that we will not be able to include. This could be due to data limitations or ignorance (Woolridge, 2020, p.82). If we have omitted factors that are correlated with both aid given and reliance on Russian fossil fuels, we will violate the zero conditional mean assumption. We could think that might be the case, if we have overlooked some variables. If this is the case this will create a bias in our OLS estimation.

4.4.5 MLR.5 Homoscedasticity

In figure 6 we already saw some signs of heteroscedasticity. Now we have omitted the variable *eastblock*. Without this variable we get a new scatter plot for the fitted values against the residuals for *totcomeu_gdp* shown in figure 8.

Figure 8



[1] Results available upon request.
[2] Results available upon request.

From figure 8 it still seems that we have a larger variation from the fitted values for higher values. We will now perform the Breusch-Pagan test (BP test) to see if we have heteroscedasticity. Here we set up a null hypothesis that states that assumption MLR.5 is true and that homoscedasticity holds. If we assume a linear function of the squared residuals:

(4.6) $u^2 = \delta_0 + \delta_1 x_1 + \delta_2 x_2 + \cdots + \delta_k x_k + error$

Then we have the null hypothesis of homoscedasticity:

(4.7) $H_0: \delta_1 = \delta_2 = \cdots = \delta_k = 0$

To perform the BP test, we first estimate the model using OLS as we will show in the results section. Then we obtain the squared residuals for each observation and run the regression on equation (4.6). From this we get the R-squared $R^2_{u^2}$. Then we can form the LM statistic:

(4.8) $LM = n * R^2_{u^2}$

From this we perform a hypothesis test, using a χ^2_k distribution (Woolridge, 2020, p.270). We run this test in STATA and get the following results when testing for the predicted model:

chi2(5) = 36.46

Prob > chi2 = 0.0000

We see that the p-value is very small so we reject the null-hypothesis of homoscedasticity. This implies that the variance of the error term is not constant. We specify the tests for each of the different variables to see if the variance of the error term is constant for any of these. The results are shown in table 6.

Table 6

Variable	**chi2(1)**	**Prob > chi2**
relfos2020	0.00	0.9839
distance	3.24	0.0789
eu	3.78	0.0517
tradeukraine	17.76	0.0000
milspend21	34.39	0.0362

We see that when testing the individual variables, we reject the null hypothesis of heteroscedasticity with a 5% significance level for the variables *relfos2020*, *distance* and *eu*. Thus, we have homoscedasticity when these variables are examined alone. We have the same problem of heteroscedasticity in the restricted model with only the EU countries[3]. Heteroscedasticity does not create bias with the OLS estimators of the β_j. However, the consequence of heteroscedasticity is that the estimators of the variances, $Var(\beta_j)$, are biased. The OLS standard errors are based on the variances and because these are not reliable, we have a problem when creating confidence intervals and test statistics. We can no longer know that the t-statistic has a t-distribution or that the LM statistic has an asymptotic chi distribution. Therefore, the test statistics we use to test hypotheses under the MLR are not valid if we have heteroscedasticity (Woolridge, 2020, p.263). Going further with our analysis we will therefore be very careful about drawing conclusions from the hypothesis tests we run in our dataset. However, for the purpose of the analysis, we still move on with the model.

4.4.6 MLR.6 Normality

There are various methods to test for normality. We chose to use the Shapiro-Wilk test, as this is an appropriate method for smaller sample sizes (<50) (Mishra et.al., 2019, p.70). Here STATA set up a null hypothesis that we have normality in the data. If we obtain a p-value lower than 0.05 we reject the null hypothesis with a 95% confidence level. The results from the Shapiro-Wilk test are shown in table 7.

Table 7

Test	Observations	z	Prob>z
1	34	3.847	000006
2	34	0.785	0.21632

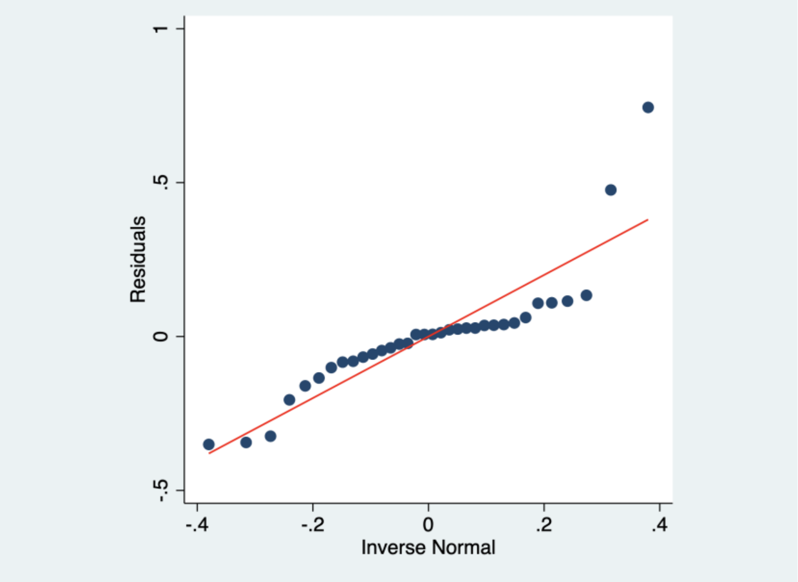
Test 1 shows the result from our main model up until now. From test 1 we get the p-value:
p-value=0.00006<0.05

We reject the null hypothesis about normality in the data. We can see this visually as well by plotting the obtained residuals along the normality line. This is shown in figure 9. Here the

[3] Results available upon request.

residuals obtained from the model are shown as blue dots against the red line that indicates perfect normality.

Figure 9



If we would have normality, we would see that the blue residual dots would follow the red line. We see that this is not the case and we do not have normality in our data.
For the restricted model with only EU countries we also get a very small p-value so that we reject the null-hypothesis about normality [4]. A normally distributed random variable is characterized by being symmetrically distributed around the mean and more than 95% of the area under the distribution lies within two standard deviations. This is essential to get exact inference based on the t and F statistic. When the normality assumption is violated, we therefore have problems with concluding based on these hypothesis tests. For a large sample size we could do a test to see if the OLS estimators satisfy asymptotic normality (Woolridge, 2020, p.168-170). However, since we have a smaller sample size, it is hard to conclude about this. A possible solution to the normality assumption is to transform the dependent variable to log terms (Woolridge, 2020, p.119). Then the model would look like this:

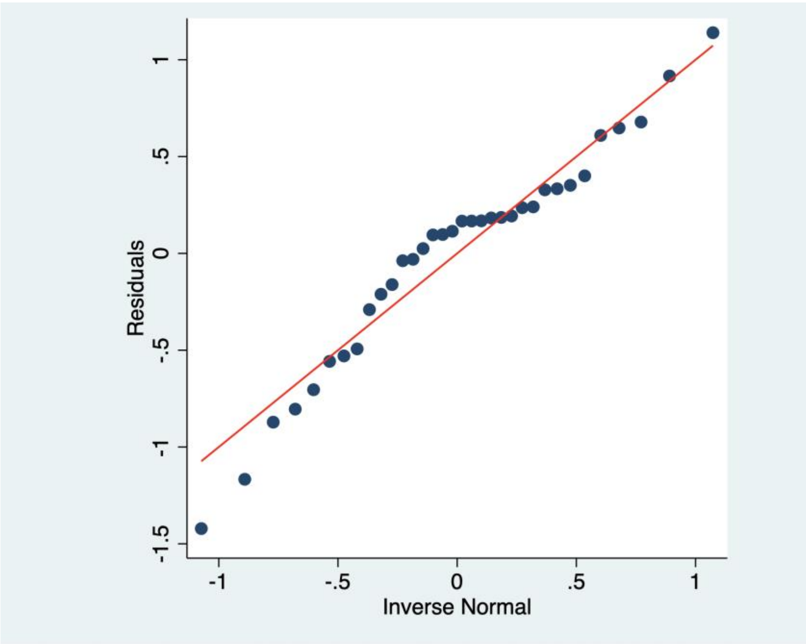
$$\log(\text{totcomeu\_gdp}) = \beta_0 + \beta_1 relfos2020 + \beta_2 distance + \beta_3 eu + \beta_4 milspend21 + \beta_5 tradeukaine + u$$

[4] Results available upon request

The output from the Shapiro-Wilk test is shown in table 7 as test 2. Here we see that we obtain a higher p-value:
p-value=0.21632>0.05.

We do not reject the null hypothesis about normality in the data. This does not mean that we have normality in the data, but since we cannot reject that we have it, this is an indication that we do have it. We then analyze the log-model visually by plotting the residuals against the normality line in figure 10.

Figure 10



Here we see that this model is closer to the normality line and gives a better estimation of normality in the data. We therefore choose to include this in estimating our main model.

5. Results

Table 8 shows the results from the regression of the unrestricted model. The p-values in the table refers to $H_0: \beta_j = 0$. In column 1 we try to estimate the simple regression model with only our interest variable and our independent variable:
I*: totcomeu_gdp= $\beta_0 + \beta_1 relfos2020$

In Column 2 we try to estimate the model with our control variables:
I: totcomeu_gdp= $\beta_0 + \beta_1 relfos2020 + \beta_2 distance + \beta_3 eu + \beta_4 milspend21 + \beta_5 tradeukaine + u$

As explained above, we take the log of the independent variable to get a more normal distribution of the variables. In column 3 and 4 we will try to estimate the logarithmically transformed model. First with the simple regression, estimated in column 3:
II*: log(totcomeu_gdp) $= \beta_0 + \beta_1 relfos2020$

Then with the control variables added:
II: log(totcomeu_gdp) $= \beta_0 + \beta_1 relfos2020 + \beta_2 distance + \beta_3 eu + \beta_4 milspend21 + \beta_5 tradeukaine + u$

The results from model II are shown in column 4.

Table 8

	(1) totcomeu_gdp	(2) totcomeu_gdp	(3) logtotcome~p	(4) logtotcome~p
relfos2020	**0.463***	**-0.254**	**2.055***	**-0.452**
	(0.224)	**(0.258)**	**(0.904)**	**(0.728)**
eu		**0.133**		**0.748***
		(0.124)		**(0.350)**
distance		**-0.0000120**		**-0.000190*****
		(0.0000155)		**(0.0000437)**
milspend21		**0.0830**		**0.407***
		(0.0535)		**(0.151)**
tradeukraine		**0.127***		**0.119**
		(0.0476)		**(0.134)**
_cons	**0.278*****	**0.0506**	**-1.740*****	**-2.336*****
	(0.0563)	**(0.153)**	**(0.228)**	**(0.431)**
N	**34**	**34**	**34**	**34**
R-sq	**0.118**	**0.458**	**0.139**	**0.742**

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

From column 1 and 3 we see the estimations of the simple regression models, model I* and model II*. This suggests a positive relationship between the reliance on Russian fossil fuels and the amount of aid given to Ukraine. The coefficients from table 8 gives us the estimated models:

I: totcomeu_gdp= $0.0506 - 0.254 relfos2020 - 0.0000120 distance + 0.133 eu + 0.0830 milspend21 + 0.127 tradeukaine$

II: log(totcomeu_gdp) $= -2.336 - 0.452 relfos2020 - 0.00019 distance + 0.748 eu + 0.407 milspend21 + 0.119 tradeukaine$

When adding our control variables, we see that the coefficient for *relfos2020* shifts from positive to negative. To see if the estimated model II shows if there is a significant association between the *relfos2020* and *logtotcomeu_gdp* we set up the null hypothesis stating that there is no association and the parameter β_1 is equal to zero:

$$H_0: \beta_1 = 0$$
$$H_a: \beta_1 \neq 0$$

We perform a two-tailed test with significance level 5% with the values from the model estimated after the log-transformation. We focus on model II because the tests for normality indicate that this is closer to satisfy the MLR6., and therefore, the test statistic is more likely to be valid for this model. The test is shown in the appendix and from this we cannot reject the null-hypothesis. This means that we cannot conclude that there is a significant association between *relfos2020* and *logtotcomeu_gdp* with a significance level of 95%. When performing the test for model I, we also reject the null hypothesis.[5]

Furthermore, we read from the coefficients and the calculated p-values that there is a positive relationship between both being a member of the EU and military spending on the amount of aid given with a confidence level of 95%. We see that there is a negative relationship between distance and the amount of aid given with a confidence level of 99.9%. In addition, the results shows a positive coefficient for *tradeukraine*, but we cannot reject the null hypothesis about if this has an effect or not. Regarding if the control variables have a positive or negative effect on the dependent variable, model I indicates the same pattern as model II. However, from the p-values, we see that *tradeukraine* is the only variable that seems to have a significant effect at a 95% confidence level. The differences in which control variables are significant in model I and model II under the t-statistics, show how the violation of MLR.6 changes the outcome of hypothesis testing.

[5] Hypothesis tests are shown in the appendix.

Now we look at the outcome for specific types of bilateral commitments. The outcome for these regressions are shown in table 9 with p-values referring to $H_0: \beta_j = 0$. In column 1 we try to estimate the model for military commitments:

III: milcom_gdp= $\beta_0 + \beta_1 relfos2020 + \beta_2 distance + \beta_3 eu + \beta_4 milspend21 + \beta_4 tradeukaine + u$

Column 2 shows the estimated model for humanitarian commitments:

IV: humcom_gdp= $\beta_0 + \beta_1 relfos2020 + \beta_2 distance + \beta_3 eu + \beta_4 milspend21 + \beta_4 tradeukaine + u$

For financial commitments, the estimated model is shown in column 3:

V: fincom_gdp= $\beta_0 + \beta_1 relfos2020 + \beta_2 distance + \beta_3 eu + \beta_4 milspend21 + \beta_4 tradeukaine + u$

Table 9

	(1) milcom_gdp	(2) humcom_gdp	(3) fincom_gdp
relfos2020	-0.00282	0.000526	-0.000158
	(0.00260)	(0.000343)	(0.000494)
eu	-0.000106	-0.000333	-0.000521*
	(0.00125)	(0.000165)	(0.000237)
distance	-4.03e-08	-3.36e-08	-4.43e-08
	(0.000000156)	(2.06e-08)	(2.97e-08)
milspend21	0.000670	-0.0000909	0.000122
	(0.000540)	(0.0000711)	(0.000102)
tradeukraine	0.00118*	0.0000276	0.0000438
	(0.000480)	(0.0000632)	(0.0000911)
_cons	-0.000418	0.000597**	0.000542
	(0.00154)	(0.000203)	(0.000292)
N	34	34	34
R-sq	0.268	0.232	0.215

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

We see that we have a negative relationship between *relfos2020* and military commitments and financial commitments, respectively. We also see that there is a positive relationship between *relfos2020* and humanitarian commitments. None of these are statistically significant for a confidence level of 95%. However, when performing the hypothesis tests for the model it is important to be aware of the possible violation of the MLR.6 for these models. We still perform the analysis but will be very careful to draw conclusions based on this. We see that there are only two statistically significant results with a confidence level of 95%. These are *tradeukraine* on military commitments, which seems to have a slightly positive relationship, as well as a negative relationship between being a member of the EU and financial commitments. Generally, we observe a negative relationship for the EU variable for all categories of aid in model III, IV and V. At first this looks peculiar as we saw a positive relationship for the EU variable and aid given in model I and II. This discrepancy comes from the fact that models III, IV and V only look at bilateral commitments, excluding EU shares. Thus, the amount of aid from EU-countries will be lower in these models.

Now we look at the restricted model for only bilateral aid from the EU countries. The results are shown in table 10 with p-values referring to $H_0\colon \beta_j = 0$. We first try to estimate a model for total bilateral commitments shown in column 1:

VI: totcom_gdp= $\beta_0 + \beta_1 relfos2020 + \beta_2 distance + \beta_3 milspend21 + \beta_4 tradeukaine + u$

Then we separate for different types of bilateral aid for the restricted model. We try to estimate the model for only military commitments in column 2:

VII: milcom_gdp= $\beta_0 + \beta_1 relfos2020 + \beta_2 distance + \beta_3 milspend21 + \beta_4 tradeukaine + u$

Column 3 shows the regression for estimating the model with only humanitarian assistance:

VIII: humcom_gdp= $\beta_0 + \beta_1 relfos2020 + \beta_2 distance + \beta_3 milspend21 + \beta_4 tradeukaine + u$

The model for financial commitments is estimated in column 4:

IX: fincom_gdp= $\beta_0 + \beta_1 relfos2020 + \beta_2 distance + \beta_3 milspend21 + \beta_4 tradeukaine + u$

Table 10

	(1)	(2)	(3)	(4)
	totcom_gdp	milcom_gdp	humcom_gdp	fincom_gdp
relfos2020	-0.252	-0.00306	0.000696*	-0.000154
	(0.306)	(0.00301)	(0.000323)	(0.000462)
distance	0.0000826	0.000000706	-0.000000166	0.000000286
	(0.000112)	(0.00000110)	(0.000000118)	(0.000000169)
tradeukraine	0.158*	0.00143*	-0.0000161	0.000165
	(0.0676)	(0.000665)	(0.0000713)	(0.000102)
milspend21	0.0810	0.000892	-0.000212*	0.000130
	(0.0775)	(0.000761)	(0.0000817)	(0.000117)
_cons	-0.154	-0.00173	0.000585*	-0.000398
	(0.204)	(0.00201)	(0.000215)	(0.000308)
N	26	26	26	26
R-sq	0.291	0.264	0.369	0.176

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

We see that we have a negative coefficient for *relfos2020* on total aid given, military aid given and financial aid given. From the observed p-values, we see that none of these values are statistically significant with a confidence level of 95%. Again, it is important to be aware of the possible violation of the MLR.6 and the implications for hypothesis testing. For humanitarian assistance, we have a positive coefficient for *relfos2020* with a confidence level of 95%. This indicates that the reliance on Russian fossil fuels are positively correlated with humanitarian aid given. We also see that with a confidence level of 95% military spending is negatively correlated with humanitarian aid. For the other control variables, we reject the null hypothesis about a statistically significant impact on humanitarian aid. We also see that the only coefficient that is significantly positively correlated with the total bilateral commitments given and military commitments is *tradeukraine*.

6. Discussion

Now that we have presented our results, we will discuss their implications and what we may learn from them. As we have mentioned in our data section, it is crucial to have the limitations of our thesis in mind when discussing our results. Among these is the fact that the Ukraine support tracker does not include refugee cost for their estimation of aid given to Ukraine. A publication by Paul J.J. Welfens argues that this could present a problem when estimating the total aid a country gives to Ukraine as a percentage of GDP (Welfens, 2022, p.183). Ukrainian refugees account for a large share of actual humanitarian spending on aid, and for some countries, a large share of the total amount of aid given (Welfens, 2022, p.183). Therefore, the data set might present an incomplete picture of total aid given.

Another limitation of the data set is that it only looks at countries that actually send support. That is, the minimum level of sent aid is higher than zero. Therefore, our results only indicate if the reliance on fossil fuels gives an incentive to send more or less aid, not if it affects the decision to send aid to Ukraine at all. In addition, we have a rather low number of observations and confidence intervals that are inconclusive. As a consequence, we make any and all assertions carefully, and only with full awareness of the fact that they do not have as strong a foundation as would optimally be the case. While these elements restrict our ability to generalize from the data we have collected, there are some meaningful outcomes that deserve to be discussed in more detail.

One result of particular interest is, perhaps naturally, our main independent variable. When running the regression with only fossil fuel reliance and total commitments, our results show a positive relationship, implying that the more a country imports from Russia the more it sends in aid to Ukraine. While this result in and of itself is interesting, even more so is the fact that the relationship changes when control variables are included. The specific variable responsible is trade with Ukraine, showing us that bilateral trade captures some common factor that is also captured by reliance on fossil fuels. We will discuss this relationship in more detail in a moment. Such a finding would support a claim that the level of fossil fuel imports does indeed affect how much support is given to Ukraine, and that the direction of said effect is negative. While one could calculate the exact effect, due to the aforementioned econometric problems it is likely to be limited in its accuracy. We will therefore discuss the general direction of the results, as they may be more meaningful.

If the negative relationship between reliance on Russian fossil fuels and support given is indeed reflective of the real world, then our results would be in line with some of the effects one could expect from Russia's energy strategies. Ozawa and Iftimie proposed that the Russian state has attempted to align countries to its strategic objectives (Ozawa & Iftimie, 2020, p.16-17). In harmony with this, our model and its results would suggest that countries that are more exposed to this pressure send less aid. As we have mentioned in our theory, many of the donor countries are worried that their energy security might be at risk. As policymakers worry about the consequences of a lack of fossil fuels, it may not be out of the question to lessen the flow of aid to Ukraine. On the other hand, some countries, perhaps especially those in eastern Europe, will find that their defense interests could dictate them to send more aid to Ukraine in order to weaken Russia. This could also be reflected in the slight negative correlation of distance with aid. However, this effect is minute, and should be tested with more rigorous research in the future.

As elaborated in our theory section, trade may affect how reliance on Russian fossil fuels plays out for the allocation of aid for some countries. In harmony with this, bilateral trade with Ukraine has a noticeable effect on our results. From the estimations of all our models, except model VIII, we have a positive coefficient for *tradeukraine*. The exception of model VIII could be due to EU-commitments being left out, which could skew the result. In total, these results imply that countries with closer economic ties to Ukraine are expected to send more aid. Such a result is in line with the results of previous literature and might well be a manifestation of the commercial self-interest mentioned in our theory.

It is also of interest to note that for our main models I and II, our findings suggest that EU countries give more aid than non-EU countries. As found in the literature, a large portion of EU citizens believe Ukraine matters to their own security, and many are of the belief that the EU should step up to the task of defending Ukraine. With this in mind, the observed relationship could be a reflection of the pressure that citizens put on their respective governments.

When separating the bilateral commitments into the categories humanitarian, financial and military, we generally observe the same results for financial and military aid as we do with the total amount of aid given. However, for humanitarian aid we see that there are some differences. In contrast with the other aid variables, we observe a positive relationship between the reliance on fossil fuels and humanitarian aid. This could be an indication that countries are not as concerned about potential negative responses from Russia when choosing how much humanitarian aid to send to Ukraine. We also see that there is a negative relationship between military spending and humanitarian assistance. One explanation could be that countries that spend less on military, focus more on humanitarian assistance than military and financial forms of assistance. However, this could also be a result of the limitation we have when not including refugees. The difference in the results for the *humcom_gdp* variable could thus come from it being an incomplete measure of actual humanitarian support.

When looking at the restricted model for only the EU countries, we see the same relationships regarding the factors influencing different types of aid. The differences in the results between humanitarian aid and the other categories is also largely the same as in the previous models. With the results being similar in both restricted models for EU countries and unrestricted, it serves as an indication that the relationships are somewhat consistent for donor countries in general and EU-members specifically.

7. Conclusion

In this thesis we have investigated if there is a correlation between a country's reliance on Russian fossil fuels prior to the invasion of Ukraine in 2022, and the amount of aid sent to help Ukraine after the invasion. We cannot see a statistically significant relationship between these two variables and cannot conclude that there is an effect. However, we have attempted to discuss what results we have obtained, with the aim that they might match the results of future work in the field. The OLS estimates suggest a negative relationship between fossil fuel imports on bilateral aid sent to Ukraine, and we have then discussed if this could be an effect of deliberate Russian strategies. Our results also indicate that trade and commercial interests affect the level of aid given, which supports earlier findings in aid theory. The insignificant results could partly be due to a low number of observations, as well as limitations in both our data set and how much data exists on the topic. As the situation develops and a peaceful solution is hopefully found, it will be interesting to see if future research is able to provide a more definitive answer.

8. Sources

Alesina A. & Dollar D. (2000). Who Gives Foreign Aid to Whom and Why? *Journal of Economic Growth*, 5: 33–63 https://link.springer.com/article/10.1023/A:1009874203400

Antezza, A., Bushnell, K., Frank, A., Frank, P., Franz, L., Kharitonov, I., Rebinskaya, E. & Trebesch, C. (2022). The Ukraine Support Tracker: Which countries help Ukraine and how?. *Kiel Working Paper, No. 2218*, 1-65. https://www.ifw-kiel.de/fileadmin/Dateiverwaltung/IfW-Publications/-ifw/Kiel_Working_Paper/2022/KWP_2218_Which_countries_help_Ukraine_and_how_/KWP_2218_Trebesch_et_al_Ukraine_Support_Tracker.pdf

Balla, E. & Reinhardt, G. Y. (2008). Giving and Receiving Foreign Aid: Does Conflict Count? *World Development*, *36*(12), 2566-2585. https://www.sciencedirect.com/science/article/pii/S0305750X08001757

Berthélemy, J. C. (2006). Aid Allocation: comparing donors' behaviors. *Swedish Economic Policy Review*, 1-23. https://www.researchgate.net/profile/Jean-Claude-Berthelemy/publication/281950478_Aid_allocation_Comparing_donors_behaviour/links/607dc4258ea909241e10405b/Aid-allocation-Comparing-donors-behaviour.pdf?_sg%5B0%5D=started_experiment_milestone&origin=journalDetail

Breunig, C., Lundsgaarde, E.Prakash, A. (2010). Instrumental Philanthropy: Trade and the Allocation of Foreign Aid. *Canadian Journal of Political Science*, *43*(3), 733-761. https://www.jstor.org/stable/pdf/40983516.pdf?refreqid=excelsior%3A6f62d53d81f837654727a7c7ea555110&ab_segments=0%2Fbasic_search_gsv2%2Fcontrol&origin=&initiator=&acceptTC=1

Das Kundu, N. (2007). Russia and the Former Soviet States: Dynamics of Relations. *Policy Perspectives*, *4*(1), 49-59. https://www.jstor.org/stable/42909162

Geodatos. (2023). Distance between countries. Collected from https://www.geodatos.net/en/distances/countries

IEA. (2022). National Reliance on Russian Fossil Fuel Imports. Collected from: https://www.iea.org/reports/national-reliance-on-russian-fossil-fuel-imports

Jacobs, L. R. & Page, B. I. (2005). Who Influences U.S. Foreign Policy? *American Political Science Review*, *99*(1), 107-123. https://www.jstor.org/stable/30038922

James G., Witten D., Hastie, T., Tibshirani, R. (2013). *An Introduction to Statistical Learning: With Applications in R*. (1). New York, Springer.

Krastev, I. & Leonard, M. (2022). The crisis of European security: What Europeans think about the war in Ukraine. *European Council on Foreign Relations*, 1-16. https://www.jstor.org/stable/resrep39678

Mishra P, Pandey CM, Singh U, Gupta A, Sahu C, Keshri A. (2019). Descriptive statistics and normality tests for statistical data. *Annals of Cardiac Anaesthesia 22* (1), 67-72. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6350423/pdf/ACA-22-67.pdf

Morgenthau, H. (1962). A Political Theory of Foreign Aid. *The American Political Science Review*, *56*(2), 301-309. https://www.jstor.org/stable/1952366

Ozawa, M. & Iftimie, I. A. (2020). Russia's energy policy as a foreign policy instrument. *NATO Defence College*, 13-20. https://www.jstor.org/stable/resrep27709.8

Welfens, P.J.J. (2022). International Aid Pledges to Ukraine: Coverage, Effects, and Potential Challenges. In: Russia's Invasion of Ukraine. *Palgrave Macmillan, Cham*. https://doi.org/10.1007/978-3-031-19138-1_11

Woolridge, J. M. (2020). *Introductory econometrics: A Modern Approach*. (7). Boston, Cengage.

World Bank. (2023). Military expenditure (% of GDP). Collected from https://data.worldbank.org/indicator/MS.MIL.XPND.GD.ZS

World Integrated Trade Solution. (2023). Trade Statistics by Country / Region. Collected from https://wits.worldbank.org/countrystats.aspx?lang=en

9. Appendix

9.1 Hypothesis tests

Hypothesis tests for interest variable, model I:

For hypothesis tests with a significance level of 0.05% and t_{28}, we reject the null hypothesis if $|TS| > 2.048$

Hypothesis	Test statistic	Conclusion
H_0: β_1=0 H_a: β_1 ≠0	$TS = -\frac{0.254-0}{0.258}$=-0.984	We cannot reject H_0.

Hypothesis tests for interest variable, model II:

For hypothesis tests with a significance level of 0.05% and t_{28}, we reject the null hypothesis if $|TS| > 2.048$

Hypothesis	Test statistic	Conclusion
H_0: β_1=0 H_a: β_1 ≠0	$TS = -\frac{0.452-0}{0.728}$=-0.621	We cannot reject H_0.

NTNU

Norwegian University of
Science and Technology