COST AND TRANSIT TIME ELASTICITY ESTIMATES FOR FREIGHT TRANSPORT IN WAR-TIME UKRAINE

by

Artem Serhiienko

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Thesis Supervisor: ____________________________ Professor Oleg Nivievskyi

Approved by ____
Head of the KSE Defense Committee, Professor

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Date ______________________________________

Kyiv School of Economics

Abstract

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Adding to an ongoing discussion on rail freight tariffs in Ukraine, this thesis examines freight transport demand in the country by estimating own-cost elasticities for rail and truck transport before and after the full-scale russian invasion, started in February 2022, using a unique dataset of actual logistics decisions of a firm. The study utilizes multinomial logit model and Box-Cox transformation of explanatory variables, accounting for possible structural changes in demand over time. The results show that rail demand was inelastic before the invasion but became significantly more elastic afterward, indicating increased adaptability to cost changes during the crisis conditions caused by the war. Truck demand was estimated to be elastic in both periods. Transit time was found to have little effect on mode choice probability and the conclusion was made that it can be excluded from the model without sacrificing precision. Policy simulations based on these elasticity estimates suggest that increases in rail tariffs could lead to substantial reductions in rail's market share. The findings also provide a basis for forecasting responses to an increase in fuel prices for trucks. These results can inform tariff policy and contribute to national transport modeling efforts in Ukraine.

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LIST OF ABBREVIATIONS

UZ. Ukrzalizlytsia. (Ukrainian rail monopoly).

Chapter 1

INTRODUCTION

In Ukraine's economy, the agricultural sector is considered to be the most important in exports: in 2024, the largest category among all exported goods was cereals with 22.6% in value, and the second highest was vegetable oil, accounting for 13.3% in value (SSSU, 2025). However, the russian invasion of Ukraine, that started on February 24th, 2022, led to unforeseen disruption of supply chains, destruction of many firms' assets, that accumulated to $10.3 billion by December 2023 (Nivievskyi and Neyter, 2024), and to Black Sea blockade, which meant that russian warships did not let anyone out of Ukrainian ports for over four months. The latter became a real challenge for agricultural companies, as most of the produced grain and vegetable oil was exported by rail via seaports before the invasion, but after the blockade new routes had to be found and established. The Black Sea Grain Initiative, started in July 2022, helped to resolve the problem to some extent, but then the agreement was terminated unilaterally by russians in July 2023 (European Council, 2025), so the main alternative was exporting agricultural goods across the land border into and through Europe. This shift from ports to borders led to some conjunctions in the railway system, which meant longer and less reliable delivery. At the same time, Ukrainian state-owned rail monopoly Ukrzaliznytsia (UZ) raised its tariffs for freight rail transport by about 70% in 2022 without any talks with business, and after that there is an ongoing discussion about further increase in prices, which are explained by low demand for rail and a need to have profits (GMK Center, 2024). However, it remains unclear how exactly UZ calculates expected revenue from freight tariff increases, and whether the reaction of industrial companies was considered: a rational firm should decrease its output and substitute the more costly input (rail) for another (i.e. truck), so a 70% increase in tariffs generally will not lead to a 70% increase in revenue.

This leads to the following research question: "**How do agricultural firms adjust their demand for freight transport, facing tariff increases and shipment delays, and did this significantly change since the full-scale invasion?**"

To answer the research question, the notion of demand elasticity becomes important – a measure that captures a percentage change in a quantity of a good demanded in response to a 1% change in some variable, associated with this good (usually its price). While being a basic theoretical concept in microeconomics, demand elasticity has huge practical implications, to name a few, in driving firms' pricing decisions, calculating expected revenues from raising freight rail tariffs, exploring intermodal transport network and possibilities of transport mode substitution. There is a substantial stock of literature on own-price and cross-price elasticity of demand for different modes of transport (Dunkerley, Rohr and Daly, 2014; Jourquin, Beuthe and Urbain, 2014). However, to the best of my knowledge, there are no studies that aim to estimate price elasticity of demand for freight transport in Ukraine. Probably, the reason why similar research has not been conducted yet is that feasible data sources on transport in Ukraine are scarce, if not at all absent.

Naturally, the next question should arise: why it is not feasible to simply take a value of elasticity from one of published studies, and apply it to Ukraine? One of the short answers was given by Oum et al. (1992): "*There is no short-cut to obtaining reliable demand elasticities for a specific transport market without a detailed study of that market*". The longer answer is given in *Chapter 2*, where the relevant literature is reviewed, and it is evident from the studies that previously estimated elasticities are wide in range and there are several issues associated with those estimations, one of the most important being data reliability. So, it is indeed important to study the local market with real local data to reliably answer the question of transport demand elasticity.

The data used for this research comes from one of the largest agricultural companies in Ukraine, which operates in huge quantities and country-wide. It is an internal logistics dataset, based on which real decisions are being made, so it is a unique opportunity to get as close to the ground as possible, avoiding biases of aggregation and data modeling (discussed in more detail in *Chapter 2*) which is important both locally and in a wider research context.

Following the research question, the methodology of discrete choice modeling will be applied to the data, where the dependent variable is a probability of choosing a specific mode of transport, and the independent variables are logistics cost and transit time, and based on that, demand elasticities will be estimated. Basic hypothesis is that elasticity of demand is negative with respect to own cost and transit time, while cross cost and transit time demand elasticities for different modes of transport are positive (Jourqin and Beuthe, 2019, among others). Their magnitudes are to be estimated. Direction and magnitude of change in demand elasticity during the war (if any changes occurred) is unknown. Main hypothesis to be tested here is that demand elasticity significantly increased, meaning that firms became more adaptive.

Research aims of this paper are to estimate the relationship between demand for freight transport and logistics costs in Ukraine; to transform the unique dataset into a feasible format for econometric analysis, which include calculating total logistics costs for rail and estimating transit time for both modes of transport; to estimate the elasticities using McFaden's conditional logit model (Jourquin and Beuthe, 2019); to verify the obtained results using evidence from the literature; and to draw conclusions.

In the academic context, this research is expected to widen the discussion on freight transport demand elasticity, exploring wartime economic conditions, utilizing exceptional 'real-world' data, and in general introducing the case of Ukraine, which was not considered before. In practical and local context, the results of this research can be applied to the ongoing discussion of rail tariffs, which will be especially relevant for agricultural export businesses and policy makers, and it also could help to predict structural market changes which occur in response to sea or land blockade of export routes.

The structure of the thesis is organized as follows. *Chapter 2* gives a comprehensive literature review on the topic of cost (price) elasticities across different modes of freight transport. *Chapter 3* develops on the methodology used for the estimates. *Chapter 4* describes and analyzes the dataset acquired for the study. In *Chapter 5* the main results are presented and discussed, and *Chapter 6* summarizes the work with conclusions and policy implications.

C h a p t e r 2

LITERATURE REVIEW

Giving a comprehensive literature review on the topic is complicated for two reasons: there are a lot of published papers regarding freight transport demand elasticity (Oum et al., 1992; Jourquin, Beuthe and Urbain, 2014); to the best of my knowledge, none of these considers the Ukrainian context. In this section I follow in the footsteps of Jourquin, Beuthe and Urbain (2014) in their attempt to establish a point of reference for their work, while also adding my own findings and conclusions. They have done a comprehensive job at collecting and combining different papers on freight transport demand, which helps us to understand what knowledge gaps there are in the field, and what can be improved in the present work.

One of the earliest overviews of studies on the topic of freight transport demand elasticities comes from Oum et al., (1992). It follows that there are several issues with estimating elasticities in existing literature, which are discussed later in this section. Then, de Jong et al., (2010) review existing approaches to modeling transport and summarize different factors that influence them. Jourquin, Beuthe and Urbain (2014) combine and report multi-modes own price/cost elasticities from at least 22 papers from 1978 to 2011. They conclude that there are huge variations in estimated elasticities. Another example of meta-analysis is Dunkerley, Rohr and Daly (2014). In this work, authors go through 23 papers, from which 8 address freight transport, all being mainly relevant for the UK. Numbers stated there, though not directly comparable (different types of elasticities being analyzed), confirm findings of Jourquin, Beuthe and Urbain (2014). Most of the authors are trying to answer the question of what exactly is causing such differences in elasticity estimates across literature, and what papers (techniques, data sources) should be considered reliable for using their results as a reference in future work. Jourquin, Beuthe and Urbain (2014) conclude that problems, biases and overall differences are based on type of data used, quality of data, level of aggregation, local market circumstances and modeling framework.

Arguably, the main difference between studies of freight demand elasticity is source and type of data, and Jourquin, Beuthe and Urbain (2014) make a clear point on that, dividing their literature review into three categories by the data type on which studies were based: aggregated time-series data, aggregated cross-section data and disaggregated cross-section (discrete choice) data. Oum et al. (1992) states that elasticities estimated from these various approaches are in fact not the same, and type of data matters a lot. These ideas highlight the importance of exploring different datasets and contexts, and the conclusion can be made that this research adds to the discussion by carrying out the analysis on the real and unique data, and in the unique war-related context. See *Chapter 4* for more information on the data.

It is quite obvious and well-known that estimated elasticities are dependent on 'field' data quality, but also bias may come from data generated through modeling (Tavasszy and de Jong, 2014). Rich, Kveiborg and Hansen (2011) show that zoning definitions are important: if larger zones are being used, it appears that there are more different modes of transport available than there really are for each specific firm or individual. For instance, if there is a railway station in an area, it does not mean that all the firms in the area have access to it, which will lead to biased results. There are other issues with data aggregation, such as the fact that there is a mix of different demands in aggregated data and their analysis leads to somewhat biased average estimates. On the other hand, models based on disaggregated individual data may overestimate elasticities, and then weighted aggregations are necessary (Domencich and McFadden, 1975; Oum et al., 1992; Jourquin, Beuthe and Urbain, 2014).

Oum et al. (1992) starts a debate that there are few 'true' (full long-run) price elasticities and that there is an issue of 'compensated' vs 'ordinary' elasticities. If we talk about freight transport and firms' decisions, ordinary elasticities are derived by maximizing profit subject to a production function, which gives input demand functions. Compensated elasticities come from minimizing costs to achieve a certain level of output, which gives conditional input demand. Own-price elasticity can be expressed by the famous Slutsky equation, where the elasticity is the sum of substitution effect and scale of output effect of changes in relative prices of two inputs – this type of elasticity that includes both effects is known as 'ordinary' elasticity. However, what is found most often in the literature is 'compensated' elasticity, which neglects the scale of output effect of a price change. Cross-sectional datasets rarely include information about firms' output, so there is little data available to estimate full elasticity, but some work in this field has been done by, for instance, Oum (1979b) and de Jong (2014), who used assumed demand effects. Also, long-run changes and firms' adaptations are often neglected (Jourquin, Beuthe and Urbain, 2014).

In the case of discrete choice models, something close to 'ordinary' elasticity can be measured if a dataset includes 'non-travelers' (Oum et al., 1992). In the context of freight transport it means that a modeling approach should include a first step where firms choose whether to ship or not, and then choose a mode of transport among alternatives, if they decide that a shipment is feasible. However, this setup is rather complex, and the necessary data is not observable, so the methodology described in *Chapter 3* is related more to 'compensated' elasticity, rather than 'ordinary'.

There are multiple ways to assess a relationship between price and demand for freight transport. One of the early examples of empirical analysis may be Miklius (1967), where California lettuce transportation among two modes of transport (rail and road) was studied. He employs a simple log-log OLS model to estimate price elasticities for rail and truck as two separate equations. Obtained elasticities, however, are questionable and not consistent with later research, probably, due to a very simple and unreliable model being used. Modern researchers prefer various types of multinomial logit models to address the issue, especially if research involves discrete choice analysis. See, for instance, Jourquin, Tavasszy and Duan (2014), Jourquin and Beuthe (2019) or Kalahasthi et al. (2022). Jourquin and Beuthe (2019) use multinomial logit with Box-Cox transformation on European NUTS-2 and NUTS-3 level data. Estimated own- and cross-price point-elasticities are wide in range, but this is expected as a large origin-destination matrix was used. Other more exotic modeling approaches are also used in the literature (Adbewahab, 1998; Rich, Kveiborg and Hansen, 2011, among others).

Another issue is to find an appropriate specification for a cost function, if a cost function is being used as a part of estimation. Oum (1979a) uses trans-log cost function, Kim (1987) tests both Cobb-Douglas and trans-log, as well as log-linear and generalized Leontief production functions. Some comparisons between different functional forms and models are made by Kim (1987) and Oum (1989), where the latter study found that, given the same data, estimated elasticity varies substantially from one specification to another. It is expected that results may vary with the model specification, however, Goodwin et al. (2004) suggests that estimated coefficients are not influenced in a strong and consistent way by model form. So, there are various approaches at modeling input demand, and researchers usually use what best fits their data, or even choose functional forms arbitrarily, as in Oum (1979a).

What also seems to differ substantially from one study to another is a choice of explanatory variables for the analysis. Oum (1979a) estimates cost function based on log price ratios and technological time trend; Lewis and Widup (1982) add to that the value of the good, speed, length of haul and losses (only speed appears significant); Levin (1978) includes the cost of unreliability among other explanatory variables, but it was not statistically significant; Inaba and Wallace (1989) introduce an optimal shipment size determined by a weighted linear regression. Several studies report on the phenomenon of changing elasticities depending on distance (Oum, 1979b; Kim, 1987; Rich, Kveiborg and Hansen, 2011). Probably, it happens because trucks are relatively more competitive on shorter distances, while rail is relatively more competitive on longer haul. Overall, it can be concluded that cost and transit time are the main significant explanatory variables, although other variables may be considered (i.e. shipment size, industry output, distance etc.).

Finally, when it comes to estimated elasticity values, there seems to be no consistency between studies. Using aggregated time-series data: Oum (1979a) reports inelastic demand for both rail (-0.29) and truck (-0.16); Lewis and Widup (1982) find rail demand being close to unit elastic. Using disaggregated individual data: Winston (1981) discovers a wide range of elasticities (from -0.08 to -2.68 for rail) for different commodity groups; MacFadden et al. (1985) shows that demand elasticity is -1.16 for rails and -0.75 for trucks; de Jong and Jonson (2009) find strongly inelastic demand for both rail and truck (-0.13 and -0.03 respectively). A similar wide range of values is found in studies based on aggregated cross-section data (i.e. Kim, 1987; Oum, 1989; de Jong, 2003)

In the context of Ukraine, only a few papers can be regarded useful for the analysis. Most of them try to comprehend damage done by the war in Donbas and then by the full-scale russian invasion. First, there is a study by Miyauchi et al. (2024), where they built a general equilibrium trade model with endogenous link formation using UZ company-to-company shipments data to assess how Ukrainian companies reacted to supply chains disruptions caused by the war in the east of Ukraine. The results show that negative effects (i.e. lower output, loss of buyers and suppliers) spread much further than the area of direct violence. Furthermore, they conclude that firms are adapting by rebuilding their supply chains, which helps them reduce their losses. Second, there are several studies on destruction caused to the agricultural sector in Ukraine during the full-scale invasion. Some of the most relevant ones come from the Center for Food and Land Use Research at the Kyiv School of Economics (KSE Agrocenter). Nivievskyi and Neyter (2024) estimate that direct losses (destruction and damage to physical assets) add up to $10.3 billion by December 2023. Most of the losses caused by damage to agricultural machinery and storage facilities, and by stolen or destroyed outputs.

To conclude, there are several different approaches behind estimating freight transport demand elasticity, and the main difference comes from data type and reliability. Lots of studies were done, but obtained results vary significantly, and there seem to be no consensus on methodology. Estimated demand for rail and truck may appear elastic or inelastic depending on the quality of data, regional market conditions, level of aggregation, functional form, and explanatory variables choices. So, there is an ongoing discussion, and it is important to explore more contexts in which transport demand can be studied, but in doing so one should carefully note what type of elasticity they are studying, how the data was collected and handled, and what methodology was applied, which is sometimes unclear in the literature (Oum et al., 1992).

C h a p t e r   3

METHODOLOGY

3.1 Multinomial Logit Model

The model used in the research comes from Jourquin and Beuthe (2019), based on McFadden's conditional logit model (McFadden, 1974; Domencich and McFadden, 1975). It originates from the family of random utility models, which is based on the idea of a rational individual, who tries to maximize their utility from making a choice, given that they can rank different choices in terms of utility (McFadden, 1974; Kalahasthi et al., 2022). These models are widely used and considered a standard approach in situations where there is a decision maker, a set of mutually exclusive alternatives, and a choice to be made (Croissant, 2020). As follows from McFadden (1974), the model is called random, because a utility function is modelled as a two-part equation: one part being "common" utility from choosing an alternative m (denoted V_m), and the other part being individual-specific (idiosyncratic) component (denoted ε_m). Then, an (unobserved) utility from choosing the alternative m can be written as $U_m = V_m + \varepsilon_m$. If there is a set of two alternatives $(m \; and \; k)$, the probability of choosing m is given by

$$Pr(m) = Pr(V_m - V_k \geq \varepsilon_m - \varepsilon_k) \quad (1)$$

where 'representative' utilities V_m and V_k are expressed as a linear function of a vector of N observed independent variables X:

$$V_m = \sum_{n=1}^{N} \beta_n X_{nm} \quad (2)$$

If we assume that the error idiosyncratic component follows Gumbel distribution, one can obtain a closed-form solution for the probability of choosing an alternative m over the set of alternatives J, which is a multinomial logit model, expressed as equation (3) below.

$$Pr(m) = \frac{e^{V_m}}{\sum_{j=1}^{J} e^{V_j}} \quad (3)$$

For detailed proof, see McFadden (1974). Two important assumptions of such models are independence of irrelevant alternatives (IIA) and homogeneity of preferences. IIA is an assumption that when the third choice is introduced, it does not change the relative preferences between the first two choices, and if this assumption is violated, it will lead to substantial biases in estimation. However, in this research there are only two possible choices considered, so IIA assumption is not relevant. Assumption of homogeneous preferences should be true, because all the data in the sample comes from one company which should treat all its decisions in a similar way.

For the purposes of this analysis, a variation of the model will be used, which was introduced, among others, in Jourquin and Beuthe (2019). The model is then fine-tuned to the needs of this research, where there are only two modes of transport (truck and rail), which are assumed to be mutually exclusive and exhaustive, and where changes over time should be important. The baseline ("single-period") model equation is basically the same as (3) and specified as follows:

$$Pr_m = \frac{\exp\,(\alpha C_m + \beta T_m + \theta_m W + \gamma_m G + \delta_m)}{\sum_{j=1}^{J} \exp\,(\alpha C_j + \beta T_j + \theta_j W + \gamma_j G + \delta_j)} \quad (4)$$

Where Pr_m is a probability that mode of transport m is chosen; C_m is generalized cost of mode m; T_m is transit time for mode m; J is a number of modes of transport considered (in our case $J = 2$); α and β are estimated coefficients that are not mode specific; W and G are wartime dummy and commodity type dummy respectively with θ_m and γ_m being the corresponding mode-specific coefficients; and δ_m^p is estimated intercept.

The alternative ("two-period") model incorporates the possibility of structural change in the way cost and transit time affect choice probabilities. It is similar to (4) but is estimated separately for two periods p: Pre-War (before March 2022) and War (starting from March 2022), because transport demand and supply for each period might be different, which means coefficients α and β will be different between periods as well:

$$Pr_m^p = \frac{\exp\,(\alpha^p C_m^p + \beta^p T_m^p + \gamma_m^p G + \delta_m^p)}{\sum_{j=1}^{J} \exp\,(\alpha^p C_j^p + \beta^p T_j^p + \gamma_j^p G + \delta_j^p)} \quad (5)$$

where p represents period-specific values and coefficients.

The intercept and the dummies coefficients need to be mode-specific, because the model is not able to measure utility levels; rather it measures differences in utility between modes, so if these coefficients were not mode-specific, they would just cancel out when the difference is taken. Also, as the values are being normalized to estimate those differences, one of the intercepts conventionally will be set to 0 (Croissant, 2020). So, if rail was chosen to be a reference category (rail intercept $\delta_r = 0$), then equation (4) will produce 5 estimates: α, β, an intercept for truck δ_t, and dummies coefficients for truck θ_t and γ_t. This leads to an interesting interpretation of the intercept in the model: it captures unobserved "qualitative" characteristics of alternatives in comparison to one another (Jourquin and Beuthe, 2019). The model is solved using maximum likelihood estimator (MLE).

3.2 Box-Cox Transformation

As shown in equation (2), utility function in this model is linear, which can introduce some bias and lead to unexpected results, if the relationship between utility and independent variables X is in fact non-linear. For instance, as shown in *Chapter 4*, transit time has huge variation in the sample, and from the point of view of a decision maker a difference between 1-day and 3-day delivery could matter more than a difference between 10-day and 50-day delivery. To address this problem, following Jourquin and Beuthe (2019), I will use Box-Cox transformation (Box and Cox, 1964) of cost and transit time, which affects the shape of the utility function, shifting it from linear to convex or concave. The transformation is described as follows:

$$X_m^{p\,(\lambda_X^p)} = \begin{cases} \dfrac{X_m^{p\,\lambda_X^p} - 1}{\lambda_X^p}, if\ \lambda_X^p \neq 0 \\ \log\left(X_m^p\right), if\ \lambda_X^p = 0 \end{cases} \tag{6}$$

Overall, it can be shown that such transformation can improve maximum likelihood of the model (Jourquin, 2019). It can also help with some possible unacceptable positive signs of the coefficients on cost and transit time and reduce the problem of multicollinearity between them. Guadry (2016) suggests that when working with this approach, three main factors should be considered: what is the maximum likelihood value, what are the signs of the coefficients and whether they are statistically significant. So, for the purposes of our analysis, the set of combinations of λ_C^p and λ_T^p will be tested, each in the range $[-2, +2]$ with a step of 0.1. Then, the optimal combinations for each period will be chosen, to maximize the maximum likelihood and produce adequate (negative) and significant coefficients. These optimal lambdas also have an interpretation: if $\lambda_X^p < 1$, it means that the effect of the variable on the level of utility is diminishing (concave); if $\lambda_X^p > 1$, the effect is increasing (convex); and if $\lambda_X^p = 1$, the relationship is linear. Then the results will be compared to the estimation without Box-Cox transformation to see whether the utility function was indeed non-linear.

3.3 Elasticity Calculations

We find elasticities with respect to cost and transit time as follows (the formulas look the same for Box-Cox transformed values):

$$\varepsilon_{ii}^C = \frac{\partial Pr_m^p}{\partial C_m^p} * \frac{C_m^p}{Pr_m^p} = \alpha^p C_m^p \left(1 - Pr_m^p\right) \tag{7}$$

$$\varepsilon_{ii}^T = \frac{\partial Pr_m^p}{\partial T_m^p} * \frac{T_m^p}{Pr_m^p} = \beta^p T_m^p \left(1 - Pr_m^p\right) \tag{8}$$

Elasticities with respect to cost and time of another mode of transport (cross-elasticities) are found using equations 9 and 10:

$$\varepsilon_{ij}^{C} = \frac{\partial Pr_m^p}{\partial C_j^p} * \frac{C_j^p}{Pr_m^p} = -\alpha^p C_j^p Pr_m^p \tag{9}$$

$$\varepsilon_{ij}^{T} = \frac{\partial Pr_m^p}{\partial T_j^p} * \frac{T_j^p}{Pr_m^p} = -\beta^p T_j^p Pr_m^p \tag{10}$$

Note on calculating elasticities: In the reviewed literature, little to no attention given to the mathematical approach of calculating elasticity once the econometric model was estimated, other than equations like (7)-(10). There are several different aggregation procedures – several ways how it could be done: standard *effects()* function of the "mlogit" R package (Croissant, 2020) first calculates simple mean values of independent variables, then gets fitted values (choice probabilities) from these averaged variables, and then outputs elasticities found by equations (7)-(10). There is nothing wrong with this approach per se, but using the given data, elasticities found this way appeared to be quite overestimated (much larger than in the literature), moreover it makes it impossible to compute elasticities other than on the whole dataset, i.e. by period. So, in this research, another approach was considered: first, choice probabilities and corresponding set of elasticity values (7) – (10) were computed for each row of data, then for each of the elasticity values, median value was taken (for by-period analysis it was the median value within a period) – median elasticities found this way are presented in *Chapter 5*. The median value was chosen as a representation of an average, because it showed the most robust results compared to simple mean and interquartile mean, and the results also looked much more adequate than when using the *effects()* function. The main shortcoming of this approach is that each of the elasticity values were picked separately from one another, meaning that they are not proportionally interconnected. This should not result in a problem given the goals of this research, but it is something that a reader should be aware of. The other reasonable way to do this is to first calculate the weighted average of independent variables (weights by quantity transported), and then find choice probabilities and elasticities based on these weighted averages: some test calculations done this way showed good results, while not having the disadvantage of the previous approach. However, it also requires more complex calculations, so it was decided to use median elasticities for this analysis, but future revisions of this work or another similar research should probably contain elasticities calculated on weighted average values of independent variables.

It is also important to note that estimated elasticities will be standard discrete choice elasticities. First of all, Oum et al. (1992) stated that these are not the same as regular elasticities estimated from input demand functions, though they are related and can be compared. Domenich and McFadden (1975) suggest that derived regular demand elasticities could be about 50% lower in absolute terms than corresponding individual elasticity of choice probability. Second, estimated value of discrete choice elasticity depends on the probability of choosing the alternative, or being more concrete, on the market share of the mode of transport – lower share will produce higher value of elasticity (Jourquin and Beuthe, 2019). The problem has the same nature as the elasticity of demand going to infinity with linear demand function and low level of demand: standard discrete choice elasticity measures a percentage change in probability in response to a percentage change in independent variable, so if the probability increases from 0.020 to 0.022 (meaning 10% increase) in response to 1% decrease in cost, then standard elasticity will be -10, which is arguably an overestimation. Gaudry (2016) suggests using a percentage point measure of elasticity, which captures an absolute variation in choice probability in response to 1% change in the independent variable. It can be obtained by multiplying equations (7) and (8) by market shares of each mode of transport (or by the level of choice probability). This way, the numeric example above will produce a value of -0.2 rather then -10, which looks more sensible. For these reasons, two measures of elasticity will be reported: standard elasticity for better comparison with the literature, and percentage point elasticity. This methodology will be applied, using the "mlogit" R package (Croissant, 2020) and R version 4.3.3, which is compatible with the package.

Chapter 4

DATA

4.1 Features and Description of the Data

The data for the estimation comes from the private company, which is one of the largest agricultural companies in Ukraine and a top exporter of grain crops and vegetable oil. The dataset is unique and, compared to the literature, is quite exotic.

First of all, it is a rare instance of fully observed disaggregated data on transportation in Ukraine, where the data collection procedures are relatively poor, especially in the transport sector, and public datasets on transport flows and costs are not available. The fact that the data is disaggregated helps to avoid biases in estimation, namely aggregation bias and zoning bias, discussed in Rich, Kveiborg and Hansen (2011). Some attempts at getting similar data were made before, for instance, by Miyauchi et al. (2024), where they bought the data from UZ, which contained quantities transported, rail charges, and companies' IDs for about 6500 companies for the period from 2012 to 2016. Such means of obtaining data are costly and, most importantly, this data does not provide any useful insights into how firms make choices between different transport alternatives, which is necessary for estimating elasticity.

Second, the data for the research (mainly) comes not from modeling or any kind of estimation, but from an internal company database, based on which real firm's decisions are being made, and when estimation is necessary (i.e. some values are absent), it is made based on the other part of the dataset where the corresponding values are directly observed. This is contrary to what is usually found in the literature: when estimating generalized costs of transport (which sometimes includes time, but not always), Inaba and Wallace (1989) use a questionnaire, collecting input from grain elevator managers, Jourquin et al. (2014) use modeling techniques, Kalahasthi et al. (2022) simply use transit time between origins and destinations, extracted from Google Maps. The idea is that a model, calibrated on the data which is directly used for decision-making and not 'generated' by a researcher, should lead to more precise estimates, better connected to the real world.

This dataset contains a whole origin-destination (OD) matrix for company-related facilities, including grain elevators all over Ukraine, factories, ports and borders. For each OD cell it is possible to calculate historical prices (total logistics cost) starting from 2020. For rail, it is represented as one part of the dataset, which contains detailed rail costs which are related to OD cells and commodity type, with about 9 000 000 rows of data. The other part of the dataset is a disaggregated record of shipments (over 1 000 000 individual entries), featuring quantities transported, loading and unloading dates, mode of transport chosen, type of commodity and OD route for the period from 2020 to the end of 2023. It includes both grain crops and oilseeds, as well as produced vegetable oil, but for the purpose of the analysis the dataset will be limited to the first two commodity groups (excluding oil), and only shipments from elevators will be considered. This helps to avoid dealing with the more complex process of transporting and pricing the transportation of oil, for which full data is not available.

4.2 Data Transformation and Estimations

As follows from the equation (5), it is needed that for each shipment there are both relevant rail and truck costs, and both relevant rail and truck transit time. This can be tricky, as for each shipment there are only cost and time of the transport mode chosen. So, some estimations were carried out based on the available data.

Also, there is a need to define costs (price, generalized costs) as the definition of this seems to differ from one research to another. Overall, in literature, generalized costs are all costs associated with transportation, including transit time and other indirect costs (among recent examples see Kalahasthi et al., 2022). However, some authors, such as Jourqin and Beuthe (2019) use transit time and generalized costs as two distinct independent variables. For the purpose of this study, generalized costs, costs and price can be used interchangeably, and it measures all monetary costs related to transportation, including some time component (depending on distance), but not including transit time directly, and not including indirect costs.

First, logistics costs for rail were calculated from the first part of the dataset, as these were not included in the main dataset with shipments. The advantage of this approach is that it allows to get rail costs for the whole shipments' dataset, as it doesn't depend on whether the trip was done by truck or rail. One of the concerns is that UZ is a monopoly, so everyone faces the same rail tariffs. While this is true, logistics cost in UAH/t that occurs at any given OD cell for every commodity will be unique, and all costs are updated monthly. The main time-varying component of costs is rent of a grain carrier (railcar). This component is based on internal company assessment, but it is in line with UZ tariffs. Railcar rent has a considerable share in costs (up to 80%), so a time variation of costs should be significant. Also, railcar turnover can change from month to month. It is important to note that these costs also include 'empty trip' costs, as they account for the whole turnover of a railcar. Modifying calculations of Jourquin and Beuthe (2019) to our needs, we can obtain rail logistics cost for each OD cell l, each commodity g, and each month t as follows.

Step 1 is to find railcar rent in UAH/t as shown in equation (11)

$$r_{l,t}^{g} = \frac{turnover_{l,t} \ * \ rate_t}{tonnage^g} \tag{11}$$

where $turnover_{l,t}$ is freight railcar turnover, including empty trip (in days), specific to OD cell l, and month t; $rate_t$ is railcar rent (in UAH/day), specific to month t; $tonnage^g$ is amount of cargo (in tons) that fits in one railcar, specific to commodity g.

Step 2 is to calculate total cost in UAH/t as shown in equation (12)

$$rail\_C^g_{l,t} = ld\_cost^g{}_l + ul\_cost^g{}_l + \sum_{i=1}^{n} oth\_cost^g{}_{l,i} + r^g_{l,t} \qquad (12)$$

where $ld\_cost^g_l$ and $ul\_cost^g_l$ are loading and unloading cost respectively, specific to OD cell l, and commodity g; $\sum_{i=1}^{n} oth\_cost^g_{l,i}$ is sum of other costs, such as storage, escort, insurance, certification, other transportation costs, ets.. These costs (except for rent) are assumed to be constant over time and are based on common UZ tariffs.

Logistics cost for trucks is already given in the shipments' dataset in UAH/t for each shipment where truck was chosen, and it is assumed that these costs include loading/unloading, as well as time-specific and commodity-specific factors. However, these costs were absent, of course, for the trips made by rail, so they were estimated based on available truck costs by decomposing these costs into fixed costs (loading-unloading costs) and variable costs (depending on distance). Fixed costs were calculated as median costs of the subset of short truck trips (distance < 10 km), as variable costs are assumed to be negligible in these cases. These costs were calculated for each year, first, because they are assumed not to change as rapidly as variable costs (i.e fuel price), and second, because there were some months with no short trips. Variable costs VC_t for each month t are then calculated as a median of variable costs for each truck shipment i on route l in month t (in UAH/tkm), given by the formula

$$VC_{l,t}^{i} = \frac{TC_{l,t}^{i} - FC_y}{distance_l} \tag{13}$$

where $TC_{l,t}^{i}$ is total cost for each truck shipment i on route l in month t (in UAH/t), FC_y is calculated fixed cost for truck shipments for year y, and $distance_l$ is a distance of a route l.

Then, for each rail shipment, the corresponding expected truck costs were calculated as follows from equation (14) below:

$$truck\_C_{l,t} = FC_y + VC_t * distance_l \tag{14}$$

Figure 1 shows how these costs have been changing over time. Fixed costs were relatively stable in 2020-2021, but then there was a sharp increase in 2022-2023. The same can be said for variable costs: they were growing in 2022, becoming 2-3 times higher than in 2021, but then they gradually decreased in 2023. This fast growth in costs was caused by all the war-related disruptions.

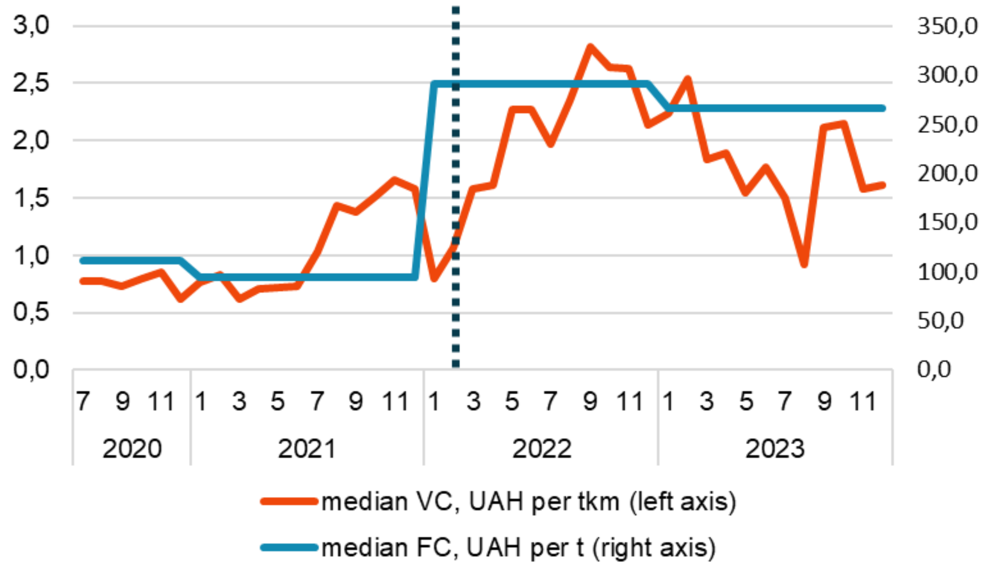

Figure 1. Decomposition of truck transit costs by fixed versus variable costs
Note: dotted line marks the beginning of the full-scale invasion (February 2022)

Transit time of each shipment was calculated from the data as a difference between a date of loading and a date of unloading, expressed in days. In the case when a delivery happens on the same day, the value of 0.5 was assigned. Then, the weighted average speed $avg\_speed_{m,t}$ was calculated for each mode of transport m for each month t, where the weights were quantities transported, so that the most popular routes would have more weight in the estimation of speed. As shown in Figure 2, average rail speed declines significantly starting from the beginning of the russian invasion, reaching as low as 50 km per day, but for truck it remains relatively stable the whole time. Based on these values, expected truck transit time was calculated for rail shipments (and vice versa), using the following formula:

$$T_{m,l,t} = \frac{distance_l}{avg\_speed_{m,t}} \tag{15}$$

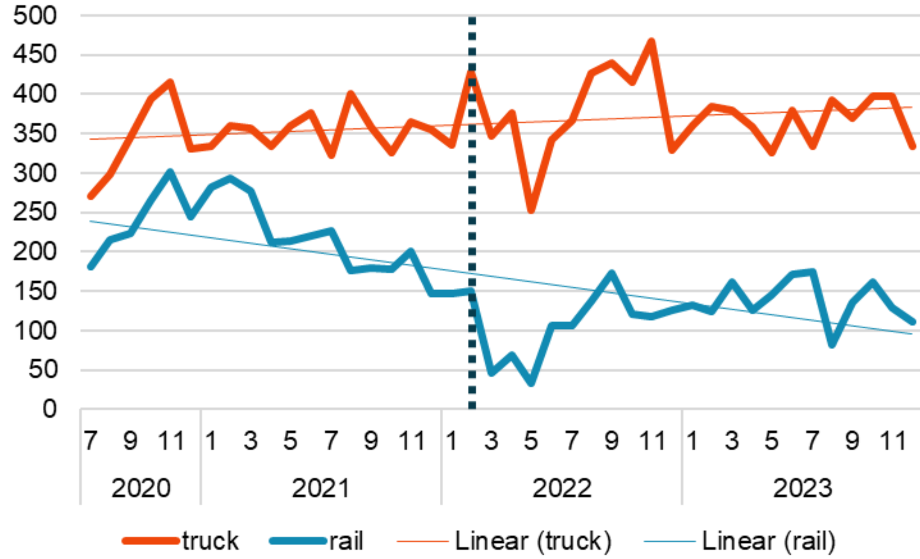

Figure 2. Weighted average speed for truck and rail (km/day)

Note: dotted line marks the beginning of the full-scale invasion (February 2022)

4.3 Descriptive Statistics

Tables 1 and 2 show descriptive statistics of the main variables from the final transformed dataset. After all the filtering and transforming there are 352 261 observations in total, from which about 208 000 belongs to the pre-war period (before March 2022), and about 144 000 belongs to the war period (starting from March 2022). In the first period, average rail cost is higher than truck cost, but in the second period it appears that trucks became much more costly than rail – this may partly be explained by larger share of long-distance shipment in the second period, on which truck cost becomes rather high. Expectedly, there is a substantial difference in transit time: before the invasion, the average transit time for rail was about two times higher than those of trucks, and after the beginning of the invasion the gap became even larger. One can see that there are some extreme values of transit time: 112 days for rail and 62 days for truck, which are coming from the beginning of the invasion, when ports were blocked by russia, and borders were difficult to cross.

Table 1. Descriptive statistics of the main variables – Period 1 (Pre-War)

Variable	N	Mean	St. Dev.	Min	Max
Rail cost (UAH/t)	208,378	834.744	295.128	242.880	2,979.180
Truck cost (UAH/t)	208,378	690.506	349.661	56.670	1,851.190
Rail transit time (days)	208,378	3.218	2.606	0.500	44.000
Truck transit time (days)	208,378	1.665	0.820	0.500	62.000
Quantity (t)	208,378	49.635	18.818	0.020	71.500
Distance (km)	208,378	577.102	272.761	2	1,168

Table 2. Descriptive statistics of the main variables – Period 2 (War)

Variable	N	Mean	St. Dev.	Min	Max
Rail cost (UAH/t)	143,883	1,129.272	499.219	178.630	4,994.070
Truck cost (UAH/t)	143,883	1,409.412	612.429	110.170	6,295.610
Rail transit time (days)	143,883	5.315	7.511	0.500	112.000
Truck transit time (days)	143,883	1.464	0.723	0.500	14.000
Quantity (t)	143,883	39.887	18.659	0.010	72.050
Distance (km)	143,883	533.499	255.590	1	1,256

4.4 Insights and Limitations of the Data

As discussed previously, some of the important considerations when working with discrete choice models are alternative availability and actual usage. For the data used in this research, it can be said for sure that all the origins and destinations have a railway station available nearby, and it is assumed that all of them also have road connections. Figure 3 presents dynamics of rail and truck usage during the period of the research. It is evident that most of the shipments happen by rail, however, trucks have become more widely used since the beginning of the invasion. Since the truck usage share is low on average (around 15-20%), it is expected that the value of elasticity will be somewhat overestimated for this mode of transport, as discussed in *Chapter 3*.

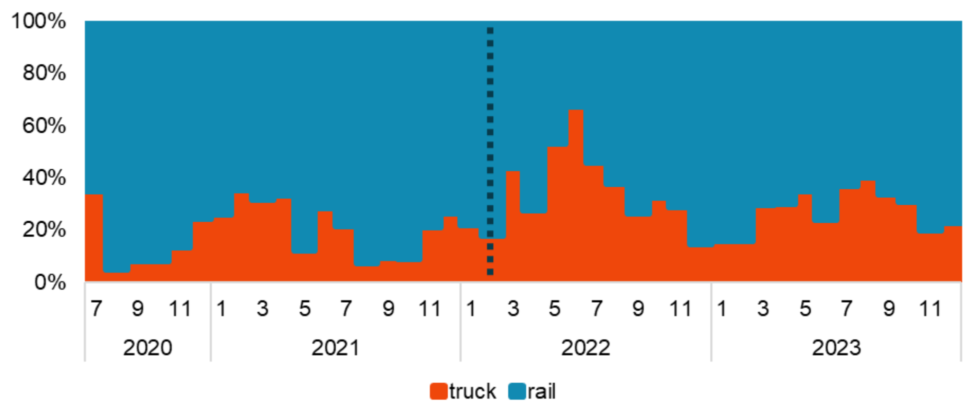

Figure 3. Monthly mode shares by quantity, %

Note: dotted line marks the beginning of the full-scale invasion (February 2022)

Another interesting observation that can be made from this data is how destination choices changed over time, especially since February 2022, which can reveal the scale of supply chains disruption caused by the war. Figure 4 shows that, before the invasion, all the goods were transported either to a plant (mostly oilseeds) or to a seaport (mostly grain crops). Since the beginning of the invasion, the situation has changed drastically: Ukrainian seaports were blocked and not available at first, and then we see the supply of grain to seaports changing following the development of the Black Sea Grain Initiative. Also, the company had to become creative in its export routes: some portion of grain was transported over the border, some was shipped to seaports outside Ukraine, such as Constanta, and even some of it was loaded on small ships in Ukrainian river ports, such as Reni.

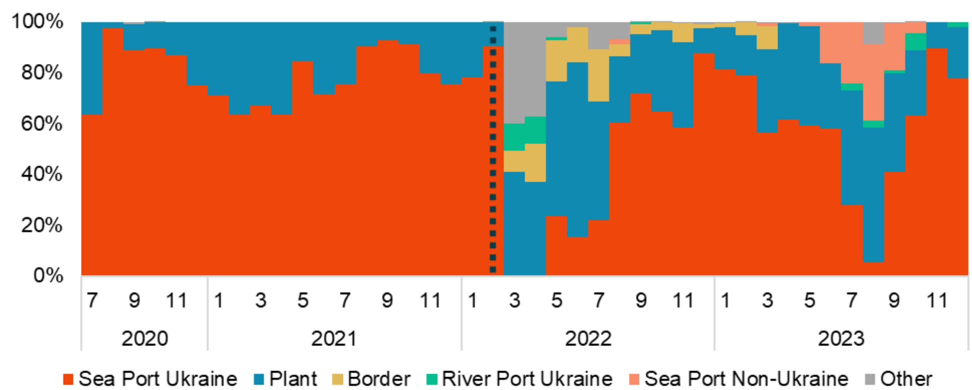

Figure 4. Monthly destination shares by quantity, %

Note: dotted line marks the beginning of the full-scale invasion (February 2022)

The main problem with this data is that it belongs to one company only and may not necessarily be representative of the whole region or the whole industry. Also, the dataset is limited to just two types of commodities and two modes of transport, paying no attention to intermodal transport. The other issue in the distinction between expected and realized values: all the costs that appear in the data (or estimated from the data) are expected costs, which means that this is the amount of money that the company expects to spend on a shipment a short time before it happens. It can be different from the actual cost realized after the contract was executed. However, a value for transit time for the mode of transport that was chosen is realized value observed after the fact of the delivery, and for the mode of transport that was not chosen it is an expected value, estimated from realized values for the same month. The argument can be made that expected values of cost and transit time just before the shipment happens are better predictors of mode choice, because the decision maker cannot observe the future, but rather they can expect some values of cost and transit time based on previous observations. It means that transit time, as it appears in the data (half realized, half expected) can lead to biased and unexpected estimation results.

Chapter 5

ESTIMATION RESULTS

5.1 Estimation Results

In this section, the estimation results are presented and discussed. When looking at estimation tables, it is important to remember that coefficients produced by logit models are hard to interpret directly; their magnitudes are almost meaningless on their own, and only signs of the coefficients are important. First, let's consider the performance of single-period models, starting from the baseline model, described in *Chapter 3* (equation (4). One can see from Table 3 that the coefficient on cost is negative, which is the expected result: higher costs should lead to lower choice probability. The intercept and dummy coefficients are also interpretable: negative intercept for trucks suggests that this mode of transport has worse unobserved qualitative characteristics when compared to rail, however during the wartime it becomes significantly more attractive (positive coefficient of wartime dummy), and during both periods it is also relatively more attractive when transporting oilseeds (positive coefficient of oilseeds dummy). What's interesting is that, consistent with previously discussed concerns, the coefficient on transit time is positive, which in theory shouldn't be true: longer transit time should decrease the probability of choice, not increase it. Moreover, all the coefficients (including transit time) are highly statistically significant, which shows that this anomaly is strongly supported by the data. Indeed, if we were to draw a histogram of the difference in transit time between modes (transit time of a chosen mode minus transit time of the other mode), we would observe that the mean difference is in fact positive and a considerable portion of such differences are greater than zero, which indicates that a chosen mode of transport often has higher transit time (Figure 5). It can be partly explained by strong preference towards rail transportation (shown by intercept estimation), which has a higher delivery time. Also, it can be suggested that transit time does not have a causal effect on choice probabilities, and the estimated positive coefficient rather shows the association between the choice probability and transit time.

Table 3. Estimation results for single-period models

	Dependent variable:		
	choice		
	Baseline	Box-Cox Transformed	Cost Only
	(1)	(2)	(3)
$Intercept_{truck}$	-2.413***	-4.513***	-2.847***
	(0.012)	(0.020)	(0.011)
Cost	-0.004***	-62.790***	-0.004***
	(0.00003)	(0.345)	(0.00002)
Transit time	0.503***	-2.351***	
	(0.004)	(0.017)	
War_dummy_{truck}	3.449***	3.095***	2.462***
	(0.022)	(0.023)	(0.018)
$Oilseeds\_dummy_{truck}$	2.586***	1.979***	2.499***
	(0.016)	(0.017)	(0.015)
Observations	352,261	352,261	352,261
R^2	0.688	0.739	0.649
Log Likelihood	-72,546.090	-60,804.190	-81,577.860
Note:			*p<0.1; **p<0.05; ***p<0.01

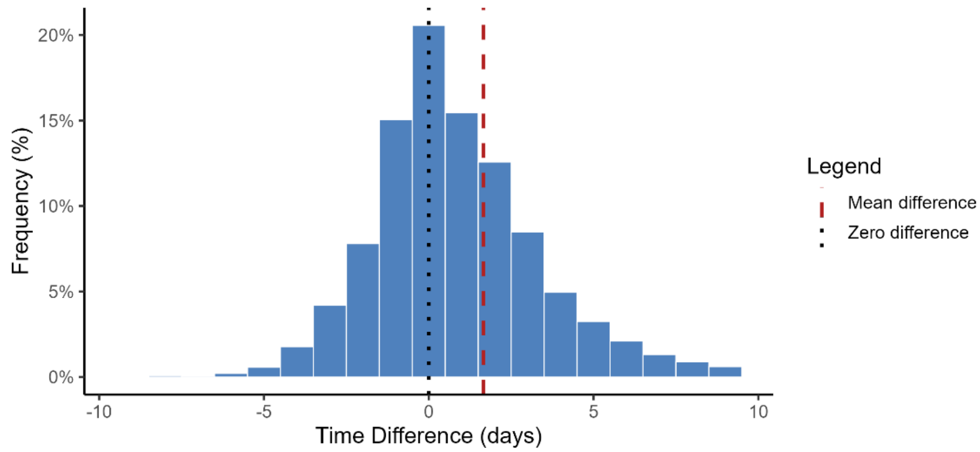

Figure 5. Distribution of transit time differences between modes (transit time of a chosen mode minus transit time of the other mode)

There were two ways out of this situation: applying the Box-Cox transformation as described in *Chapter 3* to account for possible non-linear utility or estimating the model using only cost as independent variable to see if transit time had any strong effect on other coefficients and derived elasticities.

For the proper Box-Cox transformation, an optimization procedure was carried out. From the range of lambdas [-2, 2], the optimal lambdas were found to be -0.4 for cost and -2 for transit time (they maximize the maximum likelihood of the model). This means that, in single-period model, both explanatory variables have diminishing effect on choice probabilities (i.e. higher transit time have lower impact). As shown in Table 3, this transformation helped to improve maximum likelihood of the model while also aligning the effect of transit time with the theory: in the second model the transit time coefficient is negative. However, with this setup, the effect of cost changes becomes much stronger: the cost coefficient is considerably larger. While the magnitudes of the coefficients are not too important in logit models, it is important for the estimation of elasticity, as follows from equations (7) – (10).

Finally, in the model without Box-Cox transformation and with cost as the only explanatory variable (apart from dummies) all the coefficients are adequate again. Excluding transit time from the estimation seems to somewhat decrease maximum likelihood and pseudo-R-squared, compared to the baseline model, but this result is expected following the property of increasing R-squared with a higher number of independent variables. What is important is that the cost coefficient appears to be robust to excluding transit time from the model completely: it is still negative and basically the same as in the baseline model. It is shown later (Table 5) that cost elasticities also remain rather similar.

The next set of estimations comes from two-period formulation of the model. It serves as an additional robustness check, allowing for structural changes in the effect of cost and transit time. From Table 4, one can see that the relative “attractiveness” of transportation mods was estimated to be similar to the results obtained from single-period models: truck intercept in the pre-war period corresponds to the truck intercept in the baseline single-period model, and the intercept in the war period corresponds to the sum of the intercept and wartime dummy from the single-period model (it being positive indeed suggests some shift in preferences from rail to trucks since the beginning of the invasion). However, the most interesting part of it is the difference in cost and time effects between periods. As for the cost coefficients in the baseline two-period model, it appears to be rather similar in-between periods and in line with single-period baseline model.

Table 4. Estimation results for two-period models

	Dependent variable:					
	choice					
	Baseline		Box-Cox Transformed		Cost Only	
	Pre-War	War	Pre-War	War	Pre-War	War
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Intercept}_{\text{truck}}$	-2.711***	0.521***	-4.799***	-1.234***	-3.255***	-0.387***
	(0.017)	(0.020)	(0.028)	(0.018)	(0.015)	(0.015)
Cost	-0.007***	-0.003***	-22.053***	-0.212***	-0.006***	-0.003***
	(0.000)	(0.000)	(0.166)	(0.002)	(0.000)	(0.000)
Transit time	0.867***	0.330***	-2.365***	-1.782***		
	(0.009)	(0.005)	(0.024)	(0.021)		
$\text{Oilseeds\_dummy}_{\text{truck}}$	1.930***	2.180***	1.251***	2.052***	2.189***	2.114***
	(0.030)	(0.020)	(0.031)	(0.020)	(0.026)	(0.019)
Observations	208,378	143,883	208,378	143,883	208,378	143,883
R^2	0.752	0.627	0.812	0.641	0.701	0.592
Log Likelihood	-32,520	-36,863	-24,670	-35,441	-39,270	-40,328
Note:						*p<0.1; **p<0.05; ***p<0.01

Once again, to address the problem of positive transit time coefficients, the Box-Cox transformation and optimization was applied. In the pre-war period, the lambdas that produced the highest maximum likelihood were -0.2 for cost and -2 for transit time. For the war period, the optimal lambdas were 0.4 and -2 respectively. Both sets of lambdas represent diminishing effect of explanatory variables on choice probability, however, for cost it diminishes less rapidly than in single-period model. These transformations improve maximum likelihood of the model, especially for the pre-war period (the war period improvement is marginal), and, most importantly, show negative effect of transit time on mode choice, while all the coefficients remain highly statistically significant. The main takeaway from the third (cost-only) estimation is that excluding transit time from the model doesn't significantly affect other coefficients, while marginally decreasing maximum likelihood.

5.2 Elasticity tables

In Table 5 below, elasticities produced by all the models are presented. First, we can see that rail own-cost elasticity estimated by single-period baseline model is -0.192 in the pre-war period, and -1.079 in the war period. Similar results are obtained from two-period baseline model (-0.206 and -0.946 respectively). This means that, before the full-scale invasion, a 10% increase in rail cost would lead to an approximately 2% decrease in the rail market share, while during the war the same increase in cost leads to about 10% decrease in the market share. For truck the values of own-cost elasticity are rather high: as estimated by the single-period baseline model, before the full-scale war the elasticity was -2.458, and after February 2022 it was -4.127. The results from two-period baseline model are somewhat different: -4.368 before and -3.058 during the war. It can be said that the demand for trucks is rather sensitive to changes in truck cost (elastic) during both periods, but the direction of change in elasticity between periods depends on model formulation.

Own elasticity with respect to transit time, of course, is positive in all the baseline models, following from the fact that estimated transit time coefficient in all these models was positive. However, if we consider transit time own-elasticities produced by Box-Cox transformed models, they seem to be in line with theory: for instance, rail own-elasticity with respect to transit time is -0.007 before the war and -0.072 during the war. We can also observe that in the war period demand for trucks was not affected by transit time at all (elasticity equals zero).

Table 5. Main elasticity estimates

Variable	Period	Mode	Single-Period Models						Two-Period Models					
			Baseline		Box-Cox		Cost Only		Baseline		Box-Cox		Cost Only	
			Rail	Truck	Rail	Truck	Rail	Truck	Rail	Truck	Rail	Truck	Rail	Truck
Cost	Both	Rail	-0.281	2.559	-7.680	138.828	-0.257	2.515						
		Truck	0.309	-2.621	7.733	-139.123	0.250	-2.575						
	Period 1 (Pre-War)	Rail	-0.192	2.575	-2.875	142.407	-0.200	2.544	-0.206	4.530	-1.345	78.544	-0.225	3.817
		Truck	0.184	-2.458	2.867	-142.288	0.184	-2.443	0.205	-4.368	1.336	-78.451	0.205	-3.672
	Period 2 (War)	Rail	-1.079	2.432	-37.219	110.313	-1.205	2.302	-0.946	1.826	-2.141	5.216	-1.045	1.825
		Truck	1.255	-4.127	37.421	-110.629	1.269	-3.905	1.024	-3.058	2.285	-6.382	1.005	-2.991
Transit Time	Both	Rail	0.111	-1.076	-0.015	0.874								
		Truck	-0.080	0.807	0.002	-0.756								
	Period 1 (Pre-War)	Rail	0.086	-0.991	-0.007	0.878			0.091	-1.730	-0.005	0.885		
		Truck	-0.064	0.915	0.003	-0.861			-0.069	1.609	0.001	-0.869		
	Period 2 (War)	Rail	0.300	-1.170	-0.072	0.721			0.252	-0.740	-0.051	0.550		
		Truck	-0.150	0.446	0	0			-0.111	0.280	0	0		

Given that the demand elasticity with respect to transit time is meaningful only for trucks in the pre-war period and with Box-Cox transformation (rail transit time elasticities have small economic significance), we can conclude that transit time has low to none effect on mode choice decisions. Moreover, cost elasticities coming from Box-Cox transformed models are largely overestimated; even though models with Box-Cox transformed variables perform better in predicting the right mode choice, have higher maximum likelihood and coefficients consistent with the theory, they fail to produce adequate estimates of cost elasticity, for reasons which seem to be purely mathematical. Box-Cox lambdas being < 1 scale all the cost values down, which in turn requires larger coefficient on cost in the estimated model to account for the transformation. For example, in single-period Box-Cox model optimal lambda for cost is -0.4; if we take the mean rail cost for the pre-war period – 834 $\mathrm{UAH/t}$ – it will be scaled down to the value of 2.33; estimated coefficient on cost is therefore large: -62.8 (Table 3); as shown in equation (7), elasticity is calculated as $cost\ coefficient * cost\ value * (1 - prob)$; putting in the numbers we get $-62.8 * 2.33 * (1 - prob) = -146.3\ (1 - prob)$. So, unless $(1 - \ prob)$ is close to zero, calculated elasticity will be unrealistically large. For these reasons, elasticities estimated by the simple cost-only model seem to be the most theoretically consistent and robust. One can see that they are almost the same as the ones coming from baseline models, which further proves that excluding transit time from the equation doesn't influence the estimation significantly.

So, if we do not consider the model with Box-Cox transformed variables, we observe the following ranges of own-cost elasticities: in the period before the full-scale invasion, rail own-cost demand elasticity was -0.192 to -0.225, but after the beginning of the invasion it increased to about -0,946 to -1,205. For trucks, however, the value of elasticity didn't change much: before the invasion it was in the range -2,443 to -4,368, and during the war it is estimated to be -2,991 to - 4,127. We can compare these standard elasticities to correspondent percentage-point elasticities approximated by multiplying standard elasticities by the market share of each mode of transport in each period. This way, the values look less extreme: i.e. elasticity of -2.433 for trucks in pre-war period becomes -0.782, which should give better insight into how changes in cost affect mode shares.

Table 6. Standard own-cost elasticities versus percentage-point own-cost elasticities

	Rail		Truck	
	Period 1	Period 2	Period 1	Period 2
Shares	68%	56%	32%	44%
Standard elasticities	-0.192 to -0.225	-0.946 to -1.205	-2.443 to -4.368	-2.991 to -4.127
Percentage-point elasticities	-0.131 to -0.153	-0.530 to -0.675	-0.782 to -1.398	-1.316 to -1.816

In the end, we will compare the elasticities found in this study with ones found in the published studies on the topic (Table 7). One can see that there was indeed no consistency in estimates: rail own-cost elasticities from the literature range from as low as -0.043 to as high as -3.870, and truck elasticities in the chosen studies are in range from -0.010 to -1.010. Estimates coming from the current research are generally consistent with the literature; rail own-cost elasticity before the war was rather similar to the one found by Jourquin and Beuthe (2019) for agricultural goods (considering percentage-point estimate). However, own-cost elasticity for trucks is higher then what is usually found in the literature; this can be explained by transport market circumstances of Ukraine, where rail transportation is dominant (51% of all goods in 2021 in Ukraine were transported by rail, another 36% were transported by truck (SSSU), while in Europe and in the US truck is the most popular mode of freight transport (i.e. in Europe rail share is 14%, truck share is 79% in tons (Jourquin and Beuthe, 2019) – this could lead to overestimation of rail elasticity and underestimation of truck elasticity based on European data, for the reasons discussed in *Chapter 3*. So, given that the truck share is much smaller in Ukraine, higher values of elasticity is expected.

Table 7. Comparison table of multi-mode own-cost elasticities

Study		Standard elasticities		Percentage-point elasticities	
		Rail	Truck	Rail	Truck
This study					
	(Pre-War)	-0.192 to -0.225	-2.443 to -4.368	-0.131 to -0.153	-0.782 to -1.398
	(War)	-0.946 to -1.205	-2.991 to -4.127	-0.530 to -0.675	-1.316 to -1.816
Agricultural goods					
Jourquin and Beuthe (2019)		-1.460	-0.180	-0.114	-0.158
Beuthe et al.(2014)		-0.690	-0.350		
Inaba and Wallace (1989)		-0.043 to -1.050	-0.253 to -0.921		
Various goods					
Oum (1989)		-0.600	-0.690		
de Jong (2003)		-1.400 to -3.870	-0.400 to -1.010		
Rich et al. (2011)		-0.100 to -0.400	-0.010 to -0.130		

Chapter 6

CONCLUSIONS AND POLICY IMPLICATIONS

6.1 Conclusions

This paper contributes to the understanding of firms' behavior regarding freight transport demand in Ukraine, comparing two time periods: before and after the full-scale invasion of the country. It draws conclusions based on the unique and highly valuable dataset of real firm's logistics decisions, which allows to track changes over time. While adding to the global research on freight transport demand by analyzing not modeled, but actual realized shipments data, the main value of this study is that it is the first ever attempt to estimate freight transport demand elasticity in the context of Ukraine. It is also one of the rare examples of elasticity estimation with time component included in the analysis, accounting for structural changes in the transport market.

Main results of this research include estimating several different models for transport demand, including Box-Cox variable transformation and optimization with a discussion of optimal lambdas, consequences of such transformation and some mathematics behind it, which influence the calculation of demand elasticity. Overall, 9 models were estimated and compared, which can be grouped into "single-period" and "two-period" formulations. Then, corresponding values of elasticities were calculated from each of these models.

The findings show inelastic demand for rail with respect to cost before the full-scale invasion, and it is also evident that the rail own-cost elasticity significantly increased after the beginning of the invasion (while remaining somewhat inelastic) – it means that firms became more adaptive during the crisis. This pattern is robust as it persists across all the tested models. Demand for truck with respect to truck cost was found to be elastic during both periods, but it is hard to tell if truck own-cost elasticity increased or decreased during the war – the direction of change depends on the model form. Higher own-cost demand elasticity for trucks may be partly attributed to relatively small share of this mode of transport in Ukraine's market. Another result coming from the interpretation of the intercepts is that the firm overall has a stronger preference towards rail, compared to truck (meaning that rail has better qualitative characteristics, which are neither cost nor transit time).

One of the interesting results is that Box-Cox transformation of independent variables, while being helpful in improving maximum likelihood and producing expected signs of the coefficients, did not manage to deliver reasonable elasticity estimates with respect to cost.

The study also notes that transit time has an unexpected effect on mode choice probability and proceeds with a discussion of possible reasons for such anomaly; the conclusion is made that transit time does not meaningfully affect mode choices and can be excluded from estimation without losing much precision. Also, the meaning and significance of percentage-point elasticity was discussed; some values of percentage-point elasticity were reported and compared to standard mode choice elasticity. Overall, the estimated values of own-cost elasticity are in line with the literature, with truck elasticity being somewhat larger than in other studies.

6.2 Policy Implications

These results can guide the policy design for optimizing the freight transport market in Ukraine, especially in the topic of freight rail tariffs. Using the elasticities found from the cost only two-period model, we can calculate that before the full-scale war, a 70% increase in rail cost *ceteris paribus* would lead to a roughly 15.75% decrease in the share of rail shipments. After the beginning of the invasion, a 70% increase in rail cost could lead to an astonishing 73.15% decrease in rail share

(Figure 6). Of course, we didn't observe such a drastic shift after new rail tariffs were imposed in 2022, but it is worth noting that the expected pre-war decrease in rail share almost exactly corresponds to an actual change in the market structure between the periods (i.e. 70% rail tariff increase scenario before 24.02.2022 has similar structure as the base scenario shares after 24.02.2022) – it can suggest that the estimated elasticity was indeed true, given that the tariff increase happened at the very beginning of the invasion, when companies weren't so adaptive yet. So, UZ should treat any future increases with caution, as firms seem to be adapting to the new circumstances, becoming more responsive to cost changes – it means that UZ could fail to generate expected profits after new tariff increases.

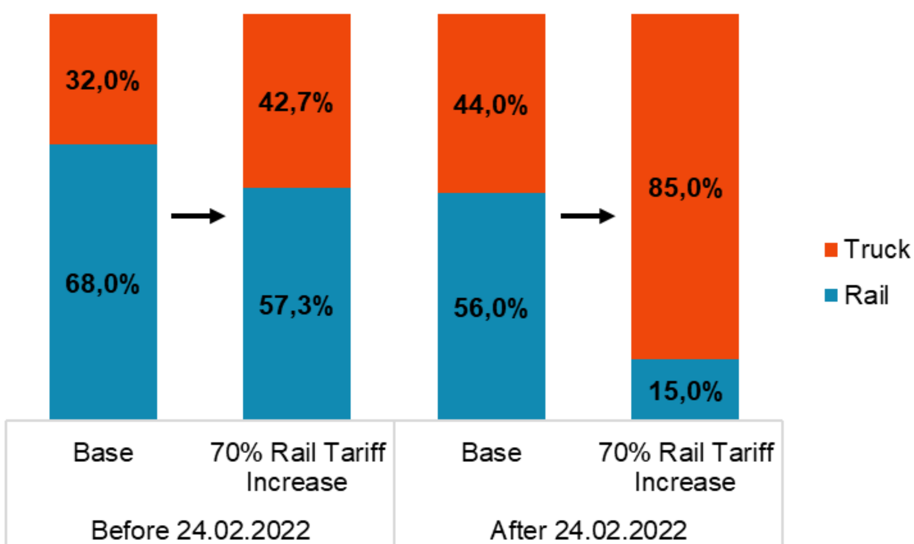

Figure 6. Expected change in freight transport market structure due to rail tariff increase, % (count of shipments)

Note: Base scenario represents shipment structure observed in the data

Another prediction that can be made using the results of this analysis is how the freight transport market will respond to fuel price increases, which impact truck logistics cost. Ukraine's Central Bank predicts that fuel price will grow in Ukraine with a rate of about 5-10% p.a. (NBU, 2025). Some evidence suggests that fuel price share in the total price of truck transportation roughly equals 30% (Cullen, 2022), meaning that a 10% increase in fuel price will lead to about 3% increase in truck shipment cost. So, scenarios shown in Figure 7 represent an effect of 3% increase in truck cost *ceteris paribus* before and after the full-scale invasion of Ukraine. Before 24.02.2022 such an increase would lead to about 11% decrease in truck market share, while after the beginning of the invasion, the same increase would decrease truck market share by about 9%, as suggested by truck own-cost elasticities coming from cost-only two-period model.

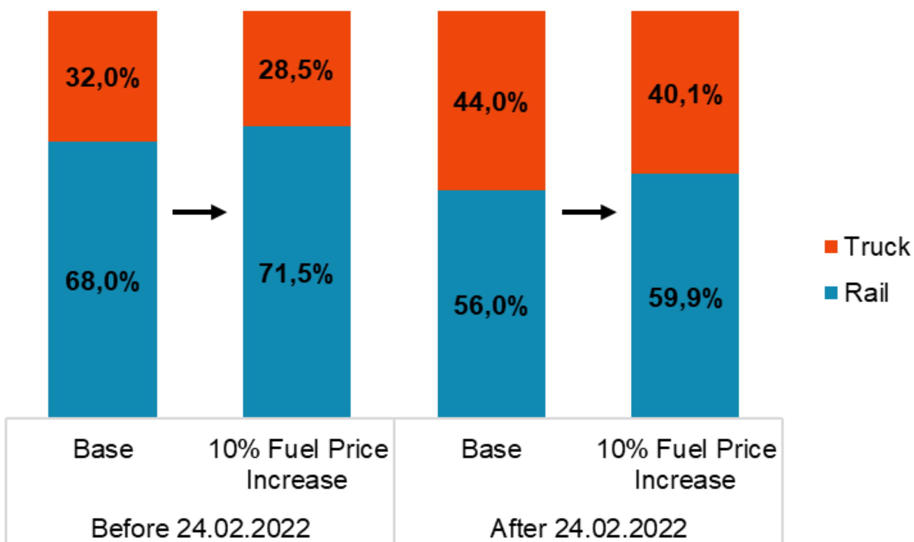

Figure 7. Expected change in freight transport market structure due to fuel price increase, % (count of shipments)

Note: Base scenario represents shipment structure observed in the data

Additional value of this analysis is that obtained numbers of elasticity could be found useful in the newly developed transport model of Ukraine, based on the EU project called "Assistance to the Ukrainian authorities for establishment of national transport model and master plan" (EU NeighboursEast, 2018). One of the goals of the project is "Quantification of the existing supply and demand regarding the transport sector", which couldn't be done without estimating demand elasticity.

As main advantages of the study come from the data, so do the main limitations: the data represents only one company and does not model intermodal transport networks, and the dataset is limited to only a few agricultural commodities. Also, the modeling approach does not include decisions on shipment size and destinations, which are often considered important in similar analysis. This opens the possibility of further study of the unique Ukrainian market, incorporating more firms and commodities, and applying more robust and sophisticated techniques.

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