# FUEL PRICE VOLATILITY AND ROAD SAFETY: AN ANALYSIS OF TRAFFIC ACCIDENTS IN UKRAINE

by

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Kyiv School of Economics

Abstract

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The thesis analyzes the impact of fuel prices on traffic accidents with fatalities and/or injuries in Ukraine. Using regional monthly panel data for 2017-2024, the study estimates fixed and random effects models, controlling for macroeconomic (GDP), weather (average temperature and precipitation), and seasonal (month) factors. The estimation results showed a statistically significant negative relationship between fuel prices and traffic fatalities. A 1% increase in fuel prices is associated with 0.3% decrease in traffic accidents fatalities.

The analysis included a shock dummy variable to model a response on fuel disruptions during April-July 2022. This period led to a significant drop in the number of total accidents and injured people, suggesting lower road usage during the period of deficit. However, it did not have a significant effect on the fatalities beyond what was already explained by the fuel prices. The interaction term further confirmed that fuel availability did not change the price effect.

These findings demonstrate the role that economic mechanisms have in driving behavior and traffic safety in the context of economic instability during fuel disruptions.

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## LIST OF ABBREVIATIONS

**DID.** Difference-in-difference.

**GDP.** Gross Domestic Product.

**GRP.** Gross Regional Product.

**FE.** Fixed Effects.

**RE.** Random Effects.

*Chapter 1*

# INTRODUCTION

In Ukraine, since 2017, 26,061 people have died, and 244,679 were injured in traffic accidents. Globally, traffic accidents are the 8th leading cause of death, with approximately 1.19 million casualties every year, predicted to become 7th by 2030, with the cost for most countries around 3% of their GDP (World Health Organization 2023). It is not only statistics – behind every number is human life. That is why road safety will always be an important topic. There is evidence showing that we can reduce the number of fatalities by using economic mechanisms.

Based on the report of UNECE (United Nations Economic Commission for Europe 2024), Ukraine has a high fatality rate on roads, which is higher than average in Europe and North America (74 vs 55 per million inhabitants). At the same time, the number of injured is among the lowest (683, with an average of 2111 per million inhabitants), which indicates that if a traffic accident happens, it is more likely to be fatal than in other countries. Therefore, it is important to conduct an analysis in our unique context to understand how economic stimulus affects behavior and potentially saves lives.

The research question is formulated as follows: "What is the impact of fuel price changes on traffic accidents with fatalities and/or injuries in Ukraine?". Based on existing literature and common sense, my hypothesis is that an increase in fuel prices is associated with a reduction in traffic accidents with fatalities and/or injuries. In short, they have an inverse relationship. There are multiple factors contributing to this. First of all, the distance traveled is reduced. When it happens, there is an obvious causation because of the linear nature of the effect (less distance = fewer accidents). People try to save money, therefore plan their route better. Secondly, they reduce risky driving, especially excessive speeding, which is the main cause of fatalities on the roads. Thirdly, in the long-term, agents change their transportation choices (Ladin et al. 2015), which leads to fewer cars on the roads, and therefore less accidents.

Despite quite large discussions in the academic community on road safety, most of them are focused on other disciplines. In the papers where the link between fuel prices and traffic accidents is considered, there is a gap in the research for developing economies, such as Ukraine. In the world, the number of vehicles is increasing, which leads to an increase in the number of fatalities. At the same time, in developed economies, it is decreasing despite the global trend. The causes of this trend are infrastructure improvements and progress in vehicle manufacturing. Additionally, microeconomic factors, such as high prices of fuel, also contribute to this (Naqvi, Quddus, and Enoch 2023).

The topic is interdisciplinary, with a wide range of policy implications, including healthcare, infrastructure, urbanism, transportation planning, and environmental. However, in the thesis, I focus on the economic context, particularly on the impact of fuel prices.

In the thesis, I focus on total traffic accidents with fatalities and/or injuries, fatalities alone, and injuries alone, because it has potentially more economic impact and, more importantly, save lives. I also include fuel price volatility analysis, which means changes in fuel prices over time.

The thesis is structured in the following way: literature review, methodology explanation, data description, estimation results, conclusions and policy recommendations.

*Chapter 2*

# LITERATURE REVIEW

The literature review is organized into three key sections. The first one reviews studies grouped by using economic indicators in methodology, to see the influence of macroeconomic conditions and fuel prices on road safety. The following section shows the influence of public policies on driving behavior and individual responses, like changes in transportation modes. In the last section, I mention related studies to enrich the review with more empirical evidence and highlight the most interesting papers that did not fit into the previous categories.

## 2.1 Economic indicators and road safety

Existing studies show that economic conditions affect behavior, and agents adjust accordingly to changes in external factors. The relationship between economic conditions and traffic accidents has been studied in developed economies.

For instance, in the widely known study about recessions and their impact on health (Ruhm 2000), Fixed Effects (FE) models were developed to detect variations in mortality rates (proxy of health) across US states. The author has found a positive impact of recessions on health, especially for causes of death that include risky behaviors, which is applicable to traffic accidents.

Building on Ruhm's (2000) findings, Antoniou et al. (2016) used the Gross Domestic Product (GDP) and unemployment rate to analyze statistical relationships between traffic fatalities with varying results. Since the nature of time series models is unstable, the results showed that only ten out of thirty studied countries had statistically significant elasticity of the fatality rate with respect to GDP of 0.63. This study emphasized that changes in economic conditions directly affect traffic volumes and, therefore, traffic accidents.

In Europe, the effects of GDP changes on road traffic fatalities were studied (Yannis, Papadimitriou, and Folla 2014) in 27 European countries from 1975 to 2011. As a result, GDP changes and mortality rates had a significant relationship. Annual GDP decreases are correlated with lower numbers of traffic accident fatalities and vice versa. Since the GDP decrease coincided with a reduction in fatalities, this economic indicator is correlated with the traffic volume and distance traveled.

Expanding on this, Naqvi et al. (2023) used two macroeconomic indicators, GDP per capita and the unemployment rate,  to analyze road traffic collisions in 28 EU countries for 2005-2018, applying panel data. They found strong evidence that a 10% increase in fuel prices is associated with a 2.6% decrease in fatal accidents. The authors concluded that the most effective way to reduce traffic fatalities is to increase fuel prices. Regarding the economic factors, higher GDP is associated with increased traffic, while unemployment rates negatively affect accident rates due to reduced travel during recessions.

Collectively, the studies mentioned above highlight the necessity of using a macroeconomic indicator, particularly GDP, in the model as a proxy for traffic volume and distance traveled. If included, it will be possible to control for these changes and analyze fuel price impact on traffic accidents.

### 2.2 Public policy and behavioral changes

While macroeconomic indicators are significant, public policies that affect fuel prices contribute to microeconomic factors and have a role in changing behavior. To support the idea of economic stimulus, in the meaning of public policies, and change in driving behavior, I would like to mention the study that employed a full difference-in-difference (DID) model and found a strong causal relationship between increased congestion charges in London and reduced traffic fatalities (Li, Graham, and Majumdar 2012). The authors concluded that the change in policy reduced total car accidents but increased the accidents with two-wheeled transport. It was one of the studies that influenced public policy implementations.

The other paper (Litman 2012) focused on strategies for reforming transport-related pricing and found evidence that an increase in fuel tax on one cent reduces per capita traffic fatality rates by 0.25%. Moreover, the author examined the Mississippi data, and with prices adjusted to inflation, a 1% increase in those prices was associated with a 0.25% reduction in total crashes per million miles traveled in the short run.

Building on this, Best (2018) analyzed the short-term effects of fuel price changes. This was motivated by the increased fatalities on the roads in New Zealand which coincided with lower prices on the fuel. The author analyzed data for 1989-2017 and found a significant negative relationship. A 10% increase in fuel prices led to a 2-3% reduction in fatalities. However, the importance of specific interventions for cyclists is mentioned, as this group has more injuries during high prices on fuel, possibly because of the substitution to less safe transport.

Furthermore, Sheehan-Connor (2015) proposed a novel approach to analyzing taxes on fuel. The idea is to analyze not only emissions but also the weight of the vehicle and road safety. In conclusion, dual targets were proposed for increasing this tax: to reduce carbon emissions, and to reduce fatalities on roads due to lower distance traveled and shift to lighter vehicles. The simulated tax is $1.14 per gallon, which is estimated to reduce fatalities by 7%.

In addition to that, Grabowski and Morrisey (2006) analyzed changes in state fuel taxes on US data and found a significant change after policy intervention. The shift towards smaller, more efficient vehicles was mentioned, and reduced miles traveled.

Public policies that influence fuel prices play a role in improving road safety and creating a framework for drivers' behavior. Studies mentioned use different methods, such as DID, regressions, and simulations, but what unites them is the relationship shown in safety benefits from developed economies. These interventions effectively reduce vehicle distance traveled and speeding and encourage changes in transportation modes, including shifts to lighter, more fuel-efficient vehicles. While this is a proven effect in developed economies, it is important to know if the effect holds in Ukrainian conditions before adopting the policies.

### 2.3 Related papers

Now, I would like to mention some of the papers to provide a broader context and understanding of the topic. A global study (Burke and Nishitateno 2015) on 153 countries found that a 1% increase in fuel prices reduced fatalities by 0.4%-0.6%. Based on this, macroeconomic intervention, such as fuel price increase, can be an effective improvement to road safety. Similarly, Grabowski and Morrisey (2004) confirmed the conclusion on the US data, adding that this effect is especially significant among young drivers.

Chi et al. (2011) concluded that behavioral changes not only reduce driving. In Mississippi, the frequency of crashes by drunk drivers with damage to property is reduced with higher prices on fuel. Additionally, in Indonesia (Maulidar, Syechalad, and Nasir 2022), the results not only reduced crashes but also influenced the income per capita. In middle-income regions, this elasticity may be even higher because of the sensitivity to price changes.

Local literature (Riabushenko, Popadynets, and Vorontsov 2024; Batyrgareieva, Kolodyazhny, and Netesa 2023) mostly describe the situation with the war context by observing trends (descriptive statistics) or based on qualitative methods (surveys). My thesis aims to bridge this gap by applying econometric models to Ukrainian data and potentially offer a new view on road safety and the factors influencing it.

In conclusion, the identified relationship is that increased fuel prices lead to reduced risky driving and speeding, as well as better route planning, which lowers the volume of traffic, and in the long term, individual responses include changes in transportation modes. This review emphasizes the importance of the interplay between economic conditions (particularly GDP), public policies (fuel tax, congestion charges, government regulations), and fluctuations in fuel prices on road safety. The gap identified is the relationship between fuel price changes and traffic accidents in developing economies and, moreover, in the Ukrainian context.

*C h a p t e r 3*

# METHODOLOGY

In this section, I outline the link between the hypothesis and the chosen model, define key variables and their expected effects, discuss the estimation method and potential issues, and provide a validation of the results.

As stated in *Chapter 1*, the hypothesis of the research is that an increase in fuel prices is associated with a reduction in traffic accidents with fatalities and/or injuries. There are three main potential factors that contribute to the effect: reduced risky driving and speeding (which is the main cause of deaths on the roads), lower volume of traffic because of better route planning and reduced unnecessary trips, and changes in transportation modes.

To test the hypothesis, I employ multiple fixed effects (FE) and random effects (RE) panel data models. This approach assures that the within-regional differences, like infrastructure or geography, do not affect the result and capture the effect itself among the same places. It also controls for potential heterogeneity and allows to isolate the impact of fuel prices, economic activity, and weather conditions on traffic accidents. It was chosen over the Pooled Ordinary Least Squares (Pooled OLS) because the second one ignores region-specific characteristics, implying the same conditions for every region.

I decided to create a panel dataset because it was the best way to increase observations while not losing the explanatory power of the model and control for unobserved heterogeneity across regions. Since the data on Ukraine is available only from 2017, the annual numbers would be too small for quantitative analysis and econometric modeling. Therefore, I obtained a sufficient number of observations to see if the relationship holds for Ukraine on the monthly granularity for the vast majority of the regions.

The model used is formulated as follows:

$$\log Y_{it} = \beta_0 + \beta_1 \log X_{it} + \beta_2\, log\, GDP_t + \beta_3\, log\, Precipitation_{it} + \beta_4\, log\, Avg\_temp_{it} + \delta Shock_t + \sum_{m=1}^{11} \gamma_m D_m + \alpha_i + \epsilon_{it} \tag{3.1}$$

Where:

$Y_{it} =$ Number of traffic accidents (number of fatalities or injured people) in region i at a time t

$X_{it} =$ Fuel prices (A92, A95, A95+, Diesel, Autogas)

$GDP_t =$ Quarterly GDP in USD transformed into monthly

$Precipitation_{it} =$ Total precipitation (weather control)

$Avg\_temp_{it} =$ Average temperature

$Shock_t$ = Shock dummy variable for the period of fuel disruptions caused by attacks on the infrastructure (for the period of April 2022-July 2022).

$D_m =$ Month dummy variables (January is a reference)

$\alpha_i =$ Region-specific fixed effects

$\epsilon_{it} =$ Error term

Logs are used to adjust the results to the same scale, so they are comparable to percentage changes and represent elasticities. It also reduces the skewness for variables with large variations. To avoid null values, it is decided to add plus one (+1) for all traffic accident variables (Total, Died, and Injured) and precipitation, and to convert Celsius temperatures into Kelvin, to avoid negative values that are ignored in a log-transformed form.

To handle multicollinearity, separate models for each fuel type are estimated, as well as for the traffic accident data. In total, there are twenty-seven models, each for one of the three dependent variables (total number of accidents with fatalities/injuries, number of fatalities, number of injured people) and for two types of models: FE and RE. The RE cannot work with null values, and since there was some missing data for the A-92 fuel type, only the FE model is considered.

The explanatory variables and the transformations implied are described below. Firstly, the fuel prices were transformed to USD based on the exchange rate data from the National Bank of Ukraine to make the research comparable with international studies and to use the same measure. Also, because of the local context, mostly the population uses USD for measuring the prices, because hryvnia has a history of high inflation.

Quarterly nominal GDP transformed to dollars was used, the same for all regions in the panel. This decision was made because of the limitations: no population data available since the full-scale invasion and GRP is provided by State Statistics Service of Ukraine only on an annual basis.

Seasonality is accounted for through the month dummies and weather controls (average temperature and precipitation).

In additional specification, the model with interaction term between fuel price and shock dummy was introduced, to test if the relationship holds during the fuel shortages. This is important to test if price sensitivity increased during deficit, or if the behavior was driven only by price, not availability of the fuel.

The full list of explanatory variables, rationale, and their expected signs are presented in Table 1.

Table 1. Explanatory variables and expected signs

| Variable | Description | Expected effect | Rationale |
|---|---|---|---|
| Log Fuel Price | Log of 1 out of 5 types of fuel price, converted into USD | Negative (-) | Increased cost of driving, reduced traffic volume, and therefore accident rates |
| Log GDP | Log of GDP (Nominal quarterly GDP, transformed to monthly, converted to USD) | Ambiguous | Higher GDP may lead to more traffic accidents because of increased mobility but also can improve infrastructure and vehicle safety. It is used as a proxy of the volume of traffic. |
| Log Precipitation | Log of total monthly precipitation (mm) | Positive (+) | Rain and snow increase the probability of traffic accidents because of the slippery roads and low visibility. |
| Log Average Temperature | Log of monthly average temperature, converted to Kelvin | Positive (+) | With the higher temperature, more cars are on the roads, and more risky driving is expected. |
| Month | Dummy variables for months (January as reference) | Ambiguous | As January is the reference month, most of the coefficients should be positive. |
| Shock | Dummy Variable | Negative (-) | It is expected to be negative, as the availability of fuel has dropped, which means fewer cars on the road and reduced risky behavior. |

To ensure the reliability of the model and robustness of the estimations, key assumptions must hold. Violations can lead to biased estimates and affect the interpretation. Below are the main assumptions and tests performed to examine them.

The first assumption is that the model does not have perfect multicollinearity. It can be checked by a correlation matrix, where the explanatory variables should not exceed a 0.8 correlation.

The second thing that needs to be careful with is homoscedasticity. It means that the variance should be constant across observations, because if it is not, standard errors will be unreliable. The Breusch-Pagan test is used to see if the residual variance depends on explanatory variables.

The next assumption is no serial autocorrelation. To ensure it, the Wooldridge test for serial correlation is used. Cross-sectional dependence is tested with Pesaran's CD test.

The results of the tests are presented in Table 2.

Table 2. Diagnostic tests

| Test | Test Statistic | Conclusion |
|---|---|---|
| Breusch–Pagan test (Heteroskedasticity) | 54.931*** | Heteroskedasticity is present |
| Wooldridge test for serial correlation | 94.448*** (F-stat) | Evidence of serial correlation |
| Pesaran's CD test (Cross-sectional dependence) | 31.929*** (z-stat) | Cross-sectional dependence is present |

Note: *p<0.1; **p<0.05; ***p<0.01

Since the tests are significant, Driscoll-Kraay standard errors are used, which are designed to correct for cross-sectional dependence, serial correlation, and homoskedasticity.

The Hausman test was performed for all model types to check which of the models was better.

The software used is:

- Excel for combining data from different sources;
- R for manipulations with data and statistical analysis (with packages “plm”, “dplyr”, “lmtest”, “stargazer”). RStudio 2024.09.1 Build 394;
- Tableau and Power BI for data visualizations. Tableau version 2024.2. Power BI version 2.141.1558.0 (March 2025).
- Grammarly for text correctness (only grammar improvements, not generating content).

In this section, the model's choice is explained, transformations applied, the model is presented and explained, explanatory variables and expected signs are discussed, and validity checks are mentioned. The following chapter goes in-depth into the sources of the data, descriptive statistics, and plots to familiarize with the data.

*Chapter 4*

# DATA

## 4.1 Data sources and preparation

There are a few categories of data. Firstly, the fuel prices, secondly, the traffic accidents data, thirdly weather data, and lastly, the economic indicator. The fuel price data were obtained from the A95 Consulting Group, the main analytical company in the Ukrainian fuel products market. They shared the average monthly prices on the five main types of fuel by region: Gasoline A-92, Gasoline A-95, Gasoline A-95+ (Premium A-95), Diesel, and Autogas (LPG).

The traffic accident data is available on the official web page of the Patrol Police (Patrol Police of Ukraine n.d.). However, they publish monthly data only for the current year, which means 2017-2023 is already aggregated for the annual. I sent an official request for public information to the Patrol Police. This way, the first result obtained was monthly data for the whole of Ukraine. Since the main idea was to create a monthly regional panel dataset, there was a need for disaggregated data. Therefore, I submitted more than 20 requests to the regional departments of the Patrol Police. Most of the regions satisfied the request fully, but some of them were unable to do so, which led to an inability to obtain the data for such regions of Ukraine: Volyn, Khmelnytskyi, Zhytomyr, Donetsk, and Kirovohrad. Also, the data for Crimea is not available since it is under occupation.

Data for the Luhansk and Kherson regions were dropped because they were partly occupied, and statistics were not representative. Therefore, the panel contains data on 19 regions and the city of Kyiv as a separate administrative unit.

Weather data was collected manually from the web page (METEOPOST n.d.). The missing data for 2022 were filled using the median of the same month in other years from the exact region to keep the seasonal structure of weather patterns and avoid null values. After copying separately the data, I obtained the total precipitation data, minimum, maximum, and average temperature, as well as average wind speed and maximum snow depth. This data was added to include some external factors in the analysis, as, intuitively, the weather should be an influencing factor for road safety. However, weather data for the Zaporizhzhia region is missing. Therefore, the final panel, including precipitation and average temperature, has 17 regions included.

Finally, the economic indicator's data is published annually on the State Statistics Service web page (State Statistics Service of Ukraine, n.d.). GDP is a quarterly indicator, which can be estimated as a monthly one. Unfortunately, because of the full-scale invasion, there has been no official data on the population since 2022. Because of the lack of GRP per capita data and based on the existing literature, GDP was used as a control variable for the models. The exchange rate data is available on the NBU web page (National Bank of Ukraine n.d.) daily and monthly. The monthly exchange rate was used to transform the prices and GDP into US dollars.

Overall, a lot of effort was put into creating such a dataset, and manual work was required. The main problem is the absence of official data at the right granularity. Most of the responses to requests for public information from regions were in PDF format, and not according to the Excel template provided, so it required time to collect it all into a single dataset with the regions and then connect it to the fuel prices and weather data.

## 4.2 Descriptive statistics and trends

The descriptive statistics in levels of the final dataset are presented in Table 3. The temperature is Celsius, for convenience.

Table 3. Descriptive statistics of the dataset in levels

| Variable | Number of observations | Mean | Standard Deviation | Min | Max |
|---|---|---|---|---|---|
| Total | 1632 | 91,50 | 57,27 | 3 | 283 |
| Died | 1632 | 11,77 | 7,38 | 0 | 47 |
| Injured | 1632 | 113,6 | 70,84 | 2 | 356 |
| GDP, USD | 1632 | 13355 | 3119,46 | 7256 | 21866 |
| A92, USD | 1606 | 1,11 | 0,19 | 0,73 | 1,83 |
| A95, USD | 1632 | 1,15 | 0,20 | 0,77 | 1,76 |
| A95+, USD | 1632 | 1,21 | 0,20 | 0,83 | 1,83 |
| Diesel, USD | 1632 | 1,13 | 0,24 | 0,75 | 1,99 |
| Autogas, USD | 1632 | 0,60 | 0,18 | 0,32 | 1,46 |
| Average temperature, °C | 1632 | 10,15 | 8,76 | -7,1 | 28,1 |
| Total precipitation, mm | 1632 | 45,17 | 33,76 | 0 | 237,4 |

This table contains the most important variables and their descriptive statistics. On average, every month and in every region for 2017-2024 in Ukraine, there were 91.5 traffic accidents with fatalities or injuries, in which 11 people died and 113 received some injuries. A maximum of 47 fatalities and 356 injuries in a single month in one region. The data contains 17 regions for 96 months, which gives 1632 observations.

Figure 1 shows the correlation matrix.

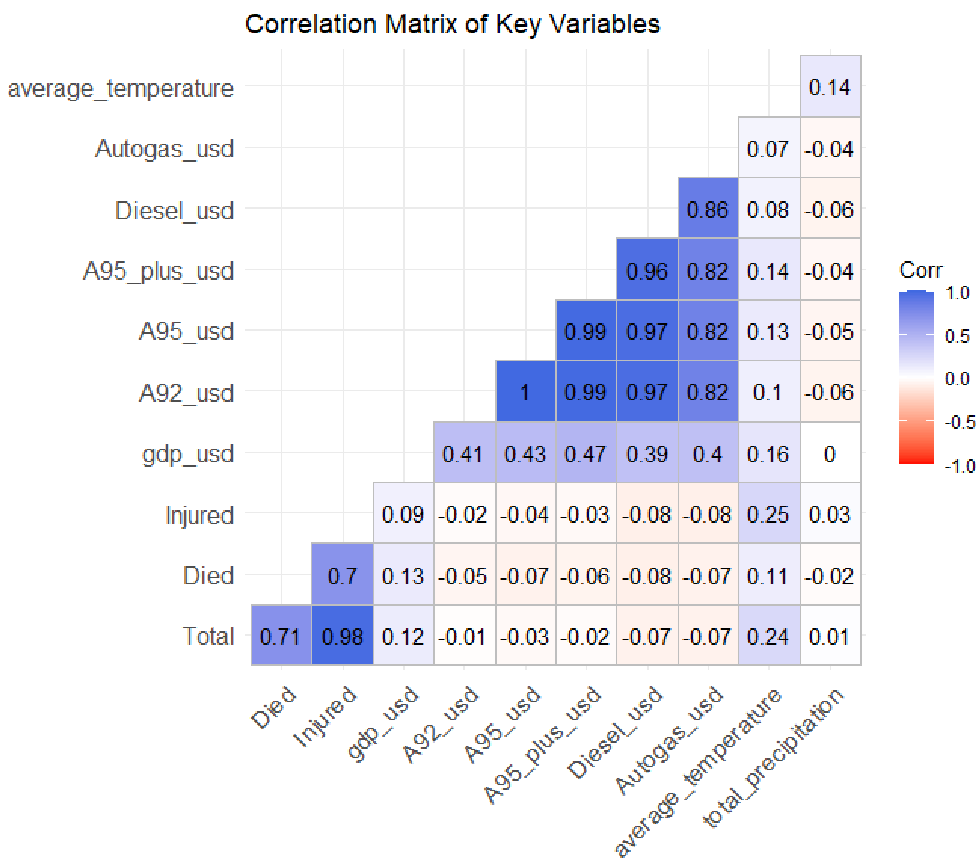


Figure 1. Correlation matrix for key variables

In the preliminary analysis (Figure 1), the fuel price data is highly correlated, as well as traffic accident statistics. Therefore, to avoid the multicollinearity issue, it is essential to create distinct models for each type of fuel and traffic accident. GDP has a moderate correlation with prices, which means higher economic activity correlates with fuel prices. It might be because of the impact of demand.

Figure 2 and 3 show the trend for the average fuel prices on different aggregation levels, and Figure 4 familiarizes with the total accidents across regions included in the analysis.

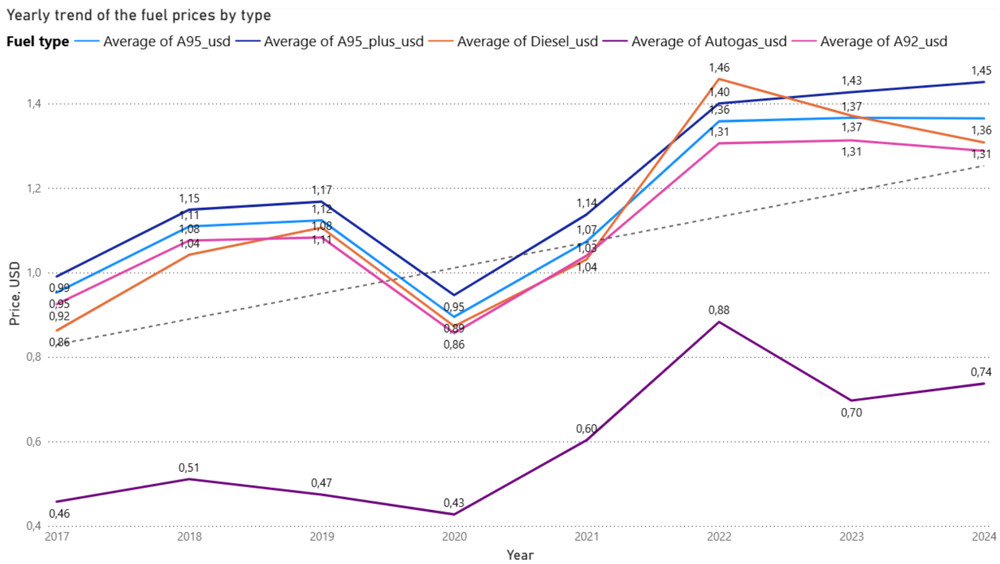


Figure 2. The trend of the yearly average of fuel prices by type

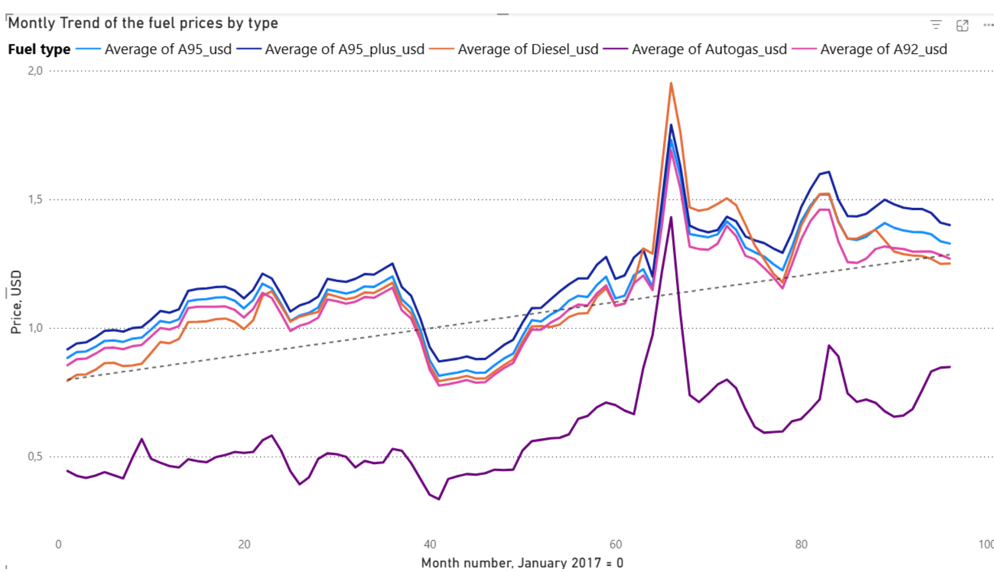


Figure 3. The trend of the monthly average of fuel prices by type

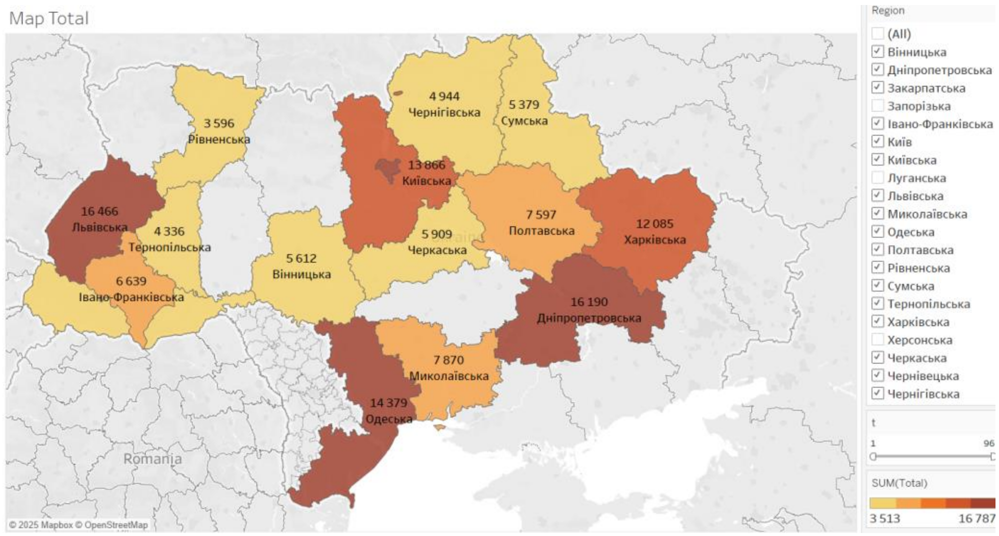


Figure 4. Total traffic accidents by regions included in the analysis

The fuel prices increase with time, as seen from the trend (Figure 2). On the monthly average trend (Figure 3), we can see the drastic increase in fuel prices for the period when oil depots were bombed, which created a deficit in the fuel available on the market for a few months before new logistical chains were established. Therefore, it is important to include a shock dummy for this period to check the robustness of the model. Most traffic accidents happen in Kyiv city, Lviv, Odesa, and Dnipropetrovs'k regions, among the available analyzed data (Figure 4), which is expected from the population number.

*Chapter 5*

# ESTIMATION RESULTS

In this section, empirical estimation results are presented and interpreted. First, the base model estimations without a shock dummy are introduced to provide an overview of the initial model calculations. Second, models incorporating a shock dummy are shown to account for the fuel disruptions. Third, the Hausman test is performed and discussed to select the final model's type. Fourth, the robustness checks performed to validate the results are described. Finally, the limitations of the research are mentioned.

## 5.1 Model without a "shock" dummy

For the initial model without the shock dummy, a combination of Total traffic accidents and Diesel fuel prices is chosen to be presented first (Table 4).

Table 4. Estimations result for Total traffic accidents with Diesel prices as a fuel variable.

| Independent variables | FE coefficient (Driscoll-Kraay robust standard errors) | RE coefficient (Driscoll-Kraay robust standard errors) |
|---|---|---|
| Log Diesel | -0.302** | -0.303** |
| | (0.127) | (0.127) |
| Log GDP | 0.057 | 0.057 |
| | (0.080) | (0.080) |
| Log average temperature | 8.745*** | 8.763*** |
| | (1.494) | (1.495) |
| Log total precipitation | 0.006 | 0.006 |
| | (0.010) | (0.010) |
| February | -0.223*** | -0.223*** |
| | (0.031) | (0.031) |

TABLE 4 — Continued

| Independent variables | FE coefficient (Driscoll-Kraay robust standard errors) | RE coefficient (Driscoll-Kraay robust standard errors) |
|---|---|---|
| March | -0.382*** | -0.382*** |
| | (0.125) | (0.125) |
| April | -0.404*** | -0.404*** |
| | (0.094) | (0.094) |
| May | -0.347*** | -0.348*** |
| | (0.103) | (0.103) |
| June | -0.400*** | -0.400*** |
| | (0.126) | (0.126) |
| July | -0.378*** | -0.379*** |
| | (0.138) | (0.138) |
| August | -0.318** | -0.320** |
| | (0.132) | (0.132) |
| September | -0.197* | -0.198* |
| | (0.105) | (0.105) |
| October | -0.023 | -0.024 |
| | (0.079) | (0.079) |
| November | 0.092* | 0.091* |
| | (0.053) | (0.053) |
| December | 0.140*** | 0.140*** |
| | (0.040) | (0.040) |
| Constant | - | -45.227*** |
| | | (8.640) |
| **Observations** | 1632 | 1632 |
| $\boldsymbol{R^2}$ | 0.441 | 0.439 |
| **Adjusted $\boldsymbol{R^2}$** | 0.430 | 0.434 |
| **F Statistic** | 84.238*** | 1,265.681*** |
| | (df = 15; 1600) | |

Note: *p<0.1; **p<0.05; ***p<0.01

As both dependent and independent variables are in the logarithmic form, the results can be interpreted as elasticities. At first glance, the coefficients for both models are the same, which proves the validity of the model overall. The fuel coefficient is significant, with the interpretation that a 1% increase in diesel prices is associated with a 0.3% decrease in total traffic accidents with fatalities and/or injuries. Most of the month variables are significant, as well as the average temperature, which demonstrates that data has a high seasonality. F-statistics are highly significant. $R^2$ values are around 44%, meaning that a large amount of variation is explained by the model, which is acceptable for panel models. Overall, this model shows that fuel prices have a significant impact on traffic safety. In Table 5, the main fuel coefficients for FE models are presented for brevity and to show the relationship between all combinations of the analyzed fuel and traffic accident variables. For full models, see Appendix: Tables 10-12.

Table 5. Fuel coefficients for all FE models

| Fuel variable | Total accidents | Fatalities | Injured |
|---|---|---|---|
| Log Autogas | -0.322*** | -0.267*** | -0.332*** |
| | (0.111) | (0.039) | (0.122) |
| Log A92 | -0.267* | -0.355*** | -0.225 |
| | (0.159) | (0.114) | (0.159) |
| Log A95 | -0.246* | -0.349*** | -0.214 |
| | (0.144) | (0.104) | (0.168) |
| Log A95+ | -0.249 | -0.381*** | -0.215 |
| | (0.152) | (0.113) | (0.177) |
| Log Diesel | -0.303** | -0.325*** | -0.287* |
| | (0.127) | (0.073) | (0.148) |

Note: *p<0.1; **p<0.05; ***p<0.01

All models have highly significant F statistics, ranging from 28 for Fatalities models, to 91 for Total accidents models, and 65-76 for Injured models. $R^2$ ranges 43%-46% for Total accidents models, 21% for Fatalities, and 38%-42% for Injured.

However, these results are not full to the context of the fuel disruptions during the full-scale invasion, therefore the models with shock dummy are introduced, to account for the drastic deficit.

### 5.2 Full model comparison with a "shock" dummy

Based on the trend of the average fuel prices (Figure 3), it is decided to introduce a shock dummy variable to account for the period of the deficit, when oil depots were bombed and fuel had restricted availability. This period was from April to July of 2022. In Table 6, FE and RE models with "Shock" dummy comparison is presented.

Table 6. Estimations result for Total traffic accidents with Diesel prices as a fuel variable, with a "Shock" dummy.

| Independent variables | FE coefficient (Driscoll-Kraay robust standard errors) | RE coefficient (Driscoll-Kraay robust standard errors) |
|---|---|---|
| Log Diesel | -0.127* | -0.127* |
| | (0.071) | (0.071) |
| Log GDP | -0.029 | -0.029 |
| | (0.067) | (0.067) |
| Log average temperature | 7.786*** | 7.803*** |
| | (1.334) | (1.338) |
| Log total precipitation | 0.009 | 0.009 |
| | (0.009) | (0.009) |
| Shock | -0.313*** | -0.312*** |
| | (0.058) | (0.058) |
| February | -0.220*** | -0.223*** |
| | (0.029) | (0.031) |
| March | -0.367*** | -0.367*** |
| | (0.123) | (0.124) |
| April | -0.320*** | -0.320*** |
| | (0.075) | (0.076) |
| May | -0.253*** | -0.254*** |
| | (0.084) | (0.085) |
| June | -0.295*** | -0.296*** |
| | (0.112) | (0.113) |

TABLE 6 — Continued

| Independent variables | FE coefficient (Driscoll-Kraay robust standard errors) | RE coefficient (Driscoll-Kraay robust standard errors) |
|---|---|---|
| July | -0.248** | -0.250** |
| | (0.123) | (0.124) |
| August | -0.225* | -0.226* |
| | (0.121) | (0.121) |
| September | -0.123 | -0.124 |
| | (0.096) | (0.096) |
| October | 0.035 | 0.035 |
| | (0.072) | (0.072) |
| November | 0.115** | 0.115** |
| | (0.047) | (0.047) |
| December | 0.169*** | 0.169*** |
| | (0.037) | (0.037) |
| Constant | - | -39.514*** |
| **Observations** | 1632 | 1632 |
| $\boldsymbol{R^2}$ | 0.465 | 0.463 |
| **Adjusted** $\boldsymbol{R^2}$ | 0.454 | 0.458 |
| **F Statistic** | 86.904*** | 1,392.654*** |
| | (df = 16; 1599) | |

Note: *p<0.1; **p<0.05; ***p<0.01

The model with the shock has a bit more explanatory power compared to the previous (46.8% vs 44.4%), and a bit higher F-statistic, which indicates better overall fit.

The shock is negative and highly significant, meaning that it had an impact on reducing the total traffic accidents. Therefore, during the fuel shortages, accidents decreased by 31.2% when controlling for weather, fuel prices, and GDP. This is consistent with the hypothesis that fuel shortages and higher prices lower the number of accidents. Diesel prices have weak significance on the $p < 0.1$ level, with a 1% increase in prices associated with a 0.127% decrease in traffic accidents.

As in the previous model, the month dummies are mostly significant, as well as the temperature, which proves the strong seasonal patterns are present in the data.

Both FE and RE models provide similar coefficients, which means the estimates are robust to specification, and unobserved regional differences do not bias the results.

In Table 7, the fuel price coefficient comparison is presented. Full results are in the Appendix, Tables 13-15.

Table 7. Fuel coefficients for all FE models, with "Shock" dummy

| Fuel variable | Total accidents | Fatalities | Injured |
|---|---|---|---|
| Log Autogas | -0.185 | -0.272*** | -0.184 |
| | (0.135) | (0.075) | (0.153) |
| Log A92 | -0.086 | -0.291*** | -0.030 |
| | (0.075) | (0.108) | (0.083) |
| Log A95 | -0.060 | -0.287*** | -0.005 |
| | (0.070) | (0.103) | (0.076) |
| Log A95+ | -0.055 | -0.317*** | 0.002 |
| | (0.076) | (0.113) | (0.082) |
| Log Diesel | -0.127* | -0.294*** | -0.083 |
| | (0.071) | (0.087) | (0.080) |

Note: *p<0.1; **p<0.05; ***p<0.01

The shock is consistently significant and had an impact on the total accidents and number of injured people. This confirms that the shortage of fuel influences traffic activity, which is consistent with the hypothesis that less fuel availability is linked to lower vehicles usage, and therefore, less accidents.

However, the models for fatalities have different results. Despite the restricted availability of fuel, the shock did not influence the number of fatalities as much. The significant and negative fuel price coefficients show that they had a long-term effect that was not changed even with the shock. This suggests that prices change not only how much people drive but also how they drive. For instance, high cost stimulates driving less and slower to save fuel. Since speeding is the main cause of the fatalities, it contributes to a lower number of them.

To dive into this further, the interaction term models for fuel multiplied by shock (log Diesel USD * Shock) were created. This allows us to test if the effect of fuel prices changed during the specific period of shock (Table 8).

Table 8. Estimations result for Fatalities, Diesel prices, and interaction term

| Independent variables | FE coefficient (Driscoll-Kraay robust standard errors) | RE coefficient (Driscoll-Kraay robust standard errors) |
|---|---|---|
| Log Diesel | -0.289*** | -0.289*** |
| | (0.090) | (0.090) |
| Log GDP | -0.007 | -0.008 |
| | (0.073) | (0.073) |
| Log average temperature | 8.258*** | 8.310*** |
| | (1.906) | (1.911) |
| Log total precipitation | 0.009 | 0.009 |
| | (0.009) | (0.009) |
| Shock | 0.011 | 0.011 |
| | (0.086) | (0.086) |
| February | -0.314*** | -0.315*** |
| | (0.050) | (0.049) |
| March | -0.390*** | -0.391*** |
| | (0.090) | (0.090) |
| April | -0.521*** | -0.523*** |
| | (0.119) | (0.118) |
| May | -0.534*** | -0.537*** |
| | (0.135) | (0.135) |
| June | -0.586*** | -0.591*** |
| | (0.177) | (0.176) |
| July | -0.492*** | -0.496*** |
| | (0.180) | (0.180) |
| August | -0.432** | -0.436** |
| | (0.179) | (0.180) |
| September | -0.272* | -0.275* |
| | (0.142) | (0.143) |

TABLE 8 — Continued

| Independent variables | FE coefficient (Driscoll-Kraay robust standard errors) | RE coefficient (Driscoll-Kraay robust standard errors) |
| --- | --- | --- |
| October | 0.008 | 0.006 |
| | (0.100) | (0.099) |
| November | 0.152** | 0.151** |
| | (0.065) | (0.065) |
| December | 0.164*** | 0.164*** |
| | (0.042) | (0.042) |
| Log Diesel:Shock | -0.130 | -0.130 |
| | (0.194) | (0.194) |
| Constant | - | -44.131*** |
| | | (10.548) |
| **Observations** | 1632 | 1632 |
| $\boldsymbol{R^2}$ | 0.218 | 0.216 |
| **Adjusted** $\boldsymbol{R^2}$ | 0.201 | 0.208 |
| **F Statistic** | 26.142*** | 445.153*** |
| | (df = 17; 1598) | |

Note: *p<0.1; **p<0.05; ***p<0.01

The diesel price coefficient is consistent with the previous model without the interaction term. Fuel prices are significantly associated with lower fatalities. During the fuel disruption, the effect of the shock itself on the fatalities was small and not significant (shock = 0.011). As expected from the previous results, the interaction term is also not statistically significant, meaning that the shock did not change the strength of the relationship meaningfully during the period of fuel disruptions. Therefore, the price remained the main reason for the reduced fatalities, not the fuel availability, unlike the total number of accidents and injured people. Therefore, a 1% increase in diesel prices is associated with a 0.3% reduction in fatalities at the <0.01 level of significance. This effect is visible in Figure 5.

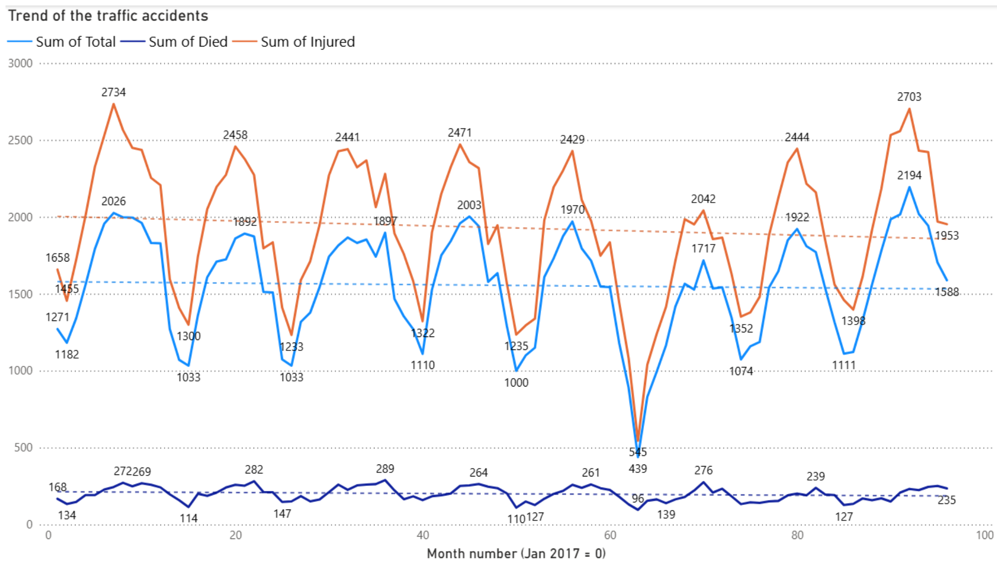


Figure 5. Trend of the traffic accidents: Total, Fatalities, Injured

While the total number of accidents dropped drastically, the number of fatalities stayed almost at the same level as in previous years.

## 5.3 Robustness checks and limitations of the research methodology and data

To ensure the reliability of the models, the mentioned in *Chapter 3* tests were implied: The Breusch–Pagan test for the presence of heteroskedasticity, the Wooldridge test for serial autocorrelation, and Pesaran's CD test for cross-sectional dependence (Table 2). Since all tests were significant, Driscoll-Kraay standard errors were used to account for it, because they are robust to these assumptions. Additionally, potential multicollinearity was addressed by creating separate models for different fuel types and statistics of traffic accidents.

To decide which model to prefer, FE or RE, the Hausman test was performed. The p-value is almost 1 for all models, indicating no statistically significant difference between the models. And since the estimate coefficients are almost the same, RE model should be preferred. However, based on the theory, and because the A92 fuel type has some missing values (which RE cannot work with), the FE models are chosen.

To verify the robustness of the results, models with exclusions of the key variables were estimated. Firstly, the core model was run without the Month dummy to prove that it is an important seasonality variable that improves explanatory power. Next, the models were re-estimated, omitting the key variables to check the sensitivity of the fuel coefficients. The results are presented in Table 9.

Table 9. Robustness of Diesel coefficients across FE model specifications on Total traffic accidents

| Specification | Diesel coefficient | $R^2$ | Comment |
|---|---|---|---|
| No "shock" dummy | -0.302** (0.127) | 0.441 | Model without the "shock" dummy. See section 5.1 |
| Full model | -0.127* (0.071) | 0.468 | Baseline model with the "shock" dummy. See section 5.2 |
| No month dummies | -0.257** (0.117) | 0.318 | The coefficient remains negative; Month dummies increase the explanatory power. GDP coefficient is highly significant: 0.373*** (0.082). "Shock" dummy is consistent: -0.309*** (0.064) |
| No GDP | -0.143* (0.082) | 0.465 | Similar coefficient to the full model. Theoretically important to include. |
| No weather controls | -0.079 | | Weather is an important factor to include, as temperature affects the other coefficients. |

TABLE 9 — Continued

| Specification | Diesel coefficient | $R^2$ | Comment |
|---|---|---|---|
| Before the full-scale invasion | -0.155* (0.083) | 0.551 | The explanatory power is stronger; the relationship holds under more stable conditions. |
| After the full-scale invasion | 0.294 (0.254) | 0.509 | Sign reversed; coefficient is not significant. Limited sample size (578), "shock" coefficient is consistent (-0.347***). |

The different specifications of the FE model with Total traffic accidents as the dependent variable and Diesel prices as a fuel type are provided. The consistency of the coefficient's significance and sign (negative) across most of the models supports the robustness of the main results, which generally indicates that higher fuel prices are associated with lower numbers of traffic accidents with injured and/or fatalities. The full model, which includes all control variables and "shock" dummy, is considered the most complete specification because it has the largest number of observations despite not being the highest model fit across all specifications. It suggests that a 1% increase in diesel prices is associated with a 0.127% reduction in traffic accidents at a 0.1 level of significance (weak significance).

Excluding the month dummies results in lower explanatory power, which means seasonality is an important factor in the traffic accident data. At the same time, the GDP coefficient becomes highly significant, meaning that it is possible that GDP is also seasonal, and these variables may confound each other. Removing GDP from the model has a small impact on the diesel coefficient; however, from a theoretical perspective, it is still an important economic indicator that needs to be included and should not be omitted. Dropping the weather variables, especially average temperature, results in a weaker diesel coefficient and proves that it is an important factor that influences both travel behavior and the number of traffic accidents. Finally, the pre-invasion sample has the highest explanatory power, with $R^2 = 0.511$, which means better model stability. On the other hand, in the post-invasion period, the coefficient becomes insignificant and positive, possibly because of the higher volatility in fuel prices, as well as emergency conditions. Interestingly, the "shock" dummy is consistently negative and similar across all of the specifications, ranging from -0.369*** (Full model) to -0.305*** (No GDP specification). This means that during April-July 2022, the total number of accidents was approximately 30-37% lower, depending on the specification, holding other variables constant.

Despite the robustness checks, several limitations should be mentioned. First, GDP data is the same for all regions, and on the quarterly granularity, it is divided into monthly. This does not allow for the capture of some of the variation in local conditions. Secondly, because of the missing weather data for a few regions and the inability of some of the regional Patrol Police offices to send the data, the panel is reduced. Thirdly, some unobserved factors are not included, such as law enforcement or the quality of the infrastructure. Lastly, the war conditions are unique to Ukraine and are not generalizable to other countries in peacetime. Although the expected causality of the effect is from prices to behavior, the potential reverse causality is not excluded completely. Because of the data limitations, instrumental variables were not used, but future research could focus on external IVs or international price shocks.

*Chapter 6*

# CONCLUSIONS AND POLICY RECOMMENDATIONS

This study aimed to analyze the link between fuel prices and traffic accidents with fatalities and/or injuries in Ukraine. The analysis was based on the panel data Fixed Effects models, using regional monthly data for 2017-2024, with controls for GDP, weather, and seasonality, with a special focus on the fuel disruptions during April-July 2022 caused by oil infrastructure bombing.

The results confirm the hypothesis that higher fuel prices are associated with a lower number of traffic accidents, especially fatalities. The results are robust to different specifications and consistent with the literature reviewed. The seasonality and weather also have a strong effect. During the modeled shock period, the total number of accidents and injuries decreased, but not fatalities. The interaction term between the shock and fuel prices further suggested that price levels themselves had a sustainable influence on the fatalities number. Therefore, it is essential to consider these factors while designing public policies.

While the causal links are not studied in the thesis, three potential mechanisms that contribute to this effect are: reduced speeding and risky driving; lower traffic volume and vehicle usage, because of better route planning and reduced unnecessary trips; changes in transportation modes in the long term.

Given the estimation results, the conclusion could be to raise the fuel prices with taxes. Many developed countries used fuel taxation to improve safety indirectly, so this approach may also work in the Ukrainian context. However, it could have unexpected harmful economic consequences, and it is a politically sensitive topic. Any implementation should be focused on the target support for the vulnerable population. Therefore, using fiscal tools can be a part of a broad strategy to improve road safety, but it should be studied further.

Based on the results, policy recommendations are as follows:

- Avoid fuel subsidies. As fuel prices are consistently associated with higher fatality rates in traffic accidents, market-based levels of prices can stimulate cost-saving behavior, which includes driving at lower speeds and reducing unnecessary usage of cars.
- Introduce dynamic or congestion-based pricing. Since prices do affect the behavior, urban drive tax during peak hours or high-risk zones can effectively lower the total number of accidents, creating a similar effect to the shock period with fuel scarcity, but in a more controlled and non-crisis way.
- Support alternative transport options, such as public transportation, as it effectively reduces the volume of the traffic, as well as improves traffic safety. This requires investment in the transportation sector, potentially subsidies for the population to encourage the long-term shift from individual transport to the public one. Since the prices mostly hurt lower-income drivers, they are also the target audience for such public policy.
- Target speed enforcement. This includes speed monitoring, increase in cameras and patrols. Enforcement could be increased during periods of lower fuel prices.
- Seasonal traffic safety campaigns and traffic control measures. Since seasonality and temperature matter, targeted public campaigns could be developed, especially when the increased accidentality is expected.

The objective of future research on the topic can be to isolate the effect and prove the causal effect of fuel prices on driving speeds, transportation mode choice, and trip frequency. This would help to understand the mechanisms influencing the traffic accident rates and behavior on the roads, as well as reactions to the policy changes.

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APPENDIX

Table 10. Estimation results for Total traffic accidents and fuel prices

| Independent variables | FE (A92) | FE (A95) | FE (A95+) | FE (Autogas) |
|---|---|---|---|---|
| Log fuel price | -0.262* | -0.242* | -0.244 | -0.313*** |
| | (0.158) | (0.143) | (0.152) | (0.112) |
| Log GDP | 0.006 | 0.001 | 0.011 | 0.135 |
| | (0.088) | (0.087) | (0.090) | (0.093) |
| Log average temperature | 8.743*** | 8.612*** | 8.642*** | 7.725*** |
| | (1.486) | (1.477) | (1.481) | (1.357) |
| Log total precipitation | 0.009 | 0.010 | 0.011 | 0.006 |
| | (0.010) | (0.010) | (0.010) | (0.009) |
| February | -0.221*** | -0.223*** | -0.223*** | -0.232*** |
| | (0.032) | (0.031) | (0.031) | (0.033) |
| March | -0.385*** | -0.381*** | -0.382*** | -0.373*** |
| | (0.129) | (0.129) | (0.129) | (0.115) |
| April | -0.404*** | -0.397*** | -0.399*** | -0.371*** |
| | (0.100) | (0.100) | (0.101) | (0.079) |
| May | -0.349*** | -0.338*** | -0.341*** | -0.293*** |
| | (0.111) | (0.110) | (0.111) | (0.083) |
| June | -0.404*** | -0.392*** | -0.394*** | -0.321*** |
| | (0.132) | (0.132) | (0.132) | (0.107) |
| July | -0.367*** | -0.355** | -0.361** | -0.319*** |
| | (0.142) | (0.140) | (0.141) | (0.122) |
| August | -0.308** | -0.292** | -0.297** | -0.259** |
| | (0.136) | (0.134) | (0.135) | (0.116) |
| September | -0.187* | -0.175* | -0.179* | -0.145 |
| | (0.106) | (0.105) | (0.106) | (0.093) |
| October | -0.008 | -0.002 | -0.006 | 0.001 |
| | (0.080) | (0.079) | (0.079) | (0.073) |
| November | 0.103* | 0.109** | 0.105** | 0.101* |
| | (0.053) | (0.052) | (0.052) | (0.053) |
| December | 0.155*** | 0.156*** | 0.153*** | 0.142*** |
| | (0.041) | (0.041) | (0.041) | (0.037) |
| **Observations** | 1,606 | 1,632 | 1,632 | 1,632 |
| $\boldsymbol{R^2}$ | 0.431 | 0.428 | 0.427 | 0.462 |
| **Adjusted** $\boldsymbol{R^2}$ | 0.420 | 0.417 | 0.416 | 0.451 |
| **F Statistic** | 79.523*** | 79.842*** | 79.549*** | 91.495*** |
| | (df=15;1574) | (df=15;1600) | (df=15;1600) | (df=15;1600) |

Note: *p<0.1; **p<0.05; ***p<0.01

Table 11. Estimation results for Fatalities and fuel prices

| Independent variables | FE (A92) | FE (A95) | FE (A95+) | FE (Autogas) |
|---|---|---|---|---|
| Log fuel price | -0.343*** | -0.338*** | -0.368*** | -0.253*** |
| | (0.115) | (0.105) | (0.115) | (0.042) |
| Log GDP | -0.022 | -0.017 | 0.009 | 0.032 |
| | (0.082) | (0.078) | (0.082) | (0.076) |
| Log average temperature | 8.758*** | 8.537*** | 8.659*** | 7.407*** |
| | (1.935) | (1.910) | (1.895) | (1.878) |
| Log total precipitation | -0.011 | -0.010 | -0.010 | -0.010 |
| | (0.010) | (0.010) | (0.009) | (0.009) |
| February | -0.326*** | -0.315*** | -0.316*** | -0.322*** |
| | (0.050) | (0.049) | (0.049) | (0.047) |
| March | -0.405*** | -0.396*** | -0.398*** | -0.383*** |
| | (0.090) | (0.090) | (0.089) | (0.086) |
| April | -0.549*** | -0.536*** | -0.543*** | -0.493*** |
| | (0.116) | (0.115) | (0.114) | (0.110) |
| May | -0.573*** | -0.554*** | -0.562*** | -0.493*** |
| | (0.134) | (0.132) | (0.130) | (0.130) |
| June | -0.636*** | -0.613*** | -0.621*** | -0.528*** |
| | (0.179) | (0.176) | (0.173) | (0.169) |
| July | -0.539*** | -0.515*** | -0.531*** | -0.443*** |
| | (0.184) | (0.178) | (0.175) | (0.169) |
| August | -0.469** | -0.445** | -0.461*** | -0.373** |
| | (0.185) | (0.180) | (0.178) | (0.173) |
| September | -0.307** | -0.280** | -0.294** | -0.221 |
| | (0.145) | (0.141) | (0.139) | (0.137) |
| October | -0.010 | 0.004 | -0.008 | 0.036 |
| | (0.100) | (0.098) | (0.096) | (0.096) |
| November | 0.147** | 0.155** | 0.145** | 0.166** |
| | (0.068) | (0.065) | (0.064) | (0.068) |
| December | 0.168*** | 0.168*** | 0.160*** | 0.171*** |
| | (0.044) | (0.042) | (0.041) | (0.044) |
| **Observations** | 1,606 | 1,632 | 1,632 | 1,632 |
| $R^2$ | 0.216 | 0.214 | 0.215 | 0.218 |
| **Adjusted** $R^2$ | 0.200 | 0.199 | 0.200 | 0.203 |
| **F Statistic** | 28.835*** (df = 15; 1574) | 29.079*** (df = 15; 1600) | 29.214*** (df = 15; 1600) | 29.722*** (df = 15; 1600) |

Note: *p<0.1; **p<0.05; ***p<0.01

Table 12. Estimation results for Injuries and fuel prices

| Independent variables | FE (A92) | FE (A95) | FE (A95+) | FE (Autogas) |
|---|---|---|---|---|
| Log fuel price | -0.220 | -0.211 | -0.211 | -0.323*** |
| | (0.158) | (0.167) | (0.176) | (0.122) |
| Log GDP | -0.086 | -0.088 | -0.080 | 0.067 |
| | (0.088) | (0.095) | (0.099) | (0.098) |
| Log average temperature | 8.686*** | 8.522*** | 8.542*** | 7.718*** |
| | (1.486) | (1.685) | (1.688) | (1.556) |
| Log total precipitation | 0.013 | 0.012 | 0.012 | 0.006 |
| | (0.010) | (0.012) | (0.012) | (0.011) |
| February | -0.244*** | -0.245*** | -0.245*** | -0.254*** |
| | (0.032) | (0.038) | (0.038) | (0.041) |
| March | -0.441*** | -0.435*** | -0.436*** | -0.429*** |
| | (0.129) | (0.134) | (0.134) | (0.119) |
| April | -0.426*** | -0.416*** | -0.417*** | -0.395*** |
| | (0.100) | (0.113) | (0.114) | (0.095) |
| May | -0.363*** | -0.349*** | -0.351*** | -0.309*** |
| | (0.111) | (0.129) | (0.130) | (0.102) |
| June | -0.400*** | -0.382** | -0.384** | -0.317** |
| | (0.132) | (0.158) | (0.158) | (0.132) |
| July | -0.326** | -0.319* | -0.323* | -0.293** |
| | (0.142) | (0.167) | (0.169) | (0.146) |
| August | -0.288** | -0.268* | -0.271* | -0.245* |
| | (0.136) | (0.157) | (0.158) | (0.136) |
| September | -0.201* | -0.187 | -0.190 | -0.166 |
| | (0.106) | (0.124) | (0.125) | (0.110) |
| October | -0.022 | -0.015 | -0.018 | -0.020 |
| | (0.080) | (0.092) | (0.093) | (0.083) |
| November | 0.052 | 0.061 | 0.058 | 0.047 |
| | (0.053) | (0.062) | (0.062) | (0.061) |
| December | 0.120*** | 0.123** | 0.120** | 0.105** |
| | (0.041) | (0.051) | (0.052) | (0.046) |
| **Observations** | 1,606 | 1,632 | 1,632 | 1,632 |
| $R^2$ | 0.386 | 0.381 | 0.381 | 0.415 |
| **Adjusted** $R^2$ | 0.374 | 0.369 | 0.369 | 0.404 |
| **F Statistic** | 65.865*** (df = 15; 1574) | 65.773*** (df = 15; 1600) | 65.576*** (df = 15; 1600) | 75.722*** (df = 15; 1600) |

Note: *p<0.1; **p<0.05; ***p<0.01

Table 13. Estimation results for Total traffic accidents with a "Shock" dummy: comparison of fuel types

| Independent variables | FE (A92) | FE (A95) | FE (A95+) | FE (Autogas) |
|---|---|---|---|---|
| Log fuel price | -0.086 | -0.060 | -0.055 | -0.185 |
| | (0.075) | (0.070) | (0.076) | (0.135) |
| Log GDP | -0.060 | -0.068 | -0.068 | 0.043 |
| | (0.072) | (0.075) | (0.075) | (0.095) |
| Log average temperature | 7.788*** | 7.570*** | 7.558*** | 7.478*** |
| | (1.349) | (1.330) | (1.328) | (1.317) |
| Log total precipitation | 0.010 | 0.012 | 0.012 | 0.008 |
| | (0.009) | (0.009) | (0.009) | (0.008) |
| Shock | -0.397*** | -0.352*** | -0.355*** | -0.221** |
| | (0.039) | (0.052) | (0.052) | (0.106) |
| February | -0.218*** | -0.219*** | -0.219*** | -0.226*** |
| | (0.030) | (0.029) | (0.029) | (0.032) |
| March | -0.369*** | -0.363*** | -0.362*** | -0.365*** |
| | (0.124) | (0.124) | (0.124) | (0.120) |
| April | -0.310*** | -0.303*** | -0.302*** | -0.325*** |
| | (0.076) | (0.075) | (0.076) | (0.077) |
| May | -0.242*** | -0.232*** | -0.231*** | -0.247*** |
| | (0.084) | (0.084) | (0.084) | (0.079) |
| June | -0.286** | -0.270** | -0.269** | -0.277*** |
| | (0.112) | (0.111) | (0.111) | (0.105) |
| July | -0.254** | -0.215* | -0.214* | -0.250** |
| | (0.123) | (0.122) | (0.122) | (0.118) |
| August | -0.217* | -0.193 | -0.193 | -0.215* |
| | (0.123) | (0.122) | (0.122) | (0.113) |
| September | -0.116 | -0.098 | -0.097 | -0.113 |
| | (0.098) | (0.097) | (0.097) | (0.090) |
| October | 0.044 | 0.056 | 0.056 | 0.033 |
| | (0.074) | (0.074) | (0.074) | (0.068) |
| November | 0.130*** | 0.139*** | 0.139*** | 0.121** |
| | (0.048) | (0.048) | (0.048) | (0.047) |
| December | 0.174*** | 0.177*** | 0.177*** | 0.160*** |
| | (0.037) | (0.038) | (0.038) | (0.034) |
| **Observations** | 1,606 | 1,632 | 1,632 | 1,632 |
| $R^2$ | 0.469 | 0.463 | 0.462 | 0.470 |
| **Adjusted** $R^2$ | 0.458 | 0.452 | 0.452 | 0.460 |
| **F Statistic** | 86.869*** (df = 16; 1573) | 86.004*** (df = 16; 1599) | 85.958*** (df = 16; 1599) | 88.732*** (df = 16; 1599) |
| Note: *p<0.1; **p<0.05; ***p<0.01 | | | | |

Table 14. Estimation results for Fatalities with a "Shock" dummy: comparison of fuel types

| Independent variables | FE (A92) | FE (A95) | FE (A95+) | FE (Autogas) | FE (Diesel) |
|---|---|---|---|---|---|
| Log fuel price | -0.291*** | -0.287*** | -0.317*** | -0.272*** | -0.294*** |
| | (0.108) | (0.103) | (0.113) | (0.075) | (0.087) |
| Log GDP | -0.042 | -0.036 | -0.013 | 0.046 | -0.005 |
| | (0.080) | (0.077) | (0.081) | (0.085) | (0.072) |
| Log average temperature | 8.476*** | 8.242*** | 8.362*** | 7.444*** | 8.251*** |
| | (1.959) | (1.939) | (1.925) | (1.867) | (1.904) |
| Log total precipitation | -0.011 | -0.009 | -0.009 | -0.011 | -0.012 |
| | (0.010) | (0.010) | (0.009) | (0.009) | (0.010) |
| Shock | -0.117** | -0.100** | -0.097** | 0.033 | -0.052 |
| | (0.048) | (0.041) | (0.041) | (0.074) | (0.049) |
| February | -0.325*** | -0.314*** | -0.315*** | -0.323*** | -0.314*** |
| | (0.050) | (0.050) | (0.050) | (0.047) | (0.050) |
| March | -0.400*** | -0.391*** | -0.392*** | -0.384*** | -0.390*** |
| | (0.091) | (0.091) | (0.090) | (0.086) | (0.089) |
| April | -0.521*** | -0.510*** | -0.517*** | -0.500*** | -0.517*** |
| | (0.119) | (0.118) | (0.117) | (0.112) | (0.117) |
| May | -0.541*** | -0.524*** | -0.532*** | -0.500*** | -0.534*** |
| | (0.138) | (0.137) | (0.135) | (0.129) | (0.135) |
| June | -0.601*** | -0.579*** | -0.587*** | -0.535*** | -0.589*** |
| | (0.181) | (0.179) | (0.177) | (0.169) | (0.177) |
| July | -0.505*** | -0.475*** | -0.491*** | -0.454*** | -0.493*** |
| | (0.186) | (0.181) | (0.179) | (0.171) | (0.181) |
| August | -0.442** | -0.417** | -0.432** | -0.379** | -0.432** |
| | (0.188) | (0.184) | (0.182) | (0.173) | (0.179) |
| September | -0.286* | -0.259* | -0.271* | -0.226* | -0.272* |
| | (0.148) | (0.144) | (0.142) | (0.136) | (0.142) |
| October | 0.005 | 0.021 | 0.009 | 0.031 | 0.008 |
| | (0.102) | (0.101) | (0.098) | (0.096) | (0.100) |
| November | 0.155** | 0.163** | 0.154** | 0.163** | 0.152** |
| | (0.068) | (0.066) | (0.065) | (0.069) | (0.065) |
| December | 0.174*** | 0.174*** | 0.166*** | 0.169*** | 0.164*** |
| | (0.044) | (0.042) | (0.042) | (0.044) | (0.042) |
| **Observations** | 1,606 | 1,632 | 1,632 | 1,632 | 1,632 |
| $R^2$ | 0.217 | 0.216 | 0.216 | 0.218 | 0.218 |
| **Adjusted** $R^2$ | 0.201 | 0.200 | 0.201 | 0.202 | 0.202 |
| **F Statistic** | 27.282*** (df = 16; 1573) | 27.470*** (df = 16; 1599) | 27.587*** (df = 16; 1599) | 27.863*** (df = 16; 1599) | 27.783*** (df = 16; 1599) |

Note: *p<0.1; **p<0.05; ***p<0.01

Table 15. Estimation results for Injured with a "Shock" dummy: comparison of fuel types

| Independent variables | FE (A92) | FE (A95) | FE (A95+) | FE (Autogas) | FE (Diesel) |
|---|---|---|---|---|---|
| Log fuel price | -0.030 | -0.005 | 0.002 | -0.173 | -0.083 |
| | (0.083) | (0.076) | (0.082) | (0.147) | (0.080) |
| Log GDP | -0.157** | -0.166** | -0.170** | -0.041 | -0.126* |
| | (0.073) | (0.075) | (0.075) | (0.097) | (0.069) |
| Log average temperature | 7.654*** | 7.346*** | 7.321*** | 7.428*** | 7.601*** |
| | (1.547) | (1.543) | (1.545) | (1.522) | (1.557) |
| Log total precipitation | 0.013 | 0.014 | 0.014 | 0.009 | 0.011 |
| | (0.011) | (0.011) | (0.011) | (0.010) | (0.011) |
| Shock | -0.429*** | -0.398*** | -0.400*** | -0.260** | -0.361*** |
| | (0.038) | (0.042) | (0.041) | (0.116) | (0.050) |
| February | -0.241*** | -0.240*** | -0.240*** | -0.247*** | -0.241*** |
| | (0.036) | (0.035) | (0.035) | (0.039) | (0.035) |
| March | -0.424*** | -0.414*** | -0.414*** | -0.420*** | -0.418*** |
| | (0.128) | (0.129) | (0.129) | (0.125) | (0.129) |
| April | -0.324*** | -0.310*** | -0.308*** | -0.341*** | -0.328*** |
| | (0.094) | (0.094) | (0.094) | (0.094) | (0.094) |
| May | -0.248** | -0.229** | -0.227** | -0.256** | -0.250** |
| | (0.103) | (0.104) | (0.105) | (0.100) | (0.105) |
| June | -0.272** | -0.245* | -0.243* | -0.265** | -0.269** |
| | (0.135) | (0.136) | (0.136) | (0.130) | (0.137) |
| July | -0.204 | -0.160 | -0.157 | -0.212 | -0.193 |
| | (0.147) | (0.147) | (0.147) | (0.143) | (0.149) |
| August | -0.189 | -0.156 | -0.154 | -0.195 | -0.187 |
| | (0.144) | (0.144) | (0.145) | (0.134) | (0.144) |
| September | -0.124 | -0.100 | -0.098 | -0.128 | -0.125 |
| | (0.115) | (0.116) | (0.116) | (0.108) | (0.115) |
| October | 0.035 | 0.050 | 0.052 | 0.017 | 0.030 |
| | (0.087) | (0.087) | (0.087) | (0.081) | (0.086) |
| November | 0.081 | 0.095 | 0.096* | 0.071 | 0.082 |
| | (0.057) | (0.058) | (0.058) | (0.055) | (0.057) |
| December | 0.140*** | 0.147*** | 0.148*** | 0.125*** | 0.136*** |
| | (0.048) | (0.048) | (0.048) | (0.043) | (0.047) |
| **Observations** | 1,606 | 1,632 | 1,632 | 1,632 | 1,632 |
| $R^2$ | 0.424 | 0.419 | 0.419 | 0.425 | 0.420 |
| **Adjusted** $R^2$ | 0.412 | 0.407 | 0.407 | 0.414 | 0.409 |
| **F Statistic** | 72.284*** (df = 16; 1573) | 72.100*** (df = 16; 1599) | 72.099*** (df = 16; 1599) | 73.972*** (df = 16; 1599) | 72.448*** (df = 16; 1599) |

Note: *p<0.1; **p<0.05; ***p<0.01