INFLUENCE OF WAR ON GENERAL PRACTITIONER VISITS IN UKRAINE

by

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Kyiv School of Economics

Abstract

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The Russian full-scale invasion of Ukraine has affected many spheres of life, including healthcare. Ukraine is undergoing active healthcare reforms, transitioning from Soviet-type systems to more efficient ones. It's important to monitor and respond to changes under these difficult conditions. This paper aims to understand the effects of war on the utilization of general practitioners, while controlling for various socioeconomic and demographic factors, as well as reasons for visits. Based on the results, policy recommendations will be suggested to address potential healthcare disruptions.

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LIST OF ABBREVIATIONS

GP. General practitioner.

Chapter 1

INTRODUCTION

Ukraine has a hybrid healthcare system which contains the public and private health provisions. Healthcare is financed through the State Budget, that guarantees the provision of basic health services to the population. Moreover, an alternative private sector of healthcare system is operating, and people can use it for more personalized and advance medical services. Healthcare faces the challenges including scarce financial sources, outdated infrastructure, and the disparities in the care quality between large cities and villages.

The general practitioners (GPs) in Ukraine are medical specialists who serve as the first line of treatment in the healthcare system. There are several types of general practitioners in Ukraine: family physicians, therapeutists, and pediatricians. They are the first people who consults the individuals with medical problems, providing default range of general healthcare services. Generally, GPs are asked about the most frequent health conditions, preventative care and the baseline consultations. GPs are accountable for primary healthcare of the individual that covers all aspects namely managing and coordinating a patient's overall healthcare and referring them to specialists when necessary so as to ensure continuity of care.

The healthcare system in Ukraine has changed dramatically since the 24 of February, 2022. The latest data from the World Health Organization indicates that around 50 % of primary healthcare facilities are experiencing staff shortages because of the war, but most continues to provide essential health services with a limited number of healthcare workers. In two-thirds of institutions the amount of services is affected by low number of visitors in some regions, while there is an increase in other regions. The majority of the surge services were related to providing short-term care for non-registered patients and replacing regular units due to hostilities. However, healthcare facilities are being restored, and the Ukrainian Government has maintained its implementation of health reforms, which aims to make the health system more efficient and patient-centred.

This hard context evokes the importance of optimized use of resources within the health care system. War-related consequences, including an increase in trauma, stress disorders and healthcare services' demand, are forecastable in the near future. Hence, we have to establish the factors that form and shape the GPs services statistics. Consequently, health care providers and policy makers should be able to set their priorities based on these numbers. As a result, those who need urgent and thorough care will be helped promptly and efficiently.

Understanding healthcare utilization pre and post-invasion is not only crucial to meet the immediate health needs of the population but also for guiding long-term policy decisions. This thesis will identify and discuss how war affected GP visits in Ukrainian regions that directly faced Russian aggression in 2022. This paper uses face-to-face poll data of people who has visited GP's in 2019 and 2022/2023 years. Number of observation is enough to receive robust results. The variables like age, gender, reason for visiting, type of settlement and inclusion in the vulnerable groups are analyzed in order to understand the impact of war on the frequency of monthly GP service visits. The difference-in-difference model is appropriate way to evaluate the difference between two groups through the time period. As treatment group were chosen regions if Ukraine that had encountered direct Russian aggression in 2022 year. As control groups are all others regions of Ukraine. The interaction term shows how changed monthly number of visits to GPs in attacked regions.

General results showed significant negative results what means that there is an evidence of decreasing monthly number of GPs in regions that affected by direct ground fighting in 2022 year compering to 2019 year. These results appeared to be opposite to the main thesis hypothesis that number of visits to GPs significantly increased due to spillovers of full-scale war. According to these results it was suggested couple of possible reasons and policy implication of appeared healthcare problems.

C h a p t e r 2

LITERATURE REVIEW

The full-scale war, despite all the tragedy, is such a big event in the lifetime of each society that it affects almost all aspects of life. It provides the opportunity for economists across the world to examine various changes in different spheres of life under war conditions. The most popular topics are related to direct economic and health consequences, human resources changes, or societal changes. Researches that narrow on the effects of war on healthcare utilization are not often encountered, because wars like the Russian-Ukrainian happen rarely. If we look at the evaluation of healthcare utilization without the effect of war, we can observe that it occupies a crucial place in the field of research. Scientists from many disciplines are investing their time and knowledge trying to find out what makes people's way of seeking and using medical care so complex. Researches in healthcare utilization cover a wide range of studies such as healthcare seeking behavior, service use across demographic categories, assessing the influence of socio-economic status on access to care, and evaluating the effectiveness of healthcare interventions aimed at improving healthcare utilization. Despite these works not estimating the direct effects of wars on healthcare utilization, they can be helpful for this paper in understanding the possible list of explanatory variables and dependent variables.

The work of Fylkesnes (1993) is based on the regression modeling of determinants of GP visits and referrals (both outpatient and hospitalization) in Northern Norway. The number of primary care visits, any kind of referral services use, and hospitalization are considered as the dependent variables for regression analysis. Logistic model was applied for the hospitalization and referral services use, and simple OLS regression for the visits to a GP. The following variables were used as independent variables in the GP visits model: Educational attainment, Town, Employment status, Cohabitation/marriage, Household size, Leisure physical activity, Smoking, Serum cholesterol, Preoccupation with health, Own control over health, Tendency to consult GP, Self-rated health, Neck/shoulder and headache, Chest pain and stomachache, Chronic disease, Banal infections.

Admas Jabulani, and Levin (2017) collected data on healthcare utilization in South Africa. They employed simple Ordinary Least Squares (OLS) regression with the dependent variable being the number of people seeking healthcare. Demographic and socio-economic information about the surveyed individuals were utilized as independent variables. The primary objective of the research was to inform the development or modification of healthcare policies. This was done in order to identify potential challenges and, if necessary, to create appropriate interventions.

Admas, Ncayiyana, and Levine (2017) did a survey on health care usage in South Africa. OLS regression was applied to acquire the dependent variable which is the number of people seeking medical attention. The demographic and socio-economic backgrounds of the studied people were treated as independent variables. The main goal of the research was guiding the existing or instituting new policies in healthcare. This was done in order to identify potential challenges and, if necessary, to create appropriate interventions.

Hoerster, Mayer and Gabbard (2011) did a study on healthcare utilization of farmworkers. They calculated health service utilization given different demographic and socioeconomic factors. The authors used logit model in their research. This dedication derives from the realization that agricultural workers represent a highly vulnerable population, with a high rate of disease occurrence and mortality.

These studies employ different statistical methods to investigate healthcare utilization, utilizing various demographic and socio-economic factors as independent variables. It sheds light on the usage of various variables in healthcare utilization. These insights will be used further in selecting variables for this research. However, while these works are interesting for examining different approaches to studying healthcare utilization and the sets of variables used in their analyses, none of them provide a suitable method to estimate the effect of war on visits to GPs in regions affected by Russian aggression.

My work aims to estimate the effect of a shock event on two different groups: those who encountered direct Russian aggression and those who did not, using various socio and demographic variables. Therefore, Obrizan's (2022) study, which applies a difference-in-difference model to estimate the impact of the Russian-Ukrainian full-scale war on various socio-economic indicators such as extreme poverty, unemployment, and displacement, is the most likely candidate for applying the method of study to my work. Obrizan's analysis focused on understanding how these indicators changed in response to the conflict, particularly in regions directly affected by ground attacks compared to those not directly affected. The author considered regions that encountered direct invasion as the treatment group and those that did not as the control group. Research revealed that people were more likely to lose their jobs as a result of invasion and migration. In areas with ground fighting, women who did not have higher education had a higher risk of not having enough money for food. Women and men with lower education were more likely to be jobless in regions where the ground attacks occurred. Despite the higher education, women were at the higher risk of poverty and unemployment. Nevertheless, this paper investigates a non-health utilization related topic. It provides a good example of a method of estimating the effects of war on different indicators.

Generally, researchers use different methods of regression analysis to understand the factors affecting healthcare utilization. The dependent variable is often the number of visits to healthcare facilities, and the explanatory variables comprise different combinations of demographic, socioeconomic, and health-related information. Given that papers on the effects of war on healthcare utilization are encountered rarely, Obrizan's (2022) study is considered to offer a good approach to assessing such research.

Chapter 3

METHODOLOGY

As mentioned in the Literature Review chapter, many other studies estimate factors that influence healthcare utilization. For this purpose, linear regression or logistic regression are the most appropriate methods for estimation. However, in the case of evaluating the differences between two groups over two years of observation, these methods may not be suitable. Therefore, to understand how Russian aggression affected the monthly visits to GPs in attacked regions between 2019 year and 2023 year, it was decided to employ a difference-in-difference (DID) methodology. The primary inspiration for choosing this approach was borrowed from Obrizan's (2022) paper. The DID methodology is a useful econometric tool for estimating causal effects when a treatment, intervention, or shock is present in observational data. In our case, DID allows us to estimate the causal impact of Russian aggression on GP visits by comparing changes in visits over time between regions directly affected by the war and those that were not, while controlling for other factors. The model representation and description of variables discussed below:

$$Y_{i,t} = const + a_1 \cdot X_{i,t} + a_2 \cdot y2023 + a_3 \cdot Attacked\_Oblast + a_4 \cdot y2023 \cdot Attacked\_Oblast + u_{i,t} \quad (1)$$

The dependent variable $Y_{i,t}$ is number of visits made to GP per month.

$X_{i,t}$ is vector of independent variables that will encompass a range of personal information about the patient:

- Age of the patient
- Gender
- Type of settlement
- Reason for the patient's visit
- Belonging to one of the vulnerable groups

The model includes 22 explanatory variables and one dependent variable.

a_1 reflects the impact of various personal characteristics, such as age, gender, settlement type, and medical institution type, on the number of GP visits.

$y2023$ is dummy variable for year, where 1 stands for 2023 year and 0 for 2019 year. a_2 captures the overall change in GP visits between 2019 and 2023, providing insight into the general trend over the specified period.

The $Attacked\_Oblast$ variable takes a value of 1 when the patient's Oblast was attacked by Russia in 2022 and 0 when it was not. The Kyiv, Luhansk, Donetsk, Chernihiv, Mykolaiv, Sumy, Kharkiv, Kherson, and Zaporizhzhia regions experienced a direct invasion in 2022. These regions will be our Treatment group. The treatment and control groups were compiled similarly to Obrizan's (2022) paper. a_3 represents the baseline effect of living in an Oblast that experienced direct fighting on the ground in 2022, irrespective of the year. The Zhytomyr region was not included in the treatment group due to experiencing minimal intrusion and destruction.

a_4 captures the interaction effect of living in an attacked Oblast in 2023 compared to 2019, providing insights into how the conflict's impact on GP visits may differ between the two years.

$u_{i,t}$ is the error term that represents unobserved factors influencing GP visits.

The DiD methodology relies on comparing changes in outcomes over time for both treatment and control groups. By comparing changes in GP visits from 2019 to 2023, we can assess whether there were any differences in trends between regions affected by the war and those that were not.

The null hypothesis states that the number of visits to GPs of those residing in an Oblast that faced direct ground aggression by Russia in 2022 did increased. The hypothesis is based on the perception that armed conflict may have substantial impacts on the health-seeking behavior of the people. Aspects like physical injuries, mental health problems, and disruptions to healthcare infrastructure might result into variations in the amount of GP visits.

Chapter 4

DATA

The primary data source comprises face-to-face surveys conducted in the years 2019 and 2023 on individuals who consulted a GP, encompassing all regions except those under Russian occupation. The surveys collected information on socio-demographic details of patients and other information related to healthcare utilization, including the count and reasons for their visits to the GP.

Initially, these datasets were utilized for the research on "Assessment of primary health care provider behavior in response to the implementation of capitation" conducted by the KSE Institute and USAID. The study consists of two reports: one from 2019 and another from 2023.

The 2019 dataset comprises 2108 observations with 141 variables, while the 2023 dataset includes 1755 observations with 138 variables.

The research focuses on the following variables:

- Number of visits to a GP per month
- Patient's age
- Administrative division or region (Oblast)
- Gender of the patient
- Type of settlement
- Reason for the patient's visit
- Inclusion in any vulnerable groups.

In the 2019 dataset, the number of visits to GP by patients was recorded over a period of nine months (from January 1, 2019, to August 31, 2019), whereas in the 2023 dataset, the same parameter was measured over a one-year period (from July 1, 2022, to June 30, 2023). Due to the differing time intervals over which the number of visits was calculated, it was decided to include the monthly count of visits as an independent variable in the model.

The dataset encompasses all age and gender categories of patients from all regions of Ukraine, excluding the Crimean Peninsula in 2019, and Crimea, Luhansk, and Kherson regions in 2023. These regions were excluded from the study due to the complete occupation of these territories by Russia. All patients were surveyed at primary healthcare centers.

After excluding unnecessary variables for the study and data cleaning, the final combined dataset of the two years comprises 3693 observations and 36 variables, with 1675 observations from the year 2023 and 2018 observations from the year 2019.

This section describes the variables included in the dataset along with their descriptive statistics. Additionally, the expected signs of each variable will be discussed. The following variables are represented in the model:

- *y2023* serves as a binary indicator variable, assuming the value of 1 if the observation refers to the year 2023 and 0 otherwise. It is expected that the variable will have a positive coefficient because we suppose that people will make more visits to GPs due to war spillovers.
- *Attacked Oblast* is a binary variable that takes the value 1 to indicate whether the patient resides in regions that encountered direct Russian aggression, 0 otherwise. The same coefficient is expected for a similar reason as for *y2023*.

Table 1. The number of observations for the years 2019-2023 and Attacked/Non-Attacked Regions.

Summary Statistics

Statistic	N
2023	1675
2019	2018
Attacked Regions	1286
Non-Attacked Regions	2407

- *number of visits per month* represents the count of visits made by patients to their general practitioner per month. It is a model-dependent variable, so there is no need to discuss its sign.
- *age* – numeric variable that denotes the age of the patient. It is expected that with an increase in age, the number of visits increases. So, the sign is positive.

Table 2. Descriptive statistics for age and number of visits of GP per month from the dataset for Attacked/Non-Attacked Regions.

Summary Statistics – Attacked Regions

Statistic	Mean	SD	Min	Max
age	45.59	20.35	1.00	97.00
number of visits per month	0.77	0.93	0.00	18.00

Summary Statistics – Non-Attacked Regions

Statistic	Mean	SD	Min	Max
age	43.28	22.15	0.50	97.00
number of visits per month	0.86	0.89	0.00	13.33

The mean age in attacked regions is slightly higher than in non-attacked regions by about 2.31 years. The mean number of visits per month in attacked regions is slightly lower than in non-attacked regions by about 0.09 visits. In the attacked regions, the maximum number of visits is 18, while in non-attacked regions, it is 13. The range of *age* variables is similar for both groups.

In summary, people who visit GPs in attacked regions tend to be slightly older compared to those in non-attacked regions. Additionally, they tend to have slightly fewer visits per month on average compared to those in non-attacked regions. The difference between attacked and non-attacked oblasts is 0.11 visits per month. It is considered significant when compared to the total mean of visits to GPs per month.

- *male* is a binary variable denoting the gender of the patient, taking the value of 1 if the patient is male and 0 otherwise. Expected sign of the coefficient is negative; men tend to have fewer visits to healthcare services.
- *town with population bigger 100k* is a binary variable indicating whether the patient resides in an urban area with a population exceeding 100,000 individuals.
- *town with population bigger 20k and less 100k* is a binary variable indicating whether the patient lives in an urban area with a population ranging between 20,000 and 100,000 individuals.
- *village* is a binary variable signifying whether the patient resides in a rural village with a population of fewer than 20,000 individuals.

Table 3. Descriptive statistics for gender and type of settlement from the dataset for Attacked/Non-Attacked Regions.

Summary Statistics – Attacked Regions

Statistic	Mean	SD
male	0.34	0.47
town with population bigger 100k	0.39	0.49

town with population bigger 20k and less 100k	0.25	0.44

Table 3. Descriptive statistics for gender and type of settlement from the dataset for Attacked/Non-Attacked Regions – Continued

Statistic	Mean	SD
village	0.35	0.48

Summary Statistics – Non-Attacked Regions

Statistic	Mean	SD
male	0.33	0.47
town with population bigger 100k	0.15	0.36
town with population bigger 20k and less 100k	0.21	0.41
village	0.64	0.48

In attacked regions, 34% of the population is male, while in non-attacked regions, this proportion is 33%. Meanwhile, there is no difference in the proportion of males between attacked and non-attacked regions. However, it can be observed that there is a significant displacement towards the female group as visitors of GPs. 66-67% of people who visited GPs are female for both groups. This fact can signify that the assumption about the sign of the male coefficient—that men tend to have fewer visits—is true.

In attacked regions, the largest proportion of patients resides in larger urban areas (towns with a population exceeding 100,000 individuals), and the smallest proportion comprises patients who live in small towns (towns with a population between 20,000 and 100,000 individuals). Conversely, in non-attacked regions, the highest proportion of patients resides in rural villages, while the smallest proportion consists of people who live in big towns. These facts can be explained by the attacked group including the most populated oblasts (Kyiv, Kharkiv, and Donetsk oblasts) and cities (Kyiv and Kharkiv).

town with population bigger 100k, *town with population bigger 20k and less 100k* and *village* are part of categorical variable divided into these three dummy variables. Therefore, coefficients will show differences compared to the reference group. *village* was chosen as the reference group. It is expected that all town variables will have a positive sign, indicating that people living in towns have more visits to GPs compared to those who live in villages.

The next set of variables comprises reasons for visits to GPs. This set includes 7 different variables.

- *regular visit* – a binary variable that takes the value 1 if the reason for the visit was a regular appointment to the doctor, and 0 otherwise.
- *acute symptoms* – a binary variable that takes the value 1 if the reason for the visit was acute symptoms of illness, and 0 otherwise.
- *prescription* – a binary variable that takes the value 1 if the reason for the visit was to obtain a prescription for medication, and 0 otherwise.
- *to get a document* – a binary variable that takes the value 1 if the reason for the visit was to obtain a certificate or document, and 0 otherwise.
- *other questions* – a binary variable that takes the value 1 if the reason for the visit was other questions for the doctor, and 0 otherwise.
- *appointment* – a binary variable that takes the value 1 if the reason for the visit was to schedule an appointment with the doctor, and 0 otherwise.
- *take tests* – a binary variable that takes the value 1 if the reason for the visit was to undergo tests or collect test results, and 0 otherwise.

All coefficients on these variables are expected to have a positive sign. The expectation of positive coefficients arises from the assumption that each type of visit, as captured by the binary variables, contributes positively to the dependent variable.

Table 4. Descriptive statistics for reasons of a visit from the dataset for Attacked/Non-Attacked Regions.

Summary Statistics – Attacked Regions

Statistic	Mean	SD
regular visit	0.18	0.39
acute symptoms	0.29	0.45
prescription	0.09	0.29
to get a document	0.12	0.32
other questions	0.12	0.32
appointment	0.04	0.20
take tests	0.10	0.30

Summary Statistics – Non-Attacked Regions

Statistic	Mean	SD
regular visit	0.20	0.40
acute symptoms	0.31	0.46
prescription	0.08	0.28
to get a document	0.11	0.31
other questions	0.16	0.37
appointment	0.01	0.12
take tests	0.07	0.26

Both groups exhibit a similar distribution of means regarding their reasons for visiting GPs. This suggests that the behavior patterns of individuals from both attacked and non-attacked regions are equal.

The last and largest set of variables indicates whether the patient is in one or more of the vulnerable groups. This set consists of 10 variables.

- *military serviceman* – a binary variable that takes the value 1 if the patient is an active military serviceman, and 0 otherwise.
- *participant in hostilities* – a binary variable that takes the value 1 if the patient is a participant in hostilities, and 0 otherwise.

- *participant in war* – a binary variable that takes the value 1 if the patient is a participant in war, and 0 otherwise.
- *have large family* – a binary variable that takes the value 1 if the patient is a member of a large family, and 0 otherwise.
- *without residence* – a binary variable that takes the value 1 if the patient is without a defined place of residence, and 0 otherwise.
- *without employment* – a binary variable that takes the value 1 if the patient is without permanent employment, and 0 otherwise.
- *national minority* – a binary variable that takes the value 1 if the patient belongs to a national minority, and 0 otherwise.
- *have less than minimal payment* – a binary variable that takes the value 1 if the net income per family member of the patient is less than the minimum wage. For 2019, the minimum wage amount is 4173 hryvnias, and for 2023, it is 6700 hryvnias.
- *displaced person* – a binary variable that takes the value 1 if the patient is an internally displaced person after 24.02.2022, and 0 otherwise.
- *relative was/is soldier* – a binary variable that takes the value 1 if the patient's first-degree relative (spouse/children/parents) has/had participated in the war with Russia as a military serviceman.

Coefficients on such variables as *military serviceman, participant in hostilities, participant in war, chronic disease,* and *relative was/is soldier* are expected to be positive because people who belong to these groups have or probably have some health issues. Meanwhile, coefficients of variables such as *having a large family, being without residence, being without employment, belonging to a national minority, having less than minimal payment,* and *being a displaced person* are expected to have negative signs. This is caused by the disability to reach healthcare facilities or the poor financial situation for treatment.

It is important to mention that vulnerable group variables are not part of categorical variables. Therefore, there is no need to choose a reference group.

Table 5. Descriptive statistics for vulnerable groups of a visit from the dataset for Attacked/Non-Attacked Regions.

Summary Statistics – Attacked Regions

Statistic	Mean	SD
military serviceman	0.01	0.12
participant in hostilities	0.005	0.07
participant in war	0.01	0.11
have large family	0.01	0.10
without residence	0.001	0.03
without employment	0.02	0.13
national minority	0.001	0.03
have less than minimal payment	0.16	0.37
displaced person	0.01	0.12
relative was/is soldier	0.02	0.13

Summary Statistics – Non-Attacked Regions

Statistic	Mean	SD
military serviceman	0.01	0.10
participant in hostilities	0.002	0.05
participant in war	0.01	0.08
have large family	0.03	0.18
without residence	0.001	0.04
without employment	0.01	0.12
national minority	0.01	0.10
have less than minimal payment	0.23	0.42
displaced person	0.01	0.11
relative was/is soldier	0.03	0.17

The distribution of means among vulnerable groups across attacked and non-attacked regions is nearly identical for all variables. The most significant difference is observed among individuals with less than minimal payment. In attacked oblasts, the mean for this variable is 0.16, whereas for non-attacked regions, it is 0.23 — a difference of 0.07. This can be explained by the fact that the non-attacked group comprises the largest proportion of people living in villages, while the attacked group has the highest proportion of individuals residing in big cities.

In conclusion, all variables were chosen according to two stages. The first one is to avoid endogeneity. Variables that indicate direct health states such as disability of different groups, having diabetes, tuberculosis, HIV/AIDS, or pregnancy were excluded from the analysis because they are considered to be endogenous. In the second stage, a bunch of mainly socioeconomic, demographic, and reasons for visit variables were selected. Almost all these variables were used in papers by other authors for research on healthcare utilization. Variable selection according to these stages will allow us to estimate the effect of war while controlling for socioeconomic, demographic factors, and reasons for visit.

Chapter 5

ESTIMATION RESULTS

Three regression models were estimated for investigation. *Model 1* includes the most variables, while *Model 2* excludes vulnerable groups and *Model 3* further excludes reasons for visit. Running several iterations of regression with different numbers of independent variables is very important for analysis. This happens for two reasons: first, it allows us to explore the dependent variable in combination with various independent variables, enabling us to identify which combination of the independent variables best explains the variation of the dependent variable; second, it helps to test different specifications what can test the robustness and stability of our findings, ensuring reliable and generalizable regression results. In the context examining the effects of war on GP visits using a DID regression, iterating over different models will help to robustly estimate the causal impact of the conflict while controlling for other factors that might influence healthcare utilization. It ensures that the results are reliable and can be attributed specifically to the war's impact rather than other unaccounted variables.

Table 6. Estimation results for three iterations of model

	Model 1:	*Model 2*:	*Model 3*:
	number of visits p.m.	*number of visits p.m.*	*number of visits p.m.*
y2023:Attacked Oblast	-0.168*** (0.062)	-0.171*** (0.062)	-0.147** (0.062)
Attacked Oblast	-0.062 (0.041)	-0.072* (0.041)	-0.080* (0.041)
y2023	-0.167*** (0.039)	-0.175*** (0.038)	-0.175*** (0.037)
male	-0.162*** (0.032)	-0.157*** (0.031)	-0.163*** (0.031)

Table 6. Estimation results for three iterations of model – Continued

	Model 1:	*Model 2*:	*Model 3*:
	number of visits p.m.	*number of visits p.m.*	*number of visit s p.m.*
age	0.001 (0.001)	0.002** (0.001)	0.002*** (0.001)
Constant	0.951*** (0.082)	0.989*** (0.081)	0.956*** (0.043)
town with population bigger 100k	-0.074* (0.038)	-0.084** (0.038)	-0.082** (0.038)
town with population bigger 20k and less 100k	-0.096** (0.037)	-0.103*** (0.037)	-0.111*** (0.037)
regular visit	0.170** (0.073)	0.155** (0.073)	
acute symptoms	-0.047 (0.071)	-0.060 (0.071)	
prescription	0.039 (0.081)	0.032 (0.081)	
to get a document	-0.063 (0.080)	-0.082 (0.080)	
other questions	-0.100 (0.076)	-0.120 (0.076)	
appointment	-0.044 (0.116)	-0.055 (0.116)	
take tests	0.092 (0.083)	0.084 (0.083)	
military serviceman	-0.210 (0.211)		
participant in hostilities	0.478* (0.259)		
participant in war	0.245 (0.240)		
have large family	0.069 (0.095)		
without residence	0.288 (0.451)		
without employment	0.065 (0.123)		
national minority	-0.147		

(0.184)

Table 6. Estimation results for three iterations of model – Continued

	Model 1: number of visits p.m.	*Model 2*: number of visits p.m.	*Model 3*: number of visits p.m.
have less than minimal payment	0.111*** (0.039)		
displaced person	0.024 (0.133)		
relative was/is soldier	0.131 (0.096)		
Observations	3,693	3,693	3,693
R^2	0.052	0.036	0.036
Note:	*p<0.1; **p<0.05; ***p<0.01		

The coefficient in *Model 1* for the interaction term *y2023:Attacked Oblast* is a statistically significant variable at the 1% level, the coefficient for this variable shows that being in an attacked oblast in 2023 has a significant effect on the number of visits to a GP. The decrease of visits to a GP per month in an attacked Oblast in the year 2023 compared to a non-attacked Oblast in the same year is 0.168, assuming other factors being equal.

Similar to *Model 1*, the coefficient in *Model 2* for the interaction term *y2023:Attacked Oblast* : is statistically significant at the 1%. It is estimated that the occurrence of Russian aggression on Oblast in 2023 reduces the number of visits to a GP by 0.171 per month, compared to the situation in the non-attacked Oblast in the same year, all other conditions remaining the same.

The pattern in *Model 3* is consistent with the previous models, with the coefficient for the interaction term *y2023:Attacked Oblast* was found to be statistically significant at the 5% level significance. Once again, in 2023, the number of visits to a GP per month is reduced by 0.147 in the attacked Oblast, compared to when they are in the non-attacked one in the same year keeping other factors equal.

The actual sign across three models is opposite to the expected one. This fact contradicts the main hypothesis that residing in an attacked oblast increases the number of monthly visits to GPs. Possible reasons for such findings will be discussed in the conclusions. Talking about magnitude, being in an attacked oblast decreases monthly visits by 0.147-0.171. Considering that the mean of visits in Attacked Oblasts is 0.86, this decrease is notable.

The negative coefficients value of (*Model1, Model2, Model3*) = (-0.167, -0.175, -0.175) of *y2023* variable, implies that the GP visits in the year 2023 will be less than that of the 2019 year, holding all other variables constant. The coefficients of this model are statistically significant at $p<0.01$, implying a strong relationship between the year 2023 and the number of GP visits.

The similar situation with the sign occurred for *y2023*. It was expected to see an increase in monthly visits, but in fact, the results show a general decrease in the number of visits. The magnitude also indicates a significant decrease compared to the mean of visits to GPs.

It seems that coefficient of *Attacked Oblast* in all the three models are not statistically significant at 5% level. It is thus possible to say that at the moment there is not enough evidence to make a conclusion that being in a treated group will lead to an increase in the number of visits to a GP.

The coefficient for *male* is negative (*Model1, Model2, Model3*) = (-0.162, -0.157, -0.163) for all three models, showing that being male is a factor that decreases the probability of visiting a GP if compared with being female. The coefficients are statistically significant at $p<0.01$ in all models, and the relationship between gender and the number of GP visits is robust in all models.

The magnitude of the *male* coefficient compared to the mean of GP visits appeared to be notable and to have the expected sign. Therefore, men have a significant difference in visits compared to women.

In *Model 1* the coefficient for *age* is not statistically significant at the 5% level. In contrast, the coefficient for *age* is statistically significant in Models 2 and 3. The positive coefficient indicates that, as a person becomes older, they are more likely to have more visits to a GP, while other factors are held constant. Age did not demonstrate robust relationship, nevertheless sign appeared to be expected.

Constant coefficient represents the baseline value of the monthly visits of GPs for the people who lives in villages. This coefficient is significant with $p<0.01$ in all three models, which indicates robust relationship. The sign is positive in all three models and coefficient equals (*Model1, Model2, Model3*) = (0.951, 0.989, 0.956). *town with population bigger 100k* coefficient is not significant in *Model 1* results and is significant with $p<0.05$ in *Model 2* and *Model 3*, what implies that there is no robust difference across all models with reference group - *village*. People who lives in towns with population bigger than one hundred thousand have approximately the same number of GP visit per month as people who lives in villages. Meanwhile, *town with population bigger 20k and less 100k* coefficient is significant with $p<0.05$ across all three models. It indicates robust difference with *village* group. Generally, people who lives in towns with population bigger than twenty thousand but less than one hundred thousand tend to have less visits to GP. Magnitudes across three models are (*Model1, Model2, Model3*) = (-0.096, -0.103, -0.111). The sign of *town with population bigger 20k and less 100k* coefficient is opposite to expected one. It indicates that initial hypothesis that people who lives in town towns with population bigger than twenty thousand but less than one hundred thousand appeared to be wrong.

In both *Model 1* and *Model 2*, *regular visit* is significant at the 0.05 level, demonstrating that it has a significant influence on the number of GP visits monthly. In *Model 1*, the coefficient is 0.170, which implies a statistically significant positive impact. It indicates that individuals who go to the healthcare facilities frequently have, on average, 0.170 additional visits to GP per month compared to those who do not go there regularly. The sign of coefficient meets expectations.

In *Model 2*, the coefficient for *regular visit* also slightly decreases to 0.155. However, the effect still remains statistically significant. Staying positive, regular visitors have 0.155 more visits per month on average than non-regular visitors. Similarly to *Model 1*, the sign of coefficient is expected.

The *have less than minimal payment* coefficient is statistically significant at the 0.01 level in *Model 1*, it indicates that receiving less than minimal payment has a significant impact on the number of visits to the GP per month. The 0.111 coefficient suggests that individuals in this category tend to have a higher number of visits to the GP compared to those who do not receive less than minimal payment. The direction of coefficient is unexpected. It was supposed that due to low income it is less affordable to have treatment.

The variables that were not mentioned are considered insignificant. The insignificance of these variables implies that they do not have a statistically significant impact on the number of visits to the GP per month.

The analysis of three models that are examining the impact of war on GPs` visits demonstrated the few crucial outcomes. There is a steady significant interaction effect between having an attacked oblast in 2023 and the year itself. It implies that in 2023, GP visits declined notably in some regions after Russian attacks on these regions. There is also a general and significant tendency to have fewer visits to GPs in the 2023 year. In addition, all models showed that males are less likely to go to the GP compared to females. The *age* variable does not present statistical significance in *Model 1*, which means that the other variables mask the effect of age on GP visits. Nevertheless, in *Model 2* and 3 age become significant, and a positive coefficient which indicates that the older the individual, they tend to visit GP more often is observed when other factors are held constant. Age as a predictor requires more precise investigation to examine the robustness of the relationship with GP visits. It was decided not to include age in the results. Moreover, the number of their monthly visits is higher among people who visit GPs due to regular reasons and have less than minimum payment.

After receiving the results, we should ensure that they are robust. A robustness check for a difference-in-difference model consists of two stages. The first stage involves running the model while specifying different control variables. This step has already been conducted. The interaction term remained significant at the $p < 0.05$ level in all three models. The second stage is to ensure that the trends for the control and treatment groups are parallel. This is a core assumption of the difference-in-difference model: that in the absence of treatment, the treatment and control groups would have followed similar trends over time. To check this fact, a placebo test could be used, but to conduct it, the data should have at least two different years of pretreatment observations. A placebo test implies choosing a time period before the treatment was implemented and pretending the treatment occurred during this placebo period. Then, run the model as if the treatment had occurred during this placebo period. But it can be suggested that in the absence of Russian full-scale aggression, the control and treatment groups would have moved in the same directions. There were preconditions for this statement. Ukrainian reforms and development were trying to be implemented uniformly across the country, in the case of healthcare too. Additionally, there were no significant events that caused changes in one part of Ukraine while the other part was not affected.

Chapter 6

CONCLUSIONS AND POLICY RECOMMENDATION

The health outcomes among the population are significantly at risk due to the main findings about the effects of attacks on GP visit frequency in Ukrainian regions that encountered direct Russian aggression. It was discovered that people residing in those regions experience a significant decrease in visits to GPs compared to the year 2019. This could result in people not accessing healthcare when they need it, which can have a negative effect on their health. The decrease in GP visits can also cause misdiagnosis in some patients and delay their medical treatment for acute or chronic diseases, thereby widening health inequalities and raising the likelihood of complications for those affected. It should also be noted that there was a general tendency of decreasing visits to GPs in 2023 compared to 2019. Similarly to the main findings, reduced GP visits in 2023 have health consequences, including possible delays in diagnosis and treatment.

Moreover, it is important to pay attention to results that show the differences across different socio-economic groups. For instance, males tend to have fewer visits to GPs than females. One reason could be that men do not prioritize preventative care and early detection. As a result, cases of unidentified illnesses could arise, leading to reduced opportunities for health promotion and systemic ill-health among male inhabitants. Another group is individuals who receive less than minimal payment. They tend to visit GPs more than people who receive more than minimal payment. This fact can indicate that people with poor living conditions suffer from more health issues and need more frequent healthcare utilization. Additionally, people who noted that their reason for visit is a regular visit to the GP tend to have significantly more visits. This result seems logical and expected.

Health security issues associated with continued conflicts or threats of violence. People fear being attacked when they move to health care facilities or while receiving medical services, especially in areas where a war is going on or there is instability. In this context, they will prioritize their lives and not go for health care. This results in reduced GP visits, which can lead to untreated health conditions and an increase in morbidity. In addition, economic instability plays a significant role in reducing access to health care and utilization. High unemployment rates, high inflation, or a depreciating currency occurred due to war burdens can limit individuals' purchasing power and ability to afford health services. In these kinds of households, health care costs may reduce families' ability to visit GPs and could force them to delay or avoid GP visits because they need to save for food, housing, or bills. Additionally, people may postpone seeking health care due to fear of out-of-pocket charges, such as consultation fees, drugs, or diagnostic procedures. Economic instability combined with inadequate access to health care can make the cycle of poor health outcomes, especially for vulnerable groups that are likely to already be disadvantaged socioeconomically.

Except for safety concerns, one of the core reasons for the decrease in GP visits can be the destruction of healthcare facilities caused by Russian attacks. The war has led to widespread damage to hospitals, clinics, and medical facilities, severely impacting the delivery of essential healthcare services. In 2023, it was estimated that since February 24, 2022 year 218 clinics and hospitals had been destroyed or damaged by Russian attacks. Many medical buildings were either partially or completely destroyed by shelling and missile attacks, making them inoperable.

To address the health care issues in these contexts due to reduced GP visits following attacks in Ukraine in 2023, there are several policy interventions that can be conducted. For the first step, targeted programs should focus on better health structure through infrastructure that guarantees medical services remain uninterrupted. These interventions could comprise the placement of mobile clinics together with installing temporary healthcare facilities in the regions where healthcare services have been interrupted by Russian aggression. The second part of the program is a gender-sensitization campaign that is designed to motivate males to prioritize preventive care and early interventions. It will therefore comprise of both community outreach programs and educational campaigns coupled with incentives to male persons on the paramount importance of health screening and checkups. To address problems with destroyed healthcare facilities, investing in the reconstruction of hospitals and clinics should be a priority. Additionally, it is essential to ensure these facilities are well-equipped and staffed. This can be achieved in conjunction with foreign investors and international organizations.

The findings suggest the negative role of Russian attacks in 2022 in GP visit frequency in Ukraine which can lead to the emergence of some disruptions in the scope of healthcare services utilization. This effect of war can lead to future problems in the economic and social spheres. Decline of visits signifies delays in diagnosis and treatment that help distribute health inequalities. The different gender health attitude leading to men needing encouragement in preventive care hints at designed interventions. The policy intervention should be focused on improving of the health care system, gender-based healthcare services, reconstruction of healthcare facilities and provision of services that would be tailored to the population encountered direct Russian aggression, as well as to other population of Ukraine. All of these interventions should be implemented in the short term to mitigate potential further problems.

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