INFORMAL PAYMENTS FOR HEALTH CARE SERVICES IN UKRAINE: THE IMPACT OF WAR

by

Kiril Terentii

A thesis submitted in partial fulfillment of
the requirements for the degree of

MA in Economic Analysis

Kyiv School of Economics

2024

Thesis Supervisor: ____________________________ Professor Maksym Obrizan

Approved by ____
Head of the KSE Defense Committee, Professor

____

____

____

Date ____________________________________

Kyiv School of Economics

Abstract

INFORMAL PAYMENTS FOR
HEALTH CARE SERVICES IN
UKRAINE: THE IMPACT OF WAR

by Kiril Terentii

Thesis Supervisor: Professor Maksym Obrizan

The ongoing war in Ukraine has exacerbated the challenges within the healthcare system, prominently highlighted by the persistence and evolution of informal payments made by patients to healthcare providers. Effective policy measures, aimed at reducing underfunding and reshaping public attitudes towards informal payments, are crucial to ensure equitable access to healthcare services and to mitigate the financial burden on patients, particularly in times of crisis. This work investigates the dynamics of these payments in a war-affected setting, analyzing how the armed conflict has influenced both the prevalence and magnitude of these payments. The study reveals that the war has significantly impacted the likelihood and amounts of informal payments, particularly in regions directly affected by hostilities, and underscores their decrease in 2023 compared to the pre-war period, likely due to economic hardships and disrupted healthcare services.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ACKNOWLEDGMENTS

The author is deeply grateful to his thesis advisor Professor Maksym Obrizan and to all Research Workshop professors for their invaluable guidance and support throughout the entire process of writing this thesis.

Additionally, the author extends his gratitude to the USAID Health Reform Support team for their cooperation and contribution to the scholarly value of this study by granting permission to use data from their project for academic purposes.

LIST OF ABBREVIATIONS

IP. Informal payment

WTP. Willingness to pay

DID. Difference-in-differences

PHC. Primary healthcare center

CPI. Consumer price index

IMR. Inverse Mills ratio

C h a p t e r 1

INTRODUCTION

In recent years, informal payments (henceforth IPs) for healthcare services have emerged as a significant concern across various nations, with Ukraine being no exception. These payments, often made under-the-table, adversely impact healthcare utilization and contribute to the exacerbation of poverty and inequality. IPs, fundamentally, represent an unregulated financial burden on patients, especially those with limited income, compelling them to forgo necessary medical assistance due to financial constraints (Habibov and Cheung 2017). The ongoing war in Ukraine, which started on February 24, 2022, has further complicated this scenario, severely disrupting multiple sectors of the country's economy, including its healthcare system. This study, therefore, aims to delve into the dynamics of IPs for health care services in Ukraine, focusing on the influence of war along with other relevant factors on their prevalence and magnitude.

The pertinence of this study lies in its focus on the unique conditions of a country at war. While previous research has explored IPs in peaceful, non-warring contexts, there is a dearth of literature examining their dynamics in conflict-ridden settings. This investigation is not only important for academic purposes but also for policy formulation, as it seeks to provide insights into how conflict shapes healthcare financing and access, thereby informing strategies to mitigate the adverse effects of IPs on vulnerable populations.

This thesis contributes to the existing literature by providing a quantitatively robust analysis of the effects of war on IPs. The study examines how the ongoing war in Ukraine influences the likelihood and amounts of IPs, taking into consideration demographic, geographic, socio-economic, and attitudinal factors.

The main hypothesis for the study is that the war in Ukraine has a statistically significant negative effect on the amounts and likelihood of IPs for healthcare services in those regions directly affected by ground-level attack after February 24, 2022, while demographic, socio-economic and other relevant factors moderate the relationship between the war and informal payments, influencing the extent of this impact.

The other hypothesis being tested in the study posits that in regions of Ukraine that experienced significant internal migration, particularly those situated predominantly in the western part of the country and deemed safer due to their distance from the war zone, IPs are expected to be both quantitatively and probabilistically higher. The increased flow of people to these regions may contribute to a greater prevalence of IPs within various sectors including health care compared to regions that are closer to the conflict areas.

The analysis confirms that the year 2023 sees a discernible decrease in both the likelihood and the magnitude of informal payments, suggesting that the socioeconomic disruptions brought about by the war may have constrained the usual practices of informal transactions in healthcare. Intriguingly, in regions directly affected by the conflict, this decrease is less pronounced, indicating a complex relationship between conflict impact and healthcare payment behaviors.

The remainder of the thesis is structured as follows: Chapter 2 presents a comprehensive literature review, laying the groundwork for understanding IPs in various contexts. Chapter 3 details the econometric model and hypotheses underpinning this study. Chapter 4 describes the sample composition and data utilized for analysis. Chapter 5 discusses the model estimation and interprets the results. Finally, Chapter 6 concludes the paper by summarizing the main findings and offering policy recommendations based on the insights gained from this research.

Chapter 2

LITERATURE REVIEW

Although the various definitions of informal payments are still disputed, in general IPs for health care can be described as unofficial payments, in kind or in cash, made by patients or their families to healthcare providers. This includes "envelope" payments to physicians and "contributions" to hospitals as well as the value of medical supplies purchased by patients and drugs obtained from private pharmacies but intended to be part of government-financed health care services (Lewis 2007). At the same time, Gaal et al. (2006) in their conceptual framework differentiate between two types of IPs: 1) donation payments, made voluntarily by patients as a form of gratitude, reflecting socio-cultural norms; and 2) fee-for-service payments, made due to an explicit or implicit understanding that payment is necessary for service provision, often involving some element of coercion.

IPs, distinct from formal fees, often exist in a gray area of healthcare financing. They differ from out-of-pocket payments, which are legal, regulated, and officially sanctioned contributions towards healthcare costs. Also, unlike illegal payments, which are outright violations of laws and ethical standards, IPs occupy an ambiguous space – they are not officially sanctioned but often arise due to systemic gaps in healthcare funding and delivery (Lewis 2007). Understanding the nature of IPs, particularly in the backdrop of a national crisis such as war, is crucial for comprehending their impact on healthcare access and equity.

Numerous studies have focused on IPs in healthcare in developing and transitional economies, where the economic and socio-cultural environment often fosters such forms of exchange. In these countries, the substantial presence of IPs contributes to a dual-tier healthcare system: lower-income individuals often resort to less specialized institutions with lower levels of IPs, while wealthier families have access to advanced facilities with superior technologies and laboratories (Balabanova and McKee 2002; Habibov and Cheung, 2017). This disparity is influenced by the varying financial capacities to afford such informal costs.

Another important point is that these payments are also seen as means to support underfunded healthcare systems (Gaal et al. 2006; Stepurko et al. 2015; Habibov and Cheung 2017). It reflects a complex interplay between inadequate systemic funding and the personal or institutional practices within healthcare delivery. In many healthcare systems, particularly in developing or transitional countries, public healthcare funding may not be sufficient to cover all operational costs, including salaries for healthcare workers, medical supplies, and infrastructure maintenance. IPs can become a supplementary income source that helps healthcare providers maintain service delivery in the face of inadequate government funding.

One of the seminal works in this field is by Ensor and Savelyeva (1998), which explores the nature and impact of IPs in Kazakhstan. Their study is pivotal in understanding the dynamics of these payments in the context of the Former Soviet Union. The authors found that socio-economic factors influencing IPs include income levels, education, urban versus rural settings, and the general economic stability of a country. Research has shown that lower-income and less-educated individuals are often more susceptible to the burden of IPs, exacerbating existing inequalities in healthcare access (Ensor and Savelyeva 1998).

Further research has compared the situation in different post-Soviet states, highlighting both the commonalities and differences in the nature of IPs across these regions. Stepurko et al.'s 2015 investigation into IPs for healthcare services in Lithuania, Poland, and Ukraine offers detailed insights into this pervasive issue. Specifically, the research found notable differences in the frequency and size of these payments, reflecting the varied economic and healthcare landscapes of each country. For instance, Lithuania and Ukraine showed higher instances of IPs compared to Poland (Stepurko et al. 2015). The study also highlighted that these payments, ranging from cash to gifts, often represented a significant portion of the household expenditure on healthcare, indicating a substantial economic impact on patients.

Another important study conducted by Stepurko et al. in 2017, examines the patterns of informal patient payments in Bulgaria, Hungary, and Ukraine, revealing significant variations across these countries. The authors found that the prevalence of IPs was notably higher in Ukraine and Hungary compared to Bulgaria. As in their 2015 study concerning Lithuania, Poland, and Ukraine, the size of these payments is influenced by factors such as the type of healthcare service, patients' awareness of fees, and household income (Stepurko et al. 2017). Also, there is a significant impact of socio-economic status on the likelihood and magnitude of IPs, underscoring the inequities in healthcare access and affordability in post-communist countries.

Considerable attention has been paid to the study of factors that influence people's motivation to make IPs. The quality of medical services, salaries of health care personnel, health status of patients, household wealth, etc. are usually considered to be the most important factors explaining the prevalence of IPs (Stepurko et al. 2015). Another pivotal element contributing to the prevalence of IPs is the chronic underfunding in healthcare. This phenomenon is particularly pronounced in Ukraine, where many public sector workers, including those in healthcare, education, and road policing, receive rather low wages. Despite their continued service, these workers often anticipate receiving informal payments from their counterparts as a supplement to their inadequate incomes (Oharkov 2019). This dynamic highlights the direct impact of financial constraints on the emergence and maintenance of IPs in public services.

The study by Aboutorabi et al. (2016) investigates the factors influencing IPs in public and teaching hospitals. The research, conducted in hospitals affiliated with the Tehran University of Medical Sciences, involved 300 discharged patients selected through multi-stage random sampling. The findings indicate that 21% of participants made IPs, primarily to housekeeping staff, for enhanced services. Also, the study explores that there are various strategies, including patient and staff education, increasing employee income, and improving health service quality, that can help control and reduce IPs (Aboutorabi et al. 2016). This study contributes to understanding informal payments in Iran's health sector, emphasizing the need for further research and policy development.

A comprehensive analysis of informal payments within the Greek healthcare system is presented by Giannouchos et al. (2020). Surveying 4218 households, the authors explore the prevalence and determinants of such payments. Key findings reveal that 63% of healthcare incidents involve informal payments, with the median payment being €150. Crucial factors contributing to these payments include trust in providers, emergency services usage, provider reputation, and the nature of healthcare services, particularly in public sectors (Giannouchos et al. 2020).

Moreover, in their 2021 follow-up study, Giannouchos et al. investigate the relationship between informal healthcare payments, individuals' willingness to pay (WTP) for healthcare services, and attitudes toward the legalization of such payments. The study, involving 2841 participants, reveals that about 80% were willing to pay, on average, €95 per month for full healthcare coverage. Informal payments were prevalent, with 65% of respondents engaged in such payments, averaging €247. The study indicates that higher informal payments and supportive opinions toward legalizing these payments increase WTP (Giannouchos et al. 2021).

As for the impact of war on a country's overall healthcare system, Kevlihan, in his 2013 study, explores the formidable challenges of delivering healthcare services during the civil war in South Sudan, offering a comprehensive view of the interplay between healthcare and conflict. The research focuses on how social and political dynamics, such as power struggles and resource allocation, significantly impact health services in conflict zones. This includes the examination of the experiences and challenges faced by healthcare workers, who grapple with issues like resource scarcity, safety concerns, and ethical dilemmas in a war-torn environment (Kevlihan 2013).

In turn, Habibov and Cheung (2017) reveal that countries recently experiencing a military conflict are less likely to have IPs in the health care system compared to other peaceful countries (Habibov and Cheung 2017). This mainly can be explained by a decline in households' wealth during times of war due to loss of income sources, property damage, or increased expenses related to the conflict. Also, in times of war, economic conditions are generally challenging for everyone, and healthcare providers may become more empathetic to the financial strain on patients and be less inclined to request additional payments.

In conclusion, given the multifaceted nature of IPs in health care, and their substantial impact on health equity and access, especially in transitional economies like Ukraine, it is crucial to deepen our understanding of how these dynamics are influenced by significant societal stressors such as war. War not only affects economic stability and public resource allocation but also shifts societal norms and priorities, potentially changing the patterns of informal payments. Investigating the impact of war on IPs will not only provide insights into the adaptive mechanisms of healthcare financing during crises but also inform strategies to mitigate inequities in healthcare access.

Chapter 3

METHODOLOGY

While other studies mainly concentrate on the nature of IPs for health care and factors driving them in peaceful, non-warring countries, this study seeks to quantitatively estimate exactly the impact of the war on these IPs. To examine this effect, a difference-in-differences (DID) regression analysis was conducted.

Assuming that the IP variable is semi-continuous (i.e., it has a bunching of observations at zero and then continuous positive values), we decided to choose the two-part model, where the first part models the probability of having a non-zero outcome, and the second part models the outcome given that it is positive. The dependent variables for the two models are 1) the indicator variable for making an IP by a patient during his/her treatment period and 2) the amount of IP made by a patient during his/her treatment period[1].

For the first model, to estimate the likelihood of making an IP, we could use the probit model. Instead, however, we decided to utilize the linear probability model (LPM) since we use a DID methodology, which was developed for the case of linear models and is less suited to use in non-linear ones like probit. The reason for this is that in non-linear models, the interpretation of interaction terms is controversial and that non-linear models violate the common trend assumption of the difference-in-difference model (Coupe and Obrizan 2016). Therefore, LPM with robust standard errors (to capture heteroscedasticity) is more suitable in our case.

[1] The length of treatment can depend on a number of different factors, especially the service provided to the patient, and can range from a one-time visit to a provider to long-term treatment lasting several weeks.

The second model is a linear model (LM), used to estimate the amount of IP made during the treatment period, presented in logarithmic terms. Logarithmic transformation helps in normalizing the left-skewed data on patients' payments, leading to residuals that are more likely to meet the assumption of normality, which is important for OLS regression.

The models will be presented iteratively by adding different variable groups at each step/specification, i.e., the following model is an extended version of a previous one. In total, there will be 4 specifications of each model. Thus, this chapter is structured as follows: in the first step, we estimate the impact of the year 2023 along with geographical variables on our dependent variables; in the second step we modify our models by adding demographic variables; in the third step we also include socio-economic variables; in the fourth final step, we add attitudinal variables.

In the first specification, we define the first and second DID models. There we take into consideration the effects of the year 2023, locating in a war-affected region, the joint effect of locating in a war-affected region in 2023, and, in addition, the effect of locating in a certain macroregion as a control variable on the likelihood of IP in the first model and on the amount of IP in the second model.

$$is\_ip = \alpha_0 + \alpha_1 y2023 + \alpha_2 warreg + \alpha_3 y2023 * warreg + \alpha_i X_i + \varepsilon\,, \quad (1)$$

$$log(ip) = \beta_0 + \beta_1 y2023 + \beta_2 warreg + \beta_3 y2023 * warreg + \beta_i X_i + \varepsilon\,, \quad (2)$$

where:

is_ip – dummy for IP taking 1 if there was an IP made during the treatment period and 0 otherwise;

$log(ip)$ – continuous variable for the logarithm of the amount of IP a patient made during the treatment period;

$y2023$ – year dummy taking 1 if a year is 2023 and 0 otherwise;

$warreg$ – dummy for war-affected regions taking 1 if a region was under the ground-level attack after February 24, 2022, and 0 otherwise;

Vector of other geographic controls X includes:

is_center – dummy for macroregion of residence of a respondent taking 1 if a respondent resides in the Center macroregion and 0 otherwise (base category, not included into a regression);

is_north – dummy for macroregion of residence of a respondent taking 1 if a respondent resides in the North macroregion and 0 otherwise;

is_south – dummy for macroregion of residence of a respondent taking 1 if a respondent resides in the South macroregion and 0 otherwise;

is_west – dummy for macroregion of residence of a respondent taking 1 if a respondent resides in the West macroregion and 0 otherwise;

is_east – dummy for macroregion of residence of a respondent taking 1 if a respondent resides in the East macroregion and 0 otherwise.

It is crucial to note that the dummy variable for war-affected regions denotes the presence of settlements within Kyiv, Sumy, Chernihiv, Donetsk, Luhansk, Kharkiv, Zaporizhzhia, Kherson, and Mykolaiv regions that experienced ground-level attacks. These settlements, identified by respondents as their places of residence, are situated in close proximity (up to 10 kilometers) to the hostilities, or directly at the epicenter. This classification is based on the DeepStateMap[2] and

[2] An interactive, open-source online map detailing the hostilities in Ukraine from February 24, 2022. Is accessible at the following URL: https://deepstatemap.live/en#7/50.159/30.146.

includes locations such as Kharkiv, Vovchansk, Chuguyiv, Mariupol, Bakhmut, Tokmak, Kamyyanka-Dniprovska, Sumy, Trostianets, Chernihiv, Novotroitske, Mykolaiv, Kherson, Oleshki, Beryslav, Kakhovka, Irpin, Borodianka, Bilopilla, Severodonetsk, Bilozerka, Lysychansk, Rubizhne, and Bilovodsk.

In the second specification, we define extended versions of the first and second DID models. There we also include demographic variables as additional controls.

$$is\_ip = (as\ in\ First\ specification) + \alpha_i Y_i\ , \tag{3}$$

$$log(ip) = (as\ in\ First\ specification) + \beta_i Y_i\ , \tag{4}$$

where the vector of demographic controls Y includes:

age – continuous variable for the age of a respondent;

is_male – dummy for the gender of a respondent taking 1 if a respondent is male and 0 otherwise;

is_higher_educ – dummy for a level of education of a respondent taking 1 if a respondent has a degree of higher education (bachelor, master and other types of degree) and 0 otherwise;

is_city – dummy for settlement type of a respondent taking 1 if a respondent resides in an urban area (urban-type settlement or cities with more than 3,500 residents) and 0 otherwise;

$is\_employed$ – dummy for employment status of a respondent taking 1 if a respondent is employed (partial, full, entrepreneurship, and other types of employment) and 0 otherwise.

In the third specification, we enrich our models by adding socio-economic controls such as different income and vulnerable groups.

$$is\_ip = (as\ in\ Second\ specification) + \alpha_i K_i\ , \tag{5}$$

$$log(ip) = (as\ in\ Second\ specification) + \beta_i K_i\ , \tag{6}$$

where the vector of socio-economic controls K includes:

$is\_inc\_group\_1$ – dummy for the income level of a respondent's household taking 1 if an average monthly income for one member of a household is less than 4,500 UAH and 0 otherwise (base category, not included into a regression);

$is\_inc\_group\_2$ – dummy for the income level of a respondent's household taking 1 if an average monthly income for one member of a household is between 4,501 and 9,000 UAH and 0 otherwise;

$is\_inc\_group\_3$ – dummy for the income level of a respondent's household taking 1 if an average monthly income for one member of a household is between 9,001 and 15,000 UAH and 0 otherwise;

$is\_inc\_group\_4$ – dummy for the income level of a respondent's household taking 1 if an average monthly income for one member of a household is more than 15,000 UAH and 0 otherwise;

is_not_vuln – dummy for a respondent being in a particular vulnerable group taking 1 if a respondent does not belong to any of the vulnerable groups and 0 otherwise (base category, not included into regression);

is_vuln_social – dummy for a respondent being in a particular vulnerable group taking 1 if a respondent belongs to the socially vulnerable group and 0 otherwise;

is_vuln_health – dummy for a respondent being in a particular vulnerable group taking 1 if a respondent belongs to the vulnerable group in terms of health and 0 otherwise;

$is\_vuln\_social\_health$ – dummy for a respondent being in a particular vulnerable group taking 1 if a respondent belongs to both socially and health-vulnerable groups and 0 otherwise.

In the fourth specification, we finally add to our models the last group of variables – attitudinal variables, which include dummies for attitudes towards IPs and the variable indicating whether an IP was made by hint, request, or coercion.

$$is\_ip = (as\ in\ Third\ specification) + \alpha_i F_i\ , \tag{7}$$

$$log(ip) = (as\ in\ Third\ specification) + \beta_i F_i\ , \tag{8}$$

where the vector of attitudinal controls F includes:

$is\_neutral\_att$ – dummy for an attitude of a respondent to informal payments taking 1 if a respondent has a neutral attitude to IPs and 0 otherwise (base category, not included into regression);

$is\_negative\_att$ – dummy for an attitude of a respondent to informal payments taking 1 if a respondent has a negative attitude to IPs and 0 otherwise;

$is\_positive\_att$ – dummy for an attitude of a respondent to informal payments taking 1 if a respondent has a positive attitude to IPs and 0 otherwise;

$is\_required$ – dummy for reasons of making an IP taking 1 if an IP was made by hint, request, or coercion and 0 otherwise.

The key variables identified are expected to have significant impacts, nuanced by the complex realities of war and regional disparities. The variable representing the year 2023 serves as a temporal marker to gauge changes due to escalating conflict and policy adaptations over time. We hypothesize a negative impact from this variable, suggesting that as the conflict intensifies, there may be a decrease in both the likelihood and the amount of informal payments compared to previous periods. This expectation stems from potential economic difficulties and disruptions in healthcare services which could decrease people's ability to engage in informal payments.

Considering the regions affected by the war, we posit that the influence on informal payment practices might be dual-faceted. On one hand, increased needs and limited healthcare resources might compel higher informal payments, but on the other, the overall economic degradation and infrastructural damages might reduce people's ability to pay, leading to a hypothesized negative sign for this variable.

The interaction of the year 2023 with war-affected regions is particularly significant. It is expected to show that while the general trend indicates a reduction in informal payments, in regions continuously affected by conflict, this reduction might be less marked, but still negative. The sustained conflict likely results in continued disruption of healthcare infrastructure and services in war-affected regions. This disruption can limit the availability of healthcare providers and services, reducing the opportunities for informal payments to occur. Even if patients are willing to pay, the sheer reduction in service availability could lead to a decrease in actual payments.

The influence of regional variables like is_north, is_south, is_west, and is_east are expected to vary, potentially showing negative coefficients as they compare to a center reference region, reflecting regional economic and cultural differences that might affect informal payment practices.

Moreover, demographic factors such as age and gender are explored, with an expectation that older individuals might pay more due to increased healthcare needs, suggesting a positive relationship with age. Socio-economic factors, including income and employment status, are also considered. Higher income and being employed are hypothesized to increase the likelihood and amount of informal payments, as these factors generally enhance an individual's capacity to make such payments.

Attitudinal perspectives towards informal payments are also critically important. Positive attitudes towards making these payments are expected to correlate with an increased likelihood and amount of informal payments, illustrating how personal beliefs and cultural norms can significantly shape healthcare payment behaviors.

Chapter 4

DATA DESCRIPTION

The primary data collection method for such studies is face-to-face interviews with patients (Stepurko et al. 2010). The main source of repeated cross-sectional data for this study are two anonymous patient surveys conducted within medical institutions across Ukraine in the years 2019-2020 and 2022-2023. These surveys were the parts of 2020 (baseline) and 2023 (follow-up) studies named «The volume of informal payments at the level of specialized health care institutions for four priority services of the medical guarantee program» conducted jointly by KSE Institute and USAID[3].

The baseline study covers the period from July 1, 2019, to March 31, 2020, while the follow-up encompasses data from the period of June 1, 2022, to May 31, 2023. The four priority services analyzed in the study are 1) medical care during childbirth; 2) medical care for newborns in complex neonatal cases; 3) medical care for acute myocardial infarction; and 4) medical care for acute cerebral stroke.

The first part of this chapter focuses on the composition of the sample, while the second provides descriptive statistics for the variables.

4.1. Sample composition

The target group consists of patients (and/or their close relatives) who, in a certain period, received medical care in municipal healthcare institutions and reside in urban areas (regional centers, other cities, urban-type settlements) and rural areas (villages). Respondents were recruited through Primary Healthcare Centers (PHCs)

---

[3] The data for research was kindly provided by KSE Institute with an approval of USAID's Health Reform Support team.

by disseminating information about the study among patients who signed a declaration with PHC doctors.

The questionnaire consisted of approximately 100 questions including all necessary patients' demographics, their attitude to informal payments, along with amounts of patients' IPs, if any.

Patient responses within PHCs were collected across the five macroregions of Ukraine: North (Poltava, Sumy, Kharkiv, Chernihiv regions); South (Mykolaiv, Odesa, Kherson regions and Autonomous Republic of Crimea); West (Volyn, Ivano-Frankivsk, Zakarpattia, Lviv, Rivne, Ternopil, Khmelnytskyi, Chernivtsi regions); East (Dnipropetrovsk, Donetsk, Zaporizhzhia, Kirovohrad, Luhansk regions); and Center (Kyiv city, Kyiv, Vinnytsia, Zhytomyr, Cherkasy regions). The distribution of regions of Ukraine into macroregions is shown in Figure 1.

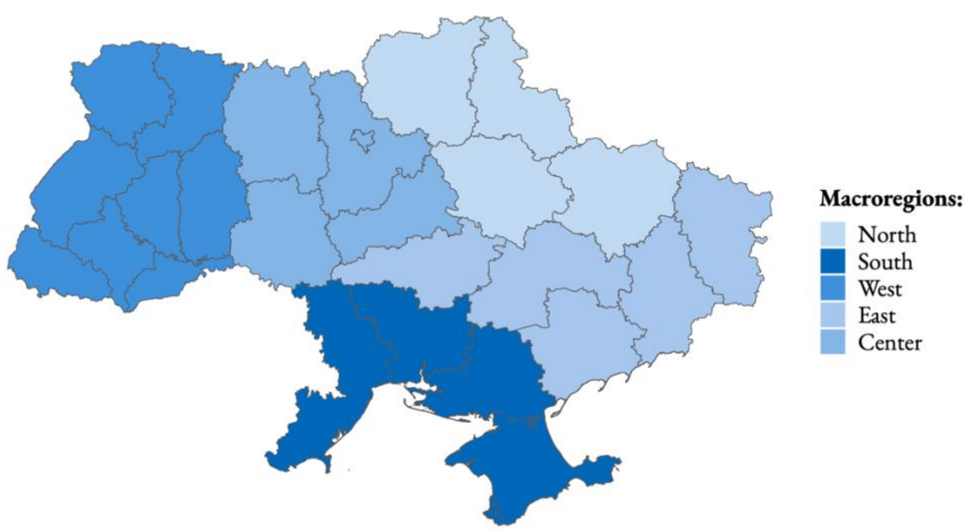

Figure 1. Geography of the study

Initially, the dataset obtained from two surveys totaled 4,079 observations. After we left only those respondents, who replied about the level of their education, we had 4,059 observations. Additionally, not all patients indicated the type of their settlement. After excluding them, we left with 4,048 observations. Then, we excluded 225 respondents, who refused to indicate their income level. Continuing with employment status and region of residence responses we are left with the final sample size of 3,795 respondents.

This sample is used to estimate the first model (likelihood of IP). However, for the second model (amount of IP) we need to filter out those respondents who have an informal payment amount of zero, that is, they did not make any IPs. The whole process of filtering by the absence of answers to certain questions and other conditions is summarized in Table 1.

Table 1. Summary of sample composition

Step description	Sample size
Initially for 2 years	4,079
Respondent replied about the level of education	4,059
Respondent replied about the settlement type	4,048
Respondent replied about the income level	3,823
Respondent replied about the employment status	3,797
Respondent replied about the region of residence	3,795
Final sample 1st model	**3,795**
Respondent made an IP	2,645
Final sample 2nd model	**2,645**

4.2. Descriptive statistics

The variables are divided into five groups: 1) primary; 2) demographic; 3) geographic; 4) socio-economic and 5) attitudinal variables, according to their nature and characteristics. The first, primary, group of variables is shown in Table 2.

Table 2. Descriptive statistics of primary variables

Variable	Mean	SD	Min	Max
Primary				
Amount of IPs made during treatment, UAH (1st model, 3795 observations)	7,915	17,395	0	532,966
Amount of IPs made during treatment, UAH (2nd model, 2645 observations)	11,357	19,877	8	532,966
IP was made during treatment, indicator variable	0.697	0.460	0	1
Year 2023, indicator variable	0.518	0.500	0	1

The first dependent variable, amount of IPs made during treatment in the period from July 1, 2019 to March 31, 2020 / from June 1, 2022 to May 31, 2023[4] for baseline / follow-up survey, has a mean of 7,915 UAH with a standard deviation of 17,395 UAH and varies from 0 UAH for respondents, who didn't make any IPs in a specified period, to 532,966 UAH for a respondent, who did make IPs for a bunch of services related to the provision of medical care during childbirth.

In the sample for the second model with 2645 observations (after filtering out zero values) amount of IPs has a mean of 11,357 UAH with a standard deviation of 19,877 UAH and varies from 8 to 532,966 UAH, suggesting that while some payments might be very low, others are significantly higher, indicating a lack of

[4] For simplicity, in the following we will only refer to the end survey years to differentiate between the two surveys and the two time periods (e.g., the 2020 survey refers to the survey conducted between 2019 and 2020 for the baseline study).

consistency in the amounts being paid. The distribution of patients' payments in the second sample is shown in Figure 2.

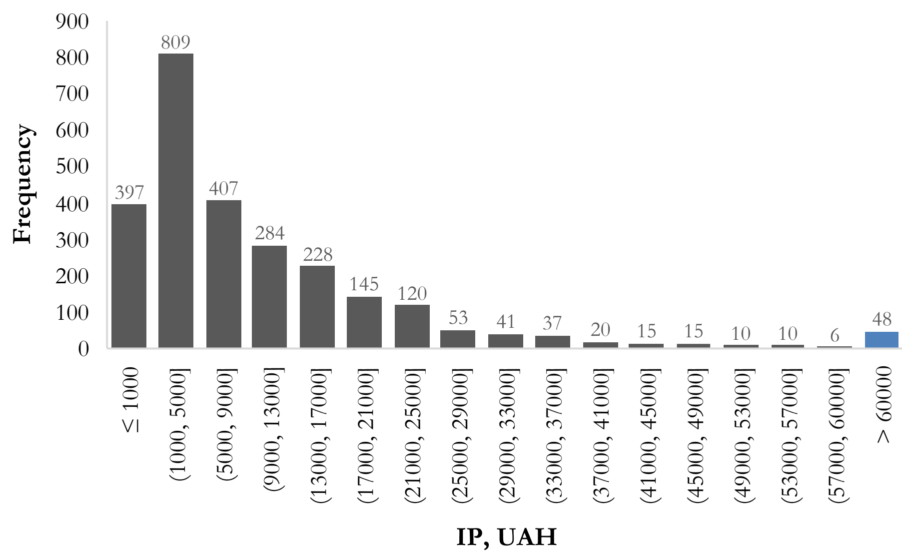

Figure 2. Distribution of IP amounts

The most common range for informal payments is from 1,000 to 5,000 UAH, with 809 respondents. As the payment range increases, the frequency of respondents significantly decreases. Very high payment amounts, such as those above 60,000 UAH, are extremely rare, having only 48 occurrences. Payment ranges from 17,001 to 21,000 UAH and from 21,001 to 25,000 UAH have notably lower frequencies of 145 and 120, respectively. Given the right-skewed distribution and wide range of IP amounts, logarithmic transformation of the payment amounts is planned for use in the second model to normalize the data and manage the influence of outliers.

As respondents provided the amounts of IPs in UAH for two distinct periods, 2020 and 2023, it was necessary to adjust the 2020 payment amounts for inflation. The adjustment was based on the consumer price index (CPI), calculated between the start dates of the two surveys. The inflation coefficient used for this purpose was roughly estimated to be 1.46, meaning that each amount from 2020 was multiplied by this factor to reflect the change in purchasing power by 2023 standards. This adjustment allows for a correct comparison of informal payment amounts across the two survey periods, facilitating a clearer understanding of the trends and changes in the magnitude of informal payments over time.

In its turn, the second dependent variable, IP was made during treatment, varies from 0.706 / 0.540 for West / South macroregions in the 2020 / 2023 survey to 0.821 / 0.691 for Center macroregion in the 2020 / 2023 survey. It is also worth mentioning, that the average likelihood of making an IP across the whole country in 2020 is greater than in 2023 (0.756 against 0.642).

The next, demographic, group of variables includes one continuous variable of age and four indicator variables such as gender, level of education, type of settlement, and employment status. Descriptive statistics of demographic variables are presented in Table 3.

Table 3. Descriptive statistics of demographic variables

Variable	Mean	SD	Min	Max
Demographic				
Age, years	46.197	19.499	18	97
Male, indicator variable	0.238	0.426	0	1
Higher education, indicator variable	0.523	0.500	0	1
Live in urban area, indicator variable	0.855	0.352	0	1
Employed, indicator variable	0.381	0.486	0	1

The final sample is represented by 904 men (23.8%) and 2,891 (71.2%) women, with a significant dominance of the latter. The age of patients (and/or their close relatives) ranges between 18 and 97 years old, while the age of majority of them lies between 23-34 and 67-74 years old. The complete age distribution of respondents is shown in Figure 3.

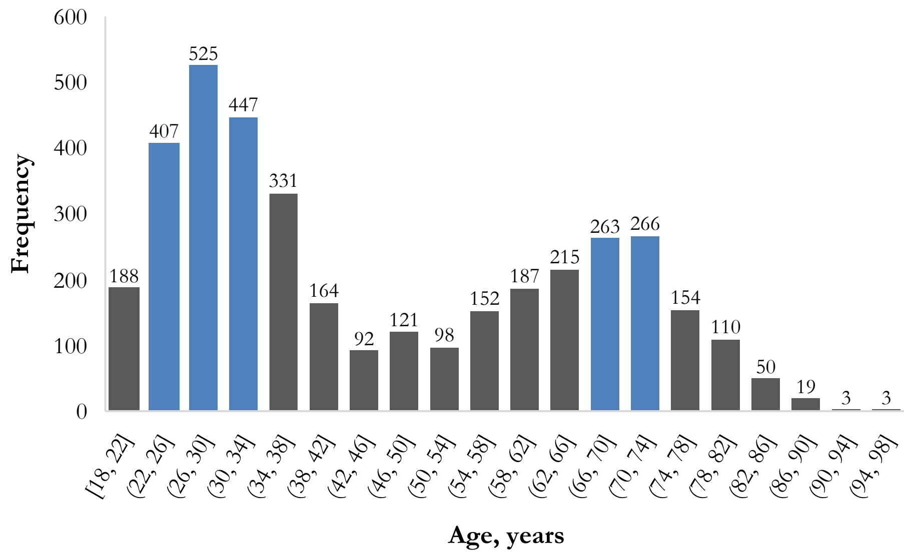

Figure 3. Distribution of respondents by age

The distribution has two "peaks" due to different priority services taken by respondents. Typically, young women aged 23-34 years received medical care during childbirth or medical care for newborns in complex neonatal cases, while elderly people, obviously, mostly applied for medical care for acute myocardial infarction or medical care for acute cerebral stroke.

The third group is geographical indicator variables. It includes dummies for each macroregion of Ukraine respondents reside in along with the dummy for ground-level attack affected regions. Descriptive statistics of geographic variables are summarized in Table 4.

Table 4. Descriptive statistics of geographic variables

Variable	Mean	SD	Min	Max
Geographic				
War-affected region, indicator variable	0.183	0.386	0	1
Center macroregion, indicator variable	0.228	0.420	0	1
North macroregion, indicator variable	0.162	0.368	0	1
South macroregion, indicator variable	0.119	0.324	0	1
West macroregion, indicator variable	0.254	0.436	0	1
East macroregion, indicator variable	0.237	0.425	0	1

The socio-economic variables are categorized into dummies representing four income brackets (less than 4,500; 4,501-9,000; 9,001-15,000; and more than 15,000 UAH per household member) and four categories of vulnerability (Social, Health, Social and Health, and Neither). These variables are detailed in Table 5.

Table 5. Descriptive statistics of socio-economic variables

Variable	Mean	SD	Min	Max
Socio-Economic				
Income group 1 (less than 4,500 UAH), indicator variable	0.422	0.494	0	1
Income group 2 (4,501-9,000 UAH), indicator variable	0.408	0.491	0	1
Income group 3 (9,001-15,000 UAH), indicator variable	0.133	0.340	0	1
Income group 4 (15,001 UAH and more), indicator variable	0.037	0.189	0	1
Vulnerable group 1 (Social), indicator variable	0.109	0.312	0	1
Vulnerable group 2 (Health), indicator variable	0.472	0.499	0	1
Vulnerable group 3 (Social and Health), indicator variable	0.173	0.379	0	1
Vulnerable group 4 (Neither), indicator variable	0.246	0.430	0	1

The most frequent income group (42.2%) among the sample is the income less than 4,500 UAH per member of a household, while the least frequent is the group with more than 15,000 UAH of income per one member of a household.

Vulnerable groups were divided into 4 categories: 1) those who fall only under the category of socially vulnerable; 2) those who fall only under the category of vulnerable in terms of health; 3) those who fall under both the socially vulnerable and health-vulnerable categories, and finally, 4) those who fall under neither category, being the base category when including these dummies into the model.

Finally, the last group of variables is called attitudinal and consists of dummies for negative, neutral, and positive attitudes towards IPs and the dummy indicating whether an IP was made by hint, request, or coercion. The descriptive statistics of these variables are shown in Table 6.

Table 6. Descriptive statistics of attitudinal variables

Variable	Mean	SD	Min	Max
Attitudinal				
Negative attitude towards IPs, indicator variable	0.647	0.478	0	1
Neutral attitude towards IPs, indicator variable	0.261	0.439	0	1
Positive attitude towards IPs, indicator variable	0.092	0.290	0	1
IP was made by hint/request/coercion, indicator variable	0.476	0.499	0	1

An interesting and quite important fact is that almost half (47.6%) of all respondents noted that they made IPs by hint, request, or coercion from the side of an individual provider of health services.

C h a p t e r 5

ESTIMATION RESULTS

According to the two-part model logic described in Chapter 3, we have two dependent variables, and thus this chapter is divided into two parts. The first part is devoted to the linear probability model main estimation results with a dummy for IP as a dependent variable, while the second part describes linear model main estimation results with a natural logarithm of the amount of IP as a dependent variable.

5.1. Likelihood of IP

The first model integrates various explanatory variables, including temporal effects of the year 2023, the impact of residing in war-affected regions, and a range of demographic and geographic factors to estimate the likelihood of IP. The main estimation results of the first model include coefficients, standard errors, signs, and statistical significance for base, geographic, and attitudinal variables.

The coefficient for the year 2023 is negative and statistically significant at a 99% significance level across all specifications, indicating a decrease in the likelihood of making an IP in 2023 compared to the baseline year. The magnitude of this effect ranges from -0.105 (10.5% less compared to 2020) in the most extensive specification, which includes all available groups of variables, to -0.137 (13.7% less) in the second specification with the first three groups of controls, suggesting that the occurrence of informal payments has lessened over time, potentially due to the economic and social impacts of the ongoing war or changes in healthcare policy. The main results are shown in Table 7.

Table 7. Main estimation results of the first model (likelihood of IP)

	(1)	(2)	(3)	(4)
Base				
Year 2023	-0.111***	-0.137***	-0.131***	-0.105***
	(0.016)	(0.018)	(0.018)	(0.018)
War-affected region	0.003	0.005	0.010	0.020
	(0.030)	(0.030)	(0.030)	(0.029)
Year 2023 * War-affected region	-0.008	-0.007	-0.015	-0.032
	(0.039)	(0.039)	(0.040)	(0.039)
Geographic				
North macroregion	-0.097***	-0.097***	-0.093***	-0.083***
	(0.031)	(0.031)	(0.031)	(0.030)
South macroregion	-0.105***	-0.096***	-0.092***	-0.104***
	(0.028)	(0.028)	(0.028)	(0.027)
West macroregion	-0.080***	-0.079***	-0.075***	-0.067***
	(0.021)	(0.021)	(0.021)	(0.021)
East macroregion	-0.036*	-0.031	-0.026	-0.039*
	(0.022)	(0.022)	(0.022)	(0.021)
Attitudinal				
Negative attitude towards IPs				-0.010
				(0.017)
Positive attitude towards IPs				0.064**
				(0.028)
IP was made by hint/request/coercion				0.203***
				(0.015)
Constant	0.812***	0.844***	0.844***	0.765***
	(0.018)	(0.035)	(0.040)	(0.041)
Observations	3,795	3,795	3,795	3,795
R-squared	0.022	0.030	0.033	0.080
Adjusted R-squared	0.021	0.027	0.028	0.075

The results show that residing in different macroregions of Ukraine has varying effects on the likelihood of making informal payments, indicating a lower likelihood of IPs compared to the baseline macroregion (Center). This might reflect regional disparities in economic conditions, healthcare infrastructure, or administrative enforcement against informal payments. Effects across various regions are as follows:

- Residents in the North macroregion have a lower likelihood of making informal payments with coefficients ranging from -0.083 (8.3% less than in Center) to -0.097 (9.7% less), significant at the 99% significance level;
- For the South macroregion, the coefficients are between -0.092 (9.2% less) and -0.105 (10.5% less), also significant at the 99% significance level, echoing similar trends of reduced likelihood as seen in the North;
- The West macroregion shows a decrease from 6,7% to 8% compared to the Center, with statistical significance at the level of 99%, suggesting a regional consistency in the lesser likelihood of informal payments;
- The East macroregion shows a smaller decrease, ranging from 2.6% to 3.9%, with the significance at the 90% significance level in some specifications, indicating a less pronounced decrease in informal payment practices compared to other macroregions.

The presence of a positive attitude towards IPs significantly increases the likelihood of making such payments, as indicated by the positive coefficient for this variable. Conversely, a negative attitude does not significantly change the likelihood, which could imply a societal normalization of informal payments irrespective of personal disapproval. Magnitudes and significance levels are the following:

- A positive attitude towards IPs significantly increases the likelihood of making such payments, with coefficients around 0.064 (6.4% more compared to a neutral attitude), significant at the 95% significance level;

- The coefficient for the influence of informal payments being made by hint/request/coercion is highly significant with values around 0.203 (20.3% more compared to no hint/request/coercion), at the 99% significance level, underscoring that coercive or suggestive pressures from healthcare providers are strong predictors of informal payments.

Being in a war-affected region along with the interaction term of the year 2023 with war-affected regions, although included, does not show consistent statistical significance, suggesting that the direct impact of recent conflicts on informal payments might be complex and mediated by other factors not directly captured by the model.

In turn, demographic variables like age, gender, and employment status show very little to no statistically significant impact. This suggests that these personal attributes do not distinctly influence the propensity to engage in informal payment practices within the Ukrainian healthcare system. Notably, higher education emerges as somewhat influential, potentially indicating that individuals with more education might be slightly more inclined or able to make such payments, possibly due to better financial stability or higher expectations of healthcare services.

On the socio-economic front, the variables relating to income levels and vulnerability do not demonstrate significant effects on the likelihood of making informal payments. This finding indicates a broad uniformity in the practice of informal payments across different income and vulnerability groups, suggesting that the phenomenon of informal payments might be driven more by systemic and cultural factors than by individual economic circumstances. The lack of significant differentiation among various socio-economic groups could imply that the motivation or pressure to make informal payments is widespread and not confined to specific economic or social strata. The magnitudes and statistical significance of each variable in the last two groups are shown in Appendix A.

5.2. Amount of IP

In the second model, to estimate the number of IPs made by a patient during the treatment period, we use a subset of the original sample of 2,645 observations, where we include only those patients who did pay a certain non-zero amount of money for one or more of the four priority services in the form of informal payment. The main results of the estimation of the second model include all necessary information about base, demographic, socio-economic, and attitudinal regressors and are presented in Table 8.

Table 8. Main estimation results of the second model (amount of IP)

	(1)	(2)	(3)	(4)
Base				
Year 2023	-0.907***	-0.950***	-0.957***	-0.868***
	(0.057)	(0.060)	(0.062)	(0.063)
War-affected region	-0.466***	-0.441***	-0.438***	-0.397***
	(0.104)	(0.103)	(0.103)	(0.102)
Year 2023 * War-affected region	0.518***	0.461***	0.448***	0.390***
	(0.143)	(0.142)	(0.142)	(0.141)
Demographic				
Age		0.009***	0.009***	0.008***
		(0.002)	(0.002)	(0.002)
Male		0.104	0.132*	0.126*
		(0.067)	(0.068)	(0.067)
Higher education		0.040	0.044	0.032
		(0.055)	(0.056)	(0.056)
Live in urban area		0.280***	0.288***	0.259***
		(0.077)	(0.078)	(0.077)
Employed		0.133**	0.135**	0.120**
		(0.057)	(0.059)	(0.058)

Table 8. Main estimation results of the second model (amount of IP) – Continued

	(1)	(2)	(3)	(4)
Socio-Economic				
Income group 2 (4,501-9,000 UAH)			-0.104*	-0.106*
			(0.060)	(0.059)
Income group 3 (9,001-15,000 UAH)			-0.040	-0.047
			(0.088)	(0.087)
Income group 4 (15,001 UAH and more)			0.008	-0.001
			(0.139)	(0.137)
Vulnerable group 1 (Social)			0.027	0.002
			(0.099)	(0.098)
Vulnerable group 2 (Health)			0.170***	0.170***
			(0.066)	(0.065)
Vulnerable group 3 (Social and Health)			0.068	0.033
			(0.084)	(0.083)
Attitudinal				
Negative attitude towards IPs				0.032
				(0.060)
Positive attitude towards IPs				0.106
				(0.095)
IP was made by hint/request/coercion				0.411***
				(0.053)
Constant	9.072***	8.332***	8.252***	8.042***
	(0.059)	(0.118)	(0.137)	(0.141)
Observations	2,645	2,645	2,645	2,645
R-squared	0.097	0.119	0.123	0.143
Adjusted R-squared	0.095	0.115	0.117	0.136

The year 2023 shows a consistently negative and statistically significant impact across all specifications, indicating a significant reduction in the amount of informal payments compared to previous years. The coefficients range from -0.868 to -0.957, suggesting a substantial decrease (by 86,8% in the fourth specification) in payment amounts during 2023. This could be due to economic constraints or changes in the regulatory or operational environment of healthcare services amid ongoing conflicts.

Demographically, the impact of age is significant and positive in all specifications, but with a small magnitude of around 0.009, indicating that older individuals tend to pay higher amounts in informal payments on average by 0.9%. Urban residency shows a positive correlation with the amount of IPs, indicating that those living in urban areas tend to make higher payments compared to rural areas (by 25.9% in the fourth specification). This might reflect higher healthcare demands or greater financial capability among these groups. Interestingly, gender (male) also shows a slight positive effect in some model specifications, suggesting that male patients might be involved in higher payments, potentially due to different healthcare needs or societal roles.

Socio-economic status, represented by income groups and vulnerability categories, yields mixed results. Higher income groups do not consistently pay more, which could suggest a ceiling effect where informal payments do not increase proportionally with income beyond a certain threshold. Vulnerable groups related to health show a positive and significant correlation with the amount of IPs, perhaps indicating higher healthcare needs or exploitation within these groups.

Attitudinal factors highlight that individuals who make payments by hint, request, or coercion pay more, as shown by a strong positive coefficient. The model finds that payments made under this condition are associated with significantly higher amounts, with a coefficient of 0.411 (41.1% bigger amounts compared to no hint/request/coercion), underscoring the influence of coercive practices on the scale of informal payments. This suggests that where informal payments are suggested or demanded by healthcare providers, the amounts involved are higher, underlining the coercive or manipulative aspects of informal payments in the healthcare setting.

The coefficient for being in a war-affected region is consistently negative across various model specifications, with values from -0.397 to -0.466, and statistically significant at the 99% significance level. This indicates that respondents from regions directly impacted by warfare tend to make lower informal payments (by 39.7% in the fourth specification). This could be due to disruptions in healthcare infrastructure, decreased financial capacity, or possibly reduced availability of healthcare services that could demand such payments.

According to our main hypothesis and our expectations stated in Chapter 3, the interaction term might have had a strong negative effect on both likelihood and amount of IPs. However, as we can observe from the model estimation results, surprisingly, the interaction term between the year 2023 and being in a war-affected region shows a positive effect, with coefficients ranging from 0.390 to 0.518, also significant at the 99% significance level.

This could suggest that while the general trend in 2023 shows a decrease in the amount of informal payments, in war-affected regions, the reduction is not as pronounced as in non-affected areas. Essentially, this interaction indicates that the decrease in IP amounts observed in 2023 is somewhat lessened in war-affected regions, possibly because the ongoing conflict maintains the pressures or conditions that lead to higher informal payments, even as the broader national trends are toward reduction, such as increased healthcare needs due to injuries or disruptions, continued or exacerbated underfunding of healthcare services, or heightened vulnerability among the population – might mitigate this decreasing trend. The war may sustain certain conditions that necessitate or encourage higher informal payments, even as the rest of the country sees a reduction due to economic hardship or policy changes aimed at curbing such payments.

These results might indicate several scenarios. The general decrease in IPs might be due to increased scrutiny or anti-corruption measures during the war, but the specific conditions of 2023 – such as intensified conflict, the collapse of formal payment systems, or other crisis-related factors – could lead to a situation where informal payments return to levels similar to non-war-affected regions. It reflects a nuanced dynamic where the war itself reduces IPs, but the specific circumstances of 2023 counteract this reduction in war-affected regions.

Additionally, residing in the West macroregion may negatively affect the amounts of informal payments, indicating regional differences in healthcare practices or economic circumstances relative to the Center macroregion. Conversely, the coefficients for the North, South, and East macroregions suggest that geographical location does not significantly influence payment behaviors. All coefficients for geographic variables, including their signs and statistical significance, are detailed in Appendix A.

5.3. Robustness of results

To provide a more realistic assessment of the data, we employ robust standard errors clustered at the macroregion level. This approach is crucial for accounting for the potential intra-group correlation that might not be captured by conventional standard errors. By clustering the standard errors by macroregion, we can better adjust for the non-independence of observations within the same regions, which is particularly important given the regional variations in the likelihood of making informal payments and their amounts.

In comparing the original model results (4^{th} specification) estimating the probability and amount of making informal payments with the results using robust standard errors clustered at the macroregion level, several key insights emerge in terms of statistical significance of the variable estimates:

- Base regressors kept their original levels of significance;

- In a geographic group of controls, only the indicator variable for residing in the East macroregion gained the higher level of statistical significance (at the level of 99% in the model with robust standard errors against 90% in the original model);
- The age in a demographic group of controls and being in the socially vulnerable group in a socio-economic group of controls gained lower levels of significance (at the level of 90% both);
- Positive attitude towards IPs became a bit more statistically significant and now is at the level of 99% instead of 95%. The significance of all other variables remained unchanged.

The slight deviations in significance observed when employing robust standard errors clustered at the macroregion level can be considered negligible. The minor variations in the statistical significance of some predictors do not substantially alter the overall interpretations and conclusions drawn from our analysis, and the relative stability in the significance of results suggests that our findings are robust. The results of re-estimation of both models with clustered standard errors are presented in Appendix B.

In our analysis to further validate the robustness of our results and check for potential selection bias, we decided to implement the Heckman selection model. This model is particularly advantageous as it allows us to examine whether the process of making informal payments is selectively based on unobserved factors that could also affect the payment amounts. Our results from the Heckman model show a high degree of similarity to those obtained from the two-part model setting, reinforcing the stability and reliability of our initial findings. The detailed results of the Heckman model estimation can also be found in Appendix B.

In the Heckman model, the inverse Mills ratio (IMR) is a critical component used to adjust for selection bias. The estimated value of the IMR is 1.805 with a standard error of 1.099. Crucially, this results in a t-value that does not provide sufficient statistical significance to reject the null hypothesis that the IMR is equal to zero (p-value > 0.1). This outcome suggests that there is no substantial selection bias present in our model, indicating that the decision to make an informal payment and the amount of payment are not significantly influenced by unobserved factors that could have biased our estimates.

The consistency between the Heckman model results and our original two-part model, along with the lack of significant selection bias, lends strong support to the integrity and accuracy of our findings. It assures that the effects we report are likely true reflections of the underlying dynamics within the dataset, rather than artifacts produced by sample selection issues. This supports the robustness of our analytical approach and confirms that the methodologies employed are well-suited for exploring the dynamics of informal payments in healthcare.

However, it is crucial to acknowledge that both models presented in the analysis provide only a snapshot based on the available data, and the true causal relationships might also be influenced by factors not captured within the models, due to the inherent limitations of the questionnaire design. Particularly, the results may struggle from issues related to model identification, notably due to the lack of continuous variables. Except for age and the amount of informal payments, the questionnaire primarily comprises categorical or binary variables, which can limit the depth of analysis and the ability to uncover more subtle nuances in the data. This constraint may hinder a comprehensive understanding of the dynamics at play, potentially obscuring other significant variables that influence the prevalence and magnitude of informal payments. As a result, while the findings provide valuable insights, they should be interpreted with caution, considering these limitations and the possibility that additional relevant factors are not included in the analysis.

Chapter 6

CONCLUSIONS AND POLICY RECOMMENDATIONS

In this thesis, we explored the intricate dynamics of informal payments within Ukraine's healthcare system, particularly under the stresses induced by the ongoing war and regional disparities. Our analysis centered on several pivotal factors: the temporal influence of the year 2023, the impacts of residing within war-affected regions, the interaction between these two factors, and various regional and demographic variables. Utilizing a robust statistical framework, we employed a two-part model to analyze the probability and magnitude of informal payments, complemented by robustness checks including a Heckman selection model to address potential selection bias.

Our findings reveal a significant temporal decline in the likelihood and magnitude of informal payments in 2023, suggesting a potential dampening effect of the ongoing war and associated economic and infrastructural disruptions on informal payment practices. This decline is posited to result from both the direct impacts of the war, which limit economic capacity and healthcare service availability, and possibly due to enhanced regulatory scrutiny or shifts in public policy and sentiment regarding informal payments.

The analysis of war-affected regions provided nuanced insights. While one might expect an increase in informal payments due to heightened needs and resource scarcity, our results indicate a complex interplay where such payments have actually decreased, potentially reflecting the overwhelming constraints on financial resources and healthcare infrastructure. Moreover, the interaction term between the year 2023 and war-affected regions was particularly revealing, showing a lesser reduction in informal payments in these regions compared to others in 2023, which may highlight a slower adaptation or persistent need in these locales relative to the national trend.

Regional variables also showed significant variances in payment practices, underscoring the socio-economic and cultural diversities across Ukraine. Certain regions exhibited lower, compared to the Center macroregion, propensities for informal payments, reflecting localized economic conditions, healthcare system characteristics, and possibly varying levels of enforcement against such practices.

Demographic and socio-economic factors, including income levels and employment status, generally did not show a consistent influence on the likelihood or amount of informal payments, suggesting that such practices are widespread and not necessarily confined to specific economic or social strata. This indicates that informal payments are a systemic issue, influenced more by overarching cultural norms and systemic healthcare deficiencies than by individual economic conditions.

Our robustness checks, employing clustered standard errors and the Heckman model, affirmed the stability of our main results. The Heckman model, in particular, indicated no significant selection bias, suggesting that our findings on the determinants of informal payments are robust and not unduly influenced by unobservable factors affecting the decision to make such payments.

These insights not only augment the academic understanding of informal payments in healthcare, particularly in a war setting but also offer critical implications for policy. Strategies aimed at reducing informal payments must consider both the broad economic and regulatory environment and the localized conditions that may predispose certain regions to higher levels of such payments. Efforts to enhance healthcare funding, improve service delivery, and strengthen regulatory frameworks could be crucial in mitigating the economic burden on patients and improving equitable access to healthcare services.

WORKS CITED

Aboutorabi, Ali, Maryam Ghiasipour, Aziz Rezapour, Abolghasem Pourreza, Ali Sarabi Asiabar, and Asghar Tanoomand. 2016. "Factors Affecting the Informal Payments in Public and Teaching Hospitals." *Medical Journal of the Islamic Republic of Iran* 30 (1). Tehran University of Medical Sciences. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4898875/pdf/mjiri-30-315.pdf

Balabanova, Dina, and Martin McKee. 2002. "Understanding Informal Payments for Health Care: The Example of Bulgaria." *Health Policy* 62 (3): 243–73. https://doi.org/10.1016/S0168-8510(02)00035-0

Coupe, Tom, and Maksym Obrizan. 2016. "The Impact of War on Happiness: The Case of Ukraine." *Journal of Economic Behavior and Organization* 132 (December). Elsevier B.V.: 228–42. http://dx.doi.org/doi:10.1016/j.jebo.2016.09.017

Ensor, Tim, and Larisa Savelyeva. 1998. "Informal Payments for Health Care in the Former Soviet Union: Some Evidence from Kazakstan." *Health Policy and Planning* 13 (1): 41–49. https://doi.org/10.1093/heapol/13.1.41

Gaal, Peter, Paolo Carlo Belli, Martin McKee, and Miklós Szócska. 2006. "Informal Payments for Health Care: Definitions, Distinctions, and Dilemmas." *Journal of Health Politics, Policy and Law*. https://doi.org/10.1215/03616878-31-2-251

Giannouchos, Theodoros V., Athanassios Vozikis, Paraskevi Koufopoulou, Leanne Fawkes, and Kyriakos Souliotis. 2020. "Informal Out-of-Pocket Payments for Healthcare Services in Greece." *Health Policy* 124 (7). Elsevier Ireland Ltd: 758–64. https://doi.org/10.1016/j.healthpol.2020.04.005

Giannouchos, Theodoros V., Benjamin Ukert, Athanassios Vozikis, Evangelia Steletou, and Kyriakos Souliotis. 2021. "Informal Out-of-Pocket Payments Experience and Individuals' Willingness-to-Pay for Healthcare Services in Greece." *Health Policy* 125 (6). Elsevier Ireland Ltd: 693–700. https://doi.org/10.1016/j.healthpol.2021.04.001

Habibov, Nazim, and Alex Cheung. 2017. "Revisiting Informal Payments in 29 Transitional Countries: The Scale and Socio-Economic Correlates." *Social Science and Medicine* 178 (April). Elsevier Ltd: 28–37. https://doi.org/10.1016/j.socscimed.2017.02.003

Kevlihan, Rob. 2013. "Providing Health Services during a Civil War: The Experience of a Garrison Town in South Sudan." *Disasters* 37 (4): 579–603. https://doi.org/10.1111/disa.12027

Lewis, Maureen. 2007. "Informal Payments and the Financing of Health Care in Developing and Transition Countries." *Health Affairs*. https://doi.org/10.1377/hlthaff.26.4.984

Oharkov, Artem. 2019. "Survival in transition: informal payments in healthcare." MA thesis, Kyiv School of Economics. https://kse.ua/wp-content/uploads/2019/04/Artem-Oharkov_Thesis.pdf

Stepurko, Tetiana, Milena Pavlova, Irena Gryga, and Wim Groot. 2010. "Empirical Studies on Informal Patient Payments for Health Care Services: A Systematic and Critical Review of Research Methods and Instruments." *BMC Health Services Research* 10. https://doi.org/10.1186/1472-6963-10-273

Stepurko, Tetiana, Milena Pavlova, Irena Gryga, Liubove Murauskiene, and Wim Groot. 2015. "Informal Payments for Health Care Services: The Case of Lithuania, Poland and Ukraine." *Journal of Eurasian Studies* 6 (1). Elsevier: 46–58. https://doi.org/10.1016/j.euras.2014.11.002

Stepurko, Tetiana, Milena Pavlova, Irena Gryga, P. Gaál, and Wim Groot. 2017. "Patterns of Informal Patient Payments in Bulgaria, Hungary and Ukraine: A Comparison across Countries, Years and Type of Services." *Health Policy and Planning* 32 (4). Oxford University Press: 453–66. https://doi.org/10.1093/heapol/czw147

APPENDIX A. Full estimation results

Table 9. Full estimation results of the first model (likelihood of IP)

	(1)	(2)	(3)	(4)
Base				
Year 2023	-0.111***	-0.137***	-0.131***	-0.105***
	(0.016)	(0.018)	(0.018)	(0.018)
War-affected region	0.003	0.005	0.010	0.020
	(0.030)	(0.030)	(0.030)	(0.029)
Year 2023 * War-affected region	-0.008	-0.007	-0.015	-0.032
	(0.039)	(0.039)	(0.040)	(0.039)
Geographic				
North macroregion	-0.097***	-0.097***	-0.093***	-0.083***
	(0.031)	(0.031)	(0.031)	(0.030)
South macroregion	-0.105***	-0.096***	-0.092***	-0.104***
	(0.028)	(0.028)	(0.028)	(0.027)
West macroregion	-0.080***	-0.079***	-0.075***	-0.067***
	(0.021)	(0.021)	(0.021)	(0.021)
East macroregion	-0.036*	-0.031	-0.026	-0.039*
	(0.022)	(0.022)	(0.022)	(0.021)
Demographic				
Age		-0.001***	-0.001***	-0.001***
		(0.0004)	(0.0004)	(0.0004)
Male		0.002	0.001	-0.0003
		(0.019)	(0.019)	(0.019)
Higher education		0.036**	0.030*	0.025
		(0.016)	(0.016)	(0.016)
Live in urban area		0.025	0.019	0.008
		(0.022)	(0.023)	(0.022)
Employed		0.016	0.008	-0.002
		(0.016)	(0.017)	(0.016)

Table 9. Full estimation results of the first model (likelihood of IP) – Continued

	(1)	(2)	(3)	(4)
Socio-Economic				
Income group 2 (4,501-9,000 UAH)			0.027	0.019
			(0.017)	(0.017)
Income group 3 (9,001-15,000 UAH)			0.014	-0.003
			(0.025)	(0.025)
Income group 4 (15,001 UAH and more)			0.045	0.036
			(0.041)	(0.040)
Vulnerable group 1 (Social)			-0.059**	-0.058**
			(0.028)	(0.027)
Vulnerable group 2 (Health)			-0.015	-0.017
			(0.019)	(0.018)
Vulnerable group 3 (Social and Health)			-0.026	-0.039*
			(0.024)	(0.023)
Attitudinal				
Negative attitude towards IPs				-0.010
				(0.017)
Positive attitude towards IPs				0.064**
				(0.028)
IP was made by hint/request/coercion				0.203***
				(0.015)
Constant	0.812***	0.844***	0.844***	0.765***
	(0.018)	(0.035)	(0.040)	(0.041)
Observations	3,795	3,795	3,795	3,795
R-Squared	0.022	0.030	0.033	0.080
Adjusted R-Squared	0.021	0.027	0.028	0.075

Table 10. Full estimation results of the second model (amount of IP)

	(1)	(2)	(3)	(4)
Base				
Year 2023	-0.907***	-0.950***	-0.957***	-0.868***
	(0.057)	(0.060)	(0.062)	(0.063)
War-affected region	-0.466***	-0.441***	-0.438***	-0.397***
	(0.104)	(0.103)	(0.103)	(0.102)
Year 2023 * War-affected region	0.518***	0.461***	0.448***	0.390***
	(0.143)	(0.142)	(0.142)	(0.141)
Geographic				
North macroregion	-0.093	-0.053	-0.056	-0.039
	(0.111)	(0.110)	(0.111)	(0.109)
South macroregion	0.074	0.142	0.141	0.108
	(0.098)	(0.097)	(0.098)	(0.097)
West macroregion	-0.208***	-0.168**	-0.183**	-0.178**
	(0.074)	(0.073)	(0.074)	(0.073)
East macroregion	0.038	0.055	0.047	0.015
	(0.074)	(0.074)	(0.074)	(0.074)
Demographic				
Age		0.009***	0.009***	0.008***
		(0.002)	(0.002)	(0.002)
Male		0.104	0.132*	0.126*
		(0.067)	(0.068)	(0.067)
Higher education		0.040	0.044	0.032
		(0.055)	(0.056)	(0.056)
Live in urban area		0.280***	0.288***	0.259***
		(0.077)	(0.078)	(0.077)
Employed		0.133**	0.135**	0.120**
		(0.057)	(0.059)	(0.058)

Table 10. Full estimation results of the second model (amount of IP) – Continued

	(1)	(2)	(3)	(4)
Socio-Economic				
Income group 2 (4,501-9,000 UAH)			-0.104*	-0.106*
			(0.060)	(0.059)
Income group 3 (9,001-15,000 UAH)			-0.040	-0.047
			(0.088)	(0.087)
Income group 4 (15,001 UAH and more)			0.008	-0.001
			(0.139)	(0.137)
Vulnerable group 1 (Social)			0.027	0.002
			(0.099)	(0.098)
Vulnerable group 2 (Health)			0.170***	0.170***
			(0.066)	(0.065)
Vulnerable group 3 (Social and Health)			0.068	0.033
			(0.084)	(0.083)
Attitudinal				
Negative attitude towards IPs				0.032
				(0.060)
Positive attitude towards IPs				0.106
				(0.095)
IP was made by hint/request/coercion				0.411***
				(0.053)
Constant	9.072***	8.332***	8.252***	8.042***
	(0.059)	(0.118)	(0.137)	(0.141)
Observations	2,645	2,645	2,645	2,645
R-Squared	0.097	0.119	0.123	0.143
Adjusted R-Squared	0.095	0.115	0.117	0.136

APPENDIX B. Robustness checks

Table 11. Results with robust standard errors clustered at macroregion level

	P(IP)	Log(IP)
Base		
Year 2023	-0.105***	-0.868***
	(0.021)	(0.099)
War-affected region	0.020	-0.397
	(0.053)	(0.421)
Year 2023 * War-affected region	-0.032	0.390**
	(0.027)	(0.155)
Geographic		
North macroregion	-0.083***	-0.039
	(0.031)	(0.277)
South macroregion	-0.104***	0.108
	(0.014)	(0.105)
West macroregion	-0.067***	-0.178***
	(0.004)	(0.024)
East macroregion	-0.039***	0.015
	(0.005)	(0.026)
Demographic		
Age	-0.001*	0.008***
	(0.0006)	(0.003)
Male	-0.0004	0.126*
	(0.018)	(0.068)
Higher education	0.025	0.032
	(0.023)	(0.069)
Live in urban area	0.008	0.259***
	(0.016)	(0.055)
Employed	-0.002	0.120*
	(0.028)	(0.066)

Table 11. Results with robust standard errors clustered at macroregion level – Continued

	P(IP)	Log(IP)
Socio-Economic		
Income group 2 (4,501-9,000 UAH)	0.019	-0.106**
	(0.015)	(0.045)
Income group 3 (9,001-15,000 UAH)	-0.003	-0.047
	(0.011)	(0.058)
Income group 4 (15,001 UAH and more)	0.036	-0.001
	(0.031)	(0.138)
Vulnerable group 1 (Social)	-0.058*	0.002
	(0.033)	(0.114)
Vulnerable group 2 (Health)	-0.017	0.170
	(0.034)	(0.208)
Vulnerable group 3 (Social and Health)	-0.039	0.033
	(0.033)	(0.144)
Attitudinal		
Negative attitude towards IPs	-0.010	0.032
	(0.007)	(0.065)
Positive attitude towards IPs	0.064***	0.106
	(0.023)	(0.080)
IP was made by hint/request/coercion	0.203***	0.411***
	(0.015)	(0.059)
Constant	0.765***	8.042***
	(0.041)	(0.195)
Observations	3,795	2,645

Table 12. Heckman selection model estimation results

	Selection Eq. (probability)	Outcome Eq. (log amount)
Base		
Year 2023	-0.360***	-1.168***
	(0.056)	(0.200)
War-affected region	0.035	-0.357***
	(0.092)	(0.131)
Year 2023 * War-affected region	-0.051	0.306*
	(0.116)	(0.179)
Geographic		
North macroregion	-0.273**	-0.248
	(0.092)	(0.187)
South macroregion	-0.323***	-0.154
	(0.085)	(0.203)
West macroregion	-0.220***	-0.351**
	(0.065)	(0.141)
East macroregion	-0.133*	-0.085
	(0.067)	(0.112)
Demographic		
Age	-0.004**	0.005
	(0.001)	(0.003)
Male	-0.008	0.121
	(0.057)	(0.082)
Higher education	0.079	0.103
	(0.048)	(0.081)
Live in urban area	0.036	0.283***
	(0.069)	(0.097)
Employed	-0.007	0.116
	(0.050)	(0.072)

Table 12. Heckman selection model estimation results – Continued

	Selection Eq. (probability)	Outcome Eq. (log amount)
Socio-Economic		
Income group 2 (4,501-9,000 UAH)	0.061	-0.056
	(0.051)	(0.080)
Income group 3 (9,001-15,000 UAH)	0.002	-0.060
	(0.076)	(0.108)
Income group 4 (15,001 UAH and more)	0.136	-0.099
	(0.129)	(0.184)
Vulnerable group 1 (Social)	-0.166**	-0.152
	(0.082)	(0.154)
Vulnerable group 2 (Health)	-0.059	0.118
	(0.057)	(0.087)
Vulnerable group 3 (Social and Health)	-0.118*	-0.070
	(0.072)	(0.121)
Attitudinal		
Negative attitude towards IPs	-0.027	0.006
	(0.052)	(0.076)
Positive attitude towards IPs	0.192**	0.271*
	(0.086)	(0.157)
IP was made by hint/request/coercion	0.622***	0.954***
	(0.046)	(0.339)
Constant	0.790***	7.320***
	(0.127)	(0.472)
Observations	3,795	2,645
Multiple R-Squared	0.144	
Adjusted R-Squared	0.137	