WARTIME MIGRATION AND ITS INFLUENCE
ON UKRAINIAN LABOR MARKET

by

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Abstract

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This thesis investigates the impact of wartime internal migration on structural unemployment in Ukraine during the period of 2022-2024 by individual-level data from monthly surveys conducted by Info Sapiens. The study examines how displacement patterns driven by russia's full-scale invasion affect employment outcomes across regions.

In this thesis we examine how internally displaced person (IDP) status affect the employment probabilities compared to non-displaced persons (NDPs) and how does the distance of internal displacement from conflict zones affect structural unemployment in Ukraine.

The study provides real-time evidence from an active conflict setting, in contrast to most research focused on post-conflict recovery.

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LIST OF ABBREVIATIONS

AME. Average margina; effect.

eCDF. Empirical cumulative distribution function.

IDP. Internally displaced person

IV. Instrumental variable.

LF. Labor force.

NPD. Non-displaced person.

PSM. Propensity score matching.

SMD. Standardized mean difference.

IDP. Internally displaced person

Chapter 1

INTRODUCTION

Migration during war is one of the most serious problems for the labor market. This is typical for regions affected by or located near hostilities. As a result of military activities in Ukraine, there is a significant displacement of the population. People need safety and relative stability - this causes significant economic and social changes.

Russia's full-scale invasion of Ukraine has led to the problem of military migration of the population. People have been forced to become internally displaced persons and move to other, safer regions of Ukraine.

The Ukrainian labor market was weakened a little earlier the full-scale invasion by COVID-19 pandemic, the occupation of Crimea and the war in eastern part of Ukraine. The war had greater impact on the destabilization of the labor market. According to the data 4.9 million Ukrainians were displaced within the country (NISS 2023) and 4.9 fled abroad (CES 2024). This mass population movement has led to a significant mismatch between demand and supply of jobs.

The phenomenon of "war migration" is not new - it is caused by people's desire to be safe - which is impossible in regions where active hostilities are taking place. According to the European commission data, the number of forcibly displaced persons is 120 million (European commission 2024).

The war led to a series of economic shocks. In 2022, Ukrainian GDP dropped by 29.1% (NBU 2023), inflation raised by 26.6% (NBU 2023), currency depreciate by 34.1% (MinFin 2023). Although economy stabilised in 2023-2024, significant structural unemployment emerged.

Structural unemployment now is a serious problem for the economy due to the active internal migration of the population of Ukraine from the frontline territories. In 2024 employees named it the largest obstacle for doing business in Ukraine according to the surveys results of Institute of Economic Research (IER 2024).

In the safer regions of Ukraine, namely in Western Ukraine, a significant increase in population has been observed since the beginning of the full-scale invasion. At the same time, jobs have not become more, which has caused a strain on resources and increased competition for limited workplaces. The most dangerous zones: Donetsk, Luhansk, Kharkiv, Zaporizhia, Mykolaiv, Kherson regions are facing economic stagnation, which is caused by a significant resettlement of the population from these regions to safer ones, the destruction of enterprises and the occupation of territories.

The main problem of war activities is the destruction of economically important Ukrainian enterprises and industries. In Donetsk and Luhansk regions, there are economically important enterprises such as large factories and mines that are now under occupation or completely destroyed. Accordingly, all employees of these enterprises have lost the opportunity to work there.

Some regions benefit from the influx of labor from other regions, while others suffer from economic stagnation. Especially, the number of open vacancies in 2022 was half that of 2021 in all professional groups, but the largest number of unemployed was observed among workers in the trade and service sectors, white-collar workers and managers, professionals and specialists (Vasylyeva, 2023). This phenomenon is called economic divergence. The western regions of Ukraine have absorbed a large part of the internally displaced persons, which has led to a local crisis of unemployment, overpopulation and lack of resources. At this time, regions close to active hostilities have experienced a decline in economic activity and many important and large enterprises have been closed permanently. A similar situation was observed during the conflicts in Iraq and Bosnia - in these countries, uneven recovery of regions was observed, which depended on geographical distance from active hostilities. In addition to the economic problems of military migration, there is also the problem of psychological and social barriers for internally displaced persons. People who have left areas of active hostilities have suffered by psychological trauma, and also face discrimination in safer regions. Especially women face double discrimination due to social expectations.

In addition to the negative consequences of migration and the unemployment it causes, opportunities for targeted policy interventions are opening up. This takes the form of investments in infrastructure restoration, workforce retraining, and the development of an inclusive economy. We see the successful experience of Bosnia and Syria, where significant attention was focused on industrial reconstruction, expanding social support systems, and promoting regional economic development. Ukraine, in this context, has significant resource potential for further long-term post-war growth.

Wars often lead to industry shifts - the militarization of the country occurs. At this time, the number of defence industries is constantly increasing, the number of military personnel is increasing, and ordinary enterprises are being re-equipped for militarization (engineering plants are reoriented to the construction of heavy military equipment, sewing factories to sewing clothes for the military, etc.). However, this creates the problem of ignoring other sectors of the economy or involving their activities, and accordingly there may be a reduction in the number of workers to reduce costs at enterprises. This also leads to the creation of structural unemployment, when a person who worked in a similar industry before the war, when migrating to another region of Ukraine, is forced to retrain in order to earn money. In Ukraine, the increase in defence production has led to a strain on resources and labor from other sectors - this has increased regional inequality in employment opportunities.

In this study, we will analyse how the large displacement of population across Ukraine creates structural unemployment in the labor market. In particular, the objectives are:

1. To study how does the distance of internal displacement from conflict zones affect structural unemployment in Ukraine.
2. Identify the regions most affected by forced migration and have the highest level of structural unemployment.
3. Investigate the problem of endogeneity at the level of individuals and regions, which is caused by the forced internal movement of the population.

We have developed the following two hypotheses according to the research questions that were mentioned above and want to investigate them:

- H1: People who move farer away from hostilities zone are driven by the availability of sustainable jobs for them. This is negatively associated with structural unemployment.
- H2: People who move away but stay closer to the hostilities zone, make a primarily security-driven decision. This displacement would positively associate with structural unemployment.

The novelty of this study lies in its use of recent data on Ukrainian migration and the impact of this migration on structural unemployment in the regions. Research on wartime labor markets is important both for Ukraine during a full-scale invasion and for future armed conflicts.

The thesis is organized as follows: Chapter 2 reviews the existing literature on wartime migration and labor market dynamics, with a focus on global case studies relevant to Ukraine. Chapter 3, the author created the methodology to examine the relationship between migration and unemployment. Chapter 4 provides a detailed description of the data sources and variables. Chapter 5 outlines the empirical findings on the key factors driving structural unemployment in Ukraine. Finally, Chapter 6 summarizes the main findings with policy recommendations.

Chapter 2

LITERATURE REVIEW

Migration of the population constantly creates problems in the labor market, including structural unemployment. It is reflected in the mismatch of the skills of the migrating population and the offers from employers in regions that are safer. This is one of the disruptions in the economy caused by military actions. The results of such a phenomenon are a global topic for research. We have reviewed similar studies that may be useful to us. Most of the research data reflect the problem of other recent military conflicts: Bosnia and Herzegovina, Israel, Iraq, Syria, Tajikistan and Ukraine. They can be used as a basis for understanding global processes of wartime migration. We integrate the ideas of the studies, which are relevant in the Ukrainian situation at the moment.

Military conflicts always destroy key sectors of the economy that are the basis of national economies. The destruction of enterprises, land mining, occupation of territory - lead to the loss of jobs. All this has increased the need for the population to find new work where it is possible. During the conflict in Bosnia and Herzegovina (Kondylis, 2008), key sectors of the economy were disproportionately affected, reflecting the problems of endogeneity of regions and labor. This led to long-term unemployment among displaced persons. They were unable to find work that matched their professional skills.

At the beginning of the full-scale invasion, the unemployment rate rose sharply. Over time, it stabilized slightly, but is still 2 times higher than the indicators before 2022. The absolute annual increase in unemployment over the past 5 years is 2.54%, while actual unemployment in Ukraine is growing by 12.64% annually (Mazniev et. al, 2024).

Ukrainian industrial centres such as Donetsk and Luhansk regions experienced similar disruptions. During the military conflict, parts of these regions were occupied, and a large number of enterprises and industrial facilities, especially mines, were destroyed. The overwhelming majority of the population in these regions had a specialty that is characteristic only for these regions: mining, metalworking and mechanical engineering. Other regions of Ukraine may offer a certain number of jobs in similar industries, but do not allow using all the means due to the limited number of work places. Therefore, most displaced persons were either forced to retrain to other industries or remain unemployed.

Vakhitova and Yavorky (2020) studied the employment-related indicators of internally displaced persons from Donetsk and Luhansk oblasts. By comparing occupations before and after migration, they found that share of managers among IDPs significantly dropped after displacement, from 12% to 5%; and the share of technicians decreased from 15% to 12%; the proportion of service and sales workers rose from 10% to 13%; factory workers from 11% to 15%, and skilled agricultural workers from 2% to 6%. These shifts indicate a process of deskilling among the displaced population. The study also found that IDPs changed their pre-conflict occupations three times more often than non-IDPs (37% compared to 11%), indicating that their previous jobs were often not in demand in the regions where they resettled.

Studies of post-conflict Bosnia (Toal and Dahlman, 2006) have shown that the return of migrants is negatively affected by factors such as: limited resources for those who want to return, uneven distribution of economic resources in the places from which the population left, and questionable sustainability of return communities. Most returnees migrate to urban areas due to increased employment opportunities in such areas. This study suggests that those who migrate due to military operations are most likely to be at the poverty line (on average, 35% of the total migrant population) (World Bank 2003).

Ukraine currently faces a serious problem with labor mobilization. Forced mobilization and the reduction of men in non-military sectors of the economy create a mismatch between available skills and labor market needs. Not all important categories of workers are eligible for reservation and can be called up for military service - this creates a labor market shortage of such specialists and leaves gaps in civilian industries. Research on labor mobilization during the Korean War (Ji-Yeon, 2005) highlights the strain on non-military sectors and the difficulties of reintegration of veterans into civilian roles. During war, there are always problems with social and psychological barriers. Psychological trauma and social discrimination further hinder the employment prospects of internally displaced people. Research by Blattman and Annan (2010) shows that such psychological consequences are long-term and usually 1 in 10 people will live as before, all others will have the psychological impact of the war. Cerkez's (2011) study shows that trauma significantly reduces labor market participation.

Gender discrimination still exists in Ukraine. Women have always faced greater difficulties in finding employment than men. However, internally displaced women usually have much less time to be employed than internally displaced men or non-internally displaced women. This issue has been raised in studies in Ukraine (Vakhitova and Iavorkyi, 2020) and Tajikistan (Shemyakina, 2011).

Ukraine is now effectively "living and functioning" on the back of international investments: compensation for the payment of wages at state-owned organisations (by USAID), financing of the defence industry, humanitarian cargo, financing of non-military sectors of the economy, provision of weapons and supplies, etc. They play a key role in mitigating structural unemployment during and after the war - after all, such investments actually create new jobs or preserve existing ones. The largest share of foreign investment goes to manufacturing - 55.18% and Agriculture and fishery - 15.4% (Sahachko et al., 2023). However, the main problem of foreign investment is low returns and inefficient distribution by type of economic activity.

People are driven to migrate for many reasons during war time. Studies of the military conflict in Syria (Ümit Seven, 2022) showed that only 25% of respondents indicated that the main reason for their migration was the intensity of actual violence of military operations, the other 75% emphasized other factors that forced them to migrate. In most cases, people choose to stay at home until a certain level of danger is reached and then they decide to migrate.

On the other hand, from Bohra-Mishra and Massey's (2011) perspective, intensity of violence during month t is key in an individual's decision to migrate, because the higher the probability of violence, the more a person will try to avoid it by migrating. The authors note that the next most common reason for migration is poverty (along with unemployment, low wages, yields economic hardships).

In the Ukrainian context after the outbreak of the war in 2014, Vakhitova and Yavorky (2018) they argued Luhansk and Donetsk oblasts of Ukraine because 1) households that did not move far from the hostilities are most likely to be driven by conflict only and 2) long-distance movers may combine economic and forced displacement motives. We would like to use these as our hypothesis and extend it in our research.

Most of the studies in this block examine labor migration in post-war contexts: such as Bosnia and Herzegovina (Kondylis, 2010; Toal and Dahlman, 2006), Syria (Ümit Seven, 2022), and Tajikistan (Shemyakina, 2011). Thus, a noticeable gap of this study is the study of how displacement influences labor markets during an ongoing war.

Most existing research evaluates the long-term impacts of conflict after hostilities have ceased, but such frameworks may not fully capture the unique challenges and dynamics that emerge when conflict is still active, labor markets remain highly uncertain, and displacement patterns continue to evolve.

To fill this gap we analyze real-time labor market impacts of internal displacement during an active conflict in Ukraine for the period 2022-2024. This research allows for the observation of short-term shocks, structural mismatches, and the role of proximity to conflict zones in shaping labor market access. Unlike post-conflict studies that assess static or lagged effects, this paper provides insights into evolving labor responses amid continuing violence, economic instability, and shifting migration flows.

Chapter 3

METHODOLOGY

In our study, we want to identify the regions for which the probability of labor force employment for IDPs and local residents is higher. To do it we will rely upon probit regression for individual level data with fixed effect for the receiving region.

Thus, our probit regression is based on the research methodology of Vakhitova and Yavorky (2020) and will look like this:

$$Pr(Y_{it} = 1|X_{it}, \alpha_r, \gamma_t) = \Phi(X_{it}\beta + \alpha_r + \gamma_t + \epsilon_{it}) \tag{1}$$

where:

Y_{it} indicates the employment status of individual i at time t (where 1 - the individual is employed, 0 - not employed);

X_{it} is a set of individual variables for individual i at time t (age, gender, education, IDP status etc); α_r - fixed effects of region r; γ_t - time fixed time effects.

However, during our analysis, the problem of endogeneity may arise at the individual and region level:

- The problem of the endogeneity of the individual is that the IDP may have a specific observable and unobservable characteristics that would correlate with both employment and displacement.
- The problem of regional endogeneity is that regions close to active hostilities have a more unpredictable economic situation (less

employment opportunities than safer regions) and a large destructions leading to higher structural unemployment.

We will use an instrumental variable to tackle individual-level endogeneity that influences displacement but is not directly related to employment outcomes. As an instrument, we construct a binary variable indicating whether the individual's region of origin was among the high-threat regions, those located close to the front line during the early phase of the full-scale invasion (e.g., Donetsk, Luhansk, Kharkiv, Kherson, Mykolaiv, Zaporizhzhia oblasts). This variable satisfies the relevance condition, as people from these regions were significantly more likely to become internally displaced due to direct military threats. It also meets the exogeneity condition, since originating from a high-threat region affects displacement likelihood, but after controlling for regional and individual characteristics - it should not directly determine employment outcomes in host regions. Thus, it only affects employment indirectly, through displacement status.

To account for regional endogeneity, we incorporate region fixed effects that control for time-invariant regional characteristics, such as economic conditions, infrastructure development, and labor market structure. Thus, we isolate the impact of displacement on employment from broader regional economic disparities.

We also apply matching techniques to pair IDPs with NDPs who share similar observable characteristics (e.g., age, education, industry of previous employment). Specifically, we use propensity score matching. Each IDP is then matched to one or more NDPs with similar propensity scores using a nearest-neighbor algorithm without replacement and a caliper restriction to ensure close matches. We aim to reduce selection bias that arises from systematic differences between IDPs and NDPs in observed characteristics. This allows us to construct a more balanced control group and obtain a more accurate estimate of the causal effect of displacement on employment probability. After matching we compare employment outcomes between the matched groups to assess the labor market disadvantage associated with displacement.

Chapter 4

DATA

We will use data from Info Sapiens regular monthly surveys. Info Sapiens conducts regular demographic surveys of Ukrainians. They provided us with the demographic block of questions for the period March 2022 - October 2024.

Since the beginning of the full-scale invasion, Info Sapiens has been collecting data for IDPs/NDPs about their region of residence, social and economic status, etc.

4.1 General data description

The main data for our research was provided by Info Sapiens and contains the following data: gender, age diapason, oblast and region in which a respondent was located before a full-scale invasion, oblast and region to which the respondent moved after a full-scale invasion, city size, IDP status, marital status of the respondent, presence of children in different age groups, employment status, level of education, financial situation, the language spoken by the respondent, month and year for which respondents were surveyed.

4.2 Descriptive statistics

The dataset that is provided by Info Sapiens for our research offers information on 31810 observations interviewed in the government-controlled areas of Ukraine, as you can see in the Table 1 below. All respondents were interviewed at different times, in different regions and settlements, and are completely random.

Table 1. Descriptive statistics

Statistic	Obs	Mean	St. Dev	Min	Max
Gender	31,810	0.5708	0.495	0	1
Age	31,810	47.5341	14.7167	18	65
Region from the respondent	31,810	3.3112	1.5877	1	6
City size	31,810	255.7433	306.2128	10	750
Relocation	31,810	0.1938	0.4992	0	2
IDP	31,810	0.1474	0.3545	0	1
Family	31,810	0.5971	0.4905	0	1
Children	31,810	0.4212	0.4938	0	1
Work	31,810	0.5636	0.496	0	1
Education, years	31,810	13.0854	2.0603	7	15
Financial situation	31,810	3.2014	1.7653	1	7
Language	31,810	0.6011	0.4897	0	1
Employed	31,810	0.4882	0.4999	0	1

Source: author's calculations, Info Sapiens survey data, 2024

The survey had the following parameters: age, gender, region and area of pre-war residence, region and area of residence during the survey, family status, presence of children, presence of employment, presence of IDP status, presence of higher education, and financial situation of the respondent. To see decoding of the variables above - please refer to Appendix A.

In our dataset, the survey included more women than men, the average age group is 40-49 years old, only 14.74% of respondents are IDPs, 59.71% are married, 42% have children, and 48% are employed.

We also checked the number of IDPs among each age group to understand the distribution of IDPs among age groups (Table 2) and saw that the largest percentage of IDPs is in the age group of 20-29. This means that respondents in this age category are more mobile and tend to move if they are in a hostility zone (due to the absence of children, acquired property, etc.).

Table 2. Percentage of IDP for each age group

Age	IDP %	NDP %	Number of observations
16-19 y.o.	18.71%	81.29%	1,037
20-29 y.o.	22.88%	77.12%	3,553
30-39 y.o.	19.24%	80.76%	6,311
40-49 y.o.	15.85%	84.15%	5,918
50-59 y.o.	11.40%	88.60%	5,704
60+ y.o.	9.46%	90.54%	9,287
Number of observations	4,688	27,122	31,810
% from total population	14.74%	85.26%	

Source: author's calculations, Info Sapiens survey data, 2024

From the diagram below (Figure 1) we see that the main age groups that make up the largest percentage of IDPs during the period are 20-29 y.o. and 16-19 y.o. and they have remained almost unchanged during the survey period. The figure clearly shows seasonality due to the start of the school year for the 16-19 age group.

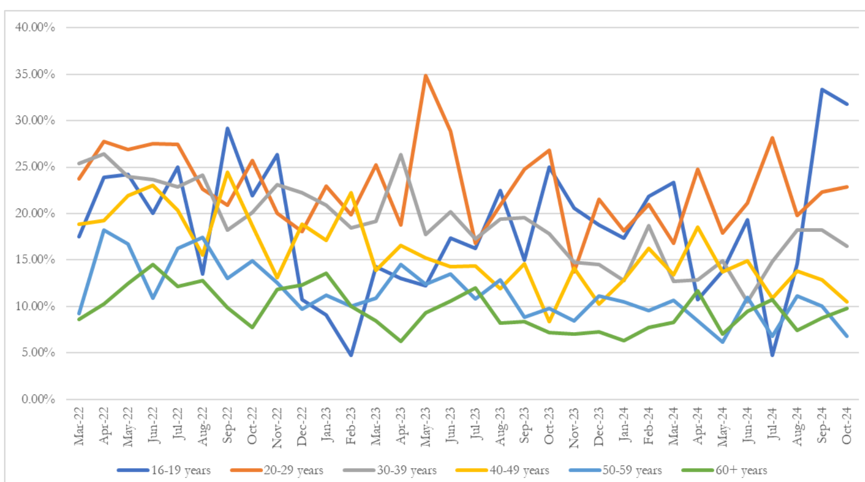

Figure 1. Percentage of IDPs among age groups through the period

Source: author's infographics based on Info Sapiens survey data, 2024

We also calculated the measure of association and checked whether the actual distribution of internally displaced persons by age is statistically significant (Table 3). X^2 in our case is 475.67, so we reject the zero hypothesis, accordingly the actual distribution of IDPs is significantly different from the expected one and the difference between the actual and expected distribution of IDPs by age groups is statistically significant.

Table 3. Statistical significance check for percentage of IDP for each age group

Age Group	Observed (O)	Expected (E)	(O-E)^2 / E
16-19	194.00	152.83	10.44
20-29	813.00	523.62	158.74
30-39	1,214.00	930.08	87.21
40-49	938.00	872.17	5.07
50-59	650.00	840.63	43.08
60+	879.00	1,368.67	171.13
Total	4,688.00	4,688.00	475.67

Source: author's calculations, Info Sapiens survey data, 2024

Regarding the distribution of IDPs among each year of surveys (Table 4), there is a clear trend of a decrease in the percentage of IDPs among respondents after the beginning of 2023. This is due to the greater predictability of the further development of the armed conflict and a certain stabilization of the situation.

Table 4. Percentage of IDP for each year of survey

Year	IDP	NDP	TOTAL	% of IDPs
2022	1,777	8,152	9,929	17.90%
2023	1,678	10,294	11,972	14.02%
2024	1,233	8,676	9,909	12.44%
TOTAL	4,688	27,122	31,810	14.79%

Source: author's calculations, Info Sapiens survey data, 2024

Our dataset was collected based on data from monthly surveys of Ukrainians in the territory controlled by Ukraine for almost 2 consecutive years and includes almost 32 thousand observations. Thus, the dataset is suitable for building a model and identifying certain patterns.

In our dataset we have the largest number of IDPs is in the South, North, and East regions (Table 5). Most of them migrate within the region.

Table 5. Distribution of IDPs by regions

To | From	West	Kyiv	South	North	East	Center
West	3%	2%	4%	2%	7%	1%
Kyiv	0%	2%	3%	1%	4%	1%
South	0%	0%	12%	0%	2%	1%
North	0%	1%	2%	7%	4%	0%
East	0%	0%	0%	0%	11%	0%
Center	0%	1%	5%	2%	17%	6%

Source: author's calculations, Info Sapiens survey data, 2024

Since we have monthly survey data, we can use it to determine seasonality. As we can see from Figure 2 the lowest level of employment was in June 2023. In October 2024 survey data shows the highest level of employment. This rate was calculated as the ratio of Employed respondents to all respondents in the labor force (sum of employed and unemployed people), according to the responses of the surveyed people. We mapped the answers of the respondents so that we could calculate the employment rate. "Employed" status was used for people who work for hire, the self-employed and military. "Unemployed" was used for people who are temporarily unemployed but looking for work. We excluded from calculation people who are not in the labor force (pensioners, students, people who are engaged in housekeeping, people who are not working and not looking for work, and who answer "Other").

The highest percentage of IDPs surveyed was in April 2022 (Appendix B). After that, the percentage of IDPs in the survey began to decrease with each month

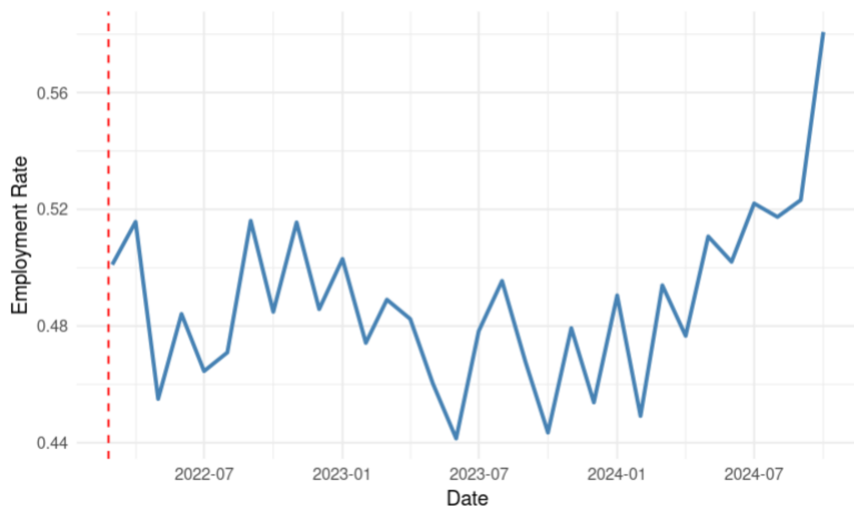

Figure 2. Employment rate over the time per survey data.

Source: author's infographics based on Info Sapiens survey data, 2024

The percentage of employed IDPs is lower than that of NDPs (Figure 3). This indicates that IDPs experience significant problems in finding employment in other regions. The lower employment rate among IDPs may indicate structural unemployment, because the skills of displaced individuals do not align with the sectoral composition of the host region's labor market, or social and institutional barriers prevent their integration.

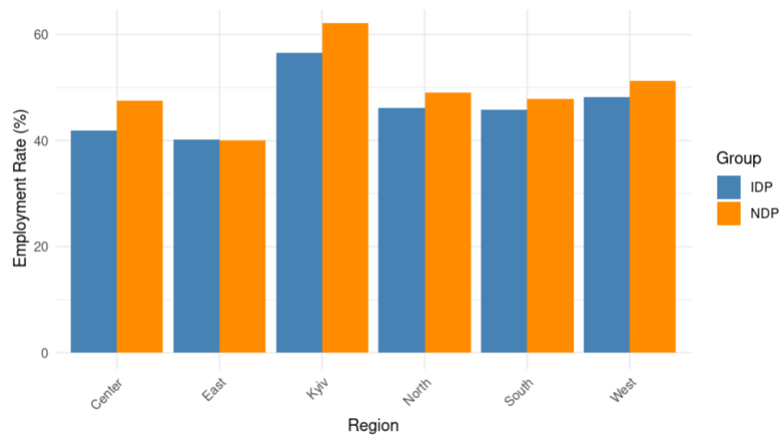

Figure 3. Percentage of employed IDPs/NDPs by regions

Source: author's infographics based on Info Sapiens survey data, 2024

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Chapter 5

ESTIMATION RESULTS

Based on the methodology and data described in the previous chapters, we built a model and obtained the results that will be described in this section.

5.1 Main model results

First of all, population movement between regions in Ukraine creates complex labor market dynamics. Migration can alleviate unemployment and increase productivity when individuals move in search of job opportunities that match their skills. Such voluntary or economically motivated relocation can reduce regional labor market imbalances and support economic efficiency.

In the context of forced displacement due to war, many IDPs are not moving toward opportunity but away from danger and are relocating to regions where their existing skills do not align with local labor market demand. IDPs face barriers to integration and require reskilling or transition to entirely different industries. Thus, while mobility can be beneficial under stable conditions, in the context of conflict-driven migration, it often exacerbates mismatches between labor supply and demand (especially when host regions are economically distinct from the regions of origin). This creates a mismatch supply and demand in the labor market, when a person with specific skills from region X moves to region Y, which cannot offer employment to this person with specific skills - this is where the problem of structural unemployment arises.

We have created an infographic that shows population movements among regions of Ukraine (Figure 4). The percentages shown in white show the movement of IDPs within regions when people move to another region - this is shown by the arrows in the infographic. Minor movements have not been shown for readability of the figure.

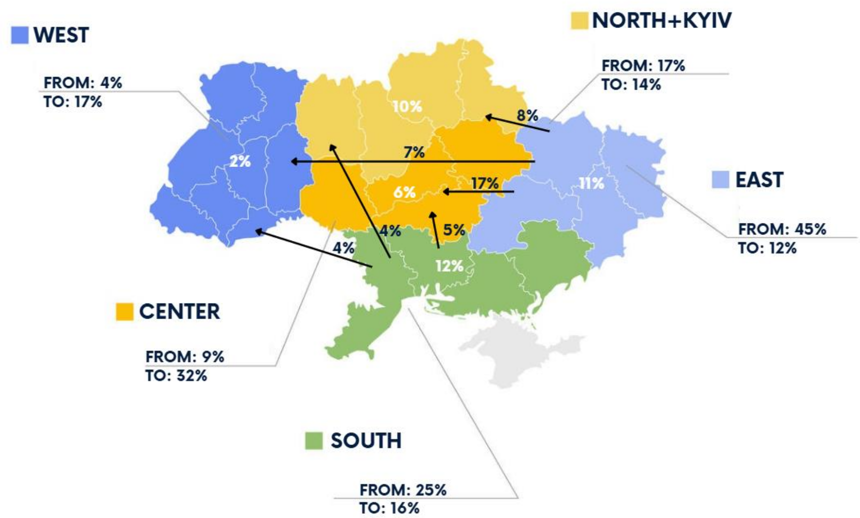

Figure 4. Map of IDP movements within Ukraine

Source: author's infographics based on Info Sapiens survey data, 2024

We could see that the largest percentage of IDPs moved from the East and South parts of Ukraine to the Center region (22% in total), and 41% of IDPs moved within regions.

According to the developed model, we obtained the results for all respondents that you can see in the Table 6 below and Appendix F.

Table 6. AME of the probit regression for all respondents

Variable	AME	Std. Err.	z	P>|z|
Age 20-29 years	0.3010	0.0122	24.7661	< 2.2e-16 ***
Age 30-39 years	0.3541	0.0124	28.5731	< 2.2e-16 ***
Age 40-49 years	0.3773	0.0117	32.1810	< 2.2e-16 ***
Age 50-59 years	0.2947	0.0121	24.3710	< 2.2e-16 ***
Age 60+ years	-0.0996	0.0171	-5.8230	5.780e-09 ***
Female	-0.1363	-0.0048	28.2688	< 2.2e-16 ***
IDP status	-0.0671	0.0073	9.1413	< 2.2e-16 ***
Secondary education	0.0717	0.0124	5.8056	6.414e-09 ***
Vocational and technical education	0.0811	0.0126	6.4164	1.395e-10 ***
Higher education	0.2445	0.0130	18.7456	< 2.2e-16 ***
From East	-0.0062	0.0141	-4.4180	0.6586614
From Kyiv	0.0544	0.0093	5.8678	4.416e-09 ***
From North	-0.0015	0.0074	-2.0210	0.8398034
From South	0.0160	0.0102	1.5679	0.1169114
From West	0.0084	0.0071	1.1858	0.2356994
Have children	-0.0030	0.0052	-5.8670	0.557392
High threat region	-0.0448	0.0119	-3.7652	0.0001664 ***

Source: author's infographics based on Info Sapiens survey data, 2024

Note: our base category is male under 20-year-old, basic education level (9 grades or less), NDP, from Central region, has no children and this category has a low base probability of being employed

Age has a strong effect on employment probability. Individuals aged 20-60 are significantly more likely to be employed than the youngest reference group. The effect increases across age brackets, peaking for those aged 40-49 (by 37.7 percentage points compared to the base category) and then slightly declining for those aged 50-59. In contrast, respondents aged 60 and older are significantly less likely to be employed (by 10 percentage points compared to the base category).

Gender plays a notable role, because females are associated with a significantly lower probability of employment (13.6 percentage points less likely to be employed compared to men), it indicates persistent gender disparities in the Ukrainian labor market.

To address the concern that individuals not actively participating in the labor market may distort the estimated effect of displacement on employment, we estimated the regression for the sub-sample which does not include people who are not in the labor force. The results suggest that IDPs face additional disadvantages in employment. The coefficient for IDP status is negative and highly significant for selection without people who are not in the labor force (because IDP status reduces the probability of employment by 6.7 percentage points), so it confirms that displacement due to conflict is associated with reduced access to employment opportunities.

This result suggests that part of the observed employment gap in the full sample may be explained by differences in labor force participation, especially the presence of non-working groups such as retirees among NDPs. However, the fact that the effect remains significant even after correcting for this selection confirms that displacement itself has an independent and robust negative impact on employment, not merely an artifact of sample composition.

Education has a linear effect. Respondents with only secondary education show a negative significant coefficient with weak employment outcomes, but are more likely to be employed than those with lower levels by 7.2 percentage points. Those with vocational or technical education show a moderate positive association with employment and are more likely to be employed than base category by 8.1 percentage points. The strongest positive effect is observed for individuals with higher education (by 24.5 percentage points more likely to be employed), whose employment probability increases substantially.

The region of origin shows mixed results. People from the East of Ukraine are not significantly more associated with employment relative to respondents from the Central region (it decreases employment probability by only 0.6 percentage points). Respondents from the North, South, and West do not differ significantly from the basic group and are close to zero. Possibly because of a wide range of labor market outcomes for displaced individuals from this conflict-affected region. However, individuals from Kyiv have a significantly higher probability of being employed (by 5.4 percentage points), which may reflect that IDPs from Kyiv have more versatile skills or can work remotely.

The presence of children has a very small, statistically insignificant decrease in employment probability by 0.3 percentage points, because of having children does not independently influence employment status when other factors are controlled for.

The high_threat_region variable, which is constructed as an instrumental variable for displacement, is negative and statistically significant (it reduces the employment probability by 4.4 percentage points). This suggests that individuals originally from regions close to the frontline in the early stages of the full-scale invasion are less likely to be employed.

Above were the results of our model for all respondents (including categories that do not belong to the labor force such as pensioners, students, the category of the population that is not ready to work and "others"). These non-LF population categories may influence the results of the models. So, to eliminate the possibility of selection bias, below you can see the results for labor force only (Table 7), which we will compare to the model results for all respondents.

Table 7. AME of the probit regression for labor force only

Variable	AME	Std. Err.	z value	Pr(>|z|)
Age 20-29 years	0.0488	0.0169	2.8810	0.0039641 **
Age 30-39 years	0.0431	0.0184	2.3492	0.0188145 *
Age 40-49 years	0.0599	0.0175	3.4181	0.0006305 ***
Age 50-59 years	0.0562	0.0171	3.2840	0.0010235 **
Age 60+ years	0.1111	0.0106	10.4769	< 2.2e-16 ***
Female	-0.0659	-0.0051	-12.8077	< 2.2e-16 ***
IDP status	-0.0884	0.0089	-9.9656	< 2.2e-16 ***
Secondary education	0.0511	0.0118	4.3225	1.543e-05 ***
Vocational and technical education	0.0317	0.0124	2.5481	0.0108307 *
Higher education	0.1598	0.0140	11.4348	< 2.2e-16 ***
From East	-0.0295	0.0161	-1.8281	0.0675339
From Kyiv	-0.0042	0.0104	-0.4026	0.6872088
From North	-0.0165	0.0087	-1.8962	0.0579303
From South	-0.0169	0.0117	-1.4472	0.1478451
From West	-0.0021	0.0082	-0.2535	0.7998867
Have children	0.0057	0.0054	1.0540	0.2918941
High threat region	-0.0444	0.0136	-3.2625	0.0011042 **

Source: author's infographics based on Info Sapiens survey data, 2024

In the full sample, all age groups between 20-59 had large positive effects on employment (30-38 percentage points), while age 60+ showed a negative effect (-9.96 percentage points). However, in the labor-force-only model, all age groups showed smaller positive effects, and strikingly, age 60+ became strongly positive (+11.11 percentage points). This reversal indicates that within the labor force, older individuals (especially seniors still working or seeking jobs) are more employable than their peers outside the workforce, who were dragging down the full-sample estimates.

The negative marginal effect for being female decreased from -13.6 percentage points to -6.6 percentage points, but remained highly significant. This probably suggests persistent gender-based barriers, though the gap narrows among active job seekers.

IDP status remained negative and significant, but its magnitude changed from the -6.7 percentage points to -8.8 percentage points in the labor force sample.

Educational effects were smaller but consistent. For instance, higher education's positive effect dropped from +24.5 percentage points to +16.0 percentage points, while vocational and technical education dropped from +8.1 percentage points to +3.2 percentage points.

Regional origin effects flattened, because in the full sample, being from Kyiv was associated with +5.4 percentage points, while in the labor force model it became statistically insignificant (-0.4 percentage points). "From East" remained negative in both, but its magnitude grew in the labor force sample (from -0.6 to -3.0 percentage points). So regional disparities persist but become less pronounced once we focus only on the labor force.

High-threat region variable stayed stable, with a negative marginal effect of about -4.4 percentage points in both models, suggesting consistency across samples.

To address the potential endogeneity of displacement status in estimating its effect on employment, we implemented a two-stage instrumental variable probit estimation. The concern is that IDP status may be correlated with unobserved factors such as risk tolerance, personal networks, or trauma exposure that also affect employment outcomes.

In the first stage, we model the probability of being IDP as a function of a set of exogenous controls and an instrumental variable, high_threat_region, which equals 1 if a person originally resided in a region close to the front line at the start of the full-scale invasion. This instrument is theoretically motivated by the fact that proximity to active hostilities significantly increased the likelihood of displacement, but it should not directly affect the ability to find a job in another region satisfying both relevance and exogeneity conditions.

The results of the first-stage probit regression (Appendix G, Table 19) confirm the instrument's relevance. The coefficient on high_threat_region is large (1.109) and highly significant. It confirms that residing in a high-threat area substantially increases the probability of becoming an IDP. Additional variables, such as age and region of origin, are also significant predictors of displacement. This step allows us to construct a predicted probability of displacement (IDP_hat), which captures only the exogenous variation in displacement status.

In the second stage (Appendix G, Table 20), we use IDP_hat in place of the endogenous IDP variable and estimate its effect on the probability of being employed using a probit model. The results show that IDP_hat is negative and statistically significant (-0.69). This confirms that, after accounting for endogeneity, displacement causally reduces the probability of employment. The magnitude of the effect is stronger than in the original model without IV. It indicates that uncorrected estimates may understate the true disadvantage faced by displaced individuals.

Other variables in the model behave as expected and are consistent with previous specifications.

During our research, we saw that most IDPs move within their regions, even in relatively safe regions such as the West, Center and Kyiv (Figure 5). We also noticed that some IDPs moved from Kyiv city to Kyiv city, which suggests that they received IDP status before the full-scale invasion and their original place of residence was in a different region prior to 2022. This creates some difficulties in determining a person's "native" region and may lead to some distortion of the research results.

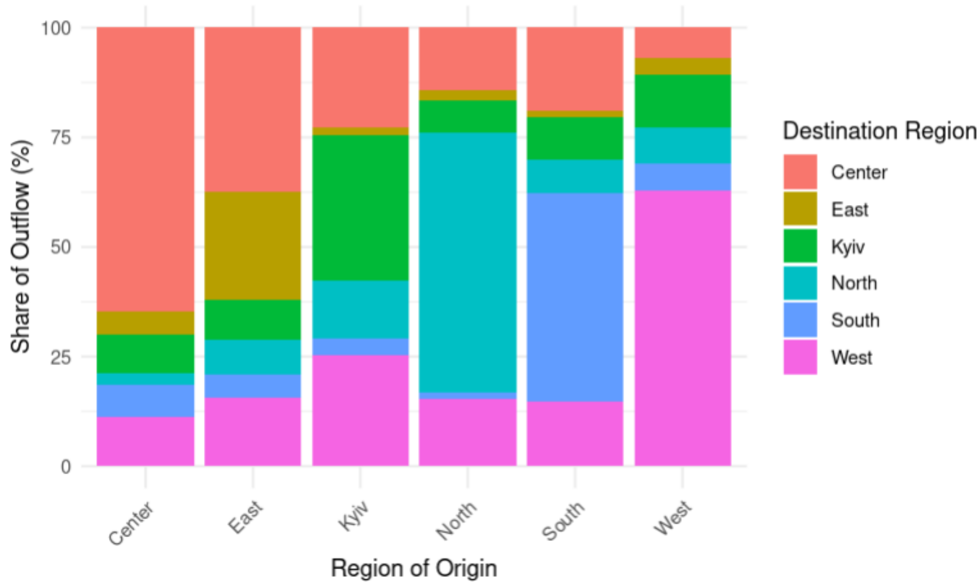

Figure 5. Movements of IDPs by regions

Source: author's infographics based on Info Sapiens survey data, 2024

5.2 Proximity to conflict zone results

We also created probit regression estimates the likelihood of being employed among IDPs in Ukraine. The primary variable of interest is moved_nearby, which indicates whether an individual moved to a nearby oblast rather than farther away from the conflict zone. The model also controls for region of origin, age, gender, education, and the presence of children (Appendix D).

The coefficient for moved_nearby is negative and statistically significant, it indicates that IDPs who relocated only short distances from the conflict zone are less likely to be employed compared to those who moved farther away. This supports the hypothesis that proximity to the frontline constrains employment outcomes, most likely because of continued insecurity, limited labor market capacity in nearby host regions, or weaker long-term integration support.

Regarding the region of origin, individuals displaced from the East and South of Ukraine are significantly less likely to be employed. It may reflect the destruction of economic infrastructure and deeper disruption of livelihoods in those areas. Conversely, IDPs originally from the West are more likely to be employed, potentially due to migration within more stable areas, greater availability of social support networks, or better individual resources. The regions of origin Kyiv and North do not show significant associations with employment status.

Age also plays a substantial role in determining employment probability. Individuals aged 20-59 are significantly more likely to be employed. Peak is observed for 40-49 age. Respondents aged 60 and above are significantly less likely to be employed.

The gender indicates that women are less likely to be employed than men, which highlights gender disparities in the labor market (even among the displaced population).

Individuals with secondary education (educ11) are more likely to be employed, and the effect is marginally significant for vocational or technical. Higher education (educ15) has the strongest positive association with employment.

The presence of children in the household is negatively associated with employment, because of caregiving responsibilities may limit the labor market participation of displaced individuals, especially women.

We also calculated the impact of the characteristics of the respondents' movements and the impact of these factors on their employment opportunities (Table 8). Below you can see a table showing the impact on employment opportunities of 3 separate factors: 1) the person only left the hostilities; 2) the person only moved within the region or to a neighboring region; 3) both the person left the hostilities and moved within the region or to a neighboring region.

Table 8. Impact of relocation on employment

Variable	AME	Std. Err.	z	P> |Z
Moved from hostilities	-0.1075	0.0143	-7.5155	5.672e-14 ***
Moved nearby	-0.0460	0.0186	-2.4793	0.013165 *
Moved nearby and from hostilities	0.0717	0.0248	2.8968	0.003770 **

Source: author's calculations, Info Sapiens survey data, 2024

The coefficient for respondents who only moved from hostilities is negative and statistically significant (-10.7 percentage points), it suggests that individuals who escaped from regions heavily affected by the war face considerable disadvantages in the labor market.

The "Only moved nearby" variable also shows a negative and statistically significant marginal effect (-4.6 percentage points). This result implies that displaced individuals who relocate only short distances often remaining close to the zone of hostilities are less likely to be employed. Proximity to the conflict may impose constraints such as market saturation in nearby host regions, insecurity, or limited institutional support for labor reintegration.

Coefficient "Moved nearby and from hostilities" has a positive and significant marginal effect (7.2 percentage points), which is very interesting. This indicates that individuals who fled high-threat areas but relocated nearby may, despite the challenges, have better employment outcomes than expected. Most likely, this is due to the fact that in the nearby oblasts that are close to the hostilities area, the labor market structure is similar to the zone from which the respondents left (for example for miner from Donetsk oblast it will be easier to get a job at a mine in the Dnipro oblast than in Western Ukraine).

So, proximity to conflict zones negatively influences employment opportunities among IDPs, but not all displacement affects employment in the same way, and that remaining near the frontline is particularly disadvantageous for labor market reintegration. The respondents who moved from hostilities zone and to nearby oblast have positive coefficient. That is, our hypothesis does not work, at least in this case for Ukraine.

5.3 Propensity score matching results

To estimate the causal effect of displacement on employment and control for observable differences between IDPs and NDPs, we implemented propensity score matching (PSM) with nearest-neighbor match without replacement. The propensity score was estimated as probit model that included age group, gender, education level, and region of origin as covariates. IDPs were matched to NDPs with similar predicted probabilities of being displaced.

Before we match it, the distribution of covariates in Appendix E showed significant imbalances between IDPs and NDPs. For example, large standardized mean differences (SMDs) were observed for region of origin, particularly for from East (SMD = +0.743) and from West (SMD = -0.927), and for the oldest age group is aged 60+ years (SMD = -0.314), it indicates that IDPs and NDPs differed substantially on key background characteristics.

After we matched it, balance was notably improved (Figure 6). All covariates had standardized mean differences close to zero, and empirical cumulative distribution function (eCDF) differences were substantially reduced. Variable "From Center" was perfectly balanced post-matching (SMD = 0). But gender, education and age distributions were brought within acceptable thresholds (all SMDs < ±0.1). This indicates that the matching procedure was successful in creating a comparable control group of NDPs for estimating employment differences.

In total, 4,688 IDPs were matched to 4,688 similar NDPs, and 22,434 unmatched NDPs were discarded from the analysis. So with this balanced sample we can make further causal inference.

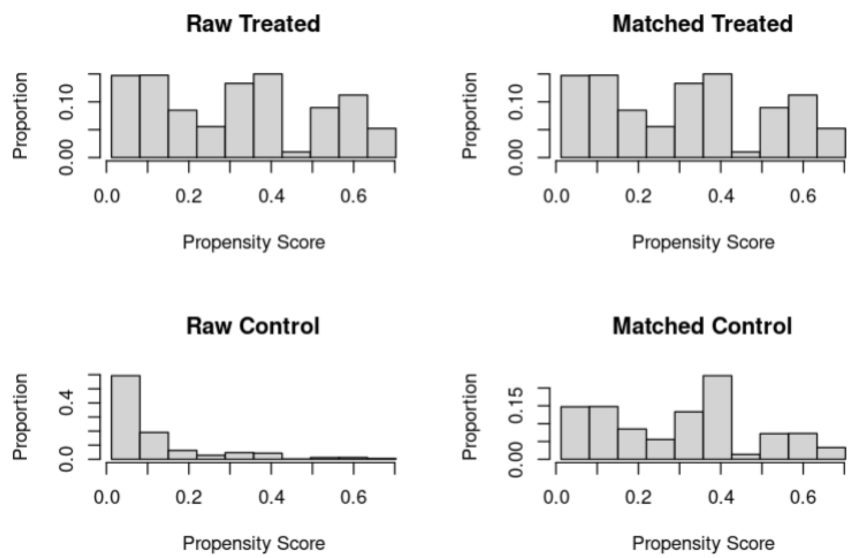

Figure 6. Propensity score distributions before and after matching

Source: author's infographics based on Info Sapiens survey data, 2024

We estimated a probit regression with employment status as the dependent variable and displacement status as the independent variable. The model reveals a negative and statistically significant effect of being an IDP on the probability of being employed (Appendix E). This result suggests that, even after we account for differences in observable characteristics such as age, gender, education, and region of origin, IDPs are 16,5% less likely to be employed than otherwise similar non-displaced persons.

This confirms that displacement imposes a structural disadvantage in access to employment, even when we compare IDPs to a matched sample of NDPs with nearly identical profiles. These findings strengthen the robustness of our earlier results and reinforce the conclusion that displacement, especially short-distance or conflict-adjacent movement, presents a major challenge for labor market integration in wartime Ukraine.

5.4 Robustness check

We performed a series of robustness checks, including alternative model specifications (logit model), and exclusion of people who are not in the labor force. Across all robustness models, the key coefficients remain stable in both sign and statistical significance, indicating that our results are not sensitive to the specific modelling choices (Appendix C). This matching procedure allowed us to compare IDPs and NDPs who are both active in the labor market and share similar observable characteristics such as age group, gender, region of origin, education, and presence of children.

In particular, the effects of age, gender, education, and IDP status consistently align with our main specification. Respondents aged from 20 to 59 continue to show significantly higher employment probabilities compared to the baseline group in the main sample, though in the labor-force-only model, these effects are reduced in magnitude. Interestingly, respondents aged 60+, who are normally less likely to be employed, show a positive association in the restricted labor force model, probably because only those who are still working or seeking work are retained. The negative effect of being female remains strong and robust in all models. Higher education retains the strongest positive impact across specifications.

The region-matched model, which pairs IDPs and non-IDPs from the same regions with similar demographic and educational characteristics, confirms the robustness of the displacement effect: the IDP coefficient remains negative and statistically significant (-0.247). It indicates that displacement continues to be associated with lower employment probabilities even after adjusting for regional heterogeneity and selection bias. Notably, this model reveals more nuanced regional effects, such as a significantly higher employment probability for individuals originally from the East, and lower probabilities for those from the North and South, it suggests that local labor market conditions may mediate the integration of IDPs.

The variable of primary interest, IDP status, remains significantly negative in all models, though with stronger effect in the labor-force-only model (–0.369). The proximity to conflict zone variable (moved_nearby) is consistently negative and statistically significant across models, supporting the conclusion that IDPs who relocate nearby (rather than far away) face greater employment disadvantages.

The instrumental variable (high_threat_region) also retains a significant negative effect in most specifications, further supporting its validity in capturing conflict exposure. Minor variations in the regional variables and the "children" variable do not materially affect the main findings and are largely insignificant across models.

These robustness checks confirm that our main results are stable, theoretically consistent, and not driven by model specification or sample selection.

Chapter 6

CONCLUSIONS

6.1 Conclusions

This study examined how wartime internal migration influences structural unemployment in Ukraine based on dataset collected by Info Sapiens between March 2022 and October 2024. The analysis focused on both individual- and region-level factors that shape employment outcomes for IDPs, with a particular emphasis on displacement patterns, proximity to conflict zones, and labor market integration in host regions.

Our first research objective was to assess how the distance of internal displacement from conflict zones affects the risk of structural unemployment. To address this, we introduced the variable moved_nearby, which captures whether an IDP moved only a short distance (e.g., to a neighboring oblast) or relocated farther from the frontline. The probit regression results indicate that IDPs who moved to nearby areas were significantly less likely to be employed than those who relocated farther away. Additionally, marginal effects analysis confirmed that individuals who fled conflict-affected regions were 10.7 percentage points less likely to be employed, while those who only moved nearby (but not necessarily from the frontline) were 4.6 percentage points. less likely to be employed. In contrast, those who both fled high-threat regions and moved nearby showed a statistically significant increase in employment probability by 7.2 percentage points, possibly due to similar labor market structure, stronger social networks or adaptive behaviours. This suggests that remaining close to the zone of hostilities imposes constraints on labor market reintegration.

Therefore, not all displacement leads to the same employment outcome; the type and geography of displacement matter. So our hypothesis does not work in the context of Ukraine.

Our second objective was to identify which regions were most affected by forced migration and currently experience the highest levels of structural unemployment. Analysis of IDP movement patterns shows that the largest flows of displaced persons originated from the East and South of Ukraine and moved primarily to the Central and Western regions.

The third objective was to address the problem of endogeneity at the individual and regional levels, specifically the concern that the decision to relocate may be correlated with unobserved characteristics affecting employment. To account for this, we introduced an instrumental variable: high_threat_region, a binary indicator capturing whether an individual originated from a region heavily affected by early-stage hostilities (such as Donetsk, Luhansk, Kharkiv, Kherson, and Zaporizhzhia oblasts). The variable is highly correlated with the probability of being displaced and is exogenous to employment outcomes conditional on other controls. We implemented a two-stage probit approach, and results from the second-stage model showed that the predicted probability of being displaced (instrumented by high_threat_region) had a significant negative effect on employment. This confirms that unobserved selection into displacement would bias naive models and validates the use of instrumental variable correction.

The empirical analysis confirmed that internal migration in Ukraine has contributed to regional labor market mismatches. Due to the industrial and economic diversity across oblasts, individuals who relocate from one oblast to another often encounter structural unemployment because their skills are not aligned with the demand in their new location. This problem is most visible in large-scale east-to-center and south-to-west movements, as illustrated by our visualizations of internal mobility flows. Overall, IDPs were found to have lower employment rates than NDPs, which highlights a clear labor market disadvantage associated with displacement.

From an economic perspective, these findings indicate that internal displacement creates structural inefficiencies in the labor market that suppress productivity and delay post-conflict recovery. For individuals, especially those who remain close to the frontline, long-term labor exclusion can lead to economic insecurity, skill depreciation, and intergenerational poverty. For policymakers in Ukraine and abroad, the results underscore the importance of active labor market programs, targeted relocation incentives, and regional economic development in host areas to mitigate structural unemployment risks among the displaced.

6.2 Contribution and limitations

This study contributes to the growing literature on wartime labor markets by providing one of the first quantitative analyses of structural unemployment among displaced individuals in Ukraine based on nationally representative microdata. The integration of individual-level displacement data with regional migration flows allows for a deeper understanding of labor mismatches and displacement-related inequality. The study also offers a methodological contribution through the use of an instrumental variable - high_threat_region to address endogeneity in the displacement-employment relationship.

Furthermore, we implemented matching approaches to assess whether the negative employment effects were driven by underlying vulnerabilities among displaced populations. When matching IDPs and non-IDPs based on observable characteristics and focusing only on those within the labor force, the negative employment effect persisted, albeit with slightly reduced magnitude. This confirms that the effect is not solely driven by persons who are not in the labor force and suggests a causal link between displacement and reduced employment opportunities.

However, several limitations remain. First, while the dataset is rich, it lacks precise geographic distance measures, which limited our ability to model proximity in continuous terms. Instead, proximity was operationalized through binary classification (moved_nearby), which may oversimplify more nuanced migration experiences. Second, some IDP classifications may reflect pre-2022 displacements, complicating efforts to identify initial regions of origin. Third, although we controlled for several demographic variables, unobserved factors such as mental health, informal employment, or access to social networks may also influence labor market outcomes and are not captured in our models.

WORKS CITED

Barkey, Henri J., Māris Cepurītis, et al. 2016. *The War in Syria: Lessons for the West*. Riga: The Centre for East European Policy Studies.

Biloshkurska, Nataliia, Mykola Biloshkurskyi, Nazariy Popadynets, Ivan Plets, and Mariya Karpyak. 2023. "Impact of Unemployment on Socio-Economic Development of Poland and Ukraine: Governance Aspects." *Zeszyty Naukowe Politechiki Czestochowskiej. Zarzadzanie Research Reviews of Czestochowa University of Technology. Management* 50: 31-45.

Blattman, Christopher, and Jeannie Annan. 2006. *The Consequences of Child Soldiering*. Job market paper.

Bohra-Mishra, P., and D. S. Massey. 2011. "Individual Decisions to Migrate During Civil Conflict." *Demography* 48 (2): 401-24.

Brychka, Bohdan, Halyna Vyslobodska, and Nadiia Voitovych. 2023. "Poverty in Ukraine: Evolution of Interpreting and Analysis of Impact Factors." *Agricultural and Resource Economics: International Scientific E-Journal* 9, no. 2.

Centre for Economic Strategy. 2024. "Ukrainian Refugees. Future Abroad and Plans for Return. The Third Wave of the Research." Accessed October 15, 2024. https://ces.org.ua/en/ukrainian-refugees-third-wave-research/.

Cheromukhina, Olha. 2024. "Labour Market in Ukraine under the Influence of a Year of Full-Scale War." *Three Seas Economic Journal* 5, no. 1.

Deininger, Klaus. 2003. "Causes and Consequences of Civil Strife: Micro-Level Evidence from Uganda." *Oxford Economic Papers* 55, no. 4: 579-606.

Devadas, Sharmila, Ibrahim Elbadawi, and Norman V. Loayza. "Growth after War in Syria." *Policy Research Working Paper* 8967.

Giacomo, A., T. Boeri, and O. Zholud. 2023. "The Labour Market in Ukraine: Rebuild Better." Accessed October 15, 2024. https://voxukraine.org/en/the-labour-market-in-ukraine-rebuild-better.

Institute of Economic Research. 2024. "In September, the Lack of Workers Became the Main Obstacle to Doing Business for the First Time - IER Survey." October 17, 2024. http://www.ier.com.ua/ua/institute/news?pid=7540.

International Organization for Migration. 2024. "IOM Report on Internal Population Movement in Ukraine: General Population Survey." Accessed October 15, 2024. https://dtm.iom.int/reports/ukraina-zvit-pro-vnutrishne-peremischennya-naselennya-v-ukraini-opituvannya-zagalnogo.

Kadusic, Alma, and Alija Suljic. 2018. "Title Unknown." *European Journal of Geography* 9, no. 4: 75-86.

Kondylis, F. 2010. "Conflict Displacement and Labor Market Outcomes in Post-War Bosnia and Herzegovina." *Journal of Development Economics* 93, no. 2: 235-48.

Korriku, Belisa, and Azeta Tartaraj. 2023. "Economic Effects of the War in Ukraine and Recession." *F1000Research*.

Mazniev, Ievgen, Yaroslav Bielousov, Yurii Luchechko, Mykhailo Rozbytskyi, Andrii Kolosok, Svitlana Shepelenko, and Mykola Dziamulych. "Analysis of Modern Trends in Labour Market Transformation in Ukraine." *Journal of Interdisciplinary Research*, 138-42.

Miguel, Edward, Shanker Satyanath, and Ernest Sergenti. 2004. "Economic Shocks and Civil Conflict: An Instrumental Variables Approach." *Journal of Political Economy* 112, no. 4: 725-53.

Mooren, Kleber. 2001. "The Impact of War in Bosnia and Herzegovina." *International Journal of Mental Health* 30, no. 2: 6-21.

Muradian, Arsen, Olexiy Kuzkin, and Natalia Remzina. 2018. "Logistics of Smart Port in Ukraine: Problems and Prospects in the Conditions of Sustainable Development." *Problemy ekorozwoju - Problems of Sustainable Development* 18, no. 2: 229-41.

National Institute for Strategic Studies. 2023. "Internal Forced Displacement: Volumes, Problems and Ways to Solve Them." Accessed October 15, 2024. https://niss.gov.ua/en/node/5096.

Nation, R. Craig. 2003. *War in the Balkans 1991-2002*. Carlisle: Strategic Studies Institute, U.S. Army War College.

Opora. 2023. "Number of Ukrainians and Their Migration Abroad Because of the War — Research by Civil Network OPORA." Accessed October 15, 2024. https://www.oporaua.org/en/viyna/24791-kilkist-ukrayintsiv-ta-yikhmigratsiia-za-kordon-cherez-viinu-doslidzhennia-gromadianskoyi-merezhi-opora-24791.

Sahachko, Yuliia, Olena Smihunova, and Olha Podolska. 2023. "Prospects for the Formation of Investment Support for the Technological Growth of the Agricultural Sector of the Ukrainian Economy in the Post-War Period." *Ukrainian Black Sea Region Agrarian Science* 27, no. 3.

Seven, Ümit. 2022. "Armed Conflict, Violence, and the Decision to Migrate: Explaining the Determinants of Displacement in Syria." *Migration and Development*.

Shemyakina, Olga. 2011. "The Effect of Armed Conflict on Accumulation of Schooling: Results from Tajikistan." *Journal of Development Economics* 95, no. 2: 186-200.

Toal, Gearóid, and Carl T. Dahlman. 2004. "The Effort to Reverse Ethnic Cleansing in Bosnia-Herzegovina: The Limits of Returns." *Eurasian Geography and Economics* 45, no. 6: 439-64.

Vakhitova, Hanna, and Pavlo Iavorskyi. 2018. "Labor Market Adaptation of Internally Displaced People: The Ukrainian Experience." Working Paper.

Vakhitova, H., and P. Iavorskyi. 2020. "Employment of Displaced and Non-Displaced Households in Luhansk and Donetsk Oblasti." *Europe-Asia Studies* 72, no. 3: 383-403. https://doi.org/10.1080/09668136.2019.1691154.

Vasylyeva, Olena, Lidia Horoshkova, and Svitlana Shvydka. "The Imbalance of the Labor Market in Ukraine: Current Trends and Guidelines for Overcoming Disproportions." *University Economic Bulletin* 57.

World Bank. 2003. *Bosnia and Herzegovina Poverty Assessment, Volume II: Data on Poverty*. Report 25343-BIH. Washington, DC: The World Bank.

Yuh, Ji-Yeon. 2005. "Moved by War: Migration, Diaspora, and the Korean War." *Journal of Asian American Studies* 8, no. 3: 277-91.

APPENDIX A

Table 9. Decoding of the variables

Variable	Decoding
Gender	0 - Male 1 - Female
Age	The average value from the diapason.
City size	The average value from the diapason in thousand.
Relocation status	0 - Moved within the oblast 1 - Moved to the nearest oblast 2 - Moved to a distant oblast
Moved nearby	0 - Not applicable 1 - Moved to a distant oblast 2 - Moved to the nearest oblast or within the oblast
IDP status	0 - NDP 1 - IDP
Family status	0 - Unmarried 1 - Married
Children	0 - No children 1 - Have children
Employment	0 - Unemployed 1 - Employed

TABLE 9 - Continued

Variable	Decoding
Education	Indicate average amount of full years needed to finish indicated degrees: 7 - Basic general average or below (9 grades or less) 11 - Completed secondary education (completed secondary education)/Incomplete higher education/initial higher education (graduated from a technical school, college) 13 - Vocational and technical (graduated from a vocational and technical educational institution) 15 - Higher (graduated from a higher education institution, received a bachelor's degree or higher)
Financial situation	Ordinarily arranged responses about individual welfare: 1 - Forced to save on food 2 - Enough for food. To buy clothes, shoes is necessary 3 - Hard to say 4 - Enough for food and necessary clothes, shoes. For such 5 - Enough for food, clothes, shoes, other purchases. But for 6 - Enough for food, clothes, shoes, expensive purchases. For and 7 - I can make any necessary purchases at any time
Soldier	1 - Individual is recruited in the Army Force of Ukraine 0 - Individual is civilian

APPENDIX B

Table 10. Monthly respondent structure

Year	Month	IDP	NDP	TOTAL	% of IDPs
2022	3	167	799	966	17.29%
2022	4	201	786	987	20.36%
2022	5	198	802	1,000	19.80%
2022	6	195	813	1,008	19.35%
2022	7	191	810	1,001	19.08%
2022	8	179	819	998	17.94%
2022	9	168	828	996	16.87%
2022	10	162	828	990	16.36%
2022	11	163	836	999	16.32%
2022	12	153	831	984	15.55%
2023	1	166	836	1,002	16.57%
2023	2	152	856	1,008	15.08%
2023	3	143	861	1,004	14.24%
2023	4	151	844	995	15.18%
2023	5	154	854	1,008	15.28%
2023	6	157	842	999	15.72%
2023	7	138	851	989	13.95%
2023	8	135	856	991	13.62%
2023	9	134	860	994	13.48%
2023	10	125	883	1,008	12.40%
2023	11	110	879	989	11.12%
2023	12	113	872	985	11.47%
2024	1	109	890	999	10.91%
2024	2	134	879	1,013	13.23%
2024	3	117	875	992	11.79%
2024	4	138	867	1,005	13.73%
2024	5	108	873	981	11.01%
2024	6	122	872	994	12.27%
2024	7	122	855	977	12.49%
2024	8	124	854	978	12.68%
2024	9	136	856	992	13.71%
2024	10	123	855	978	12.58%
	TOTAL	4,688	27,122	31,810	14.73%

Source: author's calculations, Info Sapiens survey data, 2024

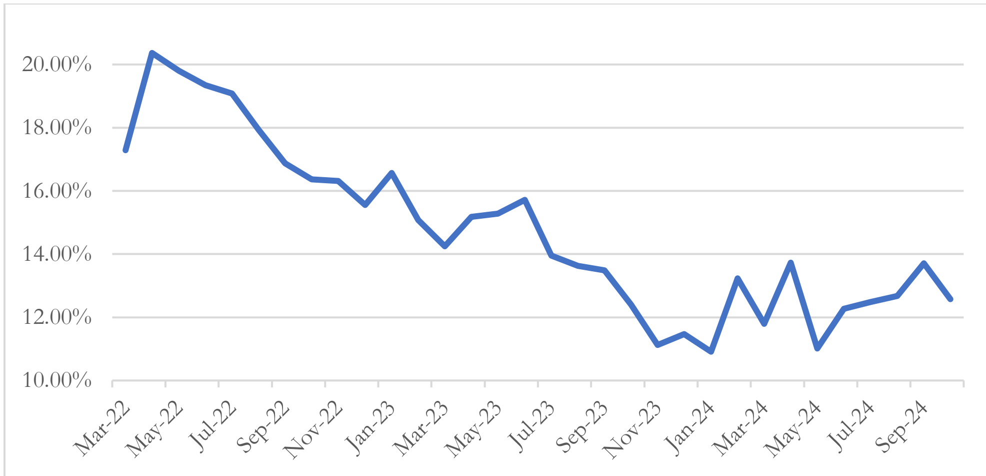

Figure 7. Monthly IDPs percentage

Source: author's calculations, Info Sapiens survey data, 2024

APPENDIX C

Table 11. Results of the robustness check

Variable	Probit model	Logit model	Model with LF only
Age 20-29 years	1.109 ***	1.859 ***	0.251 ***
	(0.054)	(0.095)	(0.096)
Age 30-39 years	1.257 ***	2.101 ***	0.212 **
	(0.053)	(0.094)	(0.095)
Age 40-49 years	1.362 ***	2.288 ***	0.302 ***
	(0.053)	(0.094)	(0.095)
Age 50-59 years	1.076 ***	1.818 ***	0.286 ***
	(0.052)	(0.093)	(0.094)
Age 60+ years	-0.318 ***	-0.556 ***	0.732 ***
	(0.052)	(0.094)	(0.106)
Female	-0.455 ***	-0.778 ***	-0.310 ***
	(0.016)	(0.028)	(0.024)
IDP statur	-0.227 ***	-0.188*	-0.369 ***
	(0.025)	(0.11)	(0.033)
Moved nearby		-0.128*	
		(0.069)	
Secondary education	0.250 ***	0.407 ***	0.257 ***
	(0.045)	(0.074)	(0.064)
Vocational and technical education	0.282 ***	0.453 ***	0.156 **
	(0.045)	(0.076)	(0.064)
Higher education	0.801 ***	1.343 ***	0.734 ***
	(0.044)	(0.074)	(0.062)
From East	-0.021	-0.044	-0.132*
	(0.048)	(0.081)	(0.069)
From Kyiv	0.186 ***	0.313 ***	-20
	(0.032)	(0.055)	(0.048)
From North	-0.005	-0.012	-0.076*
	(0.025)	(0.043)	(0.039)
From South	0.054	0.087	-78
	(0.035)	(0.059)	(0.052)
From West	0.029	0.043	-10
	(0.024)	(0.041)	(0.038)

TABLE 11 - Continued

Variable	Probit model	Logit model	Model with LF only
Have children	-0.01	-0.024	0.027
	(0.018)	(0.03)	(0.026)
High threat region	-0.151 ***	-0.269 ***	-0.198 ***
	(0.04)	(0.068)	(0.058)
Constant	-0.995 ***	-1.659 ***	0.649 ***
	(0.062)	(0.109)	(0.109)

Source: author's calculations, Info Sapiens survey data, 2024

APPENDIX D

Table 12. Proximity to conflict zone model results

Variable	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-0.78577	0.18092	-4.343	1.40e-05 ***
Moved nearby	-0.08653	0.04307	-2.009	0.044533 *
From East	-0.22541	0.07825	-2.88	0.003971 **
From Kyiv	-0.06109	0.1099	-0.556	0.578313
From North	-0.02122	0.09337	-0.227	0.820185
From South	-0.1735	0.08113	-2.138	0.032478 *
From West	0.29903	0.12596	2.374	0.017597 *
Age 20-29 years	1.1105	0.12419	8.942	< 2e-16 ***
Age 30-39 years	1.14079	0.12478	9.142	< 2e-16 ***
Age 40-49 years	1.15928	0.12629	9.18	< 2e-16 ***
Age 50-59 years	0.81191	0.12741	6.372	1.86e-10 ***
Age 60+ years	-0.44921	0.13248	-3.391	0.000697 ***
Female	-0.62729	0.04287	-14.632	< 2e-16 ***
Secondary education	0.3115	0.11681	2.667	0.007662 **
Vocational and technical education	0.22259	0.11804	1.886	0.059327
Higher education	0.88271	0.11418	7.731	1.07e-14 ***
Have children	-0.14757	0.04535	-3.254	0.001138 **

Source: author’s calculations, Info Sapiens survey data, 2024

APPENDIX E

Table 13. Propensity score matching for All Data

Variable	Means Treated	Means Control	Std. Mean Diff.	Var. Ratio	eCDF Mean	eCDF Max
Distance	0.3236	0.1169	1.0075	2.465	0.3350	0.4891
Age before 20 years	0.0414	0.0311	0.0517	-	0.0103	0.0103
Age 20-29 years	0.1734	0.1010	0.1912	-	0.0724	0.0724
Age 30-39 years	0.2590	0.1879	0.1621	-	0.0710	0.0710
Age 40-49 years	0.2001	0.1836	0.0412	-	0.0165	0.0165
Age 50-59 years	0.1387	0.1863	(0.1380)	-	0.0477	0.0477
Age 60+ years	0.1875	0.3100	(0.3139)	-	0.1225	0.1225
Male	0.4102	0.4325	(0.0453)	-	0.0223	0.0223
Female	0.5898	0.5675	0.0453	-	0.0223	0.0223
Basic education (9 grades or less)	0.0378	0.0371	0.0035	-	0.0007	0.0007
Secondary education	0.2660	0.2906	(0.0558)	-	0.0247	0.0247
Vocational and technical education	0.2280	0.2356	(0.0181)	-	0.0076	0.0076
Higher education	0.4682	0.4367	0.0632	-	0.0316	0.0316
From Center	0.0849	0.2744	(0.6797)	-	0.1895	0.1895
From East	0.4544	0.0845	0.7428	-	0.3698	0.3698
From Kyiv	0.0606	0.0925	(0.1340)	-	0.0320	0.0320
From North	0.1060	0.1755	(0.2257)	-	0.0695	0.0695
From South	0.2541	0.1512	0.2363	-	0.1029	0.1029
From West	0.0401	0.2219	(0.9267)	-	0.1818	0.1818

Source: author’s calculations, Info Sapiens survey data, 2024

Table 14. Propensity score matching for Matched Data

Variable	Means Treated	Means Control	Std. Mean Diff.	Var. Ratio	eCDF Mean	eCDF Max	Std. Pair Dist.
Distance	0.3236	0.3032	0.0998	1.239	0.0081	0.0881	0.0998
Age before 20 years	0.0414	0.0352	0.0311	-	0.0062	0.0062	0.1253
Age 20-29 years	0.1734	0.1762	(0.0073)	-	0.0028	0.0028	0.2609
Age 30-39 years	0.2590	0.2206	0.0876	-	0.0384	0.0384	0.2289
Age 40-49 years	0.2001	0.1864	0.0341	-	0.0137	0.0137	0.3882
Age 50-59 years	0.1387	0.1721	(0.0969)	-	0.0335	0.0335	0.3204
Age 60+ years	0.1875	0.2095	(0.0563)	-	0.0220	0.0220	0.0563
Male	0.4102	0.4232	(0.0265)	-	0.0130	0.0130	0.3161
Female	0.5898	0.5768	0.0265	-	0.0130	0.0130	0.3161
Basic education (9 grades or less)	0.0378	0.0388	(0.0056)	-	0.0011	0.0011	0.1265
Secondary education	0.2660	0.2726	(0.0150)	-	0.0066	0.0066	0.3326
Vocational and technical education	0.2280	0.2400	(0.0285)	-	0.0119	0.0119	0.3559
Higher education	0.4682	0.4486	0.0393	-	0.0196	0.0196	0.4335
From Center	0.0849	0.0849	-	-	-	-	-
From East	0.4544	0.4253	0.0583	-	0.0290	0.0290	0.1439
From Kyiv	0.0606	0.0606	-	-	-	-	-
From North	0.1060	0.1060	-	-	-	-	-
From South	0.2541	0.2831	(0.0666)	-	0.0290	0.0290	0.1646
From West	0.0401	0.0401	-	-	-	-	-

Source: author's calculations, Info Sapiens survey data, 2024

Table 15. Frequencies and percentages for categorical variables

Variable	NDPs	IDPs
Number of observations	4688	4688
Age before 20 years	165 (3.5%)	194 (4.1%)
Age 20-29 years	826 (17.6%)	813 (17.3%)
Age 30-39 years	1034 (22.1%)	1214 (25.9%)
Age 40-49 years	874 (18.6%)	938 (20.0%)
Age 50-59 years	807 (17.2%)	650 (13.9%)
Age 60+ years	982 (20.9%)	879 (18.8%)
Female	2704 (57.7%)	2765 (59.0%)
Basic education (9 grades or less)	182 (3.9%)	177 (3.8%)
Secondary education	1278 (27.3%)	1247 (26.6%)
Vocational and technical education	1125 (24.0%)	1069 (22.8%)
Higher education	2103 (44.9%)	2195 (46.8%)
From Center	398 (8.5%)	398 (8.5%)
From East	1994 (42.5%)	2130 (45.4%)
From Kyiv	284 (6.1%)	284 (6.1%)
From North	497 (10.6%)	497 (10.6%)
From South	1327 (28.3%)	1191 (25.4%)
From West	188 (4.0%)	188 (4.0%)

Source: author's calculations, Info Sapiens survey data, 2024

Table 16. Estimation results of PSM

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	0.0535	0.0183	2.9210	0.00349 **
IDP	-0.1655	-0.0259	-6.3830	1.73e-10 ***

Source: author's calculations, Info Sapiens survey data, 2024

APPENDIX F

Table 17. Results of the probit regression for all respondents

Variable	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-0.995378	0.062205	-16.001	< 2e-16 ***
Age 20-29 years	1.109199	0.053621	20.686	< 2e-16 ***
Age 30-39 years	1.256998	0.052970	23.730	< 2e-16 ***
Age 40-49 years	1.361859	0.053014	25.689	< 2e-16 ***
Age 50-59 years	1.076426	0.052157	20.638	< 2e-16 ***
Age 60+ years	-0.317584	0.051987	-6.109	1.00e-09 ***
Female	-0.455278	0.016234	-28.045	< 2e-16 ***
IDP status	-0.227408	0.024944	-9.117	< 2e-16 ***
Secondary education	-0.250098	0.044502	5.620	1.91e-08 ***
Vocational and technical education	0.281777	0.045229	6.230	4.66e-10 ***
Higher education	0.801426	0.043926	18.245	< 2e-16 ***
From East	-0.021159	0.047857	-0.442	0.658389
From Kyiv	0.185517	0.031841	5.826	5.66e-09 ***
From North	-0.005097	0.025213	-0.202	0.839789
From South	0.054371	0.034747	1.565	0.117635
From West	0.028511	0.024052	1.185	0.235875
Have children	-0.010291	0.017552	-0.586	0.557679
High threat region	-0.151283	0.040050	-3.777	0.000158***

Source: author's calculations, Info Sapiens survey data, 2024

Table 18. Results of the probit regression for LF

Variable	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	0.6485	0.1085	5.9770	2.28e-09 ***
Age 20-29 years	0.2508	0.0956	2.6230	0.008718 **
Age 30-39 years	0.2124	0.0946	2.2450	0.024744 *
Age 40-49 years	0.3020	0.0947	3.1870	0.001436 **
Age 50-59 years	0.2857	0.0943	3.0310	0.002437 **
Age 60+ years	0.7323	0.1065	6.8760	6.15e - 12 ***
Female	-0.3105	0.0244	-12.7290	< 2e-16 ***
IDP status	-0.3689	0.0334	-11.0490	< 2e-16 ***
Secondary education	0.2572	0.0637	4.0370	5.41e-05 ***
Vocational and technical education	0.1557	0.0639	2.4360	0.014864 *
Higher education	0.7338	0.0625	11.7450	< 2e-16 ***
From East	-0.1322	0.0691	-1.9140	0.055653
From Kyiv	-0.0196	0.0483	-0.4060	0.684991
From North	-0.0759	0.0391	-1.9410	0.052268
From South	-0.0776	0.0523	-1.4830	0.138176
From West	-0.0097	0.0383	-0.2540	0.799335
Have children	0.0270	0.0257	1.0540	0.292042
High threat region	-0.1983	0.0578	-3.4330	0.000598 ***

Source: author's calculations, Info Sapiens survey data, 2024

APPENDIX G

Table 19. First stage results for instrumental variable

Variable	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-1.349779	-0.070207	-19.226	< 2e-16 ***
High threat region	1.109279	0.049306	22.498	< 2e-16 ***
Age 20-29 years	0.063417	0.058225	1.089	0.276081
Age 30-39 years	-0.169443	0.057852	-2.929	0.003402 **
Age 40-49 years	-0.397567	0.058268	-6.823	8.91e-12 ***
Age 50-59 years	-0.621045	0.058523	-10.612	< 2e-16 ***
Age 60+ years	-0.743428	0.056437	-13.173	< 2e-16 ***
Female	0.015115	0.020367	0.742	0.458001
Secondary education	0.001225	0.054539	0.022	0.982078
Vocational and technical education	0.068901	0.055751	1.236	0.216505
Higher education	0.083956	0.053958	1.556	0.119721
From East	0.546295	0.058134	9.397	< 2e-16 ***
From Kyiv	0.313106	0.041293	7.582	3.39e-14 ***
From North	0.321716	0.034665	9.281	< 2e-16 ***
From South	0.115564	0.049721	2.324	0.0200113
From West	-0.301744	0.040949	-7.369	1.72e-13 ***
Have children	0.075648	0.02195	3.446	0.000568 ***

Source: author's calculations, Info Sapiens survey data, 2024

Table 20. Second stage results for instrumental variable

Variable	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-0.944248	0.063369	-14.901	< 2e-16 ***
High threat region	-0.689594	0.124605	-5.534	3.13e-08 ***
Age 20-29 years	1.119556	0.053688	20.853	< 2e-16 ***
Age 30-39 years	1.243344	0.053023	23.449	< 2e-16 ***
Age 40-49 years	1.326448	0.053606	24.745	< 2e-16 ***
Age 50-59 years	1.024987	0.053631	19.112	< 2e-16 ***
Age 60+ years	-0.372258	0.0539	-6.906	4.97e-12 ***
Female	-0.453925	0.01622	-27.986	< 2e-16 ***
Secondary education	0.249985	0.044489	5.619	1.92e-08 ***
Vocational and technical education	0.287497	0.045264	6.352	2.13e-10 ***
Higher education	0.806108	0.043967	18.335	< 2e-16 ***
From East	0.033491	0.061349	0.546	0.585
From Kyiv	0.204389	0.032204	6.347	2.20e-10 ***
From North	0.014411	0.025743	0.56	0.576
From South	0.042368	0.033284	1.273	0.203
From West	0.014639	0.024352	0.601	0.548
Have children	-0.003898	0.017619	-0.221	0.825

Source: author's calculations, Info Sapiens survey data, 2024