EXPLORING THE TRANSFORMATIVE EFFECTS OF THE RUSSIAN-UKRAINIAN WAR ON RISK PREFERENCES IN A SELECTED SEGMENT OF THE UKRAINIAN POPULATION

by

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Abstract

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The consequences of conflict stretch beyond mere battlegrounds while also fracturing social bonds and exacerbating impatience among populations. These effects can hinder the processes of economic recovery, which are significantly influenced by shifts in risk preferences. In light of this, the present study aims to assess how the Russian-Ukrainian war has affected the risk preferences of the particular group of Ukrainian populaces. The thesis's objective is to ascertain the impact of the Russian-Ukrainian war on individuals' risk preferences, leveraging data from an online poker platform. Central inquiries revolve around discerning any inclination towards risk-taking among Ukrainians. The econometric model employs the Difference in Difference method to ascertain the war's impact on Ukrainian risk preferences. In essence, this study seeks to elucidate the intricate relationship between conflict, risk preferences, and economic behavior, offering insights crucial for post-conflict recovery strategies. In summary, the analysis findings underscore the transition of risk preferences among a specific segment of Ukraine's population, moving from being more inclined towards taking risks before the war to being more cautious after the invasion. Over the initial three months of the conflict, Ukrainians experienced a reduction in the frequency of participation in poker hands despite no significant changes in the average gameplay performance among players.

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GLOSSARY

BB. Big Blind. Mandatory bet that is placed by the player sitting two positions to the left of the dealer button before any cards are dealt.

Bet flop. Bet after the first three community cards are dealt in a game.

Bluff. The percentage of hands in which a player attempts to deceive opponents into folding stronger hands.

Flop. First three community cards dealt face-up.

Pot. The total amount of money or chips at stake on the table.

VPIP. Voluntarily Put Money In Pot. The percentage of hands in which a player voluntarily contributes money to the pot before the flop.

Win rate. The percentage of hands won by a player over a specified period.

WWSF. Won When Saw Flop. The percentage of hands in which a player wins the pot after seeing the flop.

Chapter 1

INTRODUCTION

War diverts resources away from developmental pursuits towards destructive endeavors. The resultant losses are often associated with the adverse effects stemming from the utilization of these resources and the displacement of pre-existing production. The magnitude of the latter detriment can be gauged by examining expanded military government expenditures. As an illustration, in 2021, Ukraine allocated 8.56% of its total budget to defense. Nevertheless, by 2023, Ukraine witnessed a nearly sevenfold escalation in defense expenditures, reaching 53.47% (Ministry of Finance of Ukraine 2023). However, economists frequently emphasize the substantial impact of capital damage. As of January 2024, the combined worth of living and non-living structures and infrastructure amounts to $ 155 billion. This aggregate does not factor in undamaged assets in the occupied territory after February 24, 2022. Regrettably, the extent of physical damage is persistently increasing (National Recovery Council 2024).

Another essential dimension to contemplate refers to the social costs, primarily characterized by the loss of lives and the compelled displacement of populations. As of April 19, 2024, an estimated 5.9 million Ukrainians have undergone displacement as refugees in Europe. Furthermore, by March 27, 2024, an additional 541,200 Ukrainians had sought refuge beyond the geographical confines of Europe (Operational Data Portal 2024). As of May 2023, the number of internally displaced people approached nearly 5.9 million(UNHCR 2024). The documented mortality statistics for civilian populations exhibit considerable variation across diverse sources, spanning from 10,000 to 30,000 (ACLED 2024). The spectrum of military fatalities is even more expansive, but beyond the loss of life, the war has caused a variety of psychological harm that is challenging to measure accurately. When a war affects society, there is uncertainty about whether the society can return to its previous level of growth. The impact of war on economic growth and recovery is a two-sided coin. On one hand, it can strain social connections and foster impatience, hindering economic progress. On the other hand, it can stimulate institutional improvements and shifts in people's preferences, influencing their consumption, savings, and investment choices. This, in turn, can drive economic growth and encourage the emergence of new businesses and collaborations (Kim and Lee 2014). An additional investigation, as portrayed in the subsequent study (Stewart and Roth 2001), unveiled findings indicating that entrepreneurs demonstrate a greater inclination for risk compared to managers. The endogenous growth model (Douenne 2020), which incorporates endogenous disasters and is built upon the theoretical framework presented in another job (Müller-Fürstenberger and Schumacher 2015), indicates that an increase in risk aversion and a decrease in inter-temporal elasticity of substitution could result in a positive economic growth effect in the face of disasters. Hence, it is crucial to examine the impact of the war on the risk preferences of specific population groups characterized by a heightened inclination for risk.

This thesis represents a notable addition to the extant literature on assessing risk preferences among Ukrainians in the aftermath of the invasion. It distinguishes itself by employing a field experiment, contrasting with the prevalent employment of conjoint experiments in prior research. Additionally, it innovatively utilizes a poker dataset to assess shifts in risk preferences after violent conflict.

Typically, researchers employ conjoint experiments to analyze shifts in risk-taking behavior. Nevertheless, this approach has garnered criticism within the economics community because of the absence of financial incentives for questionnaire responses and the difficulties in ensuring that respondents accurately grasp the probability distribution of the simulated game. Utilizing a poker dataset can effectively address these criticisms, as individuals engaging in poker inherently possess sufficient incentive to participate in experiments and thoroughly understand the game rules.

The central objective of this thesis is to evaluate how the Russian-Ukrainian war influences the risk preferences of a specific sample of the Ukrainian population who willingly engage in risky decision-making. While the findings may not have immediate relevance to the general population, this research provides valuable insights for individuals who exhibit behavior akin to those who voluntarily opt for risk in various scenarios, including individual investors (Moskowitz and Vissing-Jørgensen 2002).

The initial hypothesis posits that post-war individuals within Ukraine will exhibit heightened risk aversion compared to those residing in other countries. This proposition draws inspiration from a study (Cameron and Shah 2015) that focused on villages in rural Indonesia that had previously experienced earthquakes or floods. The findings of this research indicated that individuals who had witnessed such disasters tended to display increased risk aversion compared to those in unaffected villages. Notably, this heightened risk aversion was largely independent of these individuals' financial status. Instead, it originated from their perception that future adverse events were more likely, with some even assigning higher probabilities to the occurrence of another flood in the upcoming year. The research effectively measured shifts in risk preferences, considering various factors such as the proximity of the witnesses to the disaster, their financial situation, and their expectations regarding future calamities. Recognizing the selectivity of the dataset utilized in this thesis, it is acknowledged that achieving a comparable measurement may present inherent challenges.

Primary investigations focus on determining whether individuals within this demographic exhibit a propensity for heightened risk tolerance. Prior research (Doerflinger et al. 2023) has underscored the efficacy of poker as a model for comprehending the decision-making behaviors regarding investments applicable to individuals and organizations. Consequently, it is an apt tool for assessing shifts in preferences among a cohort inherently inclined towards risk-taking and investment endeavors. Acknowledging this cohort's substantial impact on the trajectory and magnitude of Ukraine's post-war recuperation is imperative.

The study utilized data from SmartHand.pro, sourced from the PokerStars platform and analyzed with the poker-specific statistical program Hand2Note. The dataset includes 3489 individuals, with Ukrainians comprising approximately 10%, alongside a control group from eight other countries. It covers two time periods, from November 2021 to February 2022 and from March 2022 to May 2022, and is known for its reliability in the poker community. The primary method employed in this study is the difference-in-difference approach, augmented with the control of individual unobserved fixed effects and incorporating the weighting of the number of played hands. Additionally, a separate model was implemented to control for country-specific unobserved effects. These methods can determine whether the war, in particular, impacted changes in the risk preferences of Ukrainians. Potential dependent variables include the size of stakes and the frequency of bets. Control variables that may be considered include win rate, general looseness, flop bet frequency, average flop bet sizing, and flop bluff frequency.

Essentially, the findings indicate a decrease in risk-seeking behavior among Ukrainian players following the invasion. The country effect yielded higher results than the individual effect, and employing individual fixed effect models without weighting towards hands resulted in lower values due to data noise. Moreover, Ukrainian poker players' performance did not improve over time.

This study is structured as follows: In Chapter 2, I delve into the theoretical and empirical literature pertinent to the topic. Chapter 3 provides an in-depth exploration of the model employed to measure risk-taking behavior. Moving forward, Chapter 4 furnishes details about the data used and offers fundamental information about poker. The ensuing Chapter 5 delves into a comprehensive discussion of the results derived from the simulated changes in risk preferences within the model. Finally, Chapter 6 serves as the conclusion, summarizing the essential findings and implications of the study.

Chapter 2

LITERATURE REVIEW

2.1 Empirical Studies on Shifts in Risk Preferences Post-Disaster

The measurement of changes in preferences following a disaster event has been the focus of numerous research studies. For example, one study explored the potential impact of the tsunami in rural Thailand disasters on individuals' long-term preferences regarding trust, risk, and time discounting (Cassar et al. 2017), employing an interval regression with the estimated Constant Relative Risk Aversion (CRRA) interval serving as the dependent variable. In addition to this dependent variable, the model adjusts for demographic factors such as the number of households in the village, the proportion of the illiterate population, and indicators of household prosperity, including access to clean water, ownership of phones and vehicles, and income levels. Moreover, it considers the level of community organization, including the presence of community cooperatives, the percentage of the population who are cooperative members, and the proportion of households participating in public meetings. The findings suggest that experiencing a disaster like a tsunami can lead to increased risk aversion, higher levels of trust, and greater impatience among individuals, highlighting the importance of policy interventions to aid recovery and promote resilience in the aftermath of such events.

In another study (Voors et al. 2012), a series of experiments conducted in two timeframes in rural Burundi aimed to explore the impact of exposure to conflict on social, risk, and time preferences. The authors employed Ordinary Least Squares to identify correlations between respondents' answers in an artificial game and the percentage of the deceased population in the area. The control variables encompass datasets concerning the ramifications of conflict on diverse geographic areas, encompassing metrics such as the proportion of casualties in assaults, the demographic attributes of the respective regions (e.g., Gini index), and individual-level attributes (e.g., gender, income, victimization index). Two-Stage Least Squares were utilized to establish causation, revealing slightly different results with a slight loss of significance. The findings suggest that exposure to violence alters behavior, potentially by influencing preferences. Individuals who have experienced violence or reside in attacked communities tend to display more altruistic behavior, increased risk-seeking tendencies, and less patience.

In the investigation (Callen et al. 2014), the researchers implemented an experimental method to determine and assess individuals' risk preferences after a violent conflict. This process entailed evaluating predictions derived from the Expected Utility model, a standard economic model used to understand decision-making under uncertainty. Additionally, they tested predictions from other behavioral models that consider certainty effects. Certainty effects refer to how individuals respond to situations where outcomes are specific compared to situations involving uncertainty. By incorporating these models, the researchers aimed to gain insights into how people in Afghanistan navigate economic decisions, especially in the context of risks and uncertainties associated with violence. The analysis accounted for the interval nature of the data by conducting interval regressions (Stewart 1983). The findings indicated that individuals, when prompted to recall fear, displayed heightened risk-averse behavior.

A different approach to gauge risk preferences is based on a hypothetical lottery question posed in Japan in 2011 and 2012 (Hanaoka et al. 2014). The authors' approach involved excluding fixed effects and measuring changes in risk preferences across different regions with varying earthquake intensities. The fundamental concept aligns with a difference-in-differences approach: the authors evaluated the earthquake's impact by comparing individuals residing in areas without earthquakes (control group) and areas directly affected by the earthquake (treatment group). The authors hypothesized that risk preferences would be consistent for both areas. This thesis employs a similar approach, with the key distinction being the utilization of panel poker data instead of hypothetical lottery questions.

An illustrative instance of assessing shifts in preferences is exemplified in the work of Yudenko (2023) within the thesis conducted at the KSE, wherein the primary objective was to evaluate temporal discounting after the invasion of Ukraine. The study revealed that individuals exposed to bombing and gunfire exhibited more patience. This assessment used a conjoint experiment between September 25th and September 29th, 2023. Control variables encompassed factors related to the war context, such as occupation, bombing experience, and well-being indicators, including injury and depression, as well as financial considerations, such as income.

The primary method employed for measuring preferences involves conducting conjoint analysis. This typically entails creating artificial choice scenarios with an approximate probability distribution representation. However, artificial experiments like these often face criticism, primarily regarding subjects' inattentiveness due to relatively small payoffs or the necessity to impose strong assumptions, assuming individuals can accurately estimate and comprehend a probability distribution.

In contrast to these limitations, poker emerges as a compelling data source. The nature of poker, with its inherent risk and real-world consequences, provides a more authentic and apprehensive dataset compared to artificial experiments.

2.2 Empirical Investigations on Assessing Risk Preferences in Poker

The authors (Lee 2021) utilized the "World Poker Tour" as a natural experiment to assess risk preferences. Tournaments provide a more effective means of evaluating risk-taking behavior due to their inherent rules known to all participants, direct monetary incentives, and factors that are challenging to replicate in a laboratory setting. To minimize skill-based heterogeneity present in poker games, the authors apply criteria for player looseness during the player selection process. This study indicates that as players face more substantial incentives for risk, such as increased potential rewards, there is a noticeable increase in their active participation and frequency of placing bets. Essentially, the model's results underscore a connection between the strength of risk incentives and the higher probability of players undertaking risk-taking actions in the examined poker games.

To quantify the level of risk preferences, the authors assess the players' chip amounts during each tournament rank. This approach bears similarities to the work (Kahneman and Tversky 1979), where the authors gauged the level of risk preferences in production by assessing variability in output. The authors employ the absolute value of the game profit in their measurements, prioritizing the frequency of risk-taking actions during the game over the total game output. This means that if two individuals were to either lose or gain the same amount of money after the game, they would yield comparable results in the analysis.

However, it is acknowledged that the variation in chip counts might underestimate risk preferences due to the game's rules, as the frequency of betting depends not only on individual preferences but also on the decisions of other participants. Additionally, the model considers the range of prizes available to players and the chip spread on the table, providing a more comprehensive understanding of the factors influencing risk preferences in poker. This thesis employs a similar approach to measure risk preferences, utilizing the valuation of chip variation. However, instead of tournaments, I focus on cash games. In place of the variation of chips, I use average flop-bet sizing as the metric. Additionally, I am replacing prizes with the player's looseness and win rate in the analysis.

In another study (Kasinger et al. 2022) exploring risk-taking behavior in online poker data, the researchers reveal a solid and robust preference for skewness among individuals. The authors measure risk-taking behavior using a novel feature introduced by the world's largest online poker platform, PokerStars, in August 2019: the "all-in cash out." This feature provides insurance against a player's risk in a showdown situation, where the outcome is solely determined by the cards drawn from the remaining deck.

In their basic model, the authors employ a dummy variable that equals one if player i chooses the insurance option in showdown j and zero otherwise, focusing on the first three moments of the underlying lottery. Including fixed effects helps control for heterogeneity in insurance choices across different games, while month-fixed effects account for month-specific heterogeneity, potentially influenced by seasonal effects or COVID-19 countermeasures. The authors employ various empirical specifications, including Probit and Logit models, to control for player-specific characteristics (such as experience and average profit per hand) and hand-specific variables (such as the initial amount of money the player started the hand with, the weekday, or the stake).

The article's authors also adhere to the common narrow-framing assumption prevalent in experimental economics, which posits that subjects have little regard for the game's influence on their overall wealth, allowing their income to be disregarded during valuation. The authors anticipate a positive (negative) sign for variance if individuals in their sample are, on average, risk-averse (risk-seeking). Skewness preferences suggest a negative skewness coefficient, signifying that individuals opt for the risky option more frequently with higher skewness. In this thesis, I also incorporate fixed effects to account for game heterogeneity. Additionally, I include hand-specific variables such as the frequency of bluffs and the number of hands in the analysis.

METHODOLOGY

3.1 Framework for Assessing Risky Decision-Making

Assessing risk-taking using a poker dataset comes with its share of challenges. One significant hurdle is that individuals may perceive risk differently in this sophisticated game. For instance, if a player engages in more bluffing but has a lower betting frequency, it might be a mistake to conclude that their risk attitude has not changed by solely measuring the frequency of bets. Another complication arises from the fact that different metrics can indicate varying degrees of change in risk-taking behavior. Relying on one metric might reveal only subtle changes in behavior, while another metric could show a significantly higher one. Recognizing these challenges in measuring risk-taking, I plan to use four different measures to capture a more comprehensive understanding of it.

The first metric draws inspiration from the research conducted by Kainulainen (2019) and outlined in the study. This approach examines the fluctuation in a player's bets and the variability in returns, also known as odds. To calculate the risk-taking metric for an individual player, the sum of all bets multiplied by the odds, minus the value of bets taken before, made over a specific period is divided by the total number of bets:

$$Y_{it} = \sum_{j=1}^{n} \frac{b_{ji}O_{ji} - b_{(j-1),i}O_{(j-1)i}}{n_i} \tag{1}$$

Here, b_{ji} represents the amount bet in bet j placed by the player i, O_{ji} represents the odds for bet j by player i, and n_i is the number of bets that person placed. This metric is deemed robust due to its alignment with the expected-utility theory and the non-expected utility approach, thus enhancing its validity and applicability within the theoretical framework. A higher value for this measure implies a lower chip variance, indicating a propensity to take fewer risks. A similar approach was proposed in a study by Kahneman and Tversky (1979), where they evaluated risk-taking behavior by examining the variability of outcomes. Furthermore, it possesses a straightforward explanation: the mean potential gross earnings.

The second method to assess risk-taking behavior is rooted in poker theory (Smith et al. 2009). By closely tracking how often someone bets, I can discern individuals' comfort levels with taking risks, particularly in situations where outcomes are uncertain and there is potential for both winning and losing. Consequently, higher betting frequencies indicate a greater likelihood for individuals to continue engaging in risky situations marked by uncertainty.

The third metric to evaluate risk-taking behavior involves considering the use of bluffs. In poker, a bluff is a tactical maneuver wherein a player places bets or raises with a hand weaker than what opponents might perceive. Players who engage in frequent bluffing may be regarded as more daring and open to risks (Smith et al. 2009), contrasting with those who seldom bluff, often perceived as adopting a more cautious approach. Consequently, the inclusion of bluffing as a factor provides valuable insights when examining a player's inclinations toward risk-taking in poker.

The final metric employed to evaluate risk-taking behavior is VPIP (Voluntarily Put $ in Pot), which denotes how often a player willingly invests money in the pot before the flop. In games with nine players, those with a VPIP below 20% are typically classified as very conservative players, whereas individuals surpassing a VPIP of 50% are seen as highly adventurous players. A heightened VPIP suggests a greater inclination towards risk-taking in a player(Advanced Poker Training 2024).

3.2 The setup of the Difference-in-Difference model

In this thesis, I primarily adopt a difference-in-difference approach, leveraging panel data to gauge changes in risk-taking behavior within a specific population. The core concept is to assess the impact of the war by contrasting individuals who were not directly affected by it (control group) with Ukrainians who experienced the war to varying degrees (treatment group). The underlying assumption is that the response to the war would differ across these groups. The difference-in-difference design allows us to single out the effects associated with the disaster, excluding influences from other concurrent factors that may not be directly linked to it, such as macroeconomic shifts, social events, or external influences.

The approach being utilized closely resembles that employed in the study by Hanaoka, Shigeoka, and Watanabe (2014), who investigated how earthquakes affected the risk preferences of the population. The fundamental model to assess whether war genuinely impacts the risk preferences of a specific group within the Ukrainian population is as follows:

$$Y_{it} = a + \beta \times X_{it} + \varphi \times Post + \gamma \times Treatment_i + \delta \times (Treatment_i \times Post) + \epsilon_{it} \quad (2)$$

where Y_{it} is the variable representing the risk preferences of player i. $Treatment_i$ is a binary variable indicating whether the observation is from Ukraine (1 for Ukraine, 0 for other countries). Additionally, $Post_t$ is another binary variable indicating whether the observation falls into the post-war period (1 for post-war, 0 for pre-war). X_{ik} encompasses the fundamental characteristics of a player's gaming tendency, such as the number of hands played and win rate. The $Treatment_i \times Post$ in the model serves to reveal the direct impact of the war on the risk preferences of a specific group within the Ukrainian population.

The methodology aims to assess how a treatment, like war, impacts subjects. It assumes that without treatment, the trajectories of both treated and control groups would be the same.The parameter δ serves as the difference-in-differences (DD) estimator, quantifying the impact of the war. This model seeks to capture shifts in risk-taking tendencies, factoring in individual, temporal, and country-specific nuances. By incorporating fixed effects and control variables, the intention is to mitigate potential confounding factors. Meanwhile, the inclusion of the $Treatment_i \times Post$ dummy variable allows us to isolate the war's effect in Ukraine using the DD estimator.

Chapter 4

DATA

Typically, researchers use conjoint experiments to assess changes in risk-taking behavior. However, this method faces criticism within the economics community due to a lack of financial incentives for questionnaire responses and challenges in ensuring respondents correctly understand the probability distribution of the artificial game. To tackle these challenges, I leverage a dataset derived from poker gameplay, where participants possess tangible financial motivations to engage. An additional advantage of this approach lies in participants' thorough comprehension of the game rules, as their primary motivation to engage in the game and potentially win money hinges on their grasp of these rules.

4.1 General Poker Description

This study utilizes no-limit $2/$16 blind tables, accommodating a maximum of six or nine players. Texas Hold 'Em, played with a standard 52-card deck, consists of four suits (spades, hearts, diamonds, and clubs), each containing 13 cards (from ace through 2). The game typically progresses through five stages. Preflop marks the initial phase, during which players receive their starting cards and place their initial bets. The Flop follows, introducing three cards onto the table. The Turn represents the third stage, where the fourth card is placed on the table. The fourth stage, known as the River, sees the placement of the fifth card on the table. Finally, the Showdown is the concluding stage, where all players reveal their cards and determine the victor.

Poker involves crucial terminology that players need to be familiar with. A "Raise" signifies an increase in the size of the betting. "Call" refers to responding to an opponent's bet. "Check" involves declining to bet and passing the play to the next player at the table. "Fold" indicates abstaining from play during a particular round. "3-bet" denotes someone re-raising the bets. A "Cont-bet," also known as a "C-bet," is made by a player who raised pre-flop. A "Donk bet" is a bet on the flop made by a player who did not display aggression on the previous street. An "Overbet" is a bet with a size more significant than the current amount in the pot.

The dealer position rotates, with the player to the left placing a small blind and the subsequent player a big blind. Each player is dealt two cards, which are visible only to them. Players decide to play or fold, either calling the big blind or raising the bet. Bets circulate until all players match the highest bet or fold.

If more than one player remains, three community cards (known as "the flop") are dealt, visible to all, and used by each player to form the best possible hand. The analysis in this thesis focuses exclusively on the flop hand, as other hands would underestimate individual risk-taking behavior since, in other situations, it depends on the risk-taking behavior of other players. Subsequent players cannot raise bets without others doing so.

In this thesis, fundamental statistics widely recognized among poker players are employed. VPIP, or Voluntarily Put $ in Pot, quantifies the percentage of hands in which a player willingly contributes money to the pot before the flop. WWSF, or Went to Showdown and Won at Flop, gauges the percentage of hands won when a player reaches the showdown after seeing the flop. Win Rate denotes the average amount won or lost per 100 hands. Flop Aggression measures the frequency of aggressive actions (bets and raises) on the flop. Bet Flop signifies the frequency of betting on the flop. Bluff quantifies the frequency of bluffing. In poker, "Looseness," characterized by VPIP, reflects the frequency with which a player voluntarily invests money in the pot before the flop. In 9-player games, individuals with a VPIP below 20% are often considered very tight players, while those exceeding a VPIP of 50% are regarded as highly loose players. A higher VPIP suggests a greater inclination toward risk-taking. Three additional variables pertain to actions on the flop, a betting round occurring after three community cards are revealed. Flop bet frequency represents the percentage of time an opponent bets (Wagers) on the flop. A player with a higher betting frequency, larger bet sizing, and increased bluffing frequency tends to have a greater appetite for risk.

Specific metrics, not contingent upon frequency, may exhibit positive or negative indications. For instance, the Risk-Taking Metric may manifest with a negative sign under circumstances where the potential to win the stake in the current scenario is lower than in the preceding ones. Therefore, during the final action step preceding the showdown period, a negative risk-taking metric is obtained if there is an overestimation of the probability and excessive betting compared to previous rounds. Similarly, another metric that may display a negative sign is the Win Rate, defined as the ratio of profit to the number of hands played, where a negative overall profit could yield a negative value for the Win Rate metric.

4.2 General data description

The data was sourced from the mining service SmartHand.pro on PokerStars and analyzed using the statistical program, mainly designed for poker players, Hand2Note. The panel dataset comprises 3489 individuals who played an average of nearly 3000 hands. Ukrainians constitute around 10% of this dataset. The control group comprises eight countries: Argentina, Belgium, Brazil, Belarus, Canada, Germany, Greece, Romania, and the United Kingdom. The data covers two time periods, from November 2021 to February 2022 and from March 2022 to May 2022. SmartHand.pro has a strong reputation in the poker community for providing high-quality data to poker players and collecting information by tracking all hands from all players.

The effects are captured by four indicator variables: Bet Flop, Risk-taking metric, VPIP, and Bluff. Bet Flop measures the frequency of betting during the flop period of the game. The Risk-taking metric was calculated according to Kainulainen (2019) and is detailed in the methodology section of the thesis. VPIP, which stands for Voluntarily Put Money into Pot, reflects the frequency with which a player willingly contributes money to the pot. Bluffing indicates the number of instances when a person bets more than necessary based on the actual value of their cards.

Table 1. Descriptive statistics for Ukrainians for two time periods

	Ukrainian players					
	Pre-24 Feb. 2022			After 24 Feb. 2022		
	Mean	Median	SD	Mean	Median	SD
Risk-Taking Metric	0.163	-4.43	117.968	17.088	-1.15	260.487
Bet Flop	34.962	34	13.637	33.155	32	14.235

Table 1. – Continued

	Ukrainian players					
	Pre-24 Feb. 2022			After 24 Feb. 2022		
	Mean	Median	SD	Mean	Median	SD
VPIP	45.817	41	17.33	41.075	37.9	15.614
Bluff	31.909	30	23.787	31.946	31	21.028
Win Rate	-54.931	-28.1	143.604	-40.88	-5.21	156.516
Hands	5616.846	616	15455.104	14635.242	2374	30684.716
Size	0.559	0.543	0.162	0.587	0.562	0.161
Flop Aggression	31.141	30	12.762	30.267	29	12.725
WWSF	40.779	41	8.111	40.329	41	10.554

The VPIP metric gauges the percentage of hands in which a player voluntarily invests money into the pot preflop. The decrease in VPIP for Ukrainians from 45.817 to 41.075 may indicate a shift towards more selective and cautious play. WWSF measures the percentage of hands won when a player sees the flop. The similar values (40.779 and 40.329) for Ukrainians suggest comparable post-flop success rates. Flop Aggression measures the frequency of aggressive actions (bets and raises) on the flop. The lower values (31.141 vs. 30.269) for Ukrainians may indicate a slightly more passive approach. Bet Flop indicates the frequency of betting on the flop. The decrease from 34.962 to 33.155 might suggest a more cautious post-flop strategy for Ukrainians. The consistent bluff tendency (31.9) and average size (0.6) suggest a balanced approach. The more cautious gameplay of Ukrainians could explain the insignificant difference between the win rate for Ukrainians and non-Ukrainians. In both periods, the Risk-Taking Metric indicates that Ukrainians typically overestimate their chances of winning during the showdown phase. However, following the invasion, there is a slight rightward shift in the median, suggesting a trend towards increased caution in their actions. Concurrently, the Win Rate reveals predominantly adverse outcomes in the dataset, with the most common loss amount per 100 hands being $28 before the war and $5 after the invasion.

Table 2. Descriptive statistics for non-Ukrainian players

	Non-Ukrainian players					
	Pre-24 Feb. 2022			After 24 Feb. 2022		
	Mean	Median	SD	Mean	Median	SD
Risk-Taking Metric	-27.189	-9.47	76.358	-47.412	-13.17	150.782
Bet Flop	34.557	33	13.946	33.97	33	14.339
VPIP	42.855	40	13.81	41.919	39.6	14.139
Bluff	31.814	31	20.416	31.556	32	18.633
Win Rate	-18.765	-22.4	1097.789	-46.468	-19.87	129.52
Hands	3945.218	1200	9096.585	8381.788	2270	19501.272
Size	0.611	0.582	0.154	0.618	0.585	0.162
Flop Aggression	31.346	30	12.368	30.869	29	13.085
WWSF	41.797	41	7.019	41.845	41	13.578

The data for non-Ukrainians exhibits slightly less variability compared to Ukrainians overall. Metrics such as VPIP, WWSF, Flop Aggression, Bet Flop, average size, and bluff remain constant, indicating stability in the main tendencies of the data. However, these metrics also reveal a slightly skewed distribution. The significant fluctuation in the number of hands played could be attributed to seasonality, as people tend to play more during winter holidays. Changes in Win Rate may be explained by increased dispersion in the data. A similar pattern emerges for non-Ukrainian players in the dataset, as they tend to wager larger sums towards the game's conclusion despite lower odds of winning. However, compared to Ukrainians, their median became even more negative following the invasion. Additionally, the Win Rate indicates that Ukrainians typically experienced more significant losses per 100 hands before the war, contrasting with the period after the invasion.

Chapter 5

ESTIMATION RESULTS

This chapter presents the estimation results, significance tests, and robustness checks related to the difference-in-difference model. To begin, Section 5.1 demonstrates the preference for fixed effects over random effects. Section 5.2 delves into the heterogeneity analysis, while section 5.3 compares outcomes between the country-level and individual models. Section 5.4 examines robustness checks.

5.1 Model specification test

The data offers significant advantages for the research, in view of the ability to compare a variety of risk preferences over time for the same person, as opposed to typical literature that relies on cross-sectional data for similar analyses. These empirical studies, lacking panel data, are prone to overlook unobserved time-invariant individual characteristics that could correlate with shifts in risk preferences. To illustrate, individuals who previously exhibited a propensity for employing various bluffing tactics are likely to continue this behavior even after the onset of conflict. Additionally, individuals with high-risk aversion were more inclined to leave Ukraine before the war began.

Moving forward, the analysis demands a statistical test to verify the null hypothesis that explanatory variables are not correlated with unobserved individual-specific characteristics. This correlation can lead to omitted variable bias, underscoring the necessity to address this issue adequately. The most appropriate way to effectively mitigate such risk is by utilizing a fixed effect model that accurately accounts for unobserved heterogeneity within individuals.

Following the Hanaoka, Shigeoka, and Watanabe (2014) article, wherein the authors endeavored to address similar challenges by implementing a cluster-robust version of the Hausman test, I adopt a similar approach. This test facilitates the comparison of the fixed effect estimator versus the random effect estimator. By undertaking this, I can determine whether the presence of unobserved individual-specific factors biases the estimated effects of the explanatory variables.

The test outcomes indicate that the null hypothesis is rejected for all four models with a p-value <2.2e-16. The rejection of the null hypothesis in the Hausman test, which suggests that the estimates from the fixed effects model significantly differ from those of the random effects model, further supports the choice of a fixed effects approach. This implies that the random effects model, which assumes that individual-specific effects are uncorrelated with the explanatory variables, may not adequately address the omitted variable bias present in the data.

5.2 Results of Heterogeneity Analysis

I investigate the impact of war on risk-taking behavior by analyzing panel data collected both before and after the commencement of the war. To account for time-invariant individual characteristics, I utilize individual fixed effects. Through panel data analysis, I segregate the effect on the treatment group (players identified by their ID codes as those living in Ukraine) from the control group (players located abroad), assuming that their responses would have been identical in the absence of the war.

Unobserved individual fixed effects emerge as a significant econometric concern, particularly given the pre-existing spectrum of risk preferences shaped by the annexation of Crimea and occupation of the east territory of Ukraine in 2014. For instance, Purcell (2021) demonstrated that individuals previously impacted by a disaster were prone to developing varied responses toward risk, potentially resulting in unobserved differences in preferences.

Considering all the points above, I utilize the heterogeneity analysis, the outcomes of which are presented in Table 3. The critical coefficient in this regression, $Treatment_i$×Post highlights changes in risk preferences after the war for different groups. The two regressions from the list indicate that Ukrainians shifted their preferences toward risk aversion after the onset of the war.

Table 3. The Results of Heterogeneity Analysis

	Risk-taking Metric	Bet Flop	VPIP	Bluff
Treatment×Post	29.908**	-0.587**	-0.617	-0.521
	(11.784)	(0.298)	(0.595)	(1.918)
Treatment	×	×	×	×
WWSF	0.080	-0.011	-0.041***	-0.102**
	(0.293)	(0.007)	(0.015)	(0.048)
Win Rate	-0.001	-0.0001	-0.00000	0.0003
	(0.003)	(0.0001)	(0.0001)	(0.0005)
Flop Aggression	-1.123***	0.981***	0.071***	0.018
	(0.424)	(0.011)	(0.021)	(0.069)
ln(№ of Hands)	-13.903***	0.021	-0.866***	-1.544***
	(2.323)	(0.059)	(0.117)	(0.378)
Average size	-30.173	-4.193***	3.990***	1.268
	(30.226)	(0.764)	(1.527)	(4.919)
Post	-14.769***	0.011	0.238	0.855
	(3.764)	(0.095)	(0.190)	(0.613)
Constant	×	×	×	×
Observations	3,477	3,477	3,477	3,477
R^2	0.047	0.859	0.056	0.016
Adjusted R^2	-1.237	0.668	-1.217	-1.312
F Statistic	10.521***	1,286.452***	12.560***	3.340***

The results depicted in Table 3, indicate that there are no values for the intercept and Treatment. This is primarily because fixed effects account for the effects of time-invariant individual-specific variables, including binary variables such as Treatment. The individual-specific effect also captures the intercept; thus, I obtained this coefficient as unspecified.

Like Kainulainen (2019), the risk-taking metric demonstrates a notable positive effect, suggesting that individuals become more risk-averse. This metric shows a positive effect, implying that, on average, Ukrainians began earning more money by playing after the war started. This indicates a reduction in the utilization of risky strategies during gameplay.

The number of bet flops also shows significance in the results, suggesting risk aversion. Based on this metric, individuals in Ukraine have significantly reduced their betting during the flop by more than half since the onset of the war. This suggests a shift towards more cautious gameplay among players following the commencement of the war.

On the flip side, VPIP does not show significance. The definition of VPIP can explain this. Risk in poker can be measured in two parameters: the amount of money you put into the pot or the frequency of making bets. VPIP indicates the frequency with which people put their money before the flop. This amount of money could be lower than big blind by the game rules, and statistically, people who usually do this rarely go to the showdown phase. Although VPIP captures a particular aspect of player behavior in poker, it may not accurately reflect players' overall risk-taking behavior or strategic decisions, as it primarily measures pre-flop actions and may not capture the full scope of betting behavior or willingness to risk money in pursuit of winning hands.

Meanwhile, bluffing also fails to yield significant results. This can be attributed to the fact that bluffing is an integral component of various poker strategies. The collective findings of the current heterogeneity analysis highlight a notable shift in risk-taking behavior among individuals in Ukraine, particularly following the onset of the war, compared to the entire dataset.

5.3. Country Fixed Effect vs. Individual Fixed Effect

In the preceding subchapter of my thesis, I showcased how the onset of the war influenced risk preferences at the individual-level estimation. The individual aids in capturing the average deviation of risk-taking behavior while also controlling for individual-specific factors that remain constant over time. This assessment method excludes time-invariant factors for individuals, such as education level, job experience, family status, etc. However, the data also permits the application of country-fixed effect estimation. This analysis can assist in addressing country-specific factors and assessing how risk preferences evolve at the country level. These evaluations involve controlling for various factors, including cultural norms and national policies.

In the subsequent subsection, I will explore how the results have altered by incorporating country-fixed effects into the model instead of individual fixed effects. The assessment commenced with executing the Hausman test across four models featuring different dependent variables. Per the test specifications, the null hypothesis posits that the random effect is superior. Conversely, the alternative hypothesis suggests the suitability of a fixed-effect model. The test primarily examines whether individual errors are correlated with regressors. The outcomes of the test are presented in Table 4.

Table 4. The results of the Hausman Test

	Risk-taking Metric	Bet Flop	VPIP	Bluff
p-value	0.9553	0.9992	0.7611	0.8197
chi2	2.0794	0.56688	4.1604	3.6445

The p-value for all regressions suggests the use of a random effect model. This finding reveals that the country-fixed effects capture the time-invariant factors influencing all individuals within one country. However, the random effect model remains superior for estimation. This may be explained by unobserved time-varying factors shared among all residents within each country. Among these factors are economic conditions, policy changes, and other country-level characteristics that cannot be captured by fixed effects but are accounted for in the random effect model.

Another plausible explanation could stem from the measures outlined in the preceding subsection. As illustrated earlier, the individual-specific fixed effect may sufficiently capture unobserved factors correlated with the independent variables. These factors, which cannot be accounted for by the country's fixed effect, are absorbed in the random effect model. Essentially, the random effect model can account for individual and country-specific factors, making it a preferable choice over the fixed effect model. The results of the estimations, recommended by the Hausman test, are presented in Table 5.

Table 5. Country Random vs. Individual Fixed Effects

	Risk-taking Metric		Bet Flop	
Effect	Country-specific	Individual-specific	Country-specific	Individual-specific
Treatment×Post	48.142***	29.908***	-0.628*	-0.587**
	(13.558)	(11.784)	(0.363)	(0.298)
Post	-15.942***	-14.769***	0.032	0.011
	(4.644)	(3.764)	(0.124)	(0.095)
Treatment	18.901	×	0.412	×
	(17.770)	×	(0.424)	×
WWSF	-0.259	0.080	-0.053***	-0.011
	(0.235)	(0.293)	(0.006)	(0.007)
Win Rate	0.003	-0.001	0.00003	-0.0001
	(0.003)	(0.003)	(0.0001)	(0.0001)
Flop Aggression	-0.389**	-1.123***	1.097***	0.981***
	(0.192)	(0.424)	(0.005)	(0.011)
Ln (№ of Hands)	-8.263***	-13.903***	0.034	0.021
	(1.225)	(2.323)	(0.033)	(0.059)
Average size	-82.875***	-30.173	-3.536***	-4.193***
	(13.697)	(30.226)	(0.366)	(0.764)
Constant	104.589***	×	4.316***	×
	(16.639)		(0.439)	
Observations	3,477	3,477	3,477	3,477
R^2	0.034	0.047	0.941	0.859
Adjusted R^2	0.032	-1.237	0.941	0.668
F Statistic	122***	10.521***	55,557***	1,286***

Table 5. – Continued

	VPIP		Bluff	
Effect	Country-specific	Individual-specific	Country-specific	Individual-specific
Treatment×Post	-3.141**	-0.617	0.510	-0.521
	(1.425)	(0.595)	(2.026)	(1.918)
Post	0.801	0.238	0.498	0.855
	(0.488)	(0.190)	(0.694)	(0.613)
Treatment	2.563	×	-0.248	×
	(1.914)		(1.209)	
WWSF	0.048*	-0.041***	0.087**	-0.102**
	(0.025)	(0.015)	(0.035)	(0.048)
Win Rate	-0.001**	-0.0000	-0.0002	0.0003
	(0.0003)	(0.0001)	(0.0004)	(0.0005)
Flop Aggression	-0.006	0.071***	0.499***	0.018
	(0.020)	(0.021)	(0.029)	(0.069)
Ln (№ of Hands)	-2.668***	-0.866***	-0.847***	-1.544***
	(0.129)	(0.117)	(0.181)	(0.378)
Average size	10.492***	3.990***	-5.244**	1.268
	(1.440)	(1.527)	(2.037)	(4.919)
Constant	53.347***	×	21.707***	×
	(1.756)		(2.341)	
Observations	3,477	3,477	3,477	3,477
R2	0.131	0.056	0.127	0.016
Adjusted R2	0.129	-1.217	0.125	-1.312
F Statistic	523***	12.560***	505.709***	3.340***

Treatment×Post demonstrates significance for three dependent variables: Risk-taking metric, Bet Flop, and VPIP. However, the Bluff regression continues to show insignificant results. Particularly intriguing is the case of the VPIP regression, where the coefficient in an individual-level fixed effects model fails to show significance. Country-level random effects models accommodate variability in the dependent variable across countries, whereas individual-level fixed effects models address variability within countries. Suppose there is more significant variability in the dependent variable between countries than within countries. In that case, the country-level random effects model may detect significant effects that the individual-level fixed effects model overlooks.

Another explanation for this phenomenon could be attributed to aggregation bias. Individual-level fixed effects models efficiently control for all time-invariant individual-specific factors, which may encompass some of the variability captured by country-level effects. However, aggregating these effects to the country level may result in aggregation bias, wherein the effects are diluted or obscured by heterogeneity within countries. In contrast, the country-level random effects model directly addresses this heterogeneity at the country level, potentially yielding more significant coefficients.

The result of Treatment×Post indicates a more significant shift toward risk aversion in the random model compared to the fixed-effect individual-level model for both the risk-taking metric and VPIP. This discrepancy can be primarily attributed to the presence of country-specific factors influencing the relationship between Treatment×Post and the dependent variable, which are not accounted for by the fixed-effect individual-level model. Such factors may include socioeconomic conditions, cultural norms, institutional factors, or policy environments. These shared factors may be challenging to capture solely by observing individual characteristics.

Another explanation could stem from differences in model assumptions. Random effects models relax the assumption of strict exogeneity required by fixed effects models, allowing time-varying covariates to correlate with the country-specific effects. This includes changes in economic growth within each country over time.

Another noteworthy observation from the table is that country-level regression tends to yield significance for certain variables across models. For instance, Average Size exhibits significance in all country-level models, whereas it was not the case regarding individual-level models. One possible explanation for this disparity could be that betting size is influenced by each country's economic situation or cultural perceptions of gambling risk, thereby leading to potential differences in betting behavior across countries.

Similarly, the significance of WWSF (Won When Saw Flop) among countries suggests that certain nationalities take poker gameplay more seriously than others, resulting in substantial variations between country-level and individual-level metrics.

5.4 Robustness Check

5.4.1 Weight of Hands

Poker theory and basic statistics suggest that the most reliable measurements come from players with a higher number of observations, precisely a more significant number of hands played. As mentioned in the website Smart Poker Study by Matsuhashi (2022), the reliability of statistics depends heavily on the number of hands played. For instance, if a player has played 1000 hands, they have participated in approximately 166 rounds of 6-max poker. With 166 rounds, the statistics can be considered reliable, allowing for trustworthy conclusions to be drawn from the measurements for all variables in the dataset. However, if a person has only played 100 hands, the statistics are highly unreliable, as they are based solely on the specific situations encountered in the first 16 rounds of the game. After 100 hands, VPIP and Bet Flop can be considered reliable measurements. After 500 hands or 83 rounds, most of the statistics become reliable and can be used for analysis.

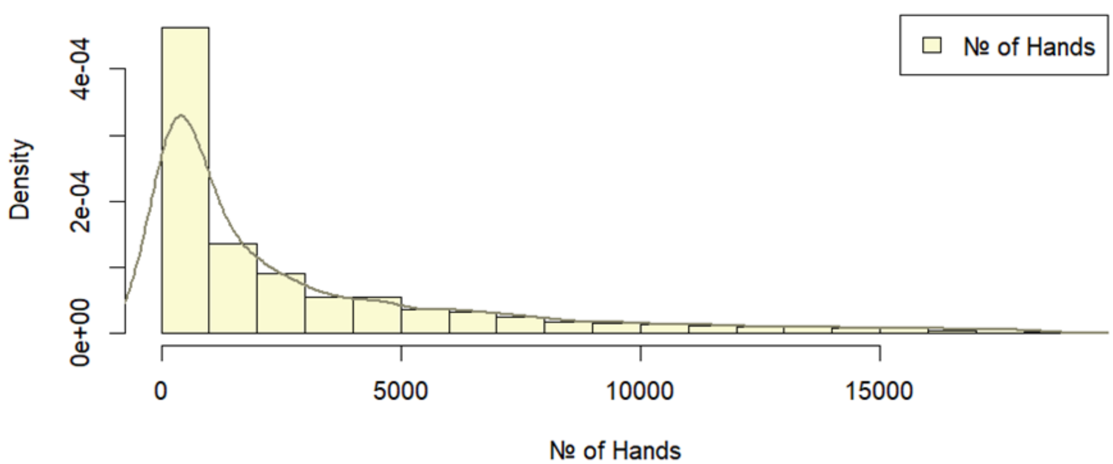

Figure 1. Frequency of Hands

Based on the overall distribution of players across hands, as illustrated in Figure 1, the highest frequency of hands played falls within the range of up to 2000 hands. So, the majority of players have played less than 1000 hands, which is acceptable since most of the coefficients will be reliable if a person plays at least 500 hands. However, these factors raise concerns about the credibility of the measurements because all previous regressions were conducted without consideration of the number of hands played. To address this issue, I perform weighted difference-in-differences regression for both individual and country levels in this subchapter. This change in regression necessitates conducting the Hausman test once again. The test results indicate that the fixed effect model is superior, with a p-value of <2.2e-16.

Table 6. The results of the regressions with taking hands weights into account.

	Risk-taking Metric		Bet Flop	
	(1)	(2)	(3)	(4)
	weighted	basic	weighted	basic
Treatment×Post	94.092***	29.908**	-0.831***	-0.587**
	(23.267)	(11.938)	(0.179)	(0.298)
Post	-37.093***	-14.769***	0.051	0.011
	(10.942)	(3.764)	(0.084)	(0.095)
WWSF	0.277	0.080	-0.003	-0.011
	(0.913)	(0.293)	(0.007)	(0.007)
Flop Aggression	-2.935**	-1.123***	0.914***	0.981***
	(1.466)	(0.424)	(0.011)	(0.011)
ln(№ of Hands)	-1.020	-13.903***	-0.204***	0.021
	(6.321)	(2.323)	(0.049)	(0.059)
Average size	-179.677*	-30.173	-4.441***	-4.193***
	(98.908)	(30.226)	(0.760)	(0.764)
Observations	3477	3477	3477	3477
R2	0.021	0.047	0.857	0.859
Adjusted R2	-1.296	-1.237	0.664	0.668

Table 6. - Continued

	VPIP		Bluff	
	(5)	(6)	(7)	(8)
	weighted	basic	weighted	basic
Treatment×Post	0.243	-0.617	-1.491*	-0.521
	(0.339)	(0.604)	(0.780)	(1.929)
Post	-0.008	0.238	0.378	0.855
	(0.159)	(0.190)	(0.367)	(0.613)
WWSF	-0.011	-0.041***	-0.019	-0.102**
	(0.013)	(0.015)	(0.031)	(0.048)
Win Rate	0.00005	-0.00000	0.0003	0.0003
	(0.0002)	(0.0001)	(0.0005)	(0.0005)
Flop Aggression	0.010	0.071***	0.021	0.018
	(0.021)	(0.021)	(0.049)	(0.069)
ln(№ of Hands)	-0.987***	-0.866***	-0.876***	-1.544***
	(0.092)	(0.117)	(0.212)	(0.378)
	5.929***	3.990***	-8.093**	1.268
Average size	(1.442)	(1.527)	(3.316)	(4.919)
Observations	3477	3477	3477	3477
R2	0.048	0.056	0.008	0.016
Adjusted R2	-1.233	-1.217	-1.327	-1.312

The first notable observation is that the difference-in-differences coefficient becomes significant in the regression where the dependent variable is Bluff. The second observation is that the inclusion of weights enhances the effect size, as it amplifies the contribution of players with a high number of hands while reducing the weight for players with less game practice. Therefore, adding weights was beneficial as it enhanced the main result.

Comparing equations (1) and (2), ln(№ of Hands) loses its significance, but Average Size instead earns. This observation suggests that the Average Size variable may offer a more robust measure of risk for individuals when considering the duration of hands played. The same conclusion can be drawn thanks to regressions (7) and (8). Ln(Hands) instead creates some noise for estimating the risk-taking metric, mainly because the dependent variable considers not just the number of hands but also the odds of winning and the size of the bet. Bet Flop instead measures just the frequency of bets, so it is not surprising that ln(Hands) appears significant in regression (3). Overall, the results for the individual-level Dif-in-Dif appear better when weights are taken into account.

To conduct a country-level analysis, I need to perform the Hausman test once more. The results of its estimation are represented in Table 7 below.

Table 7. The results of the Hausman Test

	Risk-taking Metric		Bet Flop		VPIP		Bluff	
	weighted	initial	weighted	initial	weighted	initial	weighted	initial
p-value	0.000	0.9553	0.000	0.9992	0.9541	0.7611	0.0046	0.8197
chi2	179.06	2.0794	63.672	0.56688	2.1006	4.1604	20.483	3.6445

Compared to the new model, the initial model demonstrates strong evidence for the random effect model. However, now only the model where the dependent variable is VPIP demonstrates the need for the random effect model. The results of the estimation are demonstrated in Table 8.

Table 8. Results of the regression on the country's effects

	Risk-taking Metric		Bet Flop	
	(1)	(2)	(3)	(4)
	weighted	basic	weighted	basic
Treatment×Post	266.228***	48.142***	-0.826***	-0.628*
	(29.547)	(13.558)	(0.200)	(0.363)
Post	-79.844***	-15.942***	-0.071	0.032
	(14.160)	(4.644)	(0.096)	(0.124)
Treatment	×	18.901	×	0.412
		(17.770)		(0.424)
WWSF	2.738***	-0.259	-0.046***	-0.053***
	(0.695)	(0.235)	(0.005)	(0.006)
Win Rate	0.017	0.003	-0.00004	0.00003
	(0.017)	(0.003)	(0.0001)	(0.0001)
Flop Aggression	-3.385***	-0.389**	1.123***	1.097***
	(0.635)	(0.192)	(0.004)	(0.005)
ln(№ of Hands)	15.909***	-8.263***	-0.012	0.034
	(2.444)	(1.225)	(0.017)	(0.033)
Average size	-337.23***	-82.875***	-2.263***	-3.536***
	(42.294)	(13.697)	(0.287)	(0.366)
Constant	×	104.589***	×	4.316***
		(16.639)		(0.439)
Observations	3,477	3,487	3,477	3,477
R2	0.005	0.034	0.941	0.941
Adjusted R2	-0.0001	0.032	0.940	0.941
F Statistic	31.487***	121.979***	12,364.110***	55,557.520***

Table 8. - Continued

	VPIP		Bluff	
	(5)	(6)	(7)	(8)
	weighted	basic	weighted	basic
Treatment×Post	0.450	-3.141**	0.261	0.510
	(0.947)	(1.425)	(0.707)	(2.026)
Post	0.553	0.801	0.526	0.498
	(0.418)	(0.488)	(0.339)	(0.694)
Treatment	-3.910**	2.563	×	-0.248
	(1.734)	(1.914)		(1.209)
WWSF	0.050**	0.048*	0.131***	0.087**
	(0.020)	(0.025)	(0.017)	(0.035)
Win Rate	-0.001*	-0.001**	0.0002	-0.0002
	(0.0005)	(0.0003)	(0.0004)	(0.0004)
Flop Aggression	0.071***	-0.006	0.609***	0.499***
	(0.018)	(0.020)	(0.015)	(0.029)
ln(№ of Hands)	-2.996***	-2.668***	-0.621***	-0.847***
	(0.141)	(0.129)	(0.059)	(0.181)
Average size	10.401***	10.492***	-10.327***	-5.244**
	(1.214)	(1.440)	(1.013)	(2.037)
Constant	55.557***	53.347***	×	21.707***
	(2.356)	(1.756)		(2.341)
Observations	3,477	3,477	3,477	3,477
R2	0.124	0.131	0.123	0.127
Adjusted R2	0.122	0.129	0.119	0.125
F Statistic	661.991***	523.421***	465.460***	505.709***

The principal value of interest in the case of the Risk-taking metric and Bet Flop holds its significance and amplifies the value of the effect. This is mainly because the weights magnify the effect of people who have highly credible statistics. However, VPIP did not show any significance in the weighted measurement. The assumption behind this is that the VPIP of people who played up to 500 hands could be astronomically high. Therefore, the lack of significance in the weighted estimation could result from bias and noise from low-played players.

Overall, the estimation and discussion in this subchapter showcase that implementing weights of hands amplifies the risk shift effect among Ukrainians and is better than the initial one.

5.4.2 Time alteration

Another perspective on my findings could suggest that individuals in Ukraine may have limited leisure time for gaming activities due to frequent air alarms, leading to a shift in the measurement of risk preferences. In this thesis, I measured risk in four ways: through the average size of the bet players put on the pot multiplied by the odds of winning (risk-taking metric), frequency of bets in the flop period (Bet Flop), frequency of voluntary putting money in the pot before the flop (VPIP), and the frequency of bluffing (bluff). All these measures could only be considered if players have played enough hands. Poker is a game that allows you to take risks only when another player has a similar desire or when you have at least some reasons to take a risk. For example, even the most naive player will not bet if their hand does not have a chance to win. So, usually, players fold simply because they are out of luck.

However, this observation also addresses the issue of the game's seasonality. Players tend to desire to play more during the winter holidays than during the spring period. In addition to seasonality, during the first month of the war in April, Poker Stars began to prohibit certain groups of Ukrainians from depositing money into their accounts, as mentioned in Liga Zakon by Nikolay Kirilchuk (2022). All these factors could affect the number of hands played and, consequently, the risk preferences of players.

The simplest method to assess whether these factors influence the number of hands played is to examine how the distribution of hands played has changed over time compared to other countries. This analysis is depicted in Figure 2 below.

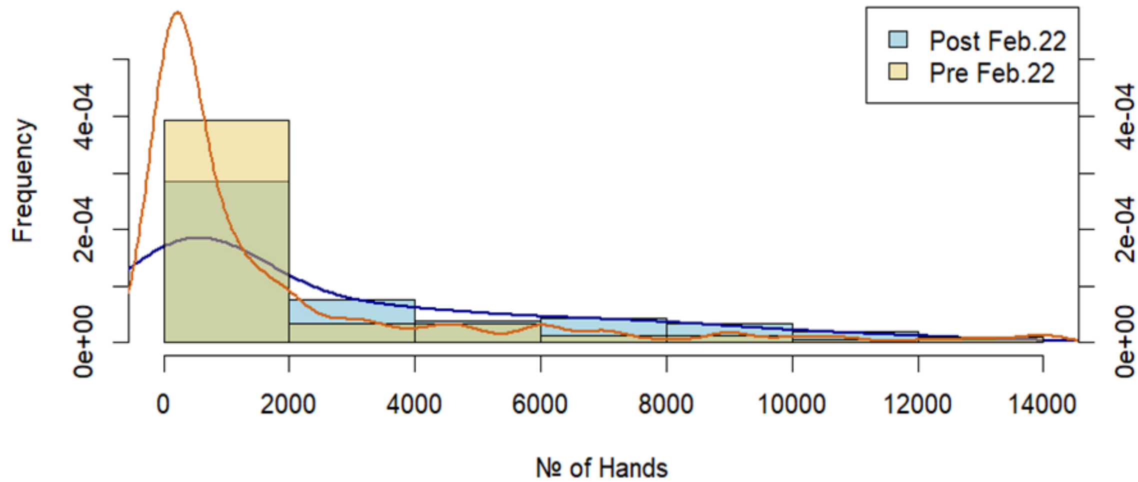

Figure 1. Distribution of Hands among Ukrainians

A fascinating insight is that the number of people playing less than 2000 hands declines, while those playing more than 2000 hands increase. The reason behind this could be that individuals more interested in poker have more time to play due to the loss of the obligation to go to work in the first weeks of the invasion. I create a similar graph for the non-Ukrainian group to compare these findings, with the results presented in Figure 3.

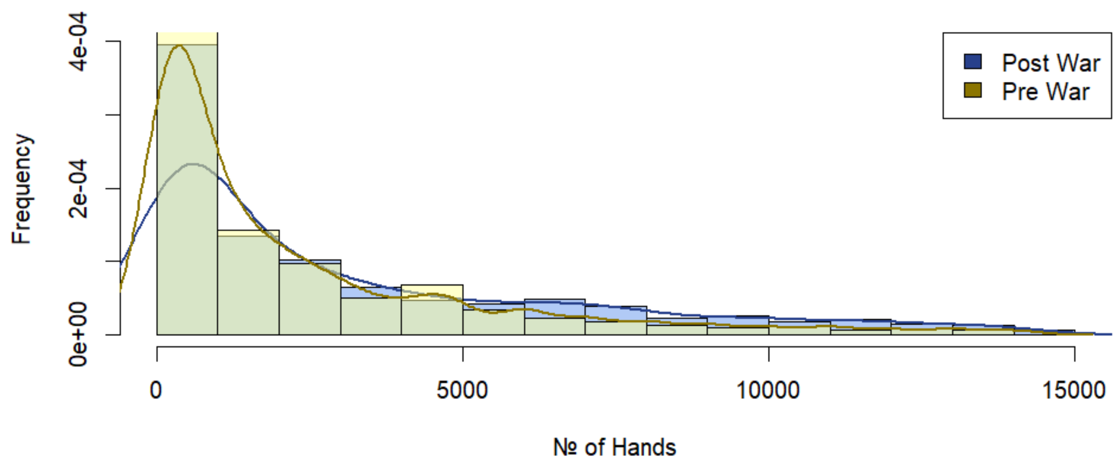

Figure 3. Distribution of Hands among non-Ukrainians

For players outside of Ukraine, the observed distributional change is not as pronounced as in earlier diagrams. Nevertheless, a decline is still evident. Moreover, a distinct seasonal pattern persists, with many individuals attempting poker during winter, all captured within the initial 2000 hands range.

Another method of examining this assumption is regression analysis, mainly by adding interactions such as Post×ln(№ of Hands) and Treatment× Δ(№ of Hands). The results of these measurements are depicted in Table 6 in the Appendix. Firstly, the hand difference is significant for the bluff and risk-taking metric but barely changes the difference-in-difference coefficient in all cases. The significance also remains unaltered after adding the difference in hands.

The regression analysis conducted after incorporating ln(№ of Hands) ×Post and Treatment×Δ(№ of Hands) revealed a truly intriguing scenario. Initially, these additional effects altered the significance and the value of the coefficient under scrutiny. For instance, in regression (10), the significance of the Treatment×Post coefficient dissipates upon the inclusion of these new interaction terms.

Estimation results (6), (9), and (12) revealed that Ukrainians do alter their frequency of play, with notable effects observed in certain instances, such as bluffing and VPIP. In these cases, the significance of the difference-in-difference coefficients was either substantially diminished or the coefficients' values were altered. This underscores the importance of considering difference(hands)*Treatment in the model, as it could significantly influence these changes.

Chapter 6

CONCLUSIONS AND POLICY RECOMMENDATIONS

Economic decision-making heavily depends on attitudes toward risk in uncertain circumstances. Traditional economic models presume stability in risk preferences over time, yet recent research suggests that various shocks may alter these preferences. However, the methods used to measure such changes and the events triggering them differ across the literature. Thus, I embarked on this study to investigate whether Ukrainians modify their risk preferences due to the onset of war and how to measure these changes using real-life uncertain situations.

To address this inquiry, I examine whether the commencement of war alters the risk preferences of a specific group of Ukrainian individuals. Leveraging a unique panel dataset allows for tracking changes in risk preferences among the same individuals before and after the war, contrasting with prior studies that rely on cross-sectional data collected post-negative shocks. Moreover, the dataset facilitates analysis at both individual and country levels.

Findings reveal that Ukrainian poker players demonstrate increased risk aversion in their behavior following the invasion. Additionally, analysis at the individual level indicates a higher degree of risk aversion compared to the country level. The poker dataset proves effective in analyzing shifts in risk preferences and suggests two robust measurements: the Risk-Taking Metric and Bet Flop.

This study holds particular significance as the war in Ukraine undoubtedly impacts its citizens, and future recovery efforts should be informed by an understanding of how the war affects individuals on a societal scale.

Despite its contributions, this study has limitations. Firstly, it only examines the effects of the war on a limited range of risk-taking behaviors, such as gambling. Secondly, it cannot assess changes in risk preferences across different regions and demographic characteristics due to data constraints. Thirdly, it cannot measure changes in risk preferences according to the intensity of war impact, such as capital loss or physical injuries. These questions fall outside the scope of this study but represent avenues for future research.

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APPENDIX A

ROBUSTNESS CHECK

Table 9. Robustness Check Considering Variations in the Number of Hands

	Risk-Taking Metric			Bet Flop		
	Initial	Post ×ln(№ of Hands)	Treatment× Δ(№ of Hands)	Initial	Post×ln(№ of Hands)	Treatment× Δ(№ of Hands)
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-37.093***	10.759	-37.095***	0.051	-0.123	-0.010
	(10.942)	(63.128)	(11.090)	(0.084)	(0.485)	(0.085)
WWSF	0.277	0.274	0.311	-0.003	-0.003	-0.004
	(0.913)	(0.914)	(0.917)	(0.007)	(0.007)	(0.007)
Win Rate	0.001	0.001	0.001	-0.00004	-0.00005	-0.00004
	(0.015)	(0.015)	(0.015)	(0.0001)	(0.0001)	(0.0001)
Flop Aggression	-2.935**	-2.899**	-2.861*	0.914***	0.914***	0.908***
	(1.466)	(1.468)	(1.486)	(0.011)	(0.011)	(0.011)
ln(№ of Hands)	-1.020	1.042	-1.527	-0.204***	-0.215***	-0.083
	(6.321)	(6.898)	(7.261)	(0.049)	(0.053)	(0.055)
Average Size	-179.677*	-182.683*	-175.335*	-4.441***	-4.380***	-4.703***
	(98.908)	(99.189)	(99.711)	(0.760)	(0.762)	(0.761)
Post×Treatment	94.092***	98.607***	96.022***	-0.831***	-0.845***	-0.710***
	(23.267)	(23.995)	(24.054)	(0.179)	(0.184)	(0.184)
Post×ln(№ of Hands)		-5.012			0.018	
		(6.507)			(0.050)	
Δ(№ of Hands)			0.027			-0.002***
			(0.090)			(0.001)
Treatment×Δ(№ of Hands)			-0.400			-0.031***
			(1.378)			(0.011)
Observations	3,477	3,477	3,477	3,477	3,477	3,477
R2	0.021	0.022	0.022	0.857	0.857	0.858
Adjusted R2	-1.296	-1.300	-1.297	0.664	0.663	0.666
F Statistic	4.057***	3.623***	3.172***	1,091.572***	953.831***	861.996***

Table 9. — Continued

	VPIP			Bluff		
	Initial	Post× ln (№ of Ha	Treatment× Δ(№ of Hands)	Initial	Post×ln(№ of Hands)	Treatment× Δ(№ of Hands)
	(7)	(8)	(9)	(10)	(11)	(12)
Post	-0.008	-1.275	-0.154	0.378	1.811	0.457
	(0.159)	(0.919)	(0.160)	(0.367)	(2.739)	(0.362)
WWSF	-0.011	-0.011	-0.012	-0.019	-0.102**	0.004
	(0.013)	(0.013)	(0.013)	(0.031)	(0.048)	(0.030)
Win Rate	0.00005	0.00004	0.00005	0.0003	0.0003	0.0003
	(0.0002)	(0.0002)	(0.0002)	(0.0005)	(0.0005)	(0.0005)
Flop Aggression	0.010	0.009	-0.004	0.021	0.017	0.079
	(0.021)	(0.021)	(0.021)	(0.049)	(0.069)	(0.049)
ln(№ of Hands)	-0.987***	-1.043***	-0.701***	-0.876***	-1.455***	-1.374***
	(0.092)	(0.100)	(0.105)	(0.212)	(0.453)	(0.237)
Average Size	5.929***	6.053***	5.324***	-8.093**	1.230	-4.848
	(1.442)	(1.445)	(1.437)	(3.316)	(4.921)	(3.257)
Post×Treatment	0.243	0.129	0.547	-1.491*	-0.488	-0.363
	(0.339)	(0.349)	(0.347)	(0.780)	(1.921)	(0.786)
Post×ln(№ of Hands)		0.132			-0.129	
		(0.095)			(0.359)	
Δ(№ of Hands)			-0.006***			0.021***
			(0.001)			(0.003)
Treatment×Δ(№ of Hands)			-0.078***			-0.225***
			(0.020)			(0.045)
Observations	3,477	3,477	3,477	3,477	3,477	3,477
R2	0.048	0.042	0.046	0.008	0.016	0.014
Adjusted R2	-1.233	-1.250	-1.240	-1.327	-1.313	-1.317
F Statistic	27.186***	23.991***	25.287***	4.260***	2.937***	12.346***