THE IMPACT OF EXPOSURE TO ARMED CONFLICT ON RISK AND AMBIGUITY ATTITUDES*

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Abstract

Exploiting a natural experiment created by the military institutions and the long running civil conflict in Turkey, we study how exposure to armed conflict affects risk and ambiguity attitudes of individuals. We build on our experimental setup with an innovative survey design and an embedded incentive-compatible lab-in-the-field experiment to identify the causal effects of exposure and the mediating pathways for the average male randomly picked from the population. We find that as the degree of exposure to the armed conflict environment increases individuals become more risk tolerant. Having traumatic direct experiences of armed violence, however, creates the opposite effect and renders them extremely risk averse. Such individuals are also more likely to be ambiguity averse. Results nominate preference change as the potential mechanism.

JEL Codes: C90, C93, D01, D74, D81
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I. Introduction

Armed conflicts are known as "development in reverse" due to their devastating economic consequences. The destruction of physical capital, and infrastructure, and the disruptions in the labor market are usually seen as the primary drivers of this developmental regress, and resultantly, recovery plans first and foremost focus on restoring capital stocks, infrastructure, and labor markets. However, a fast-growing literature reveals that conflict environments can also change individuals and their economic behaviors and attitudes.

Exposure to an armed conflict is a major shock for an individual and psychologists have long established that shocks can have persistent effects on people's worldviews and outlook on life (Carmil and Breznitz, 1991; Punamaki et al., 1997; Tedeschi and Calhoun, 2004; Janoff-Bulman, 1992) which then shape their attitudes, choices, and behaviors. But once we acknowledge the likelihood that conflicts may transform economic agents, it ceases to be obvious that a conflict-stricken economy can bounce back with just the restoration of markets, infrastructure, and capital. Therefore, to develop a full understanding of the economic consequences of armed conflicts and to design effective measures to counteract the negative ones, it is necessary to explore and map out the impacts these conflicts have on economic attitudes and behaviors of exposed individuals and the mechanisms behind these impacts. In this study, we contribute to that understanding by exploring and mapping out how exposure affects attitudes towards risk and uncertainty.

Studying armed conflicts and their effects on the exposed is a very challenging task wrought with inherent difficulties that create certain natural limitations for researchers. The most important of those difficulties is possible selection and endogeneity biases as exposure is almost always nonrandom. Relatedly, tracking exposure and identifying proper treatment and control groups pose another challenge. In many cases, control groups contain individuals who were also exposed in various degrees and types, and consequently, the true impact of conflict exposure remains concealed. Moreover, even when the impact is identified, it poses a challenge to isolate the transmitting pathways. In (post)conflict environments, mechanisms at the individual and societal level run parallel, and as such, they confound each other making it very difficult to identify and study them in isolation. Finally, difficulties associated with conducting incentivized experiments in the field with a large, random, and representative sample in natural settings introduce further limitations.

In this study, we identify and exploit a rare natural experiment that gives us a one-of-a-kind opportunity to address all these challenges. Building on this natural experiment with an innovative large-N survey that incorporates an incentivized lab-in-the field experiment, we identify random exposure to armed conflict and we measure that exposure in a precise and objective manner accounting for different types and degrees of it; we conduct a comprehensive analysis of the causal effects of exposure on the average male randomly picked from the population; we reveal the effects on not only risk attitudes but we lead the literature in deciphering the effects on ambiguity attitudes as well; and finally, we explain the effects we observe by analyzing the mediating pathways these effects transmit through.

Our natural experiment is created by the military institutions in Turkey and the long running civil conflict in the southeastern parts of the country. Turkey has a conscription army that mandates every male citizen to serve in the Armed Forces. A young man becomes draft eligible when he turns 20 and typically gets inducted within a year or so to serve at a military base determined by a deployment lottery. The military rules state that, conditional on the needs of the military across its branches and tasks, and on the province of registration of draftees, the deployment assignment is orthogonal to pre-enlistment characteristics (Official Gazette, 1927; 2019).[1] An estimated 14 million men have been drafted through this system in the 1984-2012 period to serve for a duration of 15 to 18 months, and given the organizational structure of the Turkish armed forces, about 6 million of them are expected to have been deployed to bases in eastern/south-eastern Turkey (Dünya, 2018; Mater, 1999) where an ethnic civil conflict has been going on since 1984 between the Turkish state and the Kurdish separatist guerrilla organization Kurdistan Workers' Party (PKK).

This setting creates a unique natural experiment which equips us with several important capabilities. First, the strict conscription system that mandates every healthy male citizen to serve in the military, and the deployment lottery that is embedded in this system to rule out agency in the choice of service location, enable us to decipher the causal effects of armed conflict exposure for the average adult male randomly picked from the population. Second, the geographical concentration of the conflict in the country allows us to identify isolated and finite duration exposure during service. By sampling from the peaceful western parts of the country, we eliminate the potential bias that may stem from unobserved exposure in civilian roles, and more importantly, any confounding macroenvironmental effects of armed conflict on economic behaviors and attitudes. Coupled with the richness of our data, this immunity to possible

[1] These rules are stated in the *Conscription Law* (Law Number: 1111), which was originally legislated in 1927. Deployment is conditional on the province of registration because the rules state that one cannot be assigned to bases in his home province.

environmental confounders allows us to isolate and study the individual level effects of armed conflict exposure in and of itself and the possible mechanisms that may explain these effects.

Our data on military service and its outcomes come from the Exposure to Political Violence and Individual Behavior (EXPOVIBE) survey, designed to explore the individual-level effects of armed conflict exposure. The survey was conducted in western Turkey in 2019 with 5,024 randomly selected adult males who completed their military service between 1984 and 2012. Embedded in EXPOVIBE, we conducted an incentivized lab-in-the-field experiment with a randomly selected subset of 2,502 respondents to elicit their risk and ambiguity preferences using well-established and standard measures from behavioral and experimental economics (see, Harrison and Rutstrom, 2008; Dohmen et al, 2010; Sutter et al., 2013).[2]

Our main conflict exposure measure, *Exposure to Armed Conflict Environment* (ACE), tracks conflict intensity at each respondent's location and time of service by accounting for the (standardized) total number of combatant deaths in deployment districts during service. ACE, therefore, depicts the conflict environment each individual gets exposed to during his time in the Armed Forces in a precise and objective manner. We also control for the specific experiences of armed violence one can encounter in that environment. *Traumatizing Direct Experiences of Armed Violence* (TDE) is a binary indicator of getting injured or witnessing others get injured or killed during service. While the information on individuals' military service dates, location(s), and experiences comes from EXPOVIBE, the information on casualties within those geo-temporal coordinates comes from the Turkish State-PKK Conflict Event Dataset (TPCONED) which comprehensively details the events and casualties of this long running conflict with high geotemporal precision (Kibris, 2021).

We start our analysis by testing and confirming the orthogonality of ACE to pre-deployment characteristics, such as height, ethnic background, age at enlistment, age at the time of survey, and educational attainment of respondents, controlling for the conditional random assignment covariates (military branch, military task, deployment year, and residence province) as stated in the rules.

We then examine the impact of deployment on the likelihood of TDE. These estimates reveal that conflict intensity at the time and place of service substantially increases the likelihood of getting injured and/or witnessing others get hurt or killed and provide further evidence supporting our identifying assumptions and the validity of ACE. They also show that,

[2] Because the EXPOVIBE survey included multiple field experiments, to prevent them from priming each other, each experiment was conducted with a randomly selected subsample.

once ACE and the conditional random assignment covariates account for deployment characteristics, pre-service personal characteristics do not capture any additional variation in the likelihood of TDE. In other words, our natural experiment not only randomly assigns ACE but also powerfully explains TDE as well.

We also confirm the internal and external validity of our experimentally elicited measures of risk and ambiguity attitudes. We show that our experimental measures are significant predictors of both smoking behavior in real life and self-reported attitudes towards risk taking.

Next, we move on to estimating the impacts of conflict exposure on risk and ambiguity attitudes. We find that different types of exposure have different effects. Individuals who get exposed to more intense conflict environments during their military service become more tolerant to risk. However, we see strikingly different tendencies in those who had traumatizing experiences of armed violence while serving in the army. Such people are more likely to exhibit aversion to risk and ambiguity. We also find these effects to be resilient over time.

Upon identifying the causal impacts of conflict exposure, we then focus on tackling another major void in the literature - deciphering the mechanisms. Previous literature extends theoretical discussions of several possible pathways for the effects of conflict exposure to work through, however, because they are likely get activated simultaneously and confound each other, the empirical identification of these transmitting channels and their relative importance remains elusive in many cases. Theoretical arguments identify five main channels: conflict-driven changes in constraints and incentives (Jakiela and Ozier, 2019; Cassar et al., 2017; Voors et al., 2012); wealth and income channels (Moya, 2018; Jakiela and Ozier, 2019; Hanaoke et al., 2018; Brown et al., 2019; Cassar et al., 2017); changes in beliefs and expectations about outcomes (Malmendier and Nagel, 2011; Cassar et al., 2017); emotional mechanisms that may influence the cognitive process of decision making (Ben Zur and Zeidner, 2009; Hanaoke et al., 2018; Colasante et la., 2017; Brown et al., 2019; Callen et al., 2014; Cassar et al., 2017; Moya, 2018); and finally, changes in preferences (Voors et al., 2012; Jakiela and Ozier, 2019).

Note that, in our case, mechanisms that may originate from the conflict ecology, i.e., changes in constraints and incentives, either do not apply or play a minimal role. Since our study design incorporates a clear separation between the sampling and conflict areas, our participants are immune to the physical destruction of war, they did not take any part in any form of post-conflict reconstruction, and they do not bear any risks to personal security or their property rights in their daily lives. Moreover, conscription does not hinder education as it almost always takes place after the completion of formal schooling. Second, service in conflict areas does not entitle conscripts to any kind of financial compensation (unless disabled due to severe injury during service), nor do draftees receive any favorable treatment in civilian life upon discharge (Açiksöz, 2015).[3] Therefore, the potential roles that the conflict ecology could play in influencing risk and ambiguity behaviors and attitudes are minimized.

Continuing with our exploration of potential mechanisms, we test the effects of conflict exposure on income. We fail to find any compelling evidence of exposure-induced effects on earnings that might explain our findings. Auxiliary analysis does not favor a change in beliefs about possible outcomes nor do we observe any strong evidence of psychological mechanisms. Validating our measures, those with TDE exhibit depressive symptomology and elevated feelings of insecurity, however, results do not suggest a meaningful role for these psychological outcomes in transmitting the effects of conflict exposure. These findings lead us to conclude that what we observe is most likely a change in preferences. Our conclusion is supported by the congruence of the heterogenous effects we observe depending on the type of exposure with the observed regularity that people tend to take more risks after a gain and less risk after a loss, a phenomenon known as reinforcement effects. In other words, what we observe is consistent with history-dependent risk and ambiguity preferences (Dillenberger and Rozen, 2015; Tserenjigmid, 2019).

Our study, first and foremost, speaks to the developing literature on armed conflicts and risk attitudes. Results in this literature are mixed (Schildberg-Hörisch, 2018) with some studies reporting positive associations between risk taking and conflict exposure (Voors et al., 2012), some finding higher levels of risk aversion in exposed people (Moya, 2018; Jakiela and Ozier, 2019), some presenting heterogenous effects (Rockmore et al, 2020), and yet, some others failing to find any association per se (Callen et al., 2014). Therefore, a consensus is yet to be reached. Moreover, most studies in the literature do not go beyond identifying changes in attitudes and behaviors to explore the potential mechanisms behind those changes they observe, and so the mediating pathways that transmit the effects of conflict exposure are still not clearly understood. Finally, even though many situations in the real world, including but not limited

[3] Disability status is only accorded to those with more than 40% impairment due to injury during service (https://www.mevzuat.gov.tr/MevzuatMetin/2.3.41053.pdf). Consequently, only 0.5 per thousand of the conflict area veterans receive veteran's compensation. Psychological ailments, such as PTSD, are usually not considered as qualifying disability (Güloglu, 2016).

to investment, job, and insurance choices, involve decisions where ambiguities are present, that is, where probabilities of potential outcomes are unknown (e.g., Ellsberg, 1961; Halevy, 2007; Abdellaoui et al., 2011; Ahn et al. 2014), the literature is still scant about the impacts of conflict exposure on attitudes towards ambiguity (Cavatorta and Groom, 2020).

We also contribute towards two other growing literatures. First, our paper contributes to a recent literature on the stability of economic preferences that explores whether and how individual preferences are affected by traumatic events such as natural disasters (Eckel et al. 2009; Cassar et al. 2017; Hanaoka et al. 2018; Beine et al. 2020), economic downturns (Malmendier and Nagel, 2011; Fisman et al. 2015), violent crime[4] (Nasir et al. 2017; Brown et al. 2019), and pandemics (Drichoutis and Nayga Jr., 2021; Shachat et al., 2021).[5] Second, we contribute to the literature that examines the impact of risk and ambiguity preferences on economic and health related decisions (Tanaka et al. 2010; Dohmen et al., 2011; Liu, 2013; Sutter et al. 2013; Dimmock et al., 2016; Falk et al. 2018; Bryan, 2019; Belissa et al. 2019) by providing evidence on the relationship between our measures of risk and ambiguity and respondents' field behaviors.

II. Research Design

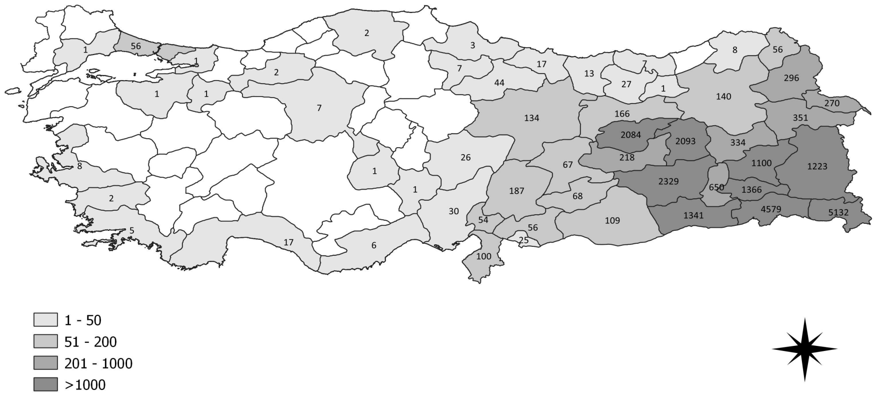
II. A. Identification Strategy

Since 1984, Turkey has been suffering from an insurgency campaign led by the Kurdish separatist guerrilla organization Kurdistan Workers' Party (PKK). The PKK was first founded with the goal of establishing an independent Kurdish state in southeastern Turkey though later in the 90s it appeared to have rolled back on its goal to a federational structure that would grant more autonomy to the region. And as Figure 1, which maps the distribution of total combatant casualties in the 1984-2018 period demonstrates, the armed conflict has remained geographically concentrated in the southeastern and eastern parts of the country over the years.

[4] Important differences exist between violent crime and armed political conflict including intensity, frequency, and type of exposure (e.g., Nasir et al. 2017). Therefore, it is unclear whether the effect of violent crime on economic preferences are identical to those of armed conflicts. To be cautious, we treat these literatures separately from each other.

[5] See Chuang and Schechter (2015) and Schildberg-Hörisch (2018) for literature reviews of the literature on stability of experimental and survey measures of economic preferences over time.

Figure 1. Geographical distribution of total combatant casualties in 1984-2018 (Kibris, 2021)



Turkey has a draft army and a mandatory military service system that requires each and every Turkish male citizen to serve in the Armed Forces. A young man becomes draft eligible when he turns 20 and typically gets inducted into the military before the age of 22 unless he is still in formal high education when he gets the draft call, in which case, he is allowed to postpone enrollment until graduation given that it is before the age of 29. While the required service length for rank-and-file was 18 months in the 80s, it was taken down to 15 months in 1992, brought back up to 18 months in 1995, taken down to 15 months in 2003, and remained so up until 2014. The drafted young men are first subject to a basic training program that lasts about a month and then are sent to military bases all over the country to serve the rest of their terms as active soldiers. Importantly, conditional on the needs of the military across its branches and task classifications, and on the province of registration, the base assignments are done randomly via a lottery system which is publicly known as the "base lottery" (Official Gazette, 1927; 2019; Mater, 1999 pp.13, 42, 114, 131, 136).[6] As they were conducted in public, recordings of such base-lottery ceremonies can still be found on social media outlets.[7] Through this institutional setup, a significant portion of the draftees find themselves assigned to bases in the eastern and southeastern regions of the country, and they get actively involved in the armed conflict against the PKK as combatants. This setting removes the risk of endogeneity between exposure to armed conflict and behavior and allows us to conduct causal inference.

[6] Mater's book, which was banned in Turkey shortly after publication, contains interviews with 42 ex-conscripts who had been deployed to intense conflict areas during their service. The interviews contain frequent references to the "lottery."

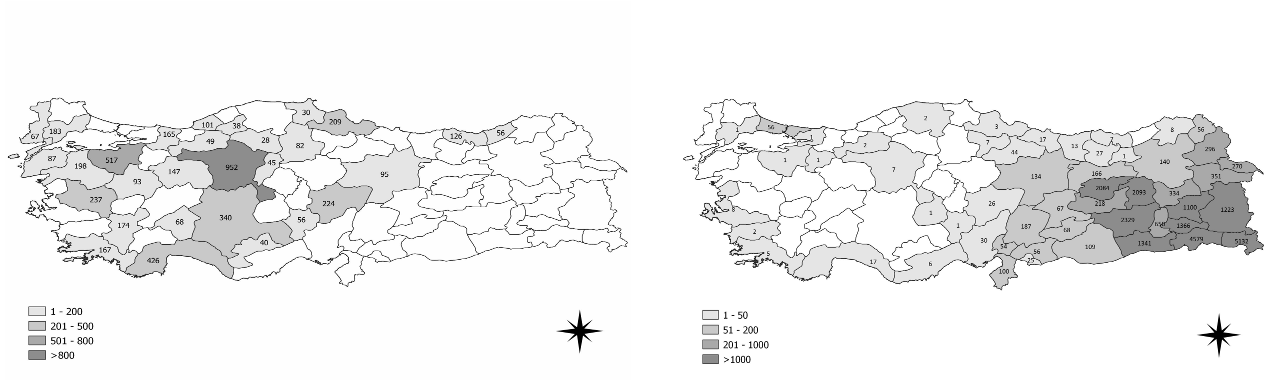
[7] As an example, see https://www.youtube.com/watch?v=D3w4i07_Wj4

The EXPOVIBE survey innovatively exploits this natural experiment. The survey was conducted in 29 Western districts with 5,024 randomly selected men who completed their military service sometime between 1984 and 2012. The focus on the 1984-2012 period is both because the 90s was the most intense period of the conflict and because the Turkish army has been going through structural changes since 2012. With new legislation enacted in late 2011, the army instituted what is called "contract soldiers" and started to employ professional soldiers on fixed term contracts. And with enough professional soldiers in place, regulations were relaxed after 2018 to allow civilians to pay their way out of military service.

To capture isolated exposure to the conflict during military service, only peaceful western provinces with negligible in-migration from conflict areas were included in the sampling frame. Figure 2 maps the distribution of the sample alongside the distribution of total combatant casualties to visualize the clear separation between the sampling and the conflict zone. The ability to identify such well-defined and isolated exposure enables us to construct clean treatment and control groups and to decipher the mechanisms while minimizing any confounding of our findings by potential macroenvironmental effects of the conflict.

Figure 2. Sampling distribution versus the distribution of total combatant casualties

Sample Distribution | Distribution of Combatant Casualties, 1984-2018



The survey included a rich battery of questions on personal traits, socioeconomic characteristics, and social, political, and economic attitudes and behaviors. And to identify exposure to the conflict, detailed information was collected on respondents' military service characteristics including dates, duration, location, branch, and task assignment. Figure 3 maps the geographical distribution of their military placements at the province level. 43% of participants declared to have served somewhere in the conflict zone. Respondents were also questioned about their specific experiences of armed violence during service.

Figure 3. Geographical distribution of military placements of respondents

The official narrative of the Turkish Armed Forces explicitly states that, conditional on the needs of the military, deployments are orthogonal to pre-service background characteristics. However, one may still question how perfectly the narrative overlaps with actual practice.[8] To address this concern, we perform formal balance tests in Section III.A, confirming our identifying assumptions.

We must also emphasize that, because sending their sons to the army involves serious risks, this assignment system and its fairness have always been under scrutiny by the public and the media in Turkey (Yıldırımkaya, 2010; Kibris, 2011). Therefore, the randomness of base assignments is a feature of the drafting system that has always carried great political costs. The Turkish Ministry of Defence and the General Staff emphasize in all their communications on the subject that the system does not discriminate. Anecdotal evidence also supports the non-discriminatory nature of the system. The list of fallen soldiers in the conflict zone includes close relatives of high-level politicians and army officials.[9] Also, the fact that the military has long been the most trusted institution in Turkey attests to the fairness perception of the public with regard to military practices (Esmer, 1999; Adaman et al., 2005).

Another relevant question regarding the credibility of our identification strategy is whether one can evade the draft or manipulate the timing or location of his service. In most

[8] An official statement of the draft system can be found on the information brochures for the prospective draftees by the Military Enrolment Services of the Turkish Defence Ministry last visited on September 27, 2022. https://www.msb.gov.tr/Askeralma/icerik/siniflandirma-islemleri
[9] A recent example is a secretary of state whose first cousin died in 2007 in a PKK attack on the Çeltikli outpost in Bitlis during his military service. https://worldbulletin.dunyabulteni.net/archive/turkish-fms-cousin-killed-in-pkk-attack-h10956.html.

countries with universal conscription, like Israel or South Korea, a significant share of eligible men can avoid active-duty service. Young Turkish men, however, have negligibly limited options to circumvent the system.[10] Health related exemptions are subject to close scrutiny and requires a panel of military doctors to approve the diagnosis of an incapacitating health problem.[11] Moreover, not only evaders face legal consequences they are also shunned by society via social rejection (Altinay and Bora, 2002). They cannot legally hold paid employment either, since employers are required by law to condition hiring on provision of valid military discharge certificate.[12] Moreover, draft evaders and those who help them risk arrest and imprisonment of up to three years if found guilty by the military court.[13] Therefore, the conscription system in Turkey constitutes a rare exception in which all Turkish men, except a small fraction due to incapacitating health ailments and illegal evasion, get inducted into the system (Akyürek, 2010).

It must, however, be noted that the system harbors an educational differentiation. Although everyone gets the draft call at the age of 20, those who are in formal high education are allowed to postpone enlistment until they complete their education (or until they are 29, whichever comes first) (Official Gazette, 1927; 2019). Moreover, while draftees with less than a college degree serve full terms as rank-and-file soldiers, college graduates serve either as full-term sub-lieutenants or serve half-term as rank-and-file depending on the needs of the Armed Forces in that draft period. What is relevant for our purposes is that college graduates are also subject to the service location assignment lottery regardless of their rank and duration of service. However, because of their military branches and tasks which are determined by the Armed Forces according to their technical specializations, they face slightly lower odds of assignment to bases in the conflict zone. Note that, while this differential in the system influences draft age, service duration, branch, task, combat zone deployment and therefore, direct armed conflict involvement likelihood, it does not constitute a threat to our identification strategy. Because it is solely based on educational attainment, which is fully observable to us

[10] Exemptions on religious, physical, psychological, or lawful grounds are possible in the Israeli system. Also the Israeli High Court of Justice ruled in 2002 that refusal to serve on conscientious or political grounds was legal (https://military-history.fandom.com/wiki/Refusal_to_serve_in_the_IDF). The South Korean system incorporates a broader definition of compulsory service that includes social work, research, full-time reserve enlistment, and industrial technical service.

[11] What constitutes an incapacitating health problem is defined in regulations (Turkish Armed Forces, Health Capability Regulation, Official Gazette 29530, 12 November 2015).

[12] https://www.haberturk.com/e-devlet-ten-askerlik-durum-belgesi-sorgulama-islemi-nasil-yapilir-hts-2378941.

[13] The Military Penal Code enacted by the law number 1632 states that evading service is punishable by up to three years in prison, and employing a fugitive is punishable by up to two years in prison. https://www.mevzuat.gov.tr/mevzuatmetin/1.3.1632.pdf.

in our data, our estimates should remain unbiased as long as we control for year of formal schooling fixed effects in our models. Moreover, we show in Appendix C (see Tables C1-C5) that all our results (including balance tests) continue to hold when we exclude college educated participants and restrict our sample to the at most high school educated.

II.B. Our Measures of Conflict Exposure

Our main variable of interest, *Exposure to Armed Conflict Environment (ACE)*, quantifies the conflict environment a conscripted soldier was exposed to during his time in service. For each respondent, ACE reports the number of combatant casualties that took place in his base district while he was stationed there.[14] We normalize the variable to have a zero mean and a standard deviation of one. Data on combatant casualties come from the Turkish State-PKK Conflict Event Database (TPCONED) (Kibris, 2021) which includes exact date, location, and casualty information on the fatal events of the conflict since its beginning in 1984.

ACE captures with high geo-temporal precision the conflict environment that each respondent was exposed to, and because it is based on an objective fact, compared to measures that rely on a person's retrospective and subjective assessment of his exposure, it is drastically more immune to response and recall biases. Relatedly, because it is based on mandatory service requirements which legally enforce the continuous presence of a soldier in his place of assignment over the duration of his service, ACE does not admit any possible unobserved movements across different environments and thus captures certain exposure to the environment defined by those geo-temporal parameters.

Another variable of interest is *Traumatizing Direct Experiences of Armed Violence* (TDE) - a binary variable that takes on the value 1 for those who got wounded in armed clashes or ever had anyone around them got killed or hurt in armed clashes during their military service. Note that while ACE characterizes the conflict environment an individual was immersed into, TDE observes specific violent experiences in that environment. Two percent of respondents declared they got wounded in armed clashes and 15 percent reported that others around them got killed or hurt during their military service. When analyzing the impact of ACE on risk and ambiguity attitudes, our preferred specification also controls for TDE.

In her book which contains in-depth interviews with 42 ex-conscripts who had served in bases in the conflict zone, Mater (1999) presents detailed qualitative accounts of the

[14] There are 973 districts in Turkey with an average area of about 800 square kilometers.

experience that our exposure measures are designed to capture quantitatively: “I shuddered when I drew Cizre in the lottery. It was to be my first time ever in the east… I lied to my family and said I drew a base somewhere on the coast.” (p.114); “He shows a photo of a mountainous terrain, this is where his friend got shot by the PKK. ‘It took the helicopter 5 hours to get to us, my friend was dead by then.’” (p. 9); “It was only 2-months into my service. I got the night watch. I was told that terrorists had cut the head off a soldier who had fallen asleep on watch right there. It was pitch dark and I was alone. It was the scariest experience of my life.” (p. 40); “Attacks on bases were very common. Suddenly bullets start raining from the sky, the whole world shakes.” (p.43) As described in these anecdotes, being a soldier in the conflict zone means immersion in a tense, scary and fatally risky combat zone with high military vigilance. Unfortunately, in many cases the experience also involves traumatic violent events like getting hurt or having others around get hurt.

One important aspect of our study is that we are not only able to measure conflict exposure in a detailed and objective fashion, but we are also able to pinpoint its timing and thereby account for the variation our subjects display in terms of time passed since their exposure. We measure time passed since exposure by *Years since Service* which is the number of years since discharge normalized to have a zero mean and a standard deviation of one.

Apart from conflict exposure measures, we include in our statistical models *Enlistment age, Height,* and *Kurdish ethnicity* as pre-treatment controls that might be associated with economic preferences, and we control for years of schooling, deployment year, branch of service, military task, and residence province fixed effects to account for the conditionality of random assignments on the needs of the Armed Forces and on the rule that draftees serve away from home.[15]

II.C. Our Measures of Risk and Ambiguity Preferences

We elicit risk and ambiguity preferences via a lab-in-the-field experiment that was administered to a randomly selected subsample of 2,502 respondents within the EXPOVIBE survey. The experiment was designed in the spirit of a classic Ellsberg experiment using the multiple price list (MPL) technique.[16]

[15] Note that controlling for enlistment age and deployment year accounts for current age as well.

[16] MPLs have been used widely to elicit risk (e.g., Holt and Laury, 2002; Harrison and Rutstrom, 2008; Dohmen et al. 2010, Dohmen et al. 2011) and ambiguity preferences (e.g., Sutter et al., 2013; Dean and Ortoleva, 2019).

As this experiment was conducted in the field with a representative sample (instead of a highly educated and homogenous university student population), special attention was paid to simplicity. In each decision problem, instead of comparing different lotteries, participants were asked to compare one simple lottery with a sure amount. The risky lottery used easily understandable 50-50 probabilities without employing technical language. Also, the words "lottery" or "gamble" were never mentioned since those concepts might carry religious connotations for Muslim participants (Falk et al., 2016; Falk et al., 2018). Respondents were simply asked to make a choice between drawing a marble from a bag for a chance to win a fixed amount of money and receiving a smaller amount for sure.[17] Exact instructions are provided in Appendix A.

Participants were physically presented with two black bags with 10 marbles in each. The marbles were either red or blue. While Bag 1 (which we will refer as the "Risky Bag") contained exactly 5 marbles of each color, the exact distribution of marbles in Bag 2 (which we will refer as the "Ambiguous Bag") was unknown. Subjects could win 2,500 TL by betting on the color of their choice to be drawn blindly from a bag by themselves.[18]

A participant was first asked to pick a color, red or blue. Then, he was asked a series of ten questions using one of the bags, followed by the same ten questions again but this time using the other bag, with the order of the bags randomly determined to control for possible order effects. In each of these ten questions, participants were to make a choice between playing the lottery by drawing a marble from the bag and accepting a sure amount. The lottery was always the same: If the randomly drawn marble from the corresponding bag is the same color as the (previously elicited) color of their choice, then the participant wins 2,500 TL, if not he wins nothing. The sure amount changed in each question. It started with 600 TL in the first question and ended at 1,500 TL in the 10th question with increments of 100 TL (see Tables A.1 and A.2 in Appendix A). The question at which subjects switch from the lottery to the safe option when the Risky (Ambiguous) Bag is used provides information regarding their certainty equivalent for that lottery and hence their risk (ambiguity) preferences.

A risk neutral individual maximizes the expected payoff regardless of the risk. Because the expected payoff for the lottery is 1,250 TL, a risk neutral individual would pick to play the

[17] Gambling is a sin in Islam. Therefore, we paid special attention to wording and the implementation of the game. The fact that it does not require the participants to bet any monetary amount of their own, and that there is no possible negative payoff we were confident that Turkish people would not consider it as gambling. As expected, most respondents agreed to participate in our experiment.
[18] At the time of the experiment, 2,500 TL corresponded to about $450, and was slightly higher than the *monthly* legal minimum wage in Turkey.

lottery in the first seven questions and then switch to the safe amount starting at 1,300 TL in the eight question and keep choosing the safe amount in the rest of the questions. Individuals who pick the lottery less (more) than seven times before switching to the safe amount are risk averse (loving). An ambiguity neutral individual would switch from the lottery to the safe option at the same question independent of which bag is used. An individual who switches from the lottery to the safe option at an earlier (a later) question when the Ambiguous Bag is used relative to the Risky Bag is ambiguity averse (loving).

To ensure incentive-compatibility, only one question was randomly selected to be paid out (Azrieli et al. 2018). At the end of the experiment, individuals picked a card randomly from a deck of cards numbered from 1 to 20. Their (potential) earnings were determined by their choice in that randomly selected question—they earned the safe amount if they picked the safe option in that question, otherwise they played the lottery by drawing a marble blindly from the corresponding bag.

Due to the extremely high cost of paying every single individual and safety concerns related to interviewers carrying large amounts of money on themselves, two randomly selected individuals out of 2,502 were paid in this experiment. Note that, the risk and ambiguity elicitation techniques we use in this study are adopted from well-documented experimental designs that produce reliable answers even in the absence of monetary incentives (Falk et al., 2016; Falk et al., 2018).[19] Moreover, in Section III.B, we confirm the internal and external validity of our risk and ambiguity measures by showing that they are associated in meaningful and expected ways with respondents' verbal assessments of their willingness to take financial risks, and with smoking behavior, respectively.

We develop our measures of risk and ambiguity preferences without relying on specific utility forms or parametric assumptions. Instead, they depend directly on participants' own choices. Our measure for risk preferences comes directly from decisions that involve the Risky Bag. We define the variable *Risk Tolerance* as the total number of times a respondent picked the lottery before switching to the safe amount when the Risky Bag is used.[20] While this

[19] In a recent study on global variation in economic preferences, Falk et al. (2018) use a similar experiment with no monetary incentives to elicit risk preferences and find that the elicited risk preferences are meaningful predictors of economic outcomes. In addition, their findings on the determinants of risk preferences concur with previous literature.

[20] Since we do not have questions with a sure amount less than 600 TL or greater than 1,500 TL, we cannot differentiate risk preferences for very low degrees of risk aversion or for very high degrees of risk seeking. While one could have overcome these issues by selecting a range for sure amount from 0 TL to 2,500 TL, we purposefully avoided asking too many questions in order not to overwhelm our respondents. In addition, we did not want to take a short cut by imposing and eliciting a unique switching point which would have made it impossible to identify confused participants.

variable provides a plain and effective way of measuring attitudes towards risk, by itself is not enough to provide a complete picture of risk preferences as it does not readily map into risk aversion or risk seeking. Therefore, to carefully distinguish the effects of violence exposure on risk preferences, we use additional measures. We define *Risk Averse (Lover)* as a dummy variable that takes value one when the respondent picks the lottery less (more) than seven times and zero otherwise.[21] Finally, we define *Extremely Risk Averse* as a dummy variable that takes value one when the respondent picks the lottery less than four times.[22]

Our measure for ambiguity preferences comes from decisions that involve the Ambiguous Bag in addition to the Risky Bag. We first start with a measure that simply reflects the level of tolerance towards an uncertain situation (without necessarily reflecting upon ambiguity preferences). We define the variable *Uncertainty Tolerance* as the total number of times a respondent picked the lottery before switching to the safe amount when the Ambiguous Bag is used. To elicit ambiguity preferences, we consider the difference between *Uncertainty Tolerance* and *Risk Tolerance*. We classify individuals for whom this difference is negative (positive) as ambiguity averse (lover). Admittedly, it is harder to classify an individual when this difference is zero, since such an individual is not necessarily ambiguity neutral. Individuals who, regardless of the bag, always choose the sure amount (lottery) might be ambiguity averse (lover) but the difference between *Uncertainty Tolerance* and *Risk Tolerance* would be zero as their choices are constrained.[23] Therefore, we define *Ambiguity Averse* (*Lover*) as an indicator dummy variable that takes a value of 1 if the difference between *Uncertainty Tolerance* and *Risk Tolerance* is negative (positive) or if the individual always chooses the safe option (the lottery) over the 20 decisions.[24] Eliciting ambiguity preferences is challenging and our measures are not perfect, nonetheless they still give us insights on the potential effects.

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[21] Individuals who pick exactly seven lotteries might be risk neutral, slightly risk averse or slightly risk loving. Since the percentage of people who picked the lottery seven times is only around 3%, the percentage of slightly risk averse or slightly risk loving individuals can be assumed to be negligible.

[22] Using even more extreme cutoff points do not alter our qualitative results. Note that because our price list is not symmetric around the amount where the expected return of the lottery equals the sure amount, we are not able to create a symmetric Extreme Risk Lover measure.

[23] The difficulty arises mainly at the corners when an individual is constrained by the action space. If an individual switches to the sure amount somewhere in the middle, then we can classify such an individual to be (approximately) ambiguity neutral when they do not change their switching point between the Risky and the Ambiguous Bags. On the other hand, people who always choose the safe option over the 20 decisions might be either ambiguity averse or ambiguity neutral. Similarly, people who always pick the lottery over the 20 decisions might be either ambiguity lover or ambiguity neutral.

[24] We also considered two strict (conservative) measures of ambiguity preferences. We define *Strictly Ambiguity Averse (Lover)* as a dummy variable that takes a value of 1 if the difference between *Uncertainty Tolerance* and *Risk Tolerance* is negative (positive) and zero otherwise. Only a small fraction, approximately 18% (11%), of the respondents are ambiguity averse (lover) according to these conservative measures. Moreover, in contrast to

III. Analyses and Results

2,262 people out of the randomly chosen 2,502 agreed to participate in the lab-in-the-field experiment. To make sure that we do not suffer from selection biases, we investigate whether and how respondents' decisions to not participate, their level of religiosity, and their conflict exposure are related. We derive our indicator of religiosity from a question that require respondents to assess on a Likert scale from 1 (no religious belief) to 7 (very religious) how religious they are. We first regress a binary indicator of refusal to participate on this religiosity measure. The estimated coefficient fails statistical significance. We also examine the effects of conflict exposure on religiosity and on refusal to participate, respectively. Results indicate no significant associations and as such indicate no such selection bias. We present these results in Table C6 in Appendix C.

EXPOVIBE also contains detailed information on the civilian residential history of respondents. 159 respondents indicated to have ever lived in a province in the conflict zone after 1984. While having ever lived in a province in the conflict zone does not indicate exposure to armed conflict, to make sure that we work with a clean control group with no conflict exposure and a clean treatment group with isolated exposure during military service, we exclude those observations from our analyses.[25]

In multiple price list experiments, it is common to observe some subjects to demonstrate multiple switch points.[26] We interpret multiple switching as confusion or loss of attention and, therefore, our analysis focuses on subjects with at most one switching point.[27] For analysis involving the Risky (Ambiguous) Bag, this corresponds to 1,970 (1,980) participants with consistent choices.

We start by presenting an overall summary view of our data. Table 1 shows the mean, standard error and median for each variable we use in this study as well as the number of observations.

Consistent with previous experimental literature, respondents are on average risk and ambiguity averse. The mean (median) number of lottery choice from the Risky Bag is 5.26 (6),

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Ambiguity Averse and Ambiguity Lover measures, we find that these conservative measures are not internally or externally valid, i.e., these measures do not predict field behavior and do not correlate with verbal risk assessment in a meaningful way. Therefore, we refrain from using them.

[25] Results are robust to keeping these observations in the sample and are available upon request.

[26] Multiple switching includes those cases where a subject "switches" from the lottery to the safe option in the first decision and then "switches back" to the lottery in a later decision. This kind of behavior violates monotonicity and cannot be explained by standard utility functions (except if one assumes idiosyncratic errors).

[27] Inconsistent observations can be included in the analyses by using the total number of times one chooses the lottery over the sure alternative when the Risky Bag (Ambiguous Bag) is used as the measure of risk (uncertainty) tolerance (Holt and Laury, 2002). Our results are robust to the inclusion of inconsistent observations.

which is less than the cutoff point of 7 for risk neutrality. Approximately 53% are risk averse, 41% are extremely risk averse, and 44% are risk lover. For the Ambiguous Bag, mean (median) number of lottery choice is 4.76 (4). This corresponds to, on average, 0.5 less choices of lotteries relative to the Risky Bag. Approximately 51% (42%) are ambiguity averse (lover). Our estimates of ambiguity attitudes are in the range of distributions reported in previous literature (Trautmann and Kuilen, 2015). In addition, they are strikingly similar to the estimates Dimmock et al. (2016) find in a lab-in-the-field experiment they conducted with a representative sample of more than three thousand respondents in the American Life Panel (ALP).

In Section III.A, we confirm the validity of our identifying assumptions, and we test the orthogonality of deployments to pre-service characteristics. We then move on to confirming the validity of our experimental measures in Section III.B. Once we ascertain the strength and validity of our setup, Sections III.C and III.D examine the effects of armed conflict exposure on risk and ambiguity preferences, respectively. Section III.E provides robustness checks. Finally, we investigate the mechanisms transmitting the effects we observe in Section IV.

Table 1. Descriptive Statistics

	Mean	**SE**	**Median**	**N**
Conflict exposure:				
ACE	0.00	0.02	-0.21	2,333
TDE	0.15	0.01	0	2,326
Years since Service (standardized)	0.00	0.02	-0.07	2,334
Risk and ambiguity:				
Risk Tolerance	5.26	0.10	6	1,977
Risk Averse	0.53	0.01	1	1,977
Risk Lover	0.44	0.01	0	1,977
Extremely Risk Averse	0.41	0.01	0	1,977
Uncertainty Tolerance	4.76	0.10	4	1,989
Ambiguity Averse	0.51	0.01	1	1,931
Ambiguity Lover	0.42	0.01	0	1,931
Demographics:				
Age	42.42	0.15	42	2,336
Height	175.36	0.14	175	2,334
Educational attainment	9.05	0.07	9.5	2,334
Kurdish ethnicity	0.05	0.00	0	2,336

	Mean	SE	Median	N
Enlistment age	20.56	0.03	20	2,334
Household income	3.12	0.04	3	2,047
Field behavior:				
Smoking	0.66	0.01	1	2,336
Verbal risk assessment	3.46	0.03	4	2,329
Emotional measures:				
Anger index	0.43	0.02	0.33	2,329
Subjective insecurity index	1.55	0.02	1.38	2,336
Depression index	0.73	0.02	0.33	2,326

III. A. Evidence on the Exogeneity of Conflict Exposure

Our identification strategy relies on the deployment lottery embedded in the mandatory military service system in Turkey which randomly exposes young adult males to an armed conflict environment. Note that randomization of base assignments implies that draftees assigned to bases in the conflict zone and draftees assigned to bases in peaceful locations in the west should be similar in terms of their pre-military characteristics. We formally test this conjecture both in the larger EXPOVIBE survey sample and in the field experiment subsample. We first present dichotomous tests that analyze the balance between those deployed to bases in the conflict zone and those deployed elsewhere in terms of age, enlistment age, ethnic background, height, and educational attainment conditioning on military branch, military task, and deployment year to account for the conditionality of the random assignment on the needs of the Armed Forces at the time of draft. Columns (1) and (2) in Table 2 present the means and standard deviations of pre-deployment variables by deployment zone. Then, conditioning on exogenous random assignment covariates, column (3) reports the normalized differences between those who served outside and those who served in the conflict zone and the associated p-values for these differences in parentheses. In these tests, we define the conflict zone as those provinces with more than the median number of total combatant casualties over the course of the conflict (eastern provinces colored by the two darkest shades in Figure 1). None of the normalized differences are statistically significant. Panel I presents the tests on the EXPOVIBE sample and Panel II presents them on the randomly selected experiment subsample.

Table 2. Evidence on the Exogeneity of Armed Conflict Exposure

	(1) Served outside the conflict zone Mean/SD	(2) Served in the conflict zone Mean/SD	(3) Normalized difference (1)-(2)
Panel I – EXPOVIBE sample			
Height	175.493	175.380	0.016
	[12.976]	[13.630]	(0.662)
Kurdish ethnicity	0.069	0.067	0.007
	[0.323]	[0.251]	(0.715)
Age	42.421	42.357	0.009
	[12.103]	[16.319]	(0.229)
Enlistment age	20.676	20.548	0.073
	[2.804]	[2.423]	(0.465)
Educational attainment	9.276	8.981	0.089
	[6.795]	[6.149]	(0.176)
Observations	2,838	2,182	
Panel II – Experiment subsample			
Height	175.395	175.238	0.023
	[10.147]	[11.169]	(0.278)
Kurdish ethnicity	0.069	0.078	-0.036
	[0.349]	[0.246]	(0.260)
Age	42.386	42.191	0.026
	[8.680]	[11.842]	(0.169)
Enlistment age	20.671	20.478	0.115
	[1.937]	[1.947]	(0.215)
Educational attainment	9.180	8.876	0.092
	[4.851]	[5.760]	(0.204)
Observations	1,410	1,089	

Notes: p-values for normalized differences in parentheses. Standard deviations in square brackets, adjusted for clustering at the training province. Residence province and deployment year fixed effects are included in all regressions. A binary indicator for college education is included in estimations on the full sample. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

The results attest to the randomness of deployment locations and the unbiasedness of the assignment lottery. We then regress the pre-military characteristics of our respondents on ACE in Table 3. Panel I reports the coefficients we estimate in the EXPOVIBE sample, and Panel II reports them for the experiment subsample. None of the estimated coefficients reach statistical significance.

Overall, these tests confirm the validity of our natural experiment and the exogeneity of our main exposure variable ACE.

Table 3. Evidence on the Exogeneity of Exposure to Armed Conflict Environment (ACE)

	Dependent Variables				
	(1) Educational attainment	(2) Height	(3) Kurdish ethnicity	(4) Age	(5) Enlistment age
Panel I - EXPOVIBE sample					
ACE	-0.035	0.115	-0.001	-0.021	-0.016
	(0.035)	(0.080)	(0.003)	(0.017)	(0.017)
Observations	4,990	4,991	4,994	4,994	4,994
Panel II – Experiment subsample					
ACE	-0.044	0.002	0.002	-0.036	-0.037
	(0.046)	(0.122)	(0.005)	(0.026)	(0.024)
Observations	2,484	2,484	2,486	2,486	2,486

Notes: Estimated parameters are from individual OLS regressions of pre-service characteristics on ACE. Residence province and deployment year fixed effects are included in all regressions. A binary indicator for college education is included in estimations on the full sample. Robust standard errors, corrected for clustering at the training province, are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Next, we focus on TDE. By definition, an important part of the variation in the likelihood of injury (self or of others around) on duty is expected to be determined by the intensity of the conflict in the environment that one gets randomly assigned to via the deployment lottery, and by those factors like military branch and task that conditions that assignment. While the remaining variation is also likely to be largely random (as it is the case in stepping on a landmine on the field or getting shot in a firefight) one might still suspect that conscripts with certain characteristics might be more likely to be selected or to self-select into more dangerous roles and situations conducting their tasks at the bases they are deployed. In such a case, the likelihood of directly experiencing armed violence becomes endogenous to those characteristics.

We address this issue in Table 4 by examining the effects of deployment and pre-service characteristics on TDE. In Column 1 we present the estimated association with ACE as the only control; in Column 2 we add the conditional random assignment covariates; then in Column 3 we include the pre-service characteristics. As these characteristics are exogenous to the likelihood of assignment to an armed conflict zone, controlling for them should have no significant influence on our coefficient estimates. As can be seen in the progression of the estimated coefficients, the addition of pre-service characteristics does not lead to any meaningful change in the estimated association between ACE and TDE. Moreover, once the conditional random assignment variables are controlled for, moving from column (2) to column (3) the R-squared statistic changes only slightly indicating that pre-service personal characteristics does not explain much variation in the likelihood of experiencing direct armed violence. In other words, as expected, our natural experiment not only randomly exposes individuals to armed combat environments but also powerfully explains their experiences of direct armed violence, and personal characteristics do not have much explanatory power on the likelihood of such experiences.

Table 4. The Impact of Deployment on Traumatic Direct Experiences (TDE)

	(1)	(2)	(3)
Panel I - EXPOVIBE sample			
ACE	0.093***	0.081***	0.082***
	(0.011)	(0.009)	(0.009)
Observations	5,001	4,976	4,969
R- squared	0.066	0.130	0.138
Panel II – Experiment subsample			
ACE	0.099***	0.088***	0.089***
	(0.009)	(0.009)	(0.009)
Observations	2,489	2,477	2,473
R- squared	0.072	0.147	0.162
Conditional Random Assignment Covariates	No	Yes	Yes
Pre-treatment Characteristics	No	No	Yes

Notes: Estimated parameters are from individual OLS regressions of TDE on ACE. Conditional random assignment covariates are included in specifications 2 and 3. Pre-treatment characteristics are included in specification 3. Robust standard errors, corrected for clustering at the training province, are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

III. B. Validation of Risk and Ambiguity Measures

Before we present our results, we demonstrate the external and internal validity of our experimental measures of individual preferences by testing the association of our measures with a self-reported real-life outcome and with verbal self-assessments of risk attitudes we have in the EXPOVIBE survey.

Previous theoretical, empirical, and experimental literatures widely document that there is a positive association between willingness to take higher risks and smoking (Dohmen et al., 2011; Falk et al. 2018).[28] Validating our experimental measures' ability to reflect risk preferences we observe similar results with our survey participants. As shown in Panel I of

[28] See Charness et al. (2020) and Cooper and Saral (2020) for reviews of the experimental literature. Note that not all papers in the literature find significant relationships and it is an open question whether experimental measures of individual preferences predict field behavior well. Our paper provides additional evidence for this recent debate.

Table 5, the odds of smoking increase with *Risk Tolerance* and are higher (lower) for a risk loving (averse) person.

Theory predicts ambiguity attitudes to be associated with smoking as well. However, the empirical and experimental evidence are still scant. Sutter et al. (2013) use a very similar experimental measure of ambiguity aversion to ours and confirm that ambiguity aversion is related to smoking behavior in the field. Concurringly, we find *Uncertainty Tolerance* to have a positive association with smoking, and respondents who are ambiguity averse to be significantly less likely to smoke. While not statistically significant at the conventional levels, the estimated association between ambiguity loving and smoking is also in the expected direction.

Next, we internally validate our experimental measures by testing whether they have any predictive power in explaining how individuals assess their own willingness to take risks. The EXPOVIBE survey includes a self-report question to measure willingness to take financial risks on a 5-point Likert scale with higher values corresponding to higher willingness. Since the question does not differentiate between known versus unknown probabilities, we expect both risk and ambiguity preferences to play a role in how individuals answer these questions. Therefore, in Panel II of Table 5 we test the predictive power of each of our experimental measures on self-assessments of risk attitudes. Both *Risk Tolerance* and *Uncertainty Tolerance* are positively correlated with how individuals assess their own willingness to take financial risks and the results are statistically significant at the 1% and 5%, respectively. In addition, results are highly significant in the predicted direction for our risk preference measures *Risk Averse* and *Risk Lover*. Finally, the coefficients of *Ambiguity Averse* and *Ambiguity Lover* are also in the expected direction and statistically significant at the 10% level.

Overall, we find strong internal and external validation for our risk and ambiguity preference measures.

Table 5. Validation of Experimental Measures

Panel I – Smoking (Logistic regressions, odd ratios)							
Risk Tolerance	1.035***						
	(0.012)						
Risk Averse		0.785**					
		(0.078)					
Risk Lover			1.360***				
			(0.132)				
Extreme Risk Averse				0.757***			
				(0.080)			
Uncertainty Tolerance					1.030**		
					(0.012)		
Ambiguity Averse						0.817**	
						(0.084)	
Ambiguity Lover							1.234
							(0.168)
Observations	2,120	2,120	2,120	2,120	2,133	2,071	2,071
Panel II – Verbal Risk Assessment (Ordered logistic regressions)							
Risk Tolerance	0.028***						
	(0.014)						
Risk Averse		-0.281***					
		(0.108)					
Risk Lover			0.309***				
			(0.117)				
Extreme Risk Averse				-0.183			
				(0.115)			
Uncertainty Tolerance					0.026**		
					(0.013)		
Ambiguity Averse						-0.192*	
						(0.103)	
Ambiguity Lover							0.215*
							(0.110)
Observations	2,115	2,115	2,115	2,115	2,128	2,066	2,066

Notes: All models include controls for age, educational attainment, height, and ethnicity. Robust standard errors, corrected for clustering at the training province, are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

III.C. Exposure to Armed Conflict and Risk Attitudes

To estimate the impact of armed conflict exposure on our outcome measures we employ the following benchmark statistical model:

$$Y_i = \alpha + \beta_1 ACE_i + \beta_2 TDE_i + \gamma X_i + \rho\theta_i + \omega R_i + \varepsilon_i \qquad (1)$$

where i denotes the respondent, and the dependent variable Y denotes the risk or ambiguity measure of interest. ACE_i is exposure to the armed conflict environment measured in terms of the standardized number of combatant casualties at the service district of i during his service. TDE_i is a binary indicator of traumatic direct experiences of armed violence during service. X_i is a vector of pre-deployment control variables (height, enlistment age, Kurdish ethnicity), θ_i includes the conditional assignment covariates (educational attainment, deployment year, residence province, military branch, and military task fixed effects). Finally, R_i is the order of the bags respondent i played with. In our baseline estimations, we correct standard errors for clustering at the training base province to account for any possible unobserved confounders across training base locations that might lead to a correlation in error terms. For ease of interpretation, we estimate Equation (1) via OLS regressions.

Panel I in Table 6 explores the impact of armed conflict exposure on *Risk Tolerance*. In column (1), we only control for ACE. We then present our preferred specification in column (2) where, alongside ACE, we also control for TDE. Column (3) includes the interaction of ACE and TDE to test whether their impacts on risk tolerance are conditional on each other.

Interestingly, we find ACE and TDE to have opposing effects. In contrast to the positive effect of ACE on risk tolerance, TDE leads people to take fewer lotteries. The estimated coefficients indicate that while exposure to a one-standard deviation higher conflict intensity during the service leads one to choose approximately 0.3 more lotteries on average, experiencing direct armed violence during that time leads him to pick 0.8 less lotteries.

Table 6. The Impact of Exposure to Conflict on Risk and Uncertainty Tolerance

Panel I - Dependent variable: Risk Tolerance			
	(1)	(2)	(3)
ACE	0.225**	0.317***	0.270*
	(0.090)	(0.076)	(0.144)
TDE		-0.817**	-0.823***
		(0.314)	(0.308)
ACE*TDE			0.066
			(0.177)
Observations	1,964	1,958	1,958
R-squared	0.120	0.124	0.124
Panel II - Dependent variable: Uncertainty Tolerance			
	(1)	(2)	(3)
ACE	0.169*	0.251***	0.111
	(0.097)	(0.082)	(0.130)
TDE		-0.754***	-0.777***
		(0.240)	(0.233)
ACE*TDE			0.202
			(0.197)
Observations	1,977	1,970	1,970
R-squared	0.104	0.106	0.106

Notes: OLS regressions. All regressions include fixed effects for the branch of service, military task, residence province, educational attainment, and deployment year. Exogenous covariates include height, ethnic background, enlistment age, and order of the bags in the game. Robust standard errors, corrected for clustering at the training province, are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

In Table 7, we further investigate the role exposure plays on risk preferences. Columns (1) to (3) (Columns (4) to (6)) examine the association between exposure and the likelihood of being risk averse (lover). Consistent with the results on *Risk Tolerance*, ACE decreases the likelihood of being risk averse while increasing the likelihood of being a risk lover. Once again, TDE exerts effects in the opposite directions especially when we focus on risk aversion. Columns (2) and (3) indicate a 6% increase in the likelihood of risk aversion, and columns (7) and (8) indicate a 10% increase in the likelihood of extreme risk aversion in response to direct experiences of armed violence.

Table 7. The Impact of Exposure to Conflict on Risk Preferences

	Risk Averse			Risk Lover			Extreme Risk Averse		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ACE	-0.025**	-0.032***	-0.026	0.033***	0.038***	0.037*	-0.019*	-0.030***	-0.022
	(0.011)	(0.010)	(0.020)	(0.011)	(0.009)	(0.019)	(0.010)	(0.008)	(0.014)
TDE		0.059**	0.060**		-0.043	-0.043		0.103***	0.104***
		(0.027)	(0.026)		(0.030)	(0.029)		(0.038)	(0.037)
ACE*TDE			-0.008			0.001			-0.011
			(0.023)			(0.023)			(0.018)
Observations	1,964	1,958	1,958	1,964	1,958	1,958	1,964	1,958	1,958
R-squared	0.112	0.114	0.114	0.109	0.111	0.111	0.126	0.131	0.132

Notes: OLS regressions. All regressions include fixed effects for the branch of service, military task, residence province, educational attainment, and deployment year. Exogenous covariates include height, ethnic background, enlistment age, and order of the bags in the game. Robust standard errors, corrected for clustering at the training province, are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

III. D. Exposure to Armed Conflict and Ambiguity Attitudes

Panel II in Table 6 examines how attitudes towards uncertainty are affected by exposure to conflict and documents the results we obtain with OLS regressions. The results depict a picture similar to the one we obtain for *Risk Tolerance*. Once again, we find our two exposure measures to have opposing effects. In contrast to the positive effect of ACE, TDE leads people to take fewer lotteries from the ambiguous bag.

Note that, because both risk and ambiguity preferences jointly play a role in the observed choices from Bag 2 (Ambiguous Bag), our measure *Uncertainty Tolerance* does not directly inform us about ambiguity preferences. Hence, we next turn to our measures of ambiguity preferences and investigate whether and how they are associated with conflict exposure.

Table 8 displays our results. Similar to the heterogeneous effects we observe on risk preferences depending on type of exposure, we find ACE to decrease ambiguity aversion and TDE to increase it. In addition, TDE exerts a significant negative effect on ambiguity seeking, however, the estimated coefficient for ACE is positive but not significant.

Table 8. The Impact of Exposure to Conflict on Ambiguity Preferences

	Ambiguity Averse			Ambiguity Lover		
	(1)	(2)	(3)	(4)	(5)	(6)
ACE	-0.010	-0.020**	-0.019	0.003	0.010	0.003
	(0.009)	(0.008)	(0.014)	(0.011)	(0.011)	(0.019)
TDE		0.087***	0.087***		-0.067***	-0.068***
		(0.029)	(0.029)		(0.021)	(0.021)
ACE*TDE			-0.001			0.010
			(0.021)			(0.025)
Observations	1,919	1,913	1,913	1,919	1,913	1,913
R-squared	0.089	0.092	0.093	0.101	0.103	0.103

Notes: OLS regressions. All regressions include fixed effects for the branch of service, military task, residence province, educational attainment, and deployment year. Exogenous covariates include height, ethnic background, enlistment age. Order of the bags in the game is controlled in regressions (1) and (2). Robust standard errors, corrected for clustering at the training province, are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

To summarize, we find that higher levels of exposure to the armed conflict environment leads to higher risk and uncertainty tolerance. Having direct experiences of armed violence, on the other hand, creates strikingly different effects. Those with such experiences become more likely to exhibit aversion towards risk and uncertainty. In other words, we find that while exposure to armed conflict significantly affects our risk preference measures, the direction of the effect depends on the nature of exposure. The estimated coefficients for ambiguity preferences are also suggestive of differential effects by the two types of exposure.

III. E. Robustness Checks

We explore the robustness of our findings to a battery of specification checks. We start by providing further evidence that the educational differentiation in the Turkish draft system which renders college educated individuals less likely to be deployed to conflict areas is not biasing our results in any way. We show in Tables C.1 to C.5 in Appendix C that all our results are robust to the exclusion of respondents with college education from the sample. Tables C1 and C2 present the balance tests to further confirm that our natural experiment guarantees the randomness of exposure and the exogeneity of ACE in this subsample. Tables C3-C5 replicate our main results on our risk and ambiguity measures.

We then explore whether the effects we document in sections III.C and III.D dissipate over time by controlling for *Years since Service* and its interaction with our exposure measures. Estimated coefficients, which we report in Table C.7 in Appendix C suggest the effects are resilient over time.

Next, we test whether the linear probability estimates we obtain on those binary preference measures are robust to employing logistic regressions. Similarly, we test the robustness of our estimates on *Risk* and *Uncertainty Tolerance* with Poisson and Tobit specifications. To economize on space and for ease of presentation, we limit the robustness exercises to our preferred model specification in which we control for ACE and TDE simultaneously. Results remain very similar. We present them in Table C8 in section C in the Appendix.

In the main analysis, we present standard errors corrected for clustering at the training province. We check the sensitivity of our estimates to clustering at the deployment province. Results, which we present in Table C9 in Appendix C, remain robust.

As we examine the impact of conflict exposure on several measures of risk and ambiguity attitudes, another potential concern might be the problem of multiple inferences which might lead to sporadic significant findings. We show in Table D1 in Appendix D that our results are robust to correcting for multiple hypotheses testing.

IV. Mechanisms

Armed conflict exposure can affect risk and ambiguity attitudes through several channels: people may be reacting to the constraints and economic incentives created by the conflict macroenvironment; conflicts can impact upon the human capital of the exposed leaving them advantaged or disadvantaged in the labor market and thereby affect their income; conflicts can impact upon beliefs and expectations people have about probability distributions of possible outcomes; exposure might also work through emotional responses; and finally, conflict experiences might lead to preference changes.

As we discussed in Section I, the first channel, operating via constraints and economic payoffs created by the conflict macroenvironment, either does not apply to or play a minimal role for the population we study. Because our respondents' exposure to the conflict environment is limited to their time in the military and they get back to their peaceful environments when their service is completed, because conscription almost always takes place after the completion of formal schooling, and because service in conflict areas does not entail any financial compensation or any favorable treatment upon discharge, the potential roles that the conflict ecology can play in influencing risk and ambiguity behavior and attitudes are silenced in our setup. Therefore, we turn our attention to other mechanisms.

IV.A. Income and Labor Market Outcomes

The second set of mechanisms originate from conflict-driven changes in human capital accumulation which might then lead to changes in income and a consequent variation in risk tolerance. In particular, standard theory is consistent with higher (lower) risk tolerance for individuals with higher (lower) income. If ACE leads to higher income, then it is not surprising to observe higher risk tolerance in individuals who served in intense conflict environments. Similarly, if TDE leads to lower income, then it is not surprising for individuals with such experiences to avoid taking risks.

Table 9. Income as a Potential Mechanism

	(1) Household Income	(2) Risk Tolerance	(3) Uncertainty Tolerance	(4) Risk Tolerance	(5) Uncertainty Tolerance
ACE	-0.057*			0.336***	0.263***
	(0.030)			(0.101)	(0.097)
TDE	-0.150			-0.914***	-0.884***
	(0.132)			(0.297)	(0.220)
Household Income		0.76	-0.026	0.072	-0.030
		(0.69)	(0.076)	(0.065)	(0.073)
Observations	2,020	1,721	1,735	1,716	1730
R-squared	0.219	0.120	0.127	0.127	0.105

Notes: OLS regressions. All regressions include fixed effects for the branch of service, military task, residence province, educational attainment, and deployment year. Exogenous covariates include height, ethnic background, and enlistment age. Robust standard errors, corrected for clustering at the training province, are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Our data do not offer any support for an income-based explanation of behavioral change. We show in Table 9 that, if anything, ACE has a weak negative impact on household income in our case. We also fail to find any significant association between TDE and income.

IV.B. Beliefs

Another possible explanation for our findings could be that exposure to conflict causes a change in beliefs. If traumatic experiences induce pessimistic beliefs about the probability of gains and losses while surviving an armed conflict environment without such extreme experiences induces optimistic beliefs, then observationally equal outcomes may eventuate in terms of choice behavior under risk and ambiguity.

Our risk measures use a simple lottery with explicitly known 50-50 probabilities and, therefore, the role of beliefs is expected to be very limited. Nevertheless, we consider the possibility that perceived probabilities might be a combination of objective probabilities and subjective beliefs about *luck*—beliefs about the probability of good things happening to one. Consequently, beliefs might play a role in how respondents make decisions in both our risk and ambiguous tasks. The EXPOVIBE survey includes a question that allows us to test such a belief-based explanation. Respondents were asked to indicate on a 5-point Likert scale how much they agreed with the statement "Good things always seem to happen to others." As we show in Column (4) of Table 10, we fail to find any significant association with the answers to this question and our conflict exposure measures. In other words, we do not observe any effect of environmental or direct exposure on beliefs about luck.

IV.C. Psychological Mechanisms

Armed conflict experiences can be deeply traumatizing, and as such, they are likely to give rise to a myriad of psychological effects with associated emotions which may then lead to a change in how one behaves under risky and ambiguous choice situations.

That emotions are the dominant drivers of decisions in life is commonly argued by psychologists (Lerner et al. 2015). The appraisal-tendency theory (Smith and Ellsworth, 1985; Lerner and Keltner, 2000), which subsumes these arguments, posits that emotions predispose individuals to appraise the environment in specific ways toward similar functional ends. Recent studies provide support for this theory in the domain of risk-taking behaviors. The literature is in its early stages and hence the list of emotions studied is still limited, nonetheless, there is now significant evidence that emotions like anger, fear, anxiety, and sadness influence risk behavior.

Consistent with appraisal-tendency theory, studies have found that anger makes people indiscriminately optimistic about their own chances of success (Fischhoff et al., 2005; Lerner et al., 2003). Fear, on the other hand, is found to elicit the opposite response by evoking pessimistic estimates and risk-averse choices (Lerner and Keltner, 2000; 2001).

Raghunathan and Pham (1999) contrast the effects of anxiety and sadness on hypothetical gambling and job-selection decisions and find that sadness, through creating a need for reward replacement, increases tendencies to favor high-risk, high-reward options, whereas anxiety, through creating a need for uncertainty reduction, increases tendencies to favor low-risk, low-reward ones. Colasante et al. (2017), on the other hand, find sadness to lead to higher risk aversion through ego-depletion. Similarly, Kuhnen and Knutson (2008) report negative emotions to dampen the propensity to take risks. Gambetti and Giusberti (2012) find that while anger is associated with risky financial decision, anxiety predicts more conservative ones. In a recent study on the effects of violence on risk attitudes in Colombia, Moya (2018) concurs these findings on anxiety and shows that phobic anxiety mediates between violence exposure and risk aversion.

Based on their review of the empirical findings and theoretical models on how trauma impacts upon risk-taking behaviors, Ben-Zur and Zeidner (2009) add an extra layer to this discussion and argue that in the case of exposure to life-threatening trauma, even fear or anxiety might lead to risk taking behaviors by triggering defensive coping strategies to counteract these negative feelings.

To summarize, the literature offers evidence that the emotions of anger, fear, anxiety, and sadness are likely to link armed conflict exposure to risk and ambiguity preferences. We test these conjectures using a 6-item depression scale (Derogatis, 1992), an 8-item insecurity scale (Vélez et al., 2016), and a 3-item anger scale (Webster et al., 2013) included in the EXPOVIBE survey. We report the scales in detail in Appendix B. Our measures are the simple averages of answers to the questions that make up each scale.

Table 10. Psychological Outcomes of Exposure to Conflict

	(1) Insecurity Index	(2) Depression Index	(3) Anger Index	(4) Pessimist Beliefs
ACE	-0.002	0.023	-0.028	0.040
	(0.015)	(0.017)	(0.024)	(0.033)
TDE	0.127**	0.130**	0.068*	0.043
	(0.061)	(0.050)	(0.034)	(0.121)
Observations	2,309	2,299	2,304	2,289
R-squared	0.123	0.110	0.137	0.139

Notes: OLS regressions. All regressions include fixed effects for the branch of service, military task, residence province, educational attainment, and deployment year. Exogenous covariates include height, ethnic background, and enlistment age. Robust standard errors, corrected for clustering at the training province, are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

The results we obtain when we have these emotional measures as the dependent variable in our benchmark model are reported in Columns (1)-(3) in Table 10. The estimated coefficients indicate that TDE leads to feelings of insecurity, depressive symptoms, and anger suggesting that psychological mechanisms may account for the risk and ambiguity aversion we observe in respondents with direct experiences of armed violence.[29] However, as the results we present in Table 11 indicate, none of these psychological measures strongly relates to Risk or Uncertainty Tolerance. Moreover, controlling for these psychological measures in our main model does not lead to any meaningful change in the estimated effects of ACE and TDE. Therefore, we conclude that these psychological mechanisms are unlikely to play a significant role in mediating the effects of exposure in our case.

Table 11. Psychological Mechanisms

	Risk Tolerance			Uncertainty Tolerance		
	(1)	(2)	(3)	(4)	(5)	(6)
ACE	0.318***	0.322***	0.308***	0.251***	0.256***	0.240***
	(0.077)	(0.078)	(0.083)	(0.083)	(0.082)	(0.089)
TDE	-0.835***	-0.784**	-0.792**	-0.781***	-0.743***	-0.730***
	(0.310)	(0.322)	(0.304)	(0.237)	(0.235)	(0.230)
Insecurity Index	0.141			0.170*		
	(0.120)			(0.101)		
Depression Index		-0.246*			-0.146	
		(0.141)			(0.105)	
Anger Index			-0.137			-0.151
			(0.108)			(0.111)
Observations	1,958	1,949	1,954	1,970	1,961	1,966
R-squared	0.125	0.127	0.125	0.107	0.108	0.107

Notes: OLS regressions. All regressions include fixed effects for the branch of service, military task, residence province, educational attainment, and deployment year. Exogenous covariates include height, ethnic background, enlistment age, and order of the bags in the game. Robust standard errors, corrected for clustering at the training province, are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Having said that, potential psychological mechanisms extend into a multitude of other perceptional biases, and it falls beyond our capability to test each of them. One such prominent mechanism highlighted in the literature is the trivialization of risks that come with perceptions that all pales in comparison to the trauma of exposure to armed violence (Rudert et al. 2015; Ben-Zur and Zeidner). Other possible candidates mentioned in the literature include carelessness, attention deficit, more attention to stereotypic judgements, (Lerner and Tiedens, 2006), pride, appraisal of control and certainty (Lerner et al. 2015), optimism and feelings of invulnerability (Gambetti and Guisberti, 2012), and self-enhancement to cope with traumatic experiences (Gupta and Bonanno, 2010). To our knowledge, these possible mechanisms remain untested and as such pose interesting questions for future research.

[29] These results on psychological indicators replicate in the main EXPOVIBE sample as well.

IV.D. Changes in Preferences

The lack of support we observe in our data for a major role for the other possible mechanisms lead us to conjecture that our results are mainly driven by changes in preferences.

One might still ask why different types of conflict exposure led to opposite changes in risk and ambiguity preferences. These opposing effects are intuitive and consistent with the literature on reinforcement effects which refers to the observed behavioral regularity that individuals take less risk after a (realized) loss and more risk after a (realized) gain. Evidence of reinforcement effects comes from both laboratory and field studies spanning a variety of contexts (Thaler and Johnson, 1990; Liu et al., 2010; Malmendier and Nagel, 2011; Imas, 2016; Nielsen, 2019).[30]

Serving in the army in a country with an ongoing civil conflict is inherently risky for an individual. Experiencing a directly traumatizing violent event in that conflict environment constitutes the realization of the negative outcome of that risk (loss), whereas surviving that environment without such an experience is the realization of the positive outcome (gain). Consistent with the reinforcing effects of experiencing previous losses and gains in risky situations, we find that traumatic direct experiences induce individuals to be extremely risk averse and ambiguity averse, while eschewing such traumatic experience induces higher risk tolerance (and even increases the likelihood of one becoming a risk lover).

V. Conclusions

Armed conflicts hurt societies in many ways both in the short and the long run. That is why they are referred to as development in reverse. Unfortunately, this reversal then triggers a vicious cycle as the conflict-induced damages on development create a fertile environment for further violence. To help countries break free of this conflict trap, it is thus imperative to thoroughly understand the dynamics and consequences of armed conflicts so that they can be effectively addressed by adequately devised policies.

Our study contributes to the development of such an understanding by empirically investigating a set of individual level consequences that are fundamentally important for economic growth, namely, whether and how exposure to armed conflict affects risk and ambiguity preferences of individuals. We exploit a rare natural experiment setting that arises out of the mandatory military service system in Turkey that randomly immerses young civilian

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[30] For more examples and details, see Dillenberger and Rozen (2015), Imas (2016), Nielson (2019) and Tserenjigmid (2019).

males in an armed conflict environment as a combatant for a significant albeit temporary period of time. By ensuring random exposure, this natural experiment setting allows us to causally identify and comprehensively understand the individual level effects of being exposed to the violence of an armed conflict.

We show that risk and uncertainty tolerance increase with the level of exposure to the conflict environment. Conscripts who served in high conflict intensity environments are more (less) likely to have risk and ambiguity loving (averse) preferences. Interestingly though, traumatic direct experiences of armed violence, like getting physically hurt or having others around do so, create a strikingly different effect and render individuals more likely to be risk averse and less tolerant towards uncertainty and ambiguity. These effects largely persist over time. With regards to mechanisms, we find potential partial transmission through negative psychological states induced by war-trauma. However, results suggest that part to be very limited (if any). We also do not find evidence of income or belief-based mechanisms. Therefore, we conjecture that our results are most likely due to changes in risk and ambiguity preferences. Moreover, the opposing effects of environmental and direct exposures on risk and ambiguity preferences are consistent with the literature on reinforcement effects that are observed in many different contexts.

Our study contributes to the growing literature on political violence exposure and economic preferences. Works in this literature exhibit mixed results and this variation in results has so far precluded the identification of general patterns. We believe that the problem mostly originates from limitations that stem from the inherent difficulties associated with studying the individual level impacts of exposure including possible endogeneity and selection biases, lack of comprehensive and reliable measures to identify clean treatment and control groups and to account for different exposure types, and the confoundment of multiple mechanisms transmitting different effects. Our study surpasses these difficulties by employing an innovative identification strategy and study design, and by emphasizing the importance of paying attention to the variation in types, duration, and timing of exposure. We believe this comprehensive approach allows us to offer significant advances over previous works in the literature and to help illuminate the big picture. We also pay utmost attention to the transparent reporting of all the details of our study design and implementation, especially in terms of sample selection, representativeness, attrition rates and possible biases, and our experimental settings. With our careful and detailed approach in these aspects we are hoping to contribute to the establishment of externally valid results in the literature. As List (2020) argues external validity can be reached from a *body* of research where each individual paper follows four transparency conditions: Selection, Attrition, Naturalness and Scaling. Since the last condition is specific to programmatic studies and is not applicable for our study, in this paper we focused on the first three conditions. First, regarding selection, we report our sample selection procedure in detail to clarify how and why our respondents are representative of the target population. Second, we report the attrition rate in our study, and we show that attrition is not related to treatment. Third, we explain in detail how our treatments come from a naturally occurring environment. We also note that while the lab-in-the-field experiments we conducted were artificial set-ups, they were nonetheless conducted in the natural living environments of respondents, and our outcome variables gave us the necessary controls to observe each respondents' risk and ambiguity attitudes. More importantly, we provide a validity check and show that our risk and ambiguity measures are correlated with respondents' field behaviors as well as their own assessments of risk taking.

A final discussion we would like to conduct is about the broader economic implications of our findings. In most armed conflicts only a relatively small portion of the population suffer from direct experiences of violent events while for most people exposure remains as having to endure the insecurity and chaos of the conflict environment. Note that our results indicate a positive causal association between exposure to an armed conflict environment and risk tolerance. Those who experience the conflict environment become strongly and significantly more risk tolerant. A common conjecture in both theoretical and policy literature on economic development is that poverty is associated with aversion to take the necessary economic risks (Azariadis et al. 2005; Banerjee, 2000). Given the destructiveness of armed conflicts, should we then read our results as an unexpected silver lining in an otherwise dark picture? Based on our results on risk attitudes, do we have sufficient grounds to expect speedy economic recoveries in post-conflict societies? As we show in Table 9, our data do not support that expectation. We fail to find any evidence that ACE reflects positively on incomes through increasing risk tolerance.

There are, however, numerous personal and psychological traits that may impact upon career success and thereby income, and conflict exposure is likely to have effects on a significant subset of those traits. While it is beyond the scope of this study to investigate all those possible effects, we would, nonetheless, like to direct attention to one important point that stems from our results which is that exposure not only renders people less risk averse but also makes them more risk loving. Note that while risk loving people are more likely to take the necessary risks required to accumulate wealth and resources, they are also less likely to buy insurance and more likely to hold *excessively* risky asset portfolios. This “polarization effect” constitutes an interesting finding whose impact on economic outcomes merits further scholarly attention.

Our conclusions are highly relevant for cases where similar institutional setups draft civilians to participate in armed combat away from their homes, a recent example of which is the mobilization of Russian conscripts in the invasion of Ukraine (Roth, 2022).[31] Further generalization into exposure in civilian roles, however, requires attention to the fact that the conflict experiences we study are likely to differ in various ways from exposure in the form of civilian victimization. One important difference is that civilian victimization is usually accompanied by conflict-induced macro-environmental changes which then may shape risk and ambiguity behaviors. In that sense, our results may not reflect the effects on civilian victims, at least for as long as they remain in the conflict environment. It must, however, be noted that our respondents are also civilians who were randomly picked from the population, and also that we observe the effects of their exposure to persist through time. Hence, our findings raise valid questions about risk and ambiguity preferences in post conflict societies when and if reconstruction measures repair and eliminate those conflict-induced macro-environmental changes.

[31] https://www.theguardian.com/world/2022/sep/22/russia-mobilisation-ukraine-war-army-drive.

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