Essays on Forced Migration and Civil Conflict

Department of Political Science

University of Dublin, Trinity College

Candidate:

Oguzhan Turkoglu

Supervisor:

Prof. Thomas Chadefaux

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Declaration

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Oguzhan Turkoglu

To Annem ve Babam

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Summary

This thesis examines the effect of conflict dynamics and rebel groups on forced migration. More specifically, it analyzes how insurgent groups impact displacement flows, decisions to flee, and attitudes toward refugees. To test its argument, it employs multivariate regression analysis of observational data and survey experiments. It consists of four papers.

The first paper answers the question of why do some countries generate more refugees than others. Previous research has focused on the role of geographical, political, and economic determinants, and little attention has been paid to civil conflict dynamics. This paper examines how a host country's support for rebel groups affects the number of refugees that they accommodate. Countries that support rebels host a higher number of refugees than others, as accommodating refugees can be the continuation of that support and help rebel groups in their armed struggle. Analysis of refugee flows between 1951 and 2011 suggests that countries that support rebel groups host twice as many refugees as others. Results are robust to various model specifications, two different sources for the main explanatory variable, matching analysis, and additional checks. Findings of this article highlight the importance of conflict dynamics in explaining the variation in refugee flows

The second paper is interested in different causes of internal and external displacement. While existing studies examine the causes of displacement in general, there is limited research on varying determinants of internal and external displacement. This paper argues that the effect of violence on displacement as a function of perpetrator and geography (i.e., how spread it is). Increases in government violence increase the number of refugees because to escape government violence, people may have to cross an international border as governments are generally effective everywhere within their borders. On the other hand, rebel group activities are limited to a certain area and by leaving the conflict zone, civilians can be free from rebel violence. However, the spread of violence determines the decision to flee. If it is limited to a small region, people can escape from that area within the country and rebel violence increases the number of IDPs. If it is widespread, civilians may not have many opportunities within the country and have to move abroad. Therefore, the effect of rebel violence on internal displacement follows a reverse U-shape. The analysis of refugee and

IDPs flows between 1989 and 2017 supports the main arguments and the results are robust to different model specifications and additional checks.

The third paper is co-authored with Sigrid Weber and it provides individual-level evidence on flight decisions in light of violence with a conjoint experiment in Turkey. The results suggest that intense indiscriminate violence nearby forces individuals into the decision to leave. In contrast to previous studies, this study finds that persistent violent threats play a more important role in flight decisions than the frequency of attacks. The experiment reveals that violence committed by the government makes a decision to flee abroad more likely than rebel violence, which is complementary to the previous chapter, and that individuals with support networks abroad are less responsive to patterns of violence, making flight decisions under less pressure than individuals without available coping mechanisms elsewhere. These findings contribute to the growing literature on forced migration with individual-level evidence on flight reactions to violence.

The final paper shifts focus from forced migration flows to attitudes toward refugees. Previous studies have mainly focused on attitudes in developed countries, which has resulted in a lack of focus on factors prevalent in developing countries but not developed ones. This paper analyzes the effect of transnational ethnic relations and security concerns through a conjoint experiment in Turkey. The results suggest that when there are ethnic tensions in the host country, natives from the majority dominant group have more negative attitudes toward refugees from the minority ethnic group compared to those without any ethnic relations. Security concerns and existing negative intergroup relations are two possible explanations for this effect, and further analysis points to negative intergroup relations as the main mechanism. Additionally, refugees coming from areas controlled by insurgents that have ties to rebels in the host country are less favored than others because refugees might be perceived as a pool of resources for the insurgents. Examining how ethnic relations and security concerns shape attitudes toward refugees has important implications in understanding the externalities of refugee inflows on the host countries.

1 Introduction

In recent years, there has been an increase in the number of forced migrants. Millions of people have left their homes and moved to somewhere else within the country or crossed an international border to seek asylum (UNHCR 2020). People search for a life free from arbitrary persecution and from violence (Moore & Shellman 2004) to climate change (Abel, Brottrager, Cuaresma & Muttarak 2019) many conditions impact decisions to flee. With the increase in displacement, scholars have started to pay more attention to the causes and effects of forced migration as well as attitudes towards forced migrants.

This thesis speaks to the literature on civil conflict and displacement. More specifically, with a focus on conflict dynamics and insurgent groups, this research focuses on the causes of displacement, determinants of refugee flows, and attitudes toward refugees.

Displacement has impacts on the host communities and those who have to flee (Fallah, Krafft & Wahba 2019, Mels, Derluyn, Broekaert & Rosseel 2010, Salehyan & Gleditsch 2006, Zhou & Shaver 2019). Therefore, examining the causes of displacement and refugee flows has critical importance for better-developed and well-informed policy-making, which plays a significant role in minimizing the detrimental effects for host and source countries as well as forced migrants. In addition, studying the determinants of attitudes toward refugees is crucial to inform asylum policy and integration of refugees (Alrababa'h, Dillon, Williamson, Hainmueller, Hangartner & Weinstein 2021, Bansak, Hainmueller & Hangartner 2016).

1.1 Refugee Flows

Why do some countries host more refugees than others? In order to answer this question, previous studies have generally examined push factors (deleterious aspects of the source country), pull factors (attractive aspects of the host country), and dyadic characteristics (Moore & Shellman 2007, Moorthy & Brathwaite 2019). Existing research has mainly focused on economic, political, and social determinants of refugee flows. For example, neighboring countries host more refugees than others and countries accommodate more refugees from their rivals (Moore & Shellman 2007, Moorthy & Brathwaite 2019, Jackson & Atkinson 2019).

Although armed conflict is the main cause of displacement and studies have paid attention to the certain aspects of civil conflicts in the analysis of the determinants of forced migration (Balcells & Steele 2016, Melander, Oberg & Hall 2009, Moore & Shellman 2004, Schmeidl 1997), the role of conflict dynamics in hosting refugees has been understudied. Civil conflicts have transnational dimensions and their effects go beyond the national boundaries of the country (Gleditsch 2007).

Countries involve in conflicts in support for the government (Regan 2002) or insurgent groups (Salehyan, Gleditsch & Cunningham 2011) and this involvement may have effects on the number of refugees they host. Chapter 2 argues that countries which support rebels host a larger number of refugees than others. The main rationale for foreign countries to support rebels is to empower them to win the conflict, as a victory for rebels is also one for the supporting country. Accommodating refugees can be the continuation of that support and help rebel groups win the conflict. By hosting refugees, countries offer a sanctuary for rebels and their families. Refugee camps can serve as 'refugee warrior communities'—a base for the armed group. In these camps, rebel groups can expand their insurgent activities such as recruitment and training. In addition, the more rebels operate in the destination, the more likely for the host to increase its influence, leverage, and power over rebel groups, and thus over the ongoing conflict.

Different than the existing studies that examine economic, political, and social determinants of refugee-hosting, the second chapter analyzes the role of rebel support and highlights the importance of conflict dynamics in explaining the variation in refugee flows.

1.2 Causes of Forced Migration

Studies on the causes of forced migration have generally adopted a utility maximization approach (Davenport, Moore & Poe 2003, Moore & Shellman 2004).[1] People flee when the expected utility of leaving exceeds the expected utility of staying. To delineate this cost-benefit analysis and to analyze why some countries generate more forced migrants than others, previous studies examine variation in violence, economic, and political conditions in the source country (Davenport, Moore & Poe 2003, Iqbal 2007, Melander, Oberg & Hall 2009, Moore & Shellman 2004, Schmeidl 1997).

Violence is one of the main determinants of forced migration as it signals the high risk of persecution. Previous research has operationalized violence

[1] A recent strand of literature has examined how motivation and opportunities affect migration decisions. For example, through interviews with Syrian refugees in Turkey, Schon (2019) has argued that those who experience violence early on in the conflict and those who have *wasta* (i.e., advantaged social position based on money and connections) exited Syria earlier during the conflict.

through civil conflict and genocide and find an increasing effect on displacement (Adhikari 2012, Adhikari 2013, Balcells & Steele 2016, Czaika & Kis-Katos 2009, Davenport, Moore & Poe 2003, Iqbal 2007, Melander, Oberg & Hall 2009, Moore & Shellman 2004, Neumayer 2005, Schon 2019, Steele 2011, Turkoglu & Chadefaux 2019, Uzonyi 2014, Weiner 1992, Weiner 1996). Violence has detrimental effects on life and economy (Abadie & Gardeazabal 2003, Bauer, Blattman, Chytilová, Henrich, Miguel & Mitts 2016, Lowes & Montero 2021). As the previous research highlighted, those who experience violence are more likely to flee. While exposure to violence affects attitudes and behaviors, the threat perception also matters (Getmansky & Zeitzoff 2014). In a recent study, Fearon & Shaver (2021) argue that people base their migration not only on violence experience and destruction from past events but also on expectations about the future. If they expect more violence and destruction in the coming year, which will make recovery and rebuilding very challenging, they are likely to flee to another country. In the study of Jewish out-migration in Nazi-era, Buggle, Mayer, Sakalli & Thoenig (2020) underscore the role of threat perception and suggest that earlier threat perception would have increased the number of people leaving the country.

Democratic countries have been argued to generate fewer forced migrants than others as people can enjoy their basic rights and have a life free from oppression in democracies (Moore & Shellman 2004, Neumayer 2005). However, statistical support for this argument is mixed (Davenport, Moore & Poe 2003, Iqbal 2007, Melander, Oberg & Hall 2009). Regime transition has been discussed to increase the number of displaced people as it is associated with instability and uncertainty (Davenport, Moore & Poe 2003, Melander, Oberg & Hall 2009, Moore & Shellman 2007). People also escape from bad living conditions and thus, economic development is expected to reduce displacement

(Melander, Oberg & Hall 2009, Moore & Shellman 2004, Neumayer 2005).

In the study of determinants of forced migration, existing research has a uniform approach and in the operationalization of the dependent variable, they generally use both refugees and IDPs (Davenport, Moore & Poe 2003, Melander, Oberg & Hall 2009, Moore & Shellman 2004, Uzonyi 2014) although there is a limited number of exceptions which focus only on refugees (Schmeidl 1997, Turkoglu & Chadefaux 2019). This widely used operationalization suggests that refugees and IDPs are affected by the same factors in the same way. This assumption is puzzling given the common utility maximization approach because variables may have diverse effects on people's cost-benefit analysis of fleeing within the country or abroad even though some factors may have a similar impact.

There are a few exceptions. Moore & Shellman (2006) is the first study that examines the different causes of internal and external displacement. They highlight the different effects of civil war and genocide and emphasizes the role of the neighborhood. However, there are serious methodological challenges which are elaborated on below. Second, in a theory-building paper, Steele (2019) argues that while government violence increases external displacement, insurgent violence leads to increases in internal displacement. Although Steele (2019) offers a compelling theory, these arguments have not yet been tested. Finally, Braithwaite, Cox & Ghosn (2020) argue that individuals that are exposed to direct violence are more likely to be refugees than IDPs whereas those who are exposed to indirect violence are more likely to be IDPs than refugees.

Chapter 3 tackles the different causes of internal and external displacement by adopting a utility maximization approach with a focus on perpetrator and geography of violence (i.e., how spread it is). Since crossing an international border is costlier than migrating within the country, civilians are expected to stay within the country whenever they can. However, sometimes, civilians cannot have a life free from fear of persecution in their country even if they leave the conflict zone. In this case, the costs of fleeing within the country exceed the costs of migrating to another country. This study argues that while government violence increases the number of refugees, it does not have a significant impact on internal displacement. To escape government violence, leaving the conflict zone may not be enough and people may have to flee another country as governments are generally effective everywhere within the country.

When it comes to escaping rebel violence, insurgent group activities are generally limited to a certain region and by leaving the conflict zone, people may be free from rebel violence. However, there is a significant variation in the spread of violence. While in some conflicts, it is limited to a small area, in others, it might be widespread across the entire country. The effect of rebel violence on internal displacement follows a reverse U-shape. If rebel violence is limited to a small area, people can escape it by leaving the conflict zone. But if rebel violence is widespread, people may not have many opportunities to flee within the country and may have to cross an international border to be free from violence. Thus, increases in the spread of rebel violence initially increase the number of IDPs, but after a certain point, it results in decreases.

Most existing research analyzes the determinants of forced migration at the country or sub-country level whereas they theorize at the individual level (Balcells & Steele 2016, Czaika & Kis-Katos 2009, Davenport, Moore & Poe 2003, Melander, Oberg & Hall 2009, Moore & Shellman 2004, Neumayer 2005, Turkoglu & Chadefaux 2019). Although these studies improve the literature on the causes of displacement, our understanding of the individual-level decision-making process leading to flights is limited. While there is a small number of studies examining forced migration at the individual level, they generally rely on surveys (Adhikari 2013, Bohra-Mishra & Massey 2011, Braithwaite, Cox & Ghosn 2020).

Furthermore, as highlighted above, previous research has generally examined the effect of violence through a binary variable of civil conflict and/or genocide (Moore & Shellman 2004, Uzonyi 2014) as well as a dichotomous variable of violence experience (Adhikari 2013). However, conflicts are complicated phenomena and their different aspects might have varying effects on displacement. Recently, a few notable exceptions examine the role of conflict processes on forced migration. By examining Colombia, Steele (2011) has discussed that a high vote share of the insurgent-backed party in certain regions may proxy to identify where the "enemy" lives and displacement is higher in these areas. Comparing Colombia and Spain, Balcells & Steele (2016) have elaborated on the timing and location of forced migration. In irregular conflicts, displacement depends on when and where groups fight, while in conventional conflicts it follows front-line changes. Finally, through a survey in Lebanon, Braithwaite, Cox & Ghosn (2020) have examined the effect of indirect violence on internal displacement and the effect of direct violence on external displacement.

Chapter 4 aims to contribute to the literature with respect to the individual-level decision-making in forced migration and heterogeneous effects of violence on displacement. This paper is co-authored with Sigrid Weber and drawing on aggregated studies of flight patterns and testing them on the micro-level, we argue that the characteristics of violence play a crucial role in explaining variation in displacement. More specifically, the decision to flee is not made lightly but depends on the patterns of violence that individuals observe such as the intensity and proximity of violence but also the perpetrator and type (i.e., discriminate and indiscriminate). Furthermore, we argue that social networks to other communities abroad—as a proxy for how well individuals can cope with violence —affect decisions to flee. Compared to individuals that do not have outside options to easily move away, those with social networks abroad focus less on the observed patterns of violence to make their decision to flee as social networks reduce the costs of fleeing, which provides higher flexibility and mobility.

To examine the heterogeneous effects of violence on individual-level decision-making, we adopt an innovative approach. We employ a conjoint experiment in the Eastern and Southeastern parts of Turkey. More specifically, we show two hypothetical scenarios to the respondents and ask them in which scenario they would flee (forced-choice design) and whether they would flee within the country or abroad. Given this history of violence, territorial conflict and displacement, and its exposure to political instability and refugee flows in the direct neighborhood, the Southeastern and Eastern parts of Turkey provide good conditions to study forced migration decisions as households in the region have plausible experiences with the difficulties of moving and fleeing under the pressure of conflict.

The results highlight the heterogeneous effects of violence on displacement and the role of the civilian agency. Individual-level analysis corroborates the country-level findings of chapter 3. The promising results underline the need for disaggregating violence in studying the causes of forced migration.

1.3 Attitudes toward Refugees

With the increase in the number of refugees, studies have paid attention to the determinants of attitudes toward refugees given their relevance for policy-making. The literature has mainly focused on egocentric, sociotropic, cultural, and humanitarian concerns. First, egocentric explanations emphasize labor market competition and individual economic well-being as the determinant of public opinion (Mayda 2006). Second, sociotropic concerns underline the economic impact of migrants on the host countries as the driver of attitudes (Bansak, Hainmueller & Hangartner 2016, Hainmueller & Hiscox 2007, Lazarev & Sharma 2017). Third, cultural concerns highlight the fear of natives about the arrival of refugees changing the local customs and traditions as the variable that shape public opinion (Adida, Lo & Platas 2019, Alrababa'h et al. 2021, Bansak, Hainmueller & Hangartner 2016, Lazarev & Sharma 2017). Finally, humanitarian concerns focus on whether individuals experience violence and escape from persecution or they look for better economic opportunities to explain variation in attitudes (Alrababa'h et al. 2021, Bansak, Hainmueller & Hangartner 2016).

Although most refugees reside in developing countries, existing literature has generally examined attitudes toward refugees in developed countries. In order to fill this gap, Alrababa'h et al. (2021) employed a conjoint experiment by using a very similar design to previous studies (Bansak, Hainmueller & Hangartner 2016) and tested the same arguments in Jordan, a developing country. While there is no difference between developing and developed countries with respect to the effects of economic egocentric, cultural, and humanitarian concerns, sociotropic economic factors affect attitudes in developed countries but not in developing ones. Similarly, Getmansky, Matakos & Sinmazdemir (2020) carried out a conjoint experiment in Turkey. Their analysis supports the previous findings, particularly those related to the education level, religion, gender, and knowledge of local language of refugees (Adida, Lo & Platas 2019, Bansak, Hainmueller & Hangartner 2016). As a novel contribution, their study reveals that refugee profiles that display social ties (i.e., friends) with locals are more favored when compared to those without any ties. In another study, Ghosn, Braithwaite & Chu (2019) analyze attitudes toward

Syrian refugees in Lebanon and underscore the positive effects of contact between refugees and natives. Finally, Buehler, Fabbe & Han (2020) highlights sub-national differences in attitudes toward refugees in Morocco. For citizens living in highly economically developed areas, cultural, identity, and security based concerns help explain variation in attitudes, for citizens living in areas with low economic development, economic concerns are critical.

The emphasis of the literature on attitudes in developed countries has resulted in the lack of focus on the factors that are prevalent in the developing countries but not in the developed ones. Conflict dynamics, ethnic relations, and security concerns are among the factors that have been understudied. Given that previous research has articulated change in the ethnic composition of the host country as a mechanism for refugees spreading conflict (Salehyan & Gleditsch 2006), it is important to understand how conflict dynamics and transnational ethnic relations affect natives' attitudes. This is crucial especially given that most refugees flee to neighboring countries where they have ethnic ties (Rüegger 2019, Moore & Shellman 2007).

Chapter 5 examines how ethnic relations, security concerns, and conflict dynamics affect attitudes toward refugees. Depending on refugees' ethnic ties to the host country, the reactions of the dominant majority group in the destination may vary. If refugees are related to the dominant group, refugees are likely to experience positive attitudes due to in-group favoritism. If refugees share ties with the ethnic minority and there are tensions or an insurgency, while natives from the minority group are likely to show positive attitudes, those from the majority group are likely to show negative attitudes. This is beyond out-group bias. Refugees might experience negative attitudes because the majority group might fear that the inflow of refugees from the minority group might place the government in a disadvantageous position in the insurgency. Additionally, pre-existing negative relations between the minority and majority groups might impact attitudes toward refugees that share ethnic ties with the host country.

Ethnic relations are not the only factor that affects security concerns and attitudes. The relations between civilians and armed groups also impact how natives react to civilians. One of the main causes of displacement is armed conflict (Schmeidl 1997) and civil wars spatially cluster (Buhaug & Gleditsch 2008). Insurgent groups in the same neighborhood may develop good relations and support each other (Högbladh, Pettersson & Themnér 2011). Previous research has suggested that living in an area under the control of an armed group can be perceived as support for that group (Kalyvas 2006, Lichtenheld 2020, Valentino, Huth & Balch-Lindsay 2004). Therefore, if refugees come from areas controlled by insurgents that have ties to rebels in the host country, natives from the majority group are likely to display negative attitudes because these refugees may be perceived as a possible pool of resources (recruitment and economic) and may place the government in a disadvantageous position.

To test these arguments, this thesis adopted another conjoint experiment in Turkey, which is an ideal case given the ongoing Kurdish insurgency, transnational ethnic relations of Kurds in the region, and recent refugee inflows from Syria. The results highlight the importance of conflict dynamics and ethnic relations in attitudes toward refugees. Furthermore, the analysis points to pre-existing negative relations as the main mechanism driving the negative effect of ethnicity rather than security concerns.

2 Supporting Rebels and Hosting Refugees: Explaining the Variation in Refugee Flows in Civil Conflicts

Abstract

Why do some countries host more refugees than others? Previous research has focused on the role of geographical, political, and economic determinants, and little attention has been paid to civil conflict dynamics. In this article, I examine how a host country's support for rebel groups may affect the number of refugees that they accommodate. Countries that support rebels host a higher number of refugees than others, as accommodating refugees can be the continuation of that support and help rebel groups in their armed struggle. By hosting people, countries may offer a sanctuary from which rebels can operate some of their insurgent activities. Rebel groups can exploit these camps for recruitment, training, and benefiting from the main services such as health care. In addition, when rebels operate in host countries, these countries may monitor, impact, or even direct the strategies of insurgent groups. Analysis of refugee flows between 1951 and 2011 suggests that countries which support rebel groups host twice as many refugees than others. Results are robust to various model specifications, two different sources for the main explanatory variable, matching analysis, and additional

checks. Findings of this article highlight the importance of conflict dynamics in explaining the variation in refugee flows.

2.1 Introduction

Countries vary greatly in space and time in the number of refugees they host. In 2016, for example, Turkey hosted more than 2.8 million Syrian refugees, whereas Saudi Arabia hosted only 19. Similarly, in 1989, Ethiopia hosted 87% (384,989) of all Sudanese refugees, but only 6% (23,516) in 2009. Why do some countries host more refugees than others?

The variation in refugee flows poses an empirical puzzle as the existing literature can only explain it to a certain degree. Previous studies have focused on the 'push' factors in the source country, the 'pull' factors in the host countries, and dyadic determinants such as geographical, historical, and political relations. Little attention, however, has been paid to the particular dynamics of civil conflicts. The literature has treated civil conflicts as uniform, largely ignoring their distinct aspects. Yet, understanding these varying dynamics is critical since most refugees come from countries in conflict.

Here, I argue that the particular aspects of civil conflicts—who is fighting whom and who is backing them—is a key answer to this puzzle. In this study, I show that refugee flows vary depending on the host country's involvement in the conflict. In particular, countries that support rebels host a larger number of refugees than others. The main rationale for foreign countries to support rebels is to empower them to win the conflict, as a victory for rebels is also one for the supporting country. Accommodating refugees can be the continuation of that support and help rebel groups win the conflict. By hosting refugees, countries offer a sanctuary for rebels and their families. Refugee camps can serve as ‘refugee warrior communities’—a base for the armed group. In these camps, rebel groups can expand their insurgent activities such as recruitment and training. In addition, the more rebels operate in the destination, the more likely for the host to increase its influence, leverage, and power over rebel groups, and thus over the ongoing conflict.

I analyze refugee flows from countries that experienced civil conflict between 1951 and 2011 to test my argument. Results corroborate my hypothesis and are robust to various model specifications and two different sources for the main explanatory variable. Countries which support rebel groups host 2.5 times more refugees than others. In addition, I employ matching to balance the data and to overcome the model dependence. This analysis also corroborates the main argument and concludes that all else equal, supporting rebels increases the number of refugees countries host on average by 11,000.

This paper makes several important contributions to civil conflict and refugee literature. By analyzing the effect of supporting rebels, it argues that conflict dynamics play a significant role in explaining the variation in refugee flows. Civil conflicts should not be treated as a binary variable, and their dynamics should be further explored. Secondly, previous studies analyze the effect of civil conflicts on forcing people to leave, but neglect to address how these conflicts may affect their destination. This paper suggests that host countries’ involvement in the conflict has a significant and robust impact on the number of refugees that they host. Lastly, existing studies generally treat host countries as passive actors in refugee movements with an understanding of refugees choosing destinations with regards to countries’ proximity, political, and economic situation. However, this study suggests that host countries—by being active players in the displacement process—may make the movement and influx of refugees easier or more difficult.

The findings of this study are relevant not only for academic research but also for policy-making, especially for international and non-governmental organizations. Understanding why some countries host more refugees than other is of critical importance for emergency responses. How the international community responds to the initial displacement crisis plays a significant role in alleviating detrimental impacts and preventing the crisis from escalating. Evidence of a systematic relationship between rebel support and refugee hosting will allow the international community to better anticipate where people go, to develop faster and more effective policies, and to minimize the negative impacts of population flows for both host societies and displaced people.

2.2 Explaining Where Refugees Go

Previous scholarship on refugee flows analyzes monadic and dyadic characteristics. For the former, studies focus on push and pull factors[1] and mainly examine variation in violence, economic development and democracy in source and host countries, respectively. There is a near consensus regarding civil conflict and genocide being positively and significantly correlated with the number of refugees as people escape persecution (Schmeidl 1997, Davenport, Moore & Poe 2003, Moore & Shellman 2004, Neumayer 2005, Iqbal 2007, Melander, Oberg & Hall 2009, Uzonyi 2014, Turkoglu & Chadefaux 2019). People also flee from poverty, bad living conditions, and oppression, escaping to places where they will not experience such problems. Therefore, the higher the level of economic development[2] and democracy in the source country, the lower the number of refugees. Similarly, increased economic development and democracy in the host increase the number of refugees due to better living condi-

[1] Push (pull) factors denote the deleterious attributes of the source (host) country.

[2] Aksoy & Poutvaara (2021) offer a more nuanced explanation based on whether skills are transferable or not between the host and source countries.

tions, making the host more attractive to those who flee, though support for the democracy argument is mixed (Davenport, Moore & Poe 2003, Moore & Shellman 2004, Moore & Shellman 2007, Neumayer 2005, Iqbal 2007, Melander, Oberg & Hall 2009, Moorthy & Brathwaite 2019). Additionally, regime transition increases the number of refugees as these countries are less stable than others (Davenport, Moore & Poe 2003, Moore & Shellman 2007).

For dyadic characteristics, previous research analyzes geographical, historical, and political relations between source and host countries. An increase in distance decreases the number of refugees as it is easier to travel to nearby areas (Neumayer 2004, Moore & Shellman 2007, Iqbal 2007, Moorthy & Brathwaite 2019).[3] Also, an increase in the number of countries adjacent to the source decreases the number of refugees in each host country because people have more alternative destinations to which they can flee (Moore & Shellman 2007).

The historical determinant of a shared colonial past makes refugees more familiar with the host country, making the destination more attractive. Therefore, countries with colonial ties to the source country host more refugees than others (Neumayer 2004, Moore & Shellman 2007, Moorthy & Brathwaite 2019). As dyadic political determinants, rivalry and alliance improve our ability to explain why some countries host more refugees than others. Rival states try to achieve outcomes unfavorable to their adversaries, attempting to undermine each other. Refugees can provide an opportunity for the host to weaken its rival because they can indicate problems at home. For instance, during the Cold War, the US facilitated the asylum application process for people from communist countries. It used the influx of refugees from communist regimes as a propaganda tool to cast those regimes in an unfavorable light (Salehyan &

[3] Quite often, refugees cannot obtain a visa or apply for asylum outside of the intended destination and thus, they may have to use irregular migration routes with the help of smugglers (Ajzenman, Aksoy & Guriev 2019).

Rosenblum 2008, Jackson & Atkinson 2019). A similar argument could also be applied to alliances. Since allied countries develop a benevolent relationship, they are less likely to host refugees. However, this hypothesis is not statistically corroborated and contrary to expectations, alliances are found to have a positive and significant effect on refugee flows (Moorthy & Brathwaite 2019). As an alternative explanation, an alliance may lower the transaction costs and provide familiarity to those who flee (Moore & Shellman 2007).

The existing literature analyzes variation in the political, economic, and violent conditions in host and source countries as well as geographical, historical, and political relations between them.[4] Yet, most studies pay little attention to the dynamics of the civil conflict itself. However, in recent years, we see an increase in the number of papers that examine the effect of conflict characteristics. Generally, researchers scrutinize how these dynamics affect people's decision to leave (Steele 2011, Schon 2019) and how they impact the security situation in the host (Salehyan & Gleditsch 2006, Böhmelt, Bove & Gleditsch 2019, Fisk 2019, Rüegger 2019). But, the effect of conflict processes on accommodating people is largely neglected. In 2017, nearly 80% of refugees were from countries experiencing civil conflict. A phenomenon which causes the most refugees to leave their homes should not be treated as a uniform concept but further disaggregated. I aim to advance the literature by analyzing the variation in host country's support for rebel groups—as one of the civil conflict dynamics— and how it affects refugee flows.

[4]While most studies analyze the determinants of refugee flows at the country-level (Moore & Shellman 2007), there is a limited number of studies examining individual level determinants. For example, Buggle et al. (2020) highlights the role of networks and social interactions within the community in decision to flee through Jewish migration out of Nazi Germany.

2.3 Supporting Rebels and Hosting Refugees

Rebels may receive support from foreign countries in various forms such as troops, intelligence, logistics or material. Any type of assistance incurs costs for the supporting countries, but they are often willing to shoulder those costs when they have an interest in the ongoing conflict. Countries that support rebels may want to weaken or even topple the warring government to change regional balances in their interest. Using rebels to achieve their goals may be more favorable for foreign countries than directly going to war. This more indirect involvement in the conflict might be a less risky option, as countries do not have to deploy their own armed forces and may avoid international sanctions and blame. For example, in the 1970s, South Africa supported rebels in Mozambique and Angola to weaken the anti-apartheid states. Similarly, the US provided military intelligence to Nicaraguan Contras to topple the Sandinista government (Salehyan, Gleditsch & Cunningham 2011). Destabilizing rival countries is not the only reason to support rebel groups. In general, rebels strive to gain independence or to capture power. Therefore, they are candidates for governing an existing state or a new one. By helping rebels, countries also increase their influence over new potential rulers and thus, their soft power. For instance, in 2011, Turkey started supporting rebel groups in the Syrian conflict because it believed, much like in other Arab Spring countries, that the fall of the Assad regime was imminent and rebels would soon seize power. If Turkey had greater influence over a new Syrian government, Turkey would gain in its conflict with Kurds, which happens to be in a zone bordering Syria (Öniş 2014).

Countries that support rebels want them to win because a victory for rebel groups is a victory for the parties which support them as well. Accommodating refugees may help rebels in the conflict; therefore, hosting refugees can be the continuation of that support. Refugee status as an international protection system is granted to people who have a well-founded fear of persecution. Insurgent groups might exploit this asylum system and use refugee camps as military bases from which they can continue their insurgency activities such as recruitment and training (Zolberg, Shurke & Aguayo 1989).[5] This exploitation may happen in several ways. First, rebels can use these camps to increase the number of their armed men.[6] For example, in the 1970s, Khmer Rouge that was in conflict with Cambodia recruited militias in camps in Thailand. The Thai government turned a blind eye to these activities because the Khmer Rouge was not only fighting against Cambodia but also against Vietnam that had invaded Cambodia. The presence of Vietnam in Cambodian soil presented a clear danger to Thailand and the Thai government supported the Khmer Rouge to undermine Vietnamese interests (Robinson 2000, Stedman & Tanner 2003).

Second, rebels may also use refugee camps as training centers. The host state may facilitate or even lead trainings, as better trained armed forces are more likely to win the conflict.[7] For instance, in the 1980s and 1990s, Pakistan supported Afghan rebel groups, particularly the Taliban and helped them train armed men in refugee camps. Pakistan supported these insurgents because they were against a pro-Soviet government in Afghanistan and in favor of a government that they could influence and dominate (Byman, Chalk, Hoffman, Rosenau & Brannan 2001).

Third, rebels may use refugee camps to collect their needs and supplies, and

[5]Host countries play a significant role in this process, as they may thwart, help or turn a blind eye to these activities. Countries that are already supporting rebels –before accommodating refugees– generally let or even help rebel groups operate in their soils.

[6]Here, recruitment does not have to be forced all the time; people may sometimes voluntarily join the armed group.

[7]In addition to the role of support, there might be a secondary mechanism at play here. Support makes rebels more capable and increases in rebel strength may increase conflict severity. Therefore, the source may generate more refugees and there may be more displaced people to host for all countries.

to benefit from public services such as health care. In some instances, rebels might be in a disadvantaged position or in a deadlock and need a break to strike harder. In those times, they can rest in the host country and prepare for the coming battles. Since it might be challenging to distinguish who is a combatant or non-combatant, insurgent groups can take advantage of it by registering as refugees and enjoy the benefits that refugees can (Reuters 2013).

Furthermore, the greater number of refugees, the more likely rebels are to operate in the host country. Thus, the host country may monitor, impact or even direct the strategies of rebel groups. For example, Turkey allowed the Syrian opposition to open an office in Istanbul (AlJazeera 2011) and hosted their meetings (Reuters 2012). Turkey let them operate on its soil and use Syrian rebels for its military operation in Northern Syria. On the other hand, Jordan did not support rebels in Syria and did not want any military activities on its soil. Thus, Jordan deported Syrian refugees who are in contact with military groups in Syria (Yahya, Kassir & el Hariri 2018). Similarly, the location of camps might be another strategy used by the host. Camps on the border might be more suitable for rebels to exploit whereas camps away from the border or dispersed populations might be challenging to manipulate. Depending on their support to insurgents, host countries may open camps on the border or far away. For example, Kenya opened camps on the border for Sudanese refugees and camps mostly away from the border for Somali refugees. In Sudan, Kenya supported rebels, while in Somalia Kenya was on the side of the government. Similarly, Tanzania who sided with the Mozambican government in the conflict with Renamo dispersed refugees across the country and Renamo could not exploit them (Camerana 2019).

Accommodating refugees is costly. In this regard, Jackson & Atkinson (2019) improve our understanding by arguing how rivalry plays a role in the cost-benefit analysis. By admitting people from states that are their ideological rivals, states can shame the source country and bolster their superiority. Thus, the benefits of hosting people outweigh its costs. Here, I agree with their conclusion but argue that the effect of support is larger than the rivalry and goes beyond symbolic gains. When the rebel group that is supported by the host wins the conflict, the host can affect policies in that country and increase its influence in the region. By supporting rebels, benefits are more tangible and can easily outweigh costs.[8] In addition to its benefits, accommodating refugees may cause economic and security problems for the host (Salehyan 2008). Host countries that support rebels do not encourage people to leave their country and settle elsewhere. They are simply more willing to accept refugees than others if people have to flee the source country.[9]

Here, I argue that: *countries that support rebel groups host a higher number of refugees than countries that do not support rebel groups.* We should observe giving support to rebels increasing the number of refugees hosted.[10] For example, in the Ethiopian case above, according to the existing research, we should have seen an increase in the number of Sudanese refugees in Ethiopia. In 1989 and 2009, both conflicts took place between the Sudanese government and the same ethnic groups. During this time, dyadic characteristics (e.g., distance and ethnic relations) between Ethiopia and Sudan stayed the same. While push

[8]In the case of support, there are direct gains or losses; however, in the rivalry, there will be changes in the relative positions more generally. This also reflects in the substantive effect of these factors. While Moorthy & Brathwaite (2019) conclude that rivalry increases the number of refugees hosted by 111, my analysis suggests that the effect of supporting rebels is around 11,000.

[9]Supporting rebels might result in interstate war (Salehyan 2008), which is very costly for the country that supports insurgents. Even though it involves risks, it is a less risky way to influence the conflict than military intervention (Salehyan, Gleditsch & Cunningham 2011). Therefore, supporting rebels might be a more favorable option than direct military involvement.

[10]If there is more than one country that supports rebels, I expect to see an increase in the number of refugees in all countries that support the insurgency. However, among these countries which one will host more refugees is determined by other economic, social, and political factors.

factors such as the level of democracy and economic development stayed stable in Sudan, pull factors improved in Ethiopia. However, what we see is a drastic decrease. The vital difference between 1989 and 2009 is that Ethiopia supported rebel groups during the former but not during the latter conflict. In 1989, Ethiopia supported the insurgency in Sudan to retaliate for Sudan's support to Eritrean secession (Ronen 2002). In 2009, Ethiopia did not back rebels because at that time both countries had benevolent relations and Ethiopia was in favor of a stable Sudan rather than a conflict-driven neighbor (Mesfin 2012).

Furthermore, countries might be selective in accommodating refugees. In other words, countries that support rebels may host refugees only from ethnic groups which fight against the government of the source country, but not from other ethnic groups.[11] For example, in 2006, SLM/A, JEM, NRF, SLM/A MM rebel groups fought against the Sudanese government. All groups fought for the Massalit and Zaghawa ethnic groups (Wucherpfennig et al. 2012) and were supported by Chad (Cunningham, Gleditsch & Salehyan 2009). In this year, the total number of refugees that originated from Sudan was 686,311, and Chad accommodated 233,025 of them. Further, 139,815 were of Massalit ethnicity, and 69,907 were from the Zaghawa ethnic group (together accounting for 209,723 refugees), composing more than 90% of Sudanese refugees that Chad hosted (Rüegger & Bohnet 2018). There were refugees from other ethnic groups in other countries, but Chad mainly accommodated Massalit and

[11]Unfortunately, because of the data availability, this argument cannot be tested. There is a dataset on the ethnicity of refugees by Rüegger & Bohnet (2018). However, the coverage of this dataset is limited. It only covers refugees from neighboring countries and the largest three ethnic groups at maximum. Therefore, creating an unbiased and efficient econometric model by using this dataset will be challenging. For example, if I use this dataset as the basis of my analysis, I have to drop around 30% of treatment observations because it limits the coverage of destinations to the countries within 950 km distance. Also, in some conflicts, rebels do not represent a certain ethnic group (e.g., FARC in Colombia (Wucherpfennig, Metternich, Cederman & Gleditsch 2012)), which also decreases the number of treatment observations and induces bias.

Zaghawa refugees because Chad supported their rebel groups.[12]

Here, I argue that hosting refugees can be the continuation of support for the rebels. However, not every country hosts refugees with the intention of supporting rebel groups. Most countries accommodate people with alternative motivations including humanitarian considerations, economic and political interests. For example, Germany's hosting hundreds of thousands of Syrian refugees may not be considered as support for rebels in Syria.[13] However, Turkey's hosting millions of Syrian refugees is a support to rebel groups, as Turkey was already supporting rebels before it started hosting refugees and kept facilitating rebels' operations on its soil. Furthermore, this paper does not stipulate a close relationship between refugees and rebels. Theoretical explanations that I propose are applicable regardless of the support from refugees to the insurgency and related to the exploitation of the asylum system and the vulnerability of refugees by rebel groups.

2.4 Data and Operationalization

This study analyzes refugee flows from countries experiencing civil conflict between 1951 and 2011.[14] Following general practice, civil conflict is operationalized using the Armed Conflict Dataset from the Uppsala Conflict Data Program/Peace Research Institute in Oslo (UCDP/PRIO) as 'a contested incompatibility that concerns government and/or territory where the use of armed force between two parties of which at least one is the government of a state,

[12]Sharing ethnic kinship might be considered as an alternative explanation. However, it fails to explain Chad's behavior because Chad shares ethnic relations with Zaghawas but not with with Massalits. If this alternative explanation holds, we should observe Chad hosting refugees from the Zaghawa only.

[13]The main reason for Germany accepting a high number of refugees may be a mixture of humanitarian and economic considerations. For more information, please see Legrain (2016) and Economist (2016).

[14]The temporal domain is ordered by data availability.

results in at least 25 battle-related deaths' (Gleditsch, Wallensteen, Eriksson, Sollenberg & Strand 2002).

The unit of observation is directed-dyad-civil conflict year, an ordered pair of countries: $country_i$ and $country_j$. While $country_i$ refers to countries that experience civil conflict—a potential source; $country_j$ is all countries other than $country_i$—a potential host (Gleditsch & Ward 1999). This dyadic approach lets me control for push and pull factors and dyadic characteristics.

The dependent variable is the number of refugees from $country_i$ in $country_j$ in year t; for example, the number of Angolan refugees in Germany in 1991. For refugees, following Neumayer (2005), Moore & Shellman (2007), Uzonyi (2015), and Moorthy & Brathwaite (2019), I use UNHCR (2018*b*) definition which identifies people who fleeing the country of their nationality because of 'well-founded fear of being persecuted for reasons of race, religion, nationality, membership of particular social group or political opinion'. Data are extracted from the UNHCR Population Statistics Database (UNHCR 2018*b*). I use the stock number of refugees since flow data are unavailable. It is a continuous variable that ranges from the minimum value of 0 to the highest value of 3,272,290.[15]

The main independent variable is *Rebel Support*, operationalized via Non-State Actor Data (NSAD) (Cunningham, Gleditsch & Salehyan 2009) and UCDP External Support Data (Högbladh, Pettersson & Themnér 2011). It is defined as support by the government of a foreign state to rebels, given to assist them in an ongoing conflict. This support can be military (e.g., sending troops) or non-military (e.g., financial aid).[16] For example, in the civil conflict between Malaysia and the Clandestine Communist Organization (CCO), Indonesia supported CCO with their troops. In the civil conflict between Ethiopia and the

[15]For more information about the dependent variable please see Appendix A.

[16]In the collection of information, both sources did not rely on only what governments declared but also other resources including but not limited to media and NGO reports.

Ethiopian Democratic Union (EDU), the USA and Saudi Arabia provided economic assistance to EDU (Cunningham, Gleditsch & Salehyan 2009). This is a binary variable indicating the presence or absence of support from the host country to rebels.

Both sources for the main explanatory variable have advantages and shortcomings. The temporal domain of NSAD is comprehensive, 1946-2011, but time-invariant. It shows whether rebels received support during the conflict without indicating in which particular year(s) rebel groups were supported. Therefore, it assumes support was provided throughout the conflict. According to NSAD, rebels received support in 1,752 dyads between 1951-2011. Contrary to NSAD, UCDP External Support Data is time-variant and indicates in which particular year(s) rebel groups were supported but covers conflicts between 1975-2009. Overall, in 942 dyads rebels received support. To exemplify the difference between NSAD and UCDP, according to former, Libya supported MNLF from 1972 to 1993; however, according to the latter, support was given between 1975-1988. Therefore, I run the whole analysis with both datasets. For statistical corroboration, the support variable should be positively correlated with the number of refugees.

I control for push and pull factors. Democracy, economic development, regime transition, interstate war, and genocide in the source country are commonly studied push factors that explain the variation in refugee flows. For democracy, I use Polity 2 variable (*Source Polity*) (Marshall, Gurr & Jaggers 2018). Economic development is operationalized through logged GDP per capita (*Source GDP per capita*) from Gleditsch (2002). For regime transition, following Moore & Shellman (2007), I use a dichotomy for Polity variable -66, -77, and -88 scores (*Source Regime Transition*) (Marshall, Gurr & Jaggers 2018). Interstate war and genocide are binary variables (*Source In-*

terstate War and *Source Genocide*) from UCDP/PRIO (Gleditsch et al. 2002) and the Political Instability Task Force (Marshall, Gurr & Harff 2017). For pull factors, I control for democracy, economic development, regime transition, interstate war, civil conflict, and genocide in the host country. I employ the same datasets and the same operationalizations that I use for push factors (*Host Polity*, *Host GDP per capita*, *Host Regime Transition*, *Host Interstate War*, and *Host Genocide*). For a dichotomous variable of civil conflict in the host, I use UCDP/PRIO (Gleditsch et al. 2002) (*Host Civil Conflict*).[17] Whether the host country ratified the UNHCR 1951 Convention or 1967 Protocol is also included in the model, as countries that have ratified these agreements might be more welcoming than others (*Host UNHCR Signatory*).

For dyadic determinants of refugee flows, I first control for the logged distance between host and source countries (*Distance*), operationalized as minimum distance between borders. Following Moore & Shellman (2007), the number of source country neighbors is also included in the model; the higher the number of neighbors, the more alternatives there are for people to flee and the fewer to each host country (*Source Neighbors Number*). Also, neighboring countries are more likely to support rebels than others (Salehyan 2007). Thus, the more neighbors countries have, the more likely rebels are to be supported. To define neighbor, following Weidmann, Kuse & Gleditsch (2010), I use a threshold of 500 km. For both distance and the number of neighbors, I use CShapes Data (Weidmann, Kuse & Gleditsch 2010). Host countries that share colonial history with the source country accommodate more refugees than others (Moore & Shellman 2007). Therefore, I add a binary variable (*Colonial Tie*), operationalized via Issues of Correlates of War Project (Hensel 2014). Following Moore & Shellman (2007) and Moorthy & Brathwaite (2019), I control

[17]Since all source countries have experienced civil conflict, I do not control for it.

for *Alliance* and *Rivalry*, as political relations between origin and destination may affect refugee-hosting behaviors. Both are dichotomous, and while the source for the alliance[18] is the Correlates of War Project, Formal Alliances Data (Gibler 2008), the rivalry is extracted from Thompson & Dreyer (2011). Lastly, I control for transnational ethnic relations between the host country and groups in the conflict zone since countries might be more willing to accommodate people of their same ethnicity (*Ethnic Relations*). This variable is also binary, operationalised using the Transborder Ethnic Kin Dataset (Vogt, Bormann, Rüegger, Cederman, Hunziker & Girardin 2015).

To control for countries' potential to generate and host refugees, I include the logged population of the source and host countries in the model (*Source Population* and *Host Population*), with data extracted from Gleditsch & Ward (1999). To account for temporal effects, I also include cubic polynomials of *Year in Conflict* (Carter & Signorino 2010). Finally, observing a high number of refugees in a host country may result from the source country having generated too many refugees. For example, in 2016, Germany hosted around 400,000 Syrian and 1,000 Egyptian refugees. In total, there were 5.5 million Syrian but 19,000 Egyptian refugees globally that year. Thus I control for the total number of refugees of the source country (*Refugees Total*).[19] Summary statistics are presented in Appendix A Table A.1.

[18]Following Moore & Shellman (2007) and Moorthy & Brathwaite (2019), I exclude nonaggression pacts, as their obligations are different from other obligations entailed by an alliance.

[19]I exclude the number of refugees in the host country itself to avoid endogeneity, as the dependent variable is on both sides of the equation.

2.5 Model and Results

The model of this study is defined as:

$$\text{Refugees}_{ijt} = \mathbf{Xb} + \beta \text{ Rebel Support}_{ijt} + \epsilon_{ijt} \tag{2.1}$$

where Refugees_{ijt} denotes the number of refugees from $country_i$ in $country_j$ in year t. $\mathbf{X}$ refers to a matrix of K control variables that are explained above and $\mathbf{b}$ is a vector of K coefficients to be estimated. While $\text{Rebel Support}_{ijt}$ is the support from $country_j$ to rebels in $country_i$ in year t, β is its coefficient. Lastly, ϵ_{ijt} is residual at the dyad-conflict year.

The dependent variable—count of refugees—can only take non-negative integer values. For more than 87% of the observations, the dependent variable is 0. Following Moore & Shellman (2007) and Moorthy & Brathwaite (2019), I employ a zero-inflated negative binomial (ZINB) model, which is suitable for count variables with excessive zeros.[20] ZINB has two stages: count and inflation. These two stages differentiate processes underlying the likelihood of refugee displacement (inflation part) and the intensity of flow (count part). In other words, the inflation stage expounds the lack of refugee flows (0 as the dependent variable), and the count part explains the variation in the number of refugees hosted. Since I do not have different theoretical expectations regarding these two stages, I include the same variables in both equations.

Results are reported under two sections. First, I estimate the model above

[20] When I include dyad or source country or host country fixed effects, the matrix could not converge and the model could not be estimated, which might stem from the use of zero-inflated negative binomial regression. Instead, OLS can be used with fixed effects although it may not be the right estimation technique given the excessive number of 0s in the dependent variable. Using OLS, when I include dyad and year fixed effects, source country and year fixed effects, and host country and year fixed effects, the results still support the main argument. Rebel support variable is always positively and significantly correlated with the number of refugees countries host.

with raw data, discussing the effect of rebel support on refugee hosting. Afterward, I run matching procedures and analyze the same model with matched data. For the regression analysis, I use two sets of control variables. In the first, I only account for polity, GDP per capita and the population of host and source countries, total number of refugees and distance between origin and destination. The second set of controls covers all variables explained above.

ZINB results are presented in Table 2.1. Incidence rate ratios (IRRs) are reported to make interpretation easier.[21] Values higher than one indicate an increase and values lower than one imply a reduction in the percentage of the expected count given one unit increase in the explanatory variable. For example, an IRR of 1.2 can be interpreted as 1 unit increase in the explanatory variable raises the number of refugees by 20%, whereas an IRR of 0.7 decreases the number of refugees by 30%. While models (1) and (2) are run with NSAD (1951-2011), models (3) and (4) are run with UCDP data (1975-2009).[22] Standard errors are clustered by dyad to account for non-independent panel observations.[23]

The regression analysis corroborates the argument. Rebel support is positively and significantly correlated with the number of refugees that countries host, robust to different model specifications and data sources of the main explanatory variable. Countries which support rebels tend to accommodate more refugees than countries that do not support rebel groups. Overall, all else equal, supporting rebels increases the number of refugees hosted by around 250%. When a country starts supporting rebels, the number of refugees it accommodates increases from 10,000 to 35,000. For instance, in 1991, the Democratic

[21] ZINB coefficients are reported in Appendix A Table A.3.

[22] As a robustness check, I use San-Akca (2016) data instead of NSAD and UCDP. Results support my argument and are reported in Appendix A Table A.4.

[23] I also cluster standard errors by conflict, source and host country. The rebel support variable is still significant.

Table 2.1: Zero-Inflated Negative Binomial Regression of the Yearly Number of Refugees in Civil Conflicts

	NSAD, 1951–2011		UCDP, 1975–2009	
	(1)	(2)	(3)	(4)
Rebel Support NSAD	3.487**	3.677**		
	(1.357)	(1.446)		
Rebel Support UCDP			3.396**	3.836**
			(1.235)	(1.253)
Host Polity	1.028	1.027	0.992	1.000
	(0.025)	(0.022)	(0.020)	(0.019)
Host GDP per capita (ln)	2.330**	2.427**	2.868**	2.859**
	(0.222)	(0.214)	(0.234)	(0.213)
Host Population (ln)	1.556**	1.542**	1.811**	1.769**
	(0.125)	(0.125)	(0.147)	(0.139)
Source Polity	0.977	0.957**	0.981	0.948**
	(0.016)	(0.013)	(0.016)	(0.013)
Source GDP per capita (ln)	0.731**	0.859	0.755**	0.867
	(0.066)	(0.080)	(0.066)	(0.079)
Source Population (ln)	0.850	1.147	0.750**	0.987
	(0.074)	(0.115)	(0.069)	(0.102)
Distance (ln)	0.386**	0.380**	0.369**	0.361**
	(0.017)	(0.018)	(0.018)	(0.019)
Refugees Total (ln)	1.104*	1.139**	1.117	1.113
	(0.047)	(0.040)	(0.070)	(0.061)
Host Regime Transition		1.276		2.018*
		(0.418)		(0.697)
Host Interstate War		1.904**		1.853*
		(0.363)		(0.454)
Host Civil War		0.576**		0.571**
		(0.117)		(0.114)
Host Genocide		1.039		1.061
		(0.274)		(0.290)
Host UNHCR Signatory		1.104		1.532
		(0.301)		(0.415)
Source Regime Transition		1.826**		1.975**
		(0.356)		(0.365)
Source Interstate War		0.878		1.054
		(0.168)		(0.206)
Source Genocide		2.250**		1.381
		(0.477)		(0.261)
Source Neighbors Number		0.938**		0.944**
		(0.018)		(0.018)
Colonial Tie		1.767		1.453
		(0.741)		(0.603)
Alliance		2.451**		2.107**
		(0.525)		(0.457)
Ethnic Relations		0.747		0.696
		(0.201)		(0.220)
Rivalry		1.444		1.102
		(0.576)		(0.475)
Observations	170947	170947	138585	138585
BIC	321622.181	317747.207	283512.750	280503.539

Incidence Rate Ratios of count part are presented. Results including inflation part are in Appendix A Table A.2. Year in conflict variables are not reported (models (2) and (4)) due to space limitation. Standard errors clustered by dyad in parenthesis. * $p < 0.05$, ** $p < 0.01$

Republic of Congo (DRC) did not support rebels and hosted 41,243 Burundian refugees. Regarding the results of this analysis, we could estimate that had the

DRC supported rebel groups, it would have accommodated 158,208 refugees. In 1994, the DRC supported rebels and indeed hosted 180,098 Burundian refugees.

Findings on the control variables corroborate previous studies. While host GDP per capita and population have a positive and significant effect, host polity score lacks explanatory power.[24] Civil conflict in the destination decreases the number of refugees hosted, as people who escape from violence do not want to get caught in violence in another country.[25] Surprisingly, interstate war in the destination has a positive and significant effect.[26] While regime transition and genocide in the source country increase the number of refugees, democracies generate fewer refugees than others. GDP per capita at source does not explain variation in displacement. Unsurprisingly, distance has a robust negative effect. Another geographical feature, increase in the number of source country's neighbors, leads to a decrease in the number of refugees in the host.

Among historical and political dyadic determinants, only the alliance variable is statistically significant. Rivalry is increases the number of refugees but the effect is not statistically significant.[27] Contrary to expectations, ethnic relations lack explanatory power and have a negative relationship with the number of refugees hosted. This unforeseen result might stem from the high collinearity with the distance variable. To further investigate, I run the models in Table 2.1 excluding distance. Then, ethnic relations are found to have a positive and significant effect on refugee flows.

[24] As an alternative operationalization, I take the difference in polity and GDP per capita of host and source countries. Results suggest that the larger the gap (i.e., more democratic and more developed host country than the source), the more refugees countries host.

[25] Host country genocide and civil conflict variables might be collinear. To overcome this issue, I run separate models for these two variables. Results are similar to those in Table 2.1, and supportive of my argument.

[26] This significance may stem from the structure of the dataset, as I only analyze countries that experienced civil conflict. Also, countries in conflict spatially cluster. Removing the distance variable from the model, the host interstate war loses its significance.

[27] Related to rivalry, I run additional robustness checks below.

2.5.1 Matching

In total, there are 170,947 observations, and the data is highly unbalanced[28], as there are many covariates from a long time span. The analysis of raw data supports my hypothesis. However, with this high number of observation and imbalance, model dependency might raise concerns. Therefore, I also perform matching and run the analysis with matched data. As a powerful nonparametric approach for improving causal inferences, matching reduces model dependence, estimation error, and bias by discarding observations outside the region of common empirical support (Ho, Imai, King & Stuart 2007, Iacus, King & Porro 2019).

Different matching techniques such as propensity score matching (PSM) (Ho et al. 2007) and coarsened exact matching (CEM) (Iacus, King & Porro 2012) can be used in the analysis.[29] In general, matching is an effective way of reducing model dependence; PSM may, however, increase imbalance and exacerbate causal inference concerns. CEM, on the other hand, guarantees a reduction in imbalance and estimation error; is robust to measurement error; restricts data to common empirical support and meets congruence principle (Iacus, King & Porro 2012, King & Nielsen 2019). Therefore, I opt for CEM over PSM.[30]

For matching, I use model (2) and (4) in Table 2.1 with 21 control variables, respectively for NSAD and UCDP.[31] Binary variables are exactly matched, whereas continuous variables are matched with 1/4, 2/4 and 3/4 intervals.[32]

[28]Imbalance refers to the difference in the distribution of covariates between treatment and control groups.

[29]A brief explanation about PSM and CEM is in Appendix A.

[30]I also use PSM and results still corroborate my argument.

[31]I exclude refugees total as including this variable may result in controlling for the dependent variable and yield biased estimates. However, as a robustness check, I run the same analyses while adding this variable to the equation and it does not affect my interpretations.

[32]Following the suggestions of Ho et al. (2007) and Iacus, King & Porro (2009), to leverage the maximum use of available information and to increase the efficiency, I match more than

Table 2.2: Zero-Inflated Negative Binomial Regression of the Yearly Number of Refugees in Civil Conflicts, Coarsened Exact Matched Data

	CEM WITH 1/4 INTERVALS				CEM WITH 1/3 INTERVALS			
	NSAD		UCDP		NSAD		UCDP	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Rebels Support NSAD	4.363**	2.300**			6.129**	3.419**		
	(1.452)	(0.729)			(1.375)	(2.609)		
Rebels Support UCDP			4.316**	5.595**			2.247**	2.232**
			(1.378)	(2.623)			(0.587)	(0.490)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
	(Basic)	(Full)	(Basic)	(Full)	(Basic)	(Full)	(Basic)	(Full)
N	2484	2484	1329	1329	9165	9165	3810	3810
BIC	4965.748	4989.324	4694.602	4724.824	14803.738	14807.746	12088.340	12104.900
Matched Treatment %	20%		29%		38%		41%	
Imbalance $\mathbf{L_1}$	0.991		0.983		1.000		0.996	
ATT	12,321		10,793		9,563		23,551	
Wilcoxon Rank Sum Test	313,330**		104,860**		2,173,700**		466,540**	
T Test	-2.167*		-2.945**		-5.681**		-4.077**	

Only count parts of zero-inflated negative binomial regression are reported. Incidence rate ratios are presented.Basic and full controls refer to control variables in model (1) and (2) in Table 2.1, respectively. Standard errors clustered by dyad in parenthesis. Full results are in Appendix A Table A.5 and A.6. * $p < 0.05$, ** $p < 0.01$

With this specification, 20% of NSAD and 29% of UCDP treatment observations are matched. After this process, the imbalance, $\mathbf{L_1}$[33] decreases to 0.991 and 0.983, respectively for NSAD and UCDP.[34] Following the matching, I run ZINB models in Table 2.1 for matched data and results are reported in Table 2.2, model (1)-(4).[35] As a robustness check, I run the same analysis, but using 1/3 and 2/3 intervals for continuous variables.[36] The decrease in imbalance is smaller than previous matching; however, the number of matched observations increases. In total, 38% and 41% of NSAD and UCDP treatment observations are matched. Relevant parameters and ZINB results can be seen in Table 2.2, model (5)-(8).[37]

The matching results show strong statistical corroboration for my hypothesis. The analysis indicates a positive and significant effect of rebel support on accommodating refugees across various specifications. Countries supporting rebels host a higher number of refugees than ones that do not. On average, rebel support increases the number of refugees hosted by 3 times. I also run t-test and Wilcoxon rank sum test (aka Mann-Whitney test) for refugees by rebel support. Across different specifications, these tests suggest dyads with rebel support are significantly different than dyads without rebel support. Furthermore, to facilitate substantive effect interpretation, I also plot the average

one control to a treatment if available and meet the matching criteria.

[33]Regarding the imbalance, following Iacus, King & Porro (2012), I use $\mathbf{L_1}$, which measures the distance between multivariate histograms of treatment and control observations (Iacus, King & Porro 2012). In $\mathbf{L_1}$, 0 refers to perfect balance and 1 denotes the largest imbalance.

[34]For raw data with NSAD and UCDP, $\mathbf{L_1}$ is 1. As expected, the data is highly imbalanced. Following the matching, the decreases in imbalance might seem low; however, in the words of Iacus, King & Porro (2012): 'The values of $\mathbf{L_1}$, provide useful relative information... This measure is relative because its meaning is conditional on the data set and chosen covariates.' Due to the nature of the dataset and the high number of continuous variables, with 20% match, 0.983 is the lowest imbalance I could obtain.

[35]I only report relevant variables. Full results are in Appendix A Table A.5.

[36]I extend the size of intervals as 'if too many treated units are discarded, inferences with CEM may be inefficient. This can be remedied by widening the degree of maximum imbalance.' (Iacus, King & Porro 2012).

[37]Full results are in Appendix A Table A.6.

treatment effect on the treated (ATT) and its 95% confidence intervals in figure 2.1. All else equal, countries that support rebels host 11,000 more refugees than others.

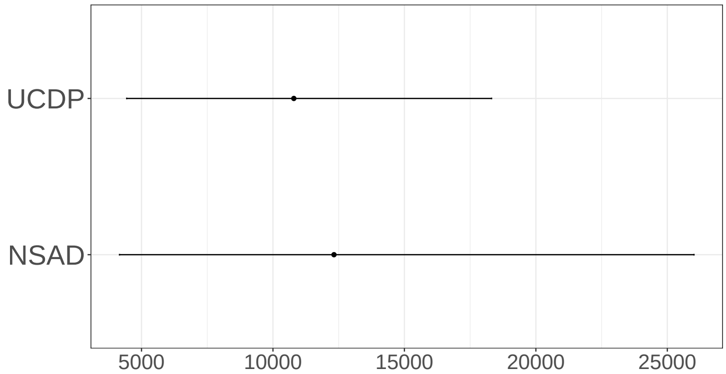


Figure 2.1: Average Treatment Effect on the Treated. Figure corresponds to matching with 1/4, 2/4 and 3/4 intervals. 95% confidence intervals are obtained by bootstrapping.

2.5.2 Robustness Checks

In this paper, the dependent variable is the stock number of refugees, which may raise serial autocorrelation and unit root concerns. Thus, I run the same analysis in Table 2.1 by including the lagged dependent variable (Appendix A Table A.7) and changing the dependent variable to the flow (Appendix A Table A.8).[38] Rebel support keeps its significance across different specifications, and its incidence rate ratio stays around 3.5. Additionally, to account for network dependencies, I employ Neumayer & Plümper (2010) directed dyad contagion spatial-effect variable (row-standardized weighted by distance). Results still support the argument.

Like many other political science papers, this study is not free from endogeneity concerns. Does hosting refugees lead to supporting rebels? Theoreti-

[38]Following Moore & Shellman (2007) and Moorthy & Brathwaite (2019), I take the difference between consecutive years, and if the difference is negative, I code it as 0.

cally, refugees live in disadvantageous situations in host societies, and are not politically powerful. They do not generally impact political decisions but are affected by them. Especially, for delicate issues such as involvement in armed conflict, refugees could play a very limited role, if at all. Thus, I do not foresee refugees influencing host countries' support for rebels in source countries. Methodologically, I run model (3) and (4) in Table 2.1 by lagging the support variable. Rebel support is still statistically significant in both models, and the substantive effect is close to the one in Table 2.1.[39]

In operationalizing rebel support, I adopt a strict approach, coding only explicit cases as support. Alleged ones are coded as if there is no support in that dyad. Including alleged ones as support, dropping them from the analysis, and splitting the support as military and non-military do not affect my inferences. Rebel support is significant in different operationalizations, though, the effect of military support is higher than non-military one.

Countries are more likely to support rebel groups when they have ethnic relations with people in the conflict zone and when rebels fight against their rival (Salehyan, Gleditsch & Cunningham 2011). In addition to controlling for rivalry and ethnic relations in the regression, I also subset the data and run the analysis: when there is rivalry, no rivalry, ethnic relations, and no ethnic relations. Results still support the argument.

Furthermore, Cold War dynamics may play a role in supporting insurgent groups since ideology is an important driver of foreign policy in this period. Thus, I run the model in Table 2.1 by adding a cold war variable, subsetting the dataset as the Cold War era and the post-Cold War era. Across different models, the analyses constantly conclude a positive and significant effect of rebel

[39] I could not run the analysis with the lagged NSAD support variable. Since it is available at conflict level, by lagging, we can only get rid of the first observations, and it does not help us to alleviate endogeneity concerns.

support on refugee hosting.

To account for regional dependencies and other conflict characteristics, I run the analysis by adding regional dummies and by incorporating territory incompatibility, internationalization of civil conflict, and conflict severity. Results still corroborate the argument.

This paper studies the effect of rebel support on refugee flows, and a similar logic may be applied to government support such that countries that support the government in a civil conflict will host fewer refugees than others. However, the mechanisms that lead to government and rebel support are different (Salehyan, Gleditsch & Cunningham 2011, Regan 2002). Thus, their effects will also vary. Therefore, I do not expect the government support to have an impact similar to rebel support. To test this argument, I run the models in Table 2.1 by replacing rebel support with government support. Qualitatively, government support lowers the number of refugees hosted. All else equal, countries accommodate fewer people when they help the government in conflict.[40] However, statistical support for this argument is weak. The model with NSAD is not significant and the one with UCDP could reach only 0.1 significance level.

Finally, in addition to the in-sample analysis, I also perform out-of-sample cross-validation procedures, which can be an effective indicator of the model's success (Ward, Greenhill & Bakke 2010, Chadefaux 2014, Chadefaux 2017*b*). This procedure reinforces the causal claim and helps to overcome the overfitting problem (Beck, King & Zeng 2000, Chadefaux 2017*a*). Results support my argument, and including rebel support in the model furthers our understanding of why some countries host more refugees than others.[41]

[40] This can also be interpreted as people not wanting to go to countries supporting the government, which they may regard as the ally of enemy.

[41] For a detailed discussion, please see Appendix A.

2.6 Conclusion

The literature on refugee flows has overlooked the specific dynamics that vary among civil conflicts. Here, I investigate the role of host countries' support to rebels—as one of the civil conflict dynamics—in explaining the variation in the number of refugees hosted. I argue that backing rebels in the source country increases the number of refugees that countries accommodate. In other words, countries which support rebels host a higher number of refugees than countries that do not. The reasoning for this argument is that accommodating refugees can be the continuation of support for the rebels.[42] Empirical analysis of the raw data corroborates this hypothesis and supporting rebels is positively correlated with the number of refugees hosted. All else equal, countries that support rebel groups accommodate 2.5 times more refugees than others. Various model specifications strengthen the robustness of results and suggest that incorporating rebel support into the analysis improves our ability to explain variation in refugee flows.

This paper employs matching to balance data and to alleviate model dependence concerns. Through an examination of similar dyads, the matching analysis also corroborates the main hypothesis and concludes that on average, supporting rebels raises the number of refugees that countries host by 11,000. As a limitation, even though matching can account for observable covariates, it fails to control for unobservable ones, which is a general limitation in political science research and can be overcome by rarely found instrumental variables or natural experiments.

The results of this study are also important for policy-making. When international organizations and NGOs expect high levels of displacement, they

[42]It should be noted that if the host country does not support rebels in the conflict, accommodating refugees may not be seen as a form of support.

should pay additional attention to countries supporting rebels as there will be more people going to these countries than others. Therefore, they can allocate their resources more efficiently and develop better policies at earlier stages of crises, mitigating negative effects for displaced people and host societies.

There are important caveats that must be taken into consideration when interpreting these findings. First of all, findings of this study are correlational and future studies might find a way to offer causal effects. Second, the main independent variable is dichotomous, accounting only for the presence of support and not for the variation in its intensity. However, depending on the level of host countries' backing of rebel groups, attitude towards accommodating refugees may vary. Theoretically, the more support host countries provide to insurgents in the source country, the more refugees they will accommodate. Unfortunately, due to the lack of fine-grained data, this study could not account for this variation. With more detailed information, future studies could overcome this shortcoming. Additionally, this paper controls for various political and economic factors in the host country, but does not include specific policies such as the open door policy that Turkey and Germany adopted for Syria because of data availability. It is an important factor to explain the variation in where refugees go, but data collection on this issue is beyond the scope of this study and needs further consideration.

This study set out to analyze why some countries host more refugees than others in line with the literature that emphasizes refugees as significant players (passive or active) in security matters in both source and host countries. This paper underscores the importance of considering civil conflict dynamics when analyzing variation in refugee flows and displacement. It advocates a disaggregated approach, rather than treating civil conflicts as a unitary concept. Encouraging results from this study will show the importance of hitherto neglected conflict characteristics, incorporating them in studies on refugee flows, extending the present results, and hence of collecting additional data.

3 Look Who Perpetrates Violence and Where: Explaining Variation in Forced Migration

Abstract

Are the causes of refugee and IDPs flows the same? While existing studies examine the causes of displacement in general, there is limited research on varying determinants of internal and external displacement. The same factors may impact the decision to move within the country and flee abroad in disparate ways. Here, I argue the effect of violence on displacement as a function of perpetrator and geography (i.e., how spread it is). Increases in government violence increase the number of refugees because to escape government violence, people may have to cross an international border as governments are generally effective everywhere within its borders. On the other hand, rebel group activities are limited to a certain area and by leaving the conflict zone, civilians can be free from rebel violence. However, the spread of violence determines the decision to flee. If it is limited to a small region, people can escape from that area within the country and rebel violence increases the number of IDPs. If it is widespread, civilians may not have many opportunities within the country and have to move abroad. Therefore, the effect of rebel violence on internal displacement follows a reverse U-shape. The analysis of refugee and IDPs flows between 1989 and 2017 supports the main arguments and results are robust to different model specifications and additional checks. This study highlights

the importance of distinguishing the causes of internal and external displacement.

3.1 Introduction

Violence creates incentives to flee. We know this from existing research that emphasizes the role of civil conflict in the displacement process (Adhikari 2012, Adhikari 2013, Balcells & Steele 2016, Czaika & Kis-Katos 2009, Davenport, Moore & Poe 2003, Iqbal 2007, Melander, Oberg & Hall 2009, Moore & Shellman 2004, Neumayer 2005, Steele 2011, Turkoglu & Chadefaux 2019, Uzonyi 2014, Weiner 1996). What is not clear, however, is why some choose to flee abroad, while others migrate to another area within the country. And why do some conflicts generate mostly IDPs, whereas others mostly refugees? The existing literature cannot explain this puzzle because previous studies (with a very few notable exceptions) do not generally differentiate internal and external displacement. I argue that depending on the perpetrator and geography (i.e., how spread it is), the effect of violence on displacement varies. While government violence increases the number of refugees, it does not have a significant impact on internal displacement. On the other hand, rebel violence has a significant effect on internal displacement, and it follows a reverse U-shape, initially resulting in more IDPs and after a certain point decreasing it.

The decision to flee abroad or within the country is based on a cost-benefit analysis. In general, crossing an international border is costlier than displacing within the country as in the destination country, people generally have to learn a new language and adapt to new culture and lifestyle in addition to financial hardship of crossing a border (e.g., paying smugglers) and security risks attached to it. Therefore, civilians are expected to stay within the country whenever they can. However, sometimes, civilians cannot have a life free from fear of persecution in their country even if they leave the conflict zone. In this case, the costs of fleeing within the country exceed the costs of migrating to another country.

When the government is the perpetrator, leaving the conflict zone is not enough to be safe because to escape government violence, people have to go to another country since the government is generally effective everywhere within its borders. Thus, government violence increases the number of refugees but does not impact the number of IDPs. In general, insurgent group activities are limited to a certain region, and by leaving the conflict zone, people may escape from rebel violence. However, there is a significant variation in the spread of violence. While in some conflicts, it is limited to a small area, in others, it might be widespread across the entire country. The effect of rebel violence on internal displacement follows a reverse U-shape. If rebel violence is limited to a small area, people can escape it by leaving the conflict zone. But if rebel violence is widespread, people may not have many opportunities to flee within the country and may have to cross an international border to be free from violence. Thus, increases in the spread of rebel violence initially increase the number of IDPs, but after a certain point, it results in decreases.

To test its arguments, the paper analyzes refugee and IDPs flows between 1989 and 2017 and the results support the main argument. The analysis suggests an increasing effect of government violence on external displacement and no effect on IDPs and an increasing effect of rebel violence on refugees and a reverse U-shape effect on internal displacement. Violence spread is measured in various ways and results are robust to different model specifications and checks.

Studying different causes of internal and external displacement has important implications. As argued by previous research, international organizations and other stakeholders may fail to predict whether civilians flee to another country or migrate within the country (Steele 2019). A substantive increase in foreign aid to refugees and IDPs has been observed in the last decades (Fearon 2011). The inability of organizations to predict displacement patterns may cause problems for providing timely and adequate services. Predicting displacement patterns will allow policy-makers to develop more effective policies. Depending on who perpetrates violence and where, organizations can take necessary actions to facilitate the settlement of displaced people within the source country or in the new destination countries.

This paper aims to make several important contributions to the literature on forced migration and civil conflict. First, siding with Moore & Shellman (2006) and Steele (2019), this study argues that internal and external displacement have distinct causes even though many factors may affect them in the same way. Second, this paper emphasizes the divergent effects of government and rebel violence in the displacement process and urges for further investigation of distinct causes of internal and external displacement. Finally, in addition to conflict intensity, this study emphasizes the importance of the spread of violence to explain variation in forced migration.

3.2 Causes of Forced Migration

The general understanding of the causes of forced migration in the literature is based on utility maximization. People flee their homes when the expected utility of leaving exceeds the expected utility of staying. To delineate this cost-benefit analysis and to analyze why some countries generate more forced migrants than others, previous studies examine variation in violence, economic, and political conditions in the source country. Before delving into the causes of forced migration, it is important to clarify what this concept refers to. There are two main forced migrant sub-groups: refugees and internally displaced persons (IDPs). While refugees cross an international border and flee to another country, IDPs flee within the country. More specifically, according to the UN Refugee Agency (2018), a refugee is defined as "someone who is unable or unwilling to return to their country of origin owing to a well-founded fear of being persecuted for reasons of race, religion, nationality, membership of a particular social group, or political opinion" and IDPs is defined as "people or groups of individuals who have been forced to leave their homes or places of habitual residence, in particular as a result of, or in order to avoid the effects of armed conflict, situations of generalized violence, violations of human rights, or natural or man-made disasters, and who have not crossed an international border."[1]

In terms of determinants, democratic countries have been argued to generate fewer forced migrants than others as people can enjoy their basic rights and have a life free from oppression in democracies (Moore & Shellman 2004, Neumayer 2005). However, statistical support for this argument is mixed (Davenport, Moore & Poe 2003, Iqbal 2007, Melander, Oberg & Hall 2009). Regime transition has been discussed to increase the number of displaced people as it is associated with instability and uncertainty (Davenport, Moore & Poe 2003, Melander, Oberg & Hall 2009, Moore & Shellman 2007). People also escape from bad living conditions and thus, economic development is expected to reduce displacement (Melander, Oberg & Hall 2009, Moore & Shellman 2004, Neumayer 2005).

Violence is one of the main determinants of forced migration as it signals the high risk of persecution. Previous research has operationalized violence through civil conflict and genocide and find an increasing effect on displacement (Adhikari 2012, Adhikari 2013, Balcells & Steele 2016, Czaika & Kis-

[1] In general, existing studies on the causes of forced migration have used both refugees and IDPs to operationalize their dependent variable (Davenport, Moore & Poe 2003, Moore & Shellman 2004, Melander, Oberg & Hall 2009).

Katos 2009, Davenport, Moore & Poe 2003, Iqbal 2007, Melander, Oberg & Hall 2009, Moore & Shellman 2004, Neumayer 2005, Schon 2019, Steele 2011, Turkoglu & Chadefaux 2019, Uzonyi 2014, Weiner 1992, Weiner 1996). Existing studies generally do not differentiate distinct aspects of civil conflicts and adopts a uniform approach. Recently, a few notable exceptions examine the role of conflict processes on forced migration. By examining Colombia, Steele (2011) has discussed that a high vote share of the insurgent-backed party in certain regions may proxy to identify where the "enemy" lives and displacement is higher in these areas. Comparing Colombia and Spain, Balcells & Steele (2016) have elaborated on the timing and location of forced migration. In irregular conflicts, displacement depends on when and where groups fight, while in conventional conflicts it follows front line changes.[2] However, they do not expound on the volume of forced migration.

Violence is the main cause of forced migration. However, not everyone who experiences violence flees their homes. In fact, most people stay. A recent strand of literature has examined how motivation and opportunities affect migration decisions. For example, through interviews with Syrian refugees in Turkey, Schon (2019) has argued that those who experience violence early on in the conflict and those who have *wasta* (i.e., advantaged social position based on money and connections) exited Syria earlier during the conflict. Similarly, previous research about migration from Colombia has shown that civilians with higher education and network connections are likely to flee to another country earlier than others (Silva & Massey 2015). Existing studies have also highlighted the role of risk preference in migration decisions. While risk-tolerant people have a significant preference for staying, risk-averse people have a preference for fleeing (Ceriani & Verme 2018). Additionally, the literature has analyzed alternative

[2]For more information on irregular and conventional conflicts, please see Kalyvas & Balcells (2010).

survival strategies that civilians can adopt other than migration. Civilians can stay in the conflict zone and try to survive by collaborating with armed groups, hiding, or protesting (Kaplan 2017, Masullo 2020, Schon 2020). Ideational factors and community relations play a significant role in surviving civil conflict (Marston Jr 2020, Masullo 2020, Schon 2020).

The literature generally has a uniform approach to the analysis of the causes of forced migration. In the operationalization of the dependent variable, studies generally use both refugees and IDPs (Davenport, Moore & Poe 2003, Melander, Oberg & Hall 2009, Moore & Shellman 2004, Uzonyi 2014) although there is a limited number of exceptions focusing only on refugees (Schmeidl 1997, Turkoglu & Chadefaux 2019). This widely used operationalization suggests that refugees and IDPs are affected by the same factors in the same way. This assumption is problematic given the common utility maximization approach because variables may have a diverse effect on people's cost-benefit analysis and thus, on refugee and IDP flows even though some factors may have a similar impact. Only exceptions to my knowledge are Moore & Shellman (2006) and Steele (2019).

Moore & Shellman (2006) is the first paper to argue that refugee and IDPs flows might have distinct causes and test their hypotheses through a global sample of displacement between 1976 and 1995. This article has two main theoretical contributions. First, it argues that genocide increases the number of refugees, while civil wars decrease it. Government and dissident violence (separately) increase the number of refugees as people escape from violence. However, the interaction between the state and dissident violence (civil war) decreases the number of people crossing international borders as "dissidents will seek to provide pockets of safe haven within the country". One of the main concerns with this argument is the neglect of direct rebel violence against civilians. The paper bases its argument on the assumption that states have a tendency to target civilians while rebels avoid targeting noncombatants.[3] This also reflects in their operationalization of the dissident violence variable as it only captures violent demonstrations and guerrilla attacks.[4] Therefore, it should be understood as conflict intensity rather than violence against civilians. Second, they emphasize the role of the neighborhood and how it may affect people's decision to flee abroad. The paper concludes that genocide and civil war in neighboring countries result in fewer refugees than IDPs.[5] Moore & Shellman (2006) deserves praises for their theoretical contributions and bringing attention on the issue. However, its operationalization is not free from problems and poses serious challenges for robust inferences, which I elaborate below.

In a theory-building paper, Steele (2019) overcomes many theoretical shortcomings of Moore & Shellman (2006) and argues that civilian resettlement pattern in civil wars depends on displacement type (individual escape, mass evasion, and political cleansing) and perpetrator of violence (government and rebel). In other words, the resettlement pattern is a product of the interaction between civilians and armed groups. When the perpetrator is rebel groups, people will displace within the country. Whereas when the government kills civilians, people may have to flee abroad as most often, the government cannot extend its operation across borders. When the displacement type is individual escape or mass evasion, people settle separately. Because by being away from

[3]According to UCDP Geo-referenced Event Dataset (Sundberg & Melander 2013), between 1989 and 2017, the number of civilians killed by rebels more than doubles those killed by governments. However, in conflicts, governments may fight against multiple rebel groups. When it is analyzed actor by actor, some governments kill more civilians than rebels. Rwanda, Syria, and DRC are among prominent examples.

[4]This variable is extracted from Cross-National Time-Series Data Archive (Banks & Wilson 2017). According to this source, while riots are defined as "any violent demonstration or clash of more than 100 citizens involving the use of physical force", guerrilla attacks are delineated as "any armed activity, sabotage, or bombings carried on by independent bands of citizens or irregular forces and aimed at the overthrow of the present regime". Even though these variables may capture fighting to a certain degree, they are not sufficient to explain the threat people perceive.

[5]The statistical analysis finds a null effect of neighborhood GDP per capita and a significant negative effect of neighborhood democracy which is against its expectation.

the conflict region and problems, people can be safe. However, when the displacement type is political cleansing, people settle together. In this case, the safety of targeted individuals is dependent on how other victims settle. If these people settle alone, armed groups can detect them and inflict further pain. But when they settle together, they decrease the risk of direct violence.[6]

In a recent study, Braithwaite, Cox & Ghosn (2020) argue that individuals who are exposed to indirect violence are more likely to be IDPs than refugees whereas those who are exposed to direct violence are more likely to be refugees than IDPs. An analysis of a survey of Lebanese residents who lived through the civil war corroborates their argument.

There is limited research on the different causes of refugee and IDPs flows. Although Moore & Shellman (2006) engage with the issue, their methodology poses problems. Steele (2019) offers compelling theoretical arguments, but they are not tested. Given that violence is the main cause of forced migration, it is crucial to examine how different perpetrators of violence affect internal and external displacement as argued by Steele (2019). In addition to perpetrator type, the geography of violence should be taken into account as conflicts vary with respect to how spread the violence is, and this is likely to affect civilians' decision-making. Further research is required on the varying determinants of internal and external displacement, and this is the main focus of the present study.

[6]Whether people settle together or separately has important implications, particularly for the spread of violence, state-building, and integration of newcomers to the host society. However, in this study, I limit the scope to whether people displace within their country or cross an international border.

3.3 Differentiating Refugees and IDPs

In civil conflict countries, due to fighting between armed groups, people face many problems from economic hardship to poor public services. There are troubles related to physical well-being and civilians might be subject to direct violence as warring parties may fund their activities through extorting and disenfranchising civilians. Some people are killed to set an example of the consequences of noncompliance with the armed group (Azam & Hoeffler 2002). Moreover, to put pressure and cut the support for the opponent, parties target civilians who support the rival (Balcells 2010). When armed groups kill people, they do not want to keep it as a secret but spread the word as it is a message to people about what happens if civilians do not comply with armed groups' rules. People read about these incidents in newspapers, learn about them from TV, and talk about these incidents to their friends from different towns. When armed groups perpetrate violence, civilians have two options: stay or leave.[7] In this paper, I examine whether people go somewhere within the country or cross an international border. I argue that people's decision is a product of violence perpetrator and its spread.

Here, following Moore & Shellman (2006) and Neumayer (2005), I adopt a rationalist account to analyze people's decisions to leave and where to go. In very general terms, people flee when the expected utility of leaving exceeds the expected utility of staying and they cross international borders if the expected utility of external migration is greater than that of staying and moving within

[7] Here, the stay option should not be interpreted as staying without taking any action. Recent research has suggested that civilians can adopt various tactics to survive in civil wars such as fighting, protesting, collaborating, or hiding, and ideational factors and community relations play a significant role in this process (Masullo 2020, Schon 2020). When civilians adopt these survival tactics (e.g., collaborating), they still stay in the conflict zone. Since in this paper, I am interested in the determinants of internal and external displacement, different tactics/options civilians can adopt in the conflict zone are treated as the stay option.

the country.

In general, the cost of migrating externally is higher than moving internally. Refugees' path to a host country involves risks to their personal safety and economic hardship. Aspiring refugees may not possess valid travel documents (e.g., passport and visa)[8], and must, therefore, cross the border illegally, at the risk of being arrested, prosecuted, and harmed. Most of the time, they also face forbidding physical obstacles such as mountains or bodies of water, and may, therefore, resort to paying smugglers at a great financial cost. Even if they manage to reach their destination, refugees often still need to learn a new language, obtain a work permit, search for employment, and adjust to the new economic, social, and cultural norms and environment of their host society (Neumayer 2005). Of course, people may experience similar problems when they displace within the country. They may face discrimination and have difficulties in finding a job. However, most of the time, people do not have to learn a new language, and adaptation to the destination's economic, social, and cultural environment is easier compared to moving abroad. Also, to migrate within the country, people generally do not have to pay smugglers and related security risks are less severe than those of crossing an international border.[9] Therefore, when people feel safe both in the country and abroad, they stay in the country as expected utility of migrating internally is greater than that of

[8]For example, Turkey canceled valid passports of dissidents (e.g., academics who signed a petition calling for peace in the traditionally Kurdish-dominated Southeast of Turkey) and does not issue passports to them so that they cannot leave the country (Amnesty International 2019). Dissidents in Turkey who do not have valid passports fled to Greece through the Evros river (Stamouli 2018).

[9]IDPs migrate within their countries. However, refugees cross an international border in addition to migrating within their country. Both IDPs and refugees may face security risks from armed groups within the country, refugees experience security risks related to crossing an international border as well. For example, between 2015 and 2020 5,613 people died in the Mediterranean Sea when they tried to reach Europe (International Organization for Migration 2021). Furthermore, while IDPs can travel by themselves within the country, refugees may resort to smugglers to cross a border. In addition to the economic costs, smugglers may cheat refugees, leave them in isolated places, and assault and rob them (Spener 2009).

external movement.

The benefits of migrating are a function of an individual's well-being (i.e., whether they feel safe and secure in their host community) and depend on the perpetrator and spread of violence. If the government perpetrates violence against civilians, people may have to leave their country to escape from violence. Government is ubiquitous and its coercive force can reach, most of the time, every part of the country. However, across borders, governments cannot operate or operate in a very limited fashion. Thus, people feel much safer in another country than their own. Since risks of staying and benefits of external migration are high, going to another country compensates its related costs. When people do not feel safe in their homeland, staying in the country is too costly, and they have to escape abroad for a life free from fear of persecution. Therefore, following Moore & Shellman (2007) and Steele (2019), I argue that *violence against civilians by government increases the number of refugees.* However, since people are not likely to escape from the government within its borders, government violence does not have a significant impact on internal displacement.

Civilians may also experience violence from rebels. In this case, most of the time, by fleeing the conflict zone within the country, people can escape from violence. Fighting is limited to a certain area and beyond this region, rebels are generally ineffective. By leaving the area in which insurgent groups are active, people can be safe. Therefore, violence against civilians by rebel groups increases the number of IDPs (Steele 2019). However, there is a significant variation in the spread of rebel violence. While some insurgent groups are active in a small region, others operate almost all around the country. When rebel violence gets wider, civilians have fewer opportunities to migrate within the country. Therefore, *the effect of rebel violence on internal displacement follows a reverse U-shape.* Increases in the spread of rebel violence initially lead to increases in the number of IDPs but after a certain point when rebel violence is widespread, it will lead to decreases.

People can be free from rebel violence by leaving the conflict zone, but they may face various other hardships. For example, bureaucratic procedures, particularly with registration for residency and schools, might be very challenging. Furthermore, internally displaced people may experience discrimination in public and private life. For instance, in Iraq, civilians who manage to escape from regions controlled by the Islamic State had difficulties finding a job within the country because they were perceived as the supporter of the insurgent group (Home Office 2018). Potential refugees choose to leave their home country only if the benefits of leaving are sufficient to compensate for these costs and risks. In general fleeing to another country is costlier than migrating within the country, but as explained above, displacing in the country is not free from costs. For some people, going to another country might be less costly because they may have relatives or friends in the destination and travel to the host country, asylum application process, and finding a job might be much easier for them (Rüegger & Bohnet 2018, Engel & Ibáñez 2007). Similarly, they may have economic means and high-skill jobs and integration in the host country might be easier (Lundborg 2013, Martén, Hainmueller & Hangartner 2019). Therefore, people who can afford to migrate abroad (e.g., those with networks, those who can speak a foreign language and those who have financial means) might opt to flee abroad rather than within the country. This is why *violence against civilians by rebel groups may increase the number of refugees.* However, the effect of insurgent violence on external displacement might not be very strong. Table 3.1 summarizes theoretical expectations.

Table 3.1: Expected Effect of Violence by Displacement Type

Violence Type	Displacement Type	Expected Effect
Government Violence	External Displacement	Positive
Government Violence	Internal Displacement	No Effect
Rebel Violence	External Displacement	Limited/Positive
Rebel Violence	Internal Displacement	Reverse U-shape

3.4 Data and Operationalization

This study examines the causes of refugee and IDPs flows in civil conflict countries. Following the general practice in the literature, civil conflict is defined through the Armed Conflict Dataset from the Uppsala Conflict Data Program/Peace Research Institute in Oslo(UCDP/PRIO) as "a contested incompatibility that concerns government and/or territory where the use of armed force between two parties of which at least one is the government of a state, results in at least 25 battle-related deaths" (Gleditsch et al. 2002). As explained above, for *refugees* and *IDPs*, I use the UN Refugee Agency (UNHCR 2018*b*) definitions. Both refugees and IDPs are displaced people, but the main difference between them is refugees crossing an international border while IDPs staying within the country. There are two dependent variables: the number of refugees from country$_i$ in year t and the number of IDPs in country$_i$ in year t.

To my knowledge, the only cross-sectional time-series data on displacement is available from UNHCR, which is used in this analysis. Of course displacement data is not free from biases. UNHCR collaborates with governments to collect displacement data. Even though countries generally use a similar definition, how forced migrant is defined may vary from country to country. Thus, a possible source of bias for displacement data might be based on the definition countries adopt. The use of country fixed effects may alleviate biases related to differences between countries. However, it is not a panacea and readers should keep this in mind assessing the findings. Additionally, for internal displacement starting from 2009, the Internal Displacement Monitoring Center (IDMC) provides information. They collaborate with multiple actors (e.g., research institutions and national Red Cross) and triangulate the data using several sources to mitigate possible biases. The analysis for internal displacement is replicated with IDMC (2019) dataset and the results still support the main arguments. In the analysis, UNHCR datasets is favored over IDMC dataset because of its extensive temporal coverage.

The main explanatory variables of this study are *government violence* and *rebel violence*, which are defined as violence deliberately and directly caused by government/rebels. They are operationalized as the number of civilian deaths[10] through the UCDP Georeferenced Event Dataset (Sundberg & Melander 2013).[11] This source allows me to distinguish between government and rebels as the perpetrator and whether fatalities are civilians or not. Unintentional civilian deaths such as those caught in the crossfire are not counted as violence against civilians but as battle-related deaths; therefore, they are not included in the operationalization.

UCDP Geo-Referenced Event Dataset (Sundberg & Melander 2013) is the only cross-sectional violent events dataset available for the time frame of this study. Although UCDP puts efforts to reduce biases and measurement error, especially compared to other event datasets (Eck 2012), it is not free from biases. Since event datasets heavily rely on media sources, reporting by country might bias results. Attacks in certain countries might be covered in more detail than others or attacks by the government (compared to rebels) might be covered in

[10] If there is more than one rebel group in a country, to create the rebel violence variables, civilians killed by all insurgent groups are summed. While increases in the number of rebel groups might increase the number of civilians killed by insurgents, it might also have other impacts on the country and civilians. To account for this, when I include the number of rebel groups into the analysis, the results are still supportive of the main arguments.

[11] Type of violence is category 3: one-sided violence.

more detail in some countries than others. The use of country-fixed effects may alleviate concerns stemming from differences between countries to a certain extent. However, readers should keep problems with violence data in mind assessing the findings.[12]

Following Moore & Shellman (2006), I control for political, economic, and geographic factors. The level of economic development is expected to impact displacement and thus, it is included in the analysis and operationalized via GDP per capita from World Bank (2018) (*GDPPC*). Democratic countries are expected to generate fewer displaced people and the level of democracy is measured via *V-Dem Polyarchy* (Coppedge et al. 2019). This variable ranges from 0 to 1 and higher values denote more democratic regimes. Due to instability and unpredictability, *Regime Transition* is argued to affect displacement (Moore & Shellman 2007, Melander, Oberg & Hall 2009) and to operationalize this variable, following Moore & Shellman (2007) and Melander, Oberg & Hall (2009), the Polity score from the Polity IV dataset is used (Marshall, Gurr & Jaggers 2018). Values of −66 (interruption period), −77 (interregnum period), and −88 (transition period) are coded as 1, 0 otherwise. Whether the source country is in war with another country affects people's decision to flee (Schmeidl 1997). Therefore, *Interstate War* as a binary variable is included in the analysis (Gleditsch et al. 2002). To account for conflict characteristics, I control for whether the conflict is internationalized (*Internationalization*), whether the incompatibility type is territory or government (*Territory Incompatibility*), and conflict intensity (*Battle Deaths*). While the first two variables are binary and operationalized through UCDP/PRIO Armed Conflict Dataset (Gleditsch

[12] Depending on measurement error in conflict and displacement data, the estimates would be biased. Underestimation in displacement data might be more severe than in conflict data because, in the collection of conflict events, UCDP follows a thorough approach, uses multiple resources, and tries to minimize errors (Eck 2012, Sundberg & Melander 2013). If this is the case, the estimates of this study would be a lower bound.

et al. 2002), the latter is the sum of battle deaths via UCDP Battle-Related Deaths Dataset best estimate (Pettersson & Eck 2018). Conflict intensity might also be an indicator of destruction as the more intense the fighting, the more will be destroyed. The destruction in the home country negatively affects social and economic life. Therefore, it is likely to affect the cost-benefit analysis in favor of fleeing. Additionally, whether the conflict/attacks happening close to the border is likely to have an effect on migration decisions. If the conflict is close to the border, it might be easier to migrate to another country. To account for this, I create a variable (*Border Conflict*) that denotes the percentage of PRIO-GRIDs that are on the border/include border within the grid (Tollefsen, Strand & Buhaug 2012).

The neighborhood of countries plays an important role in people's decision to flee abroad or displace within the country. Therefore, first, I control for the number of neighbors as the higher the number of surrounding countries, the more alternatives to flee (*N Neighbors*). Following Weidmann, Kuse & Gleditsch (2010), countries within a minimum distance of 500 km are defined as neighbors, and data is extracted from the CShapes Dataset (Weidmann, Kuse & Gleditsch 2010). To account for how democratic, in other words attractive, surrounding countries are, I use $\mathbf{w}_i Polity$ from Turkoglu & Chadefaux (2019). This variable can be understood as how democratic the location of the source country is.[13] The more democracies surrounding the country, the more people flee externally. Similarly, countries that support rebels, countries that share ethnic ties with the source, and countries that are in a rivalry with the origin are likely to be more welcoming towards refugees (Moorthy & Brathwaite 2019, Rüegger &

[13]Turkoglu & Chadefaux (2019) offers $\mathbf{w}_i GDPPC$ as well, but these two variables are highly correlated and thus, only one variable should be included into the analysis. Using $\mathbf{w}_i GDPPC$ does not affect the results. As a robustness check, I also use Moore & Shellman (2006) operationalization for the neighborhood: mean of democracy, GDPPC, and civil conflict in neighboring countries. The results still support the main argument.

Bohnet 2018). To account for these, I create three variables that denotes the percentage of neighboring states that share ties with the ethnic group fighting against the government (*Neighbor Ethnic*), the percentage of rival neighboring countries (*Neighbor Rivalry*), and the percentage of neighboring states that support insurgents (*Neighbor Support*).[14] For example, if a country has four neighbors and two of them support insurgents, the *Neighbor Support* variable is coded as 0.5. The source for ethnic relations is Transborder Ethnic Kin Dataset (Vogt et al. 2015), Non-State Actor Dataset for support (Cunningham, Gleditsch & Salehyan 2013), and Thompson & Dreyer (2011) for rivalry.[15]

Finally, to control for the potential of countries to generate displacement, I add *Population* into the analysis (World Bank 2018). To account for temporal dependencies, I include cubic polynomials of *Year in Conflict* (Carter & Signorino 2010). Summary statistics are presented in Table 3.2.

3.5 Model and Results

The unit of analysis in this paper is civil conflict country year—country$_i$ experiencing civil conflict in year t. Two different dependent variables (the number of refugees and IDPs) are used to test its arguments. Following Moore & Shellman (2006), one approach would be to use the ratio of refugees to total displacement as the dependent variable and run just one model. However, this operationalization poses challenges. First of all, it does not analyze why some countries generate more refugees and/or internal displacement than others, but it focuses on why some countries generate more refugees than IDPs. Even though it might be interesting to examine the ratio of refugees to total displacement, it is not

[14] These neighbor variables can also be considered as opportunities. If potential host countries are more likely to welcome refugees and facilitate migration (e.g., opening borders), fleeing to these countries might be easier.

[15] Since rivalry and support data are available until 2011 and this study covers years until 2017, separate models are run for these variables.

Table 3.2: Summary Statistics

Statistic	Mean	St. Dev.	Min	Max
Refugees	269,437	646,004	0	6,339,095
IDPs	289,315	767,064	0	7,410,816
V-Dem Polyarchy	0.377	0.205	0.075	0.937
GDPPC (ln)	7.033	1.362	4.631	10.994
Population (ln)	17.146	1.386	12.898	21.015
Territory Incompatibility	0.458	0.499	0	1
Internationalization	0.207	0.405	0	1
Interstate War	0.045	0.207	0	1
Regime Transition	0.123	0.329	0	1
Border Conflict	0.253	0.214	0	0.889
Neighbor Ethnic	0.059	0.134	0	1
Neighbor Rivalry	0.123	0.137	0	0.500
Neighbor Support	0.106	0.152	0	1
Neighbors	9.477	5.127	1	37
W_i Polity	56.721	31.671	−65.674	133.197
Year in Conflict	9.959	10.789	1	53
Government Violence (ln)	1.406	2.338	0	13
Rebel Violence (ln)	2.246	2.627	0	10.362
Battle Deaths (ln)	5.803	1.585	3.219	10.814

likely to capture the variation in forced migration. For example, a country with 200 refugees and 100 IDPs and another country with 2 million refugees and 1 million IDPs are treated as the same, which is troublesome to understand the magnitude of refugee and IDPs flows.[16] Furthermore, in this operationalization coding cases without displacement is problematic. Since 0 cannot be in the denominator, those cases are either coded as 0, 1, 0.5 or missing value.[17] All of these choices are problematic as they introduce bias. Additionally, if a variable

[16]Moore & Shellman (2006) uses Kosovo 1998 and 1999 as an example. The number of refugees was 0 and 857,000, the number of IDPs was 40,000 and 580,000, and the dependent variable was 0 and 0.60 in 1998 and 1999 respectively. There is a significant increase in the dependent variable in 1999, but there is a significant increase in the number of IDPs as well. Just because there is more increase in the number of refugees, it does not mean there is a decrease in the number of IDPs. This operationalization fails to capture simultaneous increases.

[17]Since the dependent variable is $\frac{Refugees}{Refugees+IDPs}$, when there is no displacement, smoothing only for IDPs (adding 1), only for refugees, for both, and for none will result in 0, 1, 0.5, and missing value, respectively.

affects both internal and external displacement in the same direction, the ratio operationalization is unable to capture this. Finally, recent research on the use of ratio variables as the dependent variable suggests that researchers should include the denominator as a control instead of using ratio as the dependent variable because ratio dependent variables cause inference problems and lead to biased estimates (Aldama & Bisbee 2021). To overcome these shortcomings and following Aldama & Bisbee (2021), I do not employ the ratio of refugees to total forced migrants as the dependent variable but separately use the number of refugees and IDPs as dependent variables.

The model of this study is defined as below:

$$\text{Refugees}_{it} = \mathbf{X}\boldsymbol{\theta} + \beta_{\mathbf{1}}\text{Government Violence}_{it} + \beta_{\mathbf{2}}\text{Rebel Violence}_{it} + \epsilon_{it}$$

where Refugees_{it} is the number of refugees from $country_i$ in year t. $\mathbf{X}$ refers to a matrix of K control variables and $\boldsymbol{\beta}$ is a vector of K coefficients to be estimated. While $\text{Government Violence}_{it}$ and $\text{Rebel Violence}_{it}$ are the main explanatory variables, $\beta_{\mathbf{1}}$ and $\beta_{\mathbf{2}}$ are their coefficients. Lastly, ϵ_{it} is the residual at country year.

Since the dependent variable is the count number of refugees, I employ negative binomial regression to estimate the model. Because the flow variables are not available, I use the stock number of refugees, which may raise serial auto-correlation concerns. To account for this, I add the lagged dependent variable into the analysis. Country and year fixed effects are included to control for unobserved heterogeneity between panels. Standard errors are clustered by country due to dependent observations within panels. Finally, to account for interdependencies between refugees and IDPs, seemingly unrelated estimation is used for corresponding models (e.g., Model 1 in Table 3.3 and Model 1 in

Table 3.4, etc.) throughout the paper.

For internal displacement, I run the same model as above, which is defined as

$$\text{IDPs}_{it} = \mathbf{X}\boldsymbol{\theta} + \beta_{\mathbf{1}}\text{Government Violence}_{it} + \beta_{\mathbf{2}}\text{Rebel Violence}_{it} + \epsilon_{it}$$

where IDPs_{it} is the number of IDPs from $country_i$ in year t. The rest is the same as above. Since the dependent variable is the count number of IDPs with excessive 0s, I use Zero-Inflated Negative Binomial Regression to estimate the model. Similar to the previous model, the lagged dependent variable is included in the analysis and standard errors are clustered by country.[18] Finally, since people can migrate abroad or within their country, I include the number of IDPs to the model for when the dependent variable is the number of refugees and the number of refugees to the model for when the dependent variable is the number of IDPs.

Here, I run the analysis to test the arguments about violence perpetrator and their effect on displacement. In the next section, I incorporate the spread of violence into analysis and test the geography argument. The results when the dependent variable is the number of refugees are reported in Table 3.3.[19] Control variables are incrementally added. First, democracy, GDP per capita, population, and time polynomials are included, which can be called as basic controls. Then, the model is run with all controls except for the battle deaths variable. Finally, conflict intensity is added to the analysis. Since neighbor

[18]Due to the excessive number of 0s, when I include country and year fixed effects to Zero-Inflated Negative Binomial Regression and Negative Binomial Regression estimations, the matrix could not converge. Even though OLS is not the right estimation technique for this model, as a robustness check, by adding time and country fixed effects, I run the model and results are still supportive of the main argument.

[19]Here, I use the stock number of refugees and IDPs as dependent variables and include the lagged dependent variable into the analysis. When I use the flow number (the difference between consecutive years and 0 if the difference is negative), the results are very similar and supportive of the main arguments.

rivalry and support variables are only available until 2011, separate models are run for them.

When the dependent variable is the number of refugees, government violence has a positive and significant effect. This variable reaches to the conventional 0.05 significance level when all control variables other than battle deaths are added. After the inclusion of conflict intensity, the government violence variable is still significant at 0.1 level in Model 4 and at 0.05 level in Model 5 and has an increasing effect. As expected, increases in violence by the government increase the number of refugees. In other words, the more people are killed by the government, the more people cross an international border. The rebel violence variable is also significantly and positively correlated with the number of refugees. However, after the inclusion of conflict intensity, rebel violence loses its significance. Although rebel violence seems to increase the number of refugees, it is difficult to conclude a robust significant impact. Interpretation of substantive effect in count models is challenging and to make it easier, I compute the change in the predicted values by setting all binary variables to 0 and continuous variables to their mean. One standard deviation increase in government violence increases the number of refugees by 39,068 and one standard deviation increase in rebel violence results in 25,099 more refugees.

The results when the dependent variable is the number of IDPs are reported in Table 3.4. Government violence does not have a significant correlation with the number of IDPs, whereas rebel violence is positively and significantly correlated with the number of people who flee within the country. In other words, the government violence variable does not have explanatory power over internal displacement and the more civilians are killed by rebels, the more people displace within the country. Similar to the previous analysis, to make the substantive effect interpretation easier, I compute the change in predicted values.

Table 3.3: Negative Binomial Regression of the Yearly Number of Refugees in Civil Conflict Countries

	(1)	(2)	(3)	(4)	(5)
Government Violence (ln)	0.059**	0.060**	0.070**	0.044†	0.059**
	(0.019)	(0.020)	(0.021)	(0.023)	(0.022)
Rebel Violence (ln)	0.063*	0.054*	0.054†	0.025	0.035
	(0.027)	(0.027)	(0.029)	(0.023)	(0.028)
V-Dem Polyarchy	0.446	0.496	0.521	0.442	0.383
	(0.842)	(0.987)	(1.110)	(0.960)	(1.109)
GDPPC (ln)	0.121	0.107	0.345*	0.085	0.321*
	(0.154)	(0.158)	(0.159)	(0.152)	(0.158)
Population (ln)	-1.082	-1.327	-1.438	-1.339	-1.350
	(0.999)	(0.931)	(1.219)	(0.874)	(1.194)
Refugees_{t-1} (ln)	0.324**	0.312**	0.275**	0.314**	0.277**
	(0.058)	(0.058)	(0.063)	(0.057)	(0.062)
Year in Conflict	0.046	0.044	0.054	0.035	0.041
	(0.034)	(0.032)	(0.041)	(0.029)	(0.040)
Year in Conflict^2	-4.374*	-4.300*	-4.705	-4.017*	-4.232
	(2.171)	(2.043)	(3.481)	(1.878)	(3.455)
Year in Conflict^3	0.085*	0.084*	0.091	0.082*	0.086
	(0.039)	(0.038)	(0.072)	(0.036)	(0.072)
Territory Incompatibility		0.209	0.112	0.177	0.095
		(0.186)	(0.251)	(0.185)	(0.244)
Internationalization		0.139	0.209	0.032	0.124
		(0.118)	(0.169)	(0.126)	(0.182)
Interstate War		0.160	-0.205	0.186	-0.180
		(0.272)	(0.170)	(0.285)	(0.166)
Regime Transition		0.024	-0.160	0.007	-0.153
		(0.182)	(0.214)	(0.174)	(0.212)
Border Conflict		-4.771*	-5.536*	-3.521†	-4.495*
		(2.170)	(2.425)	(1.869)	(2.066)
Neighbor Ethnic		5.134	6.328**	5.326†	6.461**
		(3.132)	(2.455)	(2.997)	(2.474)
N neighbors		0.161*	0.191*	0.150*	0.179*
		(0.077)	(0.078)	(0.062)	(0.070)
W_i Polity		-0.004	-0.014	-0.003	-0.013
		(0.011)	(0.011)	(0.012)	(0.011)
IDPs (ln)		0.007	-0.005	0.003	-0.006
		(0.016)	(0.018)	(0.016)	(0.017)
Neighbor Rivalry			-0.892		-0.935
			(0.836)		(0.862)
Neighbor Support			0.635		0.545
			(0.399)		(0.406)
Battle Deaths (ln)				0.126**	0.086†
				(0.045)	(0.046)
Constant	-0.233	-0.247	-0.235	-0.261†	-0.242
	(0.155)	(0.157)	(0.181)	(0.158)	(0.183)
Observations	828	828	647	828	647
BIC	20161	20207	15887	20200	15888

Standard errors clustered by country in parenthesis. Country and year dummies are not reported. Models 1, 2, and 4 cover years between 1989 and 2017 while models 3 and 5 covers years between 1989 and 2011 due to data availability. Thus, the number of observations changes. † $p < 0.1$, * $p < 0.05$, ** $p < 0.01$

Table 3.4: Zero-Inflated Negative Binomial Regression of the Yearly Number of IDPs in Civil Conflict Countries

	(1)	(2)	(3)	(4)	(5)
Government Violence (ln)	0.021	0.018	0.010	0.011	0.000
	(0.034)	(0.035)	(0.022)	(0.036)	(0.024)
Rebel Violence (ln)	0.133^{**}	0.110^{**}	0.072^{**}	0.089^{**}	0.059^{**}
	(0.035)	(0.028)	(0.022)	(0.031)	(0.021)
V-Dem Polyarchy	-1.942^{*}	$-1.815^{\dagger}$	0.799	$-1.759^{\dagger}$	0.726
	(0.856)	(1.012)	(0.764)	(0.983)	(0.728)
GDPPC (ln)	$0.244^{\dagger}$	0.142	-0.152	0.108	-0.198^{*}
	(0.130)	(0.147)	(0.098)	(0.145)	(0.097)
Population (ln)	0.181	0.182	-0.043	0.167	-0.055
	(0.142)	(0.135)	(0.108)	(0.128)	(0.113)
IDPs_{t-1} (ln)	0.067^{**}	0.055^{**}	0.050^{**}	0.060^{**}	0.052^{**}
	(0.015)	(0.014)	(0.014)	(0.014)	(0.013)
Year in Conflict	-0.014	-0.025	-0.068	-0.034	-0.079
	(0.058)	(0.071)	(0.063)	(0.074)	(0.061)
Year in Conflict^2	-0.820	-0.214	-1.315	0.018	-0.768
	(3.104)	(3.730)	(3.266)	(3.834)	(3.184)
Year in Conflict^3	0.040	0.033	0.077	0.031	0.068
	(0.043)	(0.049)	(0.049)	(0.050)	(0.048)
Territory Incompatibility		-0.015	0.506^{*}	-0.103	$0.448^{\dagger}$
		(0.248)	(0.233)	(0.242)	(0.229)
Internationalization		$0.457^{\dagger}$	0.400	0.383	0.361
		(0.245)	(0.245)	(0.240)	(0.241)
Interstate War		0.030	0.418	0.017	0.440
		(0.283)	(0.292)	(0.288)	(0.285)
Regime Transition		-0.211	-0.084	-0.274	-0.136
		(0.243)	(0.195)	(0.214)	(0.184)
Border Conflict		-0.461	-1.322^{*}	-0.340	$-1.234^{\dagger}$
		(0.961)	(0.632)	(1.006)	(0.669)
Neighbor Ethnic		0.592	-1.171^{*}	0.566	-1.035^{*}
		(0.801)	(0.554)	(0.774)	(0.525)
N neighbors		-0.002	0.001	-0.001	-0.000
		(0.040)	(0.015)	(0.042)	(0.015)
W_i Polity		0.001	-0.007	0.003	-0.004
		(0.007)	(0.007)	(0.007)	(0.008)
Refugees (ln)		0.067	0.058	0.061	0.055
		(0.043)	(0.061)	(0.040)	(0.062)
Neighbor Rivalry			6.107^{**}		6.139^{**}
			(0.695)		(0.663)
Neighbor Support			0.223		0.032
			(0.850)		(0.921)
Battle Deaths (ln)				0.106	0.076
				(0.070)	(0.059)
Constant	-0.035	-0.094	-0.372^{*}	-0.106	-0.381^{*}
	(0.133)	(0.133)	(0.185)	(0.139)	(0.190)
Observations	828	828	647	828	647
BIC	8740	8780	5749	8774	5748

Standard errors clustered by country in parenthesis. Only count part is presented. Models 1, 2, and 4 cover years between 1989 and 2017 while models 3 and 5 covers years between 1989 and 2011 due to data availability. Thus, the number of observations changes. † $p < 0.1$, * $p < 0.05$, ** $p < 0.01$

One standard deviation increase in rebel violence leads to 13,978 more IDPs.

To see the robustness of statistical significance, particularly given that the government violence variable is significant at 0.1 level and rebel violence loses its significance after controlling for conflict intensity in Table 3.3, I run permutation tests (Kennedy 1995). In this analysis, the main explanatory variable is randomly distributed within observations without replacement with $1,000$ draws. In other words, the main independent variable is permuted among observations. Afterward, the model is run and the coefficient estimate is saved. Since the variable of interest is randomly distributed, it should have a null effect (similar to a placebo test). To conclude for the main explanatory variable to have a significant effect, the main estimate of this study (model 5 in Table 3.3 and 3.4) should be significantly different than placebo estimates. Results are presented in Figure 3.1. Graphs show the histogram of placebo estimates and vertical (red) dashed lines indicate the estimate of this study. In the upper panel of the figure, the dependent variable is the number of refugees and in the lower panel, it is the number of IDPs. While the left column reports the results for government violence, the right column indicates the results for the rebel violence variable.

The permutation tests are also supportive of the regression analysis and suggest that when the dependent variable is the number of refugees, both the government violence estimate and rebel violence estimate of this study are significantly different than placebo estimates.[20] When it comes to IDPs as the dependent variable, while government violence is not distinguishable from placebo estimates, rebel violence is significantly different.

In terms of control variables, the lagged dependent variable is a strong pre-

[20]The formula for computing empirical p-values is $p = \frac{1+b}{1+B}$, where B is the number of permutations and b is the number of placebo estimates that with a $\hat{\beta}$ larger in absolute value than the estimate of this study.

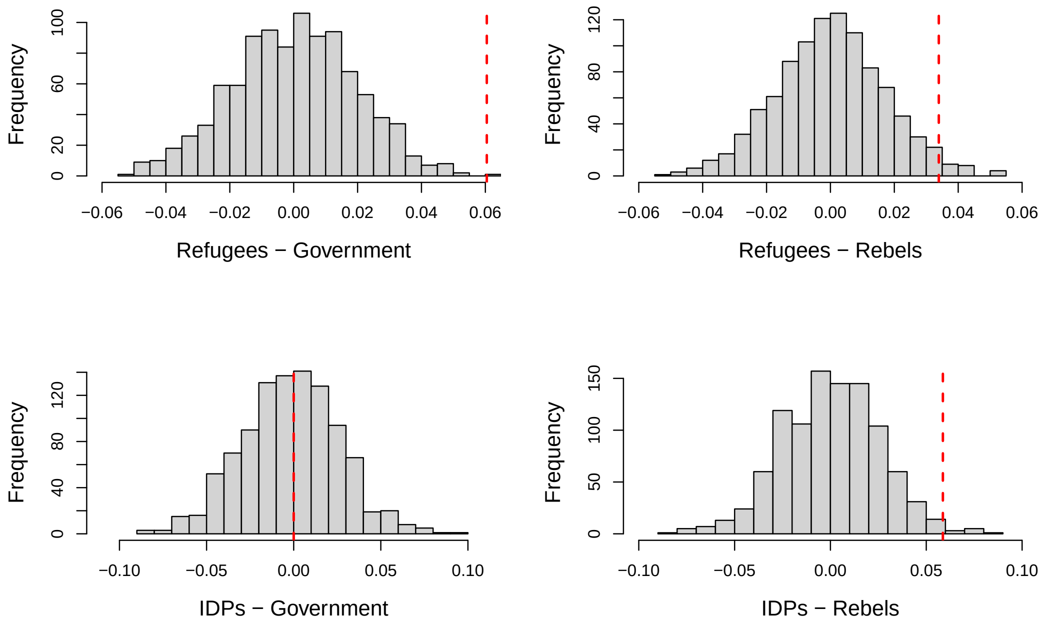


Figure 3.1: Permutation test with 1,000 draws. Model 5 in Table 3.3 (refugees as DV) and Table 3.4 (IDPs as DV) is used for computation. The graphs present histogram of placebo estimates and vertical dashed (red) lines indicate the estimates of model 5 in Table 3.3 and Table 3.4. When the dependent variable is the number of refugees, both government violence and rebel violence are significant at 0.05 level and when the dependent variable is the number of IDPs, while rebel violence is significant at 0.05 level, government violence is not statistically significant.

dictor in both analyses. In addition to rebel violence, the level of democracy and percentage of neighbors with ethnic relations variables are significantly correlated with the number of IDPs. Increases in the democracy level decrease the number of IDPs. Similarly, increases in the percentage of neighbors with ethnic ties decrease the number of IDPs as civilians are more likely to flee abroad, which is corroborated by the analysis in Table 3.3 as this variable is positively and significantly correlated with the number of refugees. Furthermore, increases in the number of neighbors result in more displacement[21] and increases in the year in

[21] In this study, for the operationalization of neighborhood characteristics, I follow Turkoglu & Chadefaux (2019) but could not find a significant effect. As a further check, adopting the operationalization of Moore & Shellman (2006), neighborhood characteristics still do not have

conflict initially lead to more refugees but after a certain point, it decreases the number of people who cross an international border. Contrary to expectations, conflicts happening on the border are negatively correlated with the number of refugees. While being close to the border may make external migration easier, it may also facilitate rebel activities which might limit migration.

Violence variables and conflict intensity are highly correlated. Therefore, the observed effect of violence variables might be based on the correlation with conflict intensity. To deal with this issue, I control for conflict intensity in the model. However, sometimes it may not be enough to alleviate concerns. Do violence variables have a direct effect or is it only mediated by conflict intensity? Therefore, I also estimate the average controlled direct effect of violence variables via the sequential g-estimation (Acharya, Blackwell & Sen 2016). This method is a two-stage regression estimation technique. First, it transforms/demediates the dependent variable by removing the effect of the mediator, and then, it estimates the effect of treatment on the demediated outcome. For statistical inference, Acharya, Blackwell & Sen (2016) suggests using bootstrapped standard errors, which I adopt in the analysis.

The sequential g-estimation analysis suggests that both government and rebel violence variables have a positive and significant direct effect on refugees and rebel violence has a significant direct effect on IDPs. The magnitude of the direct effect is closer to the estimate of the main analysis. Estimates might be biased if there are unmeasured confounders for the relationship between refugees/IDPs and conflict intensity. Thus, I perform sensitivity checks as suggested by Acharya, Blackwell & Sen (2016) and results indicates that to conclude a null effect of violence variables, the correlation between the number of refugees/IDPs and battle deaths should be negative, which is not very likely.[22]

explanatory power.

[22]The main shortcoming of this analysis that it only works for OLS regression. Since the

One of the underlying arguments of the theoretical explanations is the government's coercive force being able to reach everywhere within its borders. However, when rebels control territory, government access might be limited. As a robustness check, I interact government violence with rebel territory control from the Non-State Actor Dataset (Cunningham, Gleditsch & Salehyan 2013). While both government violence and rebel territory control are positively and significantly correlated with the number of refugees, the interaction term does not have explanatory power. Even though rebel territory control might restrict the government's land access, the government can still carry out attacks via airstrikes, drones, or remote-controlled weapons, which might be the main reason for non-significant results.

3.6 Geography of Violence

In the previous section, the analysis suggested that government and rebel violence variables have a significant effect on the number of refugees although the latter is not robust, and rebel violence is significantly and positively correlated with the number of IDPs whereas government violence does not have explanatory power over internal displacement. In this section, the geographic spread of violence against civilians is taken into account.

For refugees, the theoretical expectation is that the more spread the government and rebel violence, the more refugees countries generate. To measure the spread of violence, I use the UCDP Georeferenced Event Dataset (Sundberg & Melander 2013). More specifically, for each country-year, using the location of each attack by the government (rebel), I draw a circle with 10 km radius[23],

dependent variables are count variables, OLS is not the right estimation technique. Thus, the controlled direct effect analysis should be read with caution.

[23] This is an arbitrary choice and as a robustness check, I repeated the same procedures with five and 20 km radius, the results are still supportive of the main argument. I also run

sum the area of these circles[24] and divide it by the total size of the country. This operationalization aims to capture how much of the country is affected by violence rather than the number of civilian deaths. In other words, these measurements attempt at quantifying how spread violence is. There is a significant temporal and spatial variation in the spread of violence. While civilians in some countries do not experience violence (e.g., Mali in 2012), in others, violence is quite common (e.g., Burundi in 2000).[25]

Using these variables, I replicate the analysis above and the results when the dependent variable is the number of refugees are reported in Table 3.5. Across all specifications, the government violence spread variable is positively and significantly correlated with the number of refugees. Increases in government violence result in more external displacement. Similar to the previous analysis, the rebel violence spread variable is significant until the inclusion of conflict intensity.[26] In terms of substantive effect, setting all binary variables to 0 and continuous variables to their mean, one standard deviation increase in government violence spread leads to 26,880 more refugees and one standard deviation increase in rebel violence spread results in 30,556 more refugees.

I adopt the same operationalization for the number of IDPs as the dependent variable. However, since the effect of rebel violence spread on IDPs is expected to be a reverse U-shape, I add the squared term of rebel violence spread variable into the analysis and replicate Table 3.4.[27] The results are reported in

further checks below.

[24] Overlaps are also taken into account.

[25] The mean for government and rebel violence spread is 0.7 and 1.2 and 95th percentiles are 4.1 and 6.6 respectively. The Median for both values is 0, which means at least half of country-year observations did not experience violence. Since for each attack, a circle with 10 km radius is drawn, these values are not high. With other operationalizations below (percentage of administrative units and percentage of population experienced attacks), the values are much higher.

[26] Conflict intensity is also measured in the same way violence variables are measured (i.e., 10 km radius circles).

[27] I also present a model without the squared term to show how its inclusion affects the results.

Table 3.5: Negative Binomial Regression of the Yearly Number of Refugees in Civil Conflict Countries with Spread of Violence within 10 km Radius of Attacks

	(1)	(2)	(3)	(4)	(5)
Government Violence Reach	0.019**	0.021**	0.021**	0.020**	0.021*
	(0.006)	(0.006)	(0.007)	(0.008)	(0.009)
Rebel Violence Reach	0.043*	0.040*	0.035*	0.020	0.013
	(0.017)	(0.018)	(0.017)	(0.023)	(0.022)
Observations	828	828	647	828	647
BIC	20165	20208	15891	20212	15893

Replication of models in Table 3.3. Control variables and country and year dummies are not reported. Standard errors clustered by country in parenthesis. For the main explanatory variables, instead of the number of civilian casualties, the spread of violence is used. More specifically, using the location of each attack as the center, circles are drawn with 10 km radius and the total area of these circles in country-year is divided by country size. Models 1, 2, and 4 cover years between 1989 and 2017 while models 3 and 5 covers years between 1989 and 2011 due to data availability. Thus, the number of observations changes. † $p < 0.1$, * $p < 0.05$, ** $p < 0.01$

Table 3.6. As expected, government violence spread does not have explanatory power over internal displacement in general. In model 4 and 6, this variable reaches to the 0.05 significance level, which might stem from limited temporal coverage. When it comes to rebel violence spread, without the squared term, it is not statistically significant. After the inclusion of the squared term, both are significantly correlated with the number of IDPs and the results are suggestive of a reverse U-shape effect. To make the substantive effect interpretation easier, I compute the predicted values of IDPs over the rebel violence spread variable[28] by setting binary variables to 0 and continuous variables to their mean. The results are plotted in the left panel of Figure 3.2 and suggest that increases in rebel violence initially leads to increases in the number of IDPs but after a certain point it starts to decrease as it may not be easy to escape rebel violence when it is widespread. Instead, civilians might cross an international border or the death toll might be high and there are fewer people to migrate.

A common challenge in spatial analysis is the accuracy of the information,

[28] Since this variable ranges from 0 to 31, I use these values as bounds to prevent extrapolation.

Table 3.6: Zero-Inflated Negative Binomial Regression of the Yearly Number of IDPs in Civil Conflict Countries with Spread of Violence within 10 km Radius of Attacks

	(1)	(2)	(3)	(4)	(5)	(6)
Government Violence Spread	0.004	0.004	0.005	0.018*	0.006	0.020*
	(0.007)	(0.007)	(0.009)	(0.008)	(0.009)	(0.010)
Rebel Violence Spread	0.008	0.167**	0.150**	0.122**	0.120**	0.095**
	(0.027)	(0.060)	(0.052)	(0.033)	(0.046)	(0.036)
Rebel Violence Spread^2		-0.008**	-0.007**	-0.005**	-0.006**	-0.004**
		(0.002)	(0.002)	(0.001)	(0.002)	(0.001)
Observations	828	828	828	647	828	647
BIC	8790	8787	8814	5764	8819	5768

Models 2-6 are replication of models in Table 3.4. Model 1 is replication of model 1 in Table 3.4 without the squared term of rebel violence variable. Only count part is presented. Standard errors clustered by country in parenthesis. Control variables are not reported. For the main explanatory variables, instead of the number of civilian casualties, the spread of violence is used. More specifically, using the location of each attack as the center, circles are drawn with 10 km radius and the total area of these circles in country-year is divided by country size. Models 1, 2, 3, and 5 cover years between 1989 and 2017 while models 4 and 6 covers years between 1989 and 2011 due to data availability. Thus, the number of observations changes. † $p < 0.1$, * $p < 0.05$, ** $p < 0.01$

especially for countries experiencing civil conflict and political instability. Sometimes information might refer to administrative units rather than a specific exact location. Furthermore, in the previous analysis, I used a 10 km radius to calculate the area affected by government or rebel violence. Given the problems with the accuracy of location information, there might be concerns about this operationalization, although I used five and 20 km radius as robustness checks. In addition, sometimes attacks may target certain localities such as cities rather than exact locations, and people might be affected by attacks in their city even though the attack happened far away from their house. To alleviate relevant concerns, I adopt another operationalization in which I use the percentage of first-level administrative units[29] that experienced at least one attack per country-year to measure the spread of violence.[30] This operational-

[29] I could not use second-level administrative units because for more than 20% of events, this information was missing. Whereas for first-level administrative units, the ratio of missing observations is around 4%.

[30] For this operationalization, the mean for government and rebel violence spread is 7.9 and 12.7 and 95th percentiles are 45.5 and 64.7 respectively.

Table 3.7: Negative Binomial Regression of the Yearly Number of Refugees in Civil Conflict Countries with the Percentage of Population Experienced Attacks

	(1)	(2)	(3)	(4)	(5)
Gov. Violence Affected Pop.	0.007*	0.007*	0.009*	0.005	0.006
	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)
Rebel Violence Affected Pop.	0.008*	0.007†	0.006†	0.001	0.002
	(0.003)	(0.004)	(0.004)	(0.005)	(0.004)
Observations	828	828	647	828	647
BIC	20164	20209	15890	20202	15889

Replication of models in Table 3.3. Control variables and country and year dummies are not reported. Standard errors clustered by country in parenthesis. For the main explanatory variables, instead of the number of civilian casualties, the spread of violence is used, more specifically, the percentage of civilians that experienced an attack in country-year. Models 1, 2, and 4 cover years between 1989 and 2017 while models 3 and 5 covers years between 1989 and 2011 due to data availability. Thus, the number of observations changes. † $p < 0.1$, * $p < 0.05$, ** $p < 0.01$

ization aims at measuring violence spread in coarse ways to alleviate biases that may stem from the attacks dataset. The results support the main arguments.

Here, I measure the spread of violence in spatial/geographic terms. In general, the geographic spread is likely to be highly correlated with the number of affected people by violence. However, some attacks might happen in more isolated areas than others, which might lead to variation in the number of affected people. To alleviate relevant concerns, I adopt another operationalization to capture the percentage of affected people. More specifically, I use PRIO-GRID (Tollefsen, Strand & Buhaug 2012) and sum the population of grids that experienced at least one attack in country-year and divide it by the total population of the country. This measurement gives us an idea about how much of the population is affected by violent events. In other words, this operationalization aims at measuring spread of violence in terms of affected population rather than its geographical spread.[31] I replicate the analysis in Table 3.5 and 3.6.

The results with affected population when the dependent variable is the number of refugees are reported in Table 3.7. This analysis is also supportive of

[31] For this operationalization, the mean for government and rebel violence spread is 5.0 and 8.1 and 95th percentiles are 31.2 and 47.9 respectively.

Table 3.8: Zero-Inflated Negative Binomial Regression of the Yearly Number of IDPs in Civil Conflict Countries with the Percentage of Population Experienced Attacks

	(1)	(2)	(3)	(4)	(5)	(6)
Gov. Violence Affected Pop.	0.001	0.006	0.004	0.006	0.004	0.005
	(0.006)	(0.006)	(0.005)	(0.004)	(0.005)	(0.004)
Rebel Violence Affected Pop.	0.009	0.036^{**}	0.023^{*}	0.017^{*}	0.027^{**}	0.005
	(0.006)	(0.013)	(0.010)	(0.007)	(0.010)	(0.009)
Rebel V. Affected Pop.^{2}		-0.000^{**}	-0.000^{**}	$-0.000^{\dagger}$	-0.000^{**}	-0.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	828	828	828	647	828	647
BIC	8784	8771	8810	5757	8815	5760

Models 2-6 are replication of models in Table 3.4. Model 1 is replication of model 1 in Table 3.4 without the squared term of rebel violence variable. Only count part is presented. Standard errors clustered by country in parenthesis. Control variables are not reported. For the main explanatory variables, instead of the number of civilian casualties, the spread of violence is used, more specifically, the percentage of civilians that experienced an attack in country-year. Models 1, 2, 3, and 5 cover years between 1989 and 2017 while models 4 and 6 covers years between 1989 and 2011 due to data availability. Thus, the number of observations changes. † $p < 0.1$, * $p < 0.05$, ** $p < 0.01$

the main argument and the more spread government violence, the more refugees countries generate. Until the inclusion of the conflict intensity variable, both violence variables are statistically significant. In terms of substantive effect, one standard deviation increase in percentage of population affected by government violence results in 34,000 increase in the predicted number of refugees, and one standard deviation increase in the percentage of population affected by rebel violence leads to 11,972 increase in the predicted dependent variable.

The results when the dependent variable is the number of IDPs are reported in Table 3.8. Similar to previous analyses, government violence does not have explanatory power over internal displacement. Rebel violence spread is positively and its squared term is negatively correlated with the number of IDPs.[32] As expected, the effect of rebel violence is reverse U-shaped. Again, to make the substantive effect interpretation easier, I plot the predicted values of the dependent variable over the percentage of affected population by rebel violence

[32] Only in the final model, they lose their statistical significance which might stem from limited temporal coverage.

in Figure 3.2. Initially, rebel violence has an increasing effect on internal displacement. However, after around 40% of population experience at least one attack by insurgent groups, the effect starts to decrease. Instead of moving within the country, people are more likely to cross an international border.

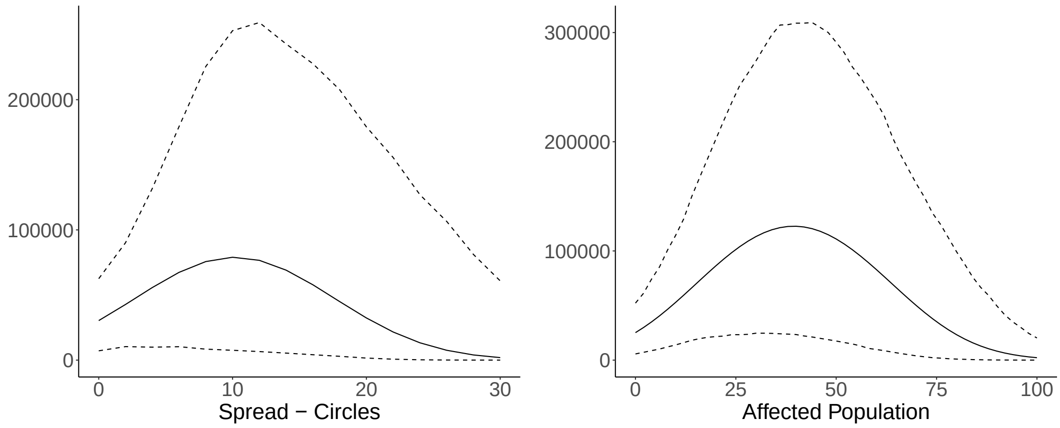


Figure 3.2: Predicted number of IDPs by operationalization. The first figure responds to Table 3.6 and the second one to Table 3.8. Dashed lines denote 95% confidence intervals obtained by bootstrapping with 1,000 draws.

3.7 Conclusion

This study set out to analyze distinct causes of refugee and IDPs flows in civil conflict countries. Even though in general, the same factors affect both internal and external displacement, depending on the perpetrator and its spread, the effect of violence varies. While government violence increases the number of refugees, rebel violence results in more internal and external displacement although the effect of rebel violence on refugees is not very robust. By fleeing the conflict zone, people can escape rebel violence. However, the government's coercive force can generally reach everywhere within its borders and to escape government violence people may have to flee to another country. But if rebel violence is widespread, leaving the conflict zone might not be enough to escape persecution. Therefore, to explain variation in forced migration, where armed groups perpetrate violence should be taken into account in addition to who the perpetrator is. While increases in government and rebel violence lead to increases in the number of refugees, the effect of rebel violence on internal displacement follows a reverse U-shape.

To test its argument, this paper examines refugee and IDPs flows between 1989 and 2017. The results corroborate the main arguments. One standard deviation increase in government violence increases the number of refugees by around 39 thousand and one standard deviation increase in rebel violence results in around 25 thousand more refugees. Since conflict intensity and violence variables are highly correlated, it may not be easy to disentangle variables' direct effect. This is why I estimate the controlled direct effect via sequential g-estimation and these estimates are close to the estimates of the regression analysis and corroborate the main results.

Previous research on the causes of refugee flows has suggested that genocidal violence by state increases the number of refugees (Moore & Shellman 2007). Additionally, in a very compelling theoretical contribution, Steele (2019) has argued that while government violence increases external displacement, rebel violence increases internal displacement. However, these arguments have not been tested. This paper complements Moore & Shellman (2007) and Steele (2019). While the theoretical argument of this study is similar to existing research, it contributes to the literature by incorporating the role of the geography of violence and how spread it is. Furthermore, in terms of refugee flows, while Steele (2019) mainly emphasizes the role of government violence, this study underscores the role of rebel violence as well.[33]

The unit of analysis in this study is country year. Thus, it exploits the variation between countries over the years. It offers useful insights for the

[33]However, the results for rebel violence are not as robust as the results for government violence.

importance of distinguishing the causes of internal and external displacement and for policy-making. However, it comes at a cost. This paper examines the individual-level preferences at the aggregate-level data, which begs the question of ecological inference. Theoretical explanations are based on utility maximization, but each individual has a different cost-benefit analysis, which this study fails to account for. In addition to further investigation of divergent causes of internal and external displacement, future research should take individual characteristics, motivation, and opportunities into account. Whether individuals have relatives abroad, whether they can speak a foreign language, whether they have enough savings to cover the costs of the initial period of displacement, and whether they experience or witness any type of violence can be a good start. Finally, findings of this study are correlational and future studies could focus on offering causal estimates.

4 When to Go? - A Conjoint Experiment on Social Networks, Violence and Forced Migration Decisions in Eastern and South-eastern Turkey[1]

Abstract

How do heterogeneous patterns of violence affect people's decision to flee? Previous research generally examines how the scale of violence affects forced migration at the national or sub-national level. We provide individual-level evidence on flight decisions in light of violence with a conjoint experiment in Turkey. The results suggest that intense indiscriminate violence nearby forces individuals into the decision to leave. In contrast to previous studies, we find that persistent violent threats play a more important role in flight decisions than the frequency of attacks. The experiment reveals that violence committed by the government makes a decision to flee abroad more likely than rebel violence and that individuals with support networks abroad are less responsive to patterns of violence, making flight decisions under less pressure than

[1]This chapter is co-authored with Sigrid Weber, a PhD student at University College London.

individuals without available coping mechanisms elsewhere. Our findings contribute to the growing literature on forced migration with individual-level evidence on flight reactions to violence.

4.1 Introduction

Understanding how individuals decide to flee from armed conflict and how this translates into flight patterns is a central endeavor in forced migration research to anticipate movements and emerging humanitarian needs. However, our understanding of the individual-level decision-making process leading to flights is limited as many studies identify predictors of refugee flows at the aggregated global, national, or sub-national level (Davenport, Moore & Poe 2003, Moore & Shellman 2004, Melander, Oberg & Hall 2009, Schmeidl 1997) and do not disaggregate violence that varies substantially across contexts. For a better understanding of flight patterns, we should understand violence as a heterogeneous cause for forced migration and investigate when and what kind of violence drives individuals' decision to flee and choose their destination.

This study focuses on individual-level decisions to flee and choose destinations within the country or abroad. First, drawing on aggregated studies of flight patterns and testing them on the micro-level, we argue that the type of violence in a country matters to understand if individuals leave their homes and risk the notoriously dangerous journey of people on the move (UNHCR 2018*a*). The decision to flee is not made lightly but depends on the patterns of violence that individuals observe such as the intensity and proximity of violence but also the perpetrator and type (i.e., discriminate and indiscriminate).

Second, we argue that social networks to other communities abroad—as a proxy for how well individuals can cope with violence —affect decisions to flee. Social networks explain variation in how individuals respond to the diverse treatment of violence in line with existing studies that have already emphasized the role of social networks in shaping migration decisions (Moore & Shellman 2007, Rüegger & Bohnet 2018). Compared to individuals that do not have outside options to easily move away, those with social networks abroad focus less on the observed patterns of violence to make their decision to flee as social networks reduce the costs of fleeing, which provides higher flexibility and mobility.

In order to understand the heterogeneous effect of different types of violence on flight decisions in an experimental setting, we conducted a conjoint experiment in the Eastern and Southeastern parts of Turkey that have experienced fighting for decades. We asked respondents to evaluate information about violent scenarios and to hypothetically choose in which scenario they would rather flee than stay and where they would go. We also examine how respondents' social networks affect their response to violence and their choice between fleeing abroad or within the country.

We find that civilians respond more strongly to nearby violence than to distant ones. Civilians also show more fear for indiscriminate violence and flee from it compared to targeted attacks. The results highlight the significance of persistent threats rather than the frequency of violence in migration decisions. While there is no significant difference in the effect of attacks happening frequently or sometimes, they are significantly different than first-time attacks and increase the probability of flight decisions. This finding is more nuanced than the existing literature that emphasizes on battle deaths or the number of violent events (Balcells & Steele 2016, Davenport, Moore & Poe 2003, Turkoglu & Chadefaux 2019). Importantly, the perpetrator of violence affects the location to which people flee. In line with Steele (2019), we find that government violence leads to flights abroad while rebel violence leads to relocation within the country. This is likely to stem from the fact that a government cannot easily be contained by the weaker non-state opposition and civilians may only feel safe abroad while exposure to rebel violence can be mitigated by moving to areas with less conflict activity.

Regarding the question of whether individuals with strong social networks respond differently to violence and make different flight decisions, we find that survey respondents with networks abroad are less responsive to different patterns of violence in their decision to flee abroad than those with no support network elsewhere. Given that individuals with support networks tend to be more inclined towards mobility in our sample, this provides a first indication that flight is not a very last resort to individuals with outside options. They make decisions to move in light of violence under less pressure and urgency.

This study makes important contributions to the literature. First, it complements existing macro-level analyses of flight patterns. The use of a conjoint experiment to study flight decisions is novel and generates new individual-level evidence. While previous studies generally analyze country-level determinants of displacement (Davenport, Moore & Poe 2003, Moore & Shellman 2004, Melander, Oberg & Hall 2009, Schmeidl 1997), our research sheds light on the individual decision-making process and overcomes the problem of ecological inference. There is a limited number of studies that examine the predictors of displacement at the individual-level using survey data and comparing people who fled and those who stayed (Adhikari 2013, Bohra-Mishra & Massey 2011). Although these studies have immensely improved our understanding of the predictors of forced migration, since people who fled and those who stayed are likely to be different on many levels, comparing these two groups may have limitations in explaining causal impacts. Our innovative approach offers experimental evidence and overcomes limitations past studies suffer.

Second, previous research has generally examined the effect of violence on flight decisions with a focus on conflict intensity and the scale of violence (Adhikari 2013, Moore & Shellman 2004, Melander, Oberg & Hall 2009, Turkoglu & Chadefaux 2019). However, violence is a heterogeneous phenomenon, and depending on the type of violence experienced, individuals may respond differently to this treatment. Individuals may not just respond to the intensity of violence but also to other aspects (e.g., type and perpetrator). This study complements the literature by disentangling which features of violence lead to the decision to flee in an experimental setting.

Third, by exploring how social networks affect flight decisions, this study contributes to the research on civilian resilience during conflicts. Previous studies have examined how social networks in the origin affect flight decisions by enabling better coping mechanisms with the problems at the hometown (Marston Jr 2020) and this research complements the literature by analyzing how social networks abroad have an impact on flight patterns. Individuals cope more easily with violence and unrest if they have support networks. This finding suggests the need to support social networks within and to conflict-prone societies to lift the burden of high-stake decision-making and to broaden the scope of action for populations suffering during conflicts.

4.2 When and Where to Go: Flight Decisions during Conflict and Violence

Research on forced migration tries to understand where people flee to during armed conflicts (Giménez-Gómez, Walle & Zergawu 2019, Kunz 1973, Moore & Shellman 2006, Steele 2019, Turkoglu & Chadefaux 2019, Weiner 1996). This growing literature predominantly conducts country-level studies to understand global forced migration patterns, finding that refugees move towards countries with lenient immigration policies (McAuliffe & Jayasuriya 2016). In addition, geographical proximity, ethnic linkages (Rüegger & Bohnet 2018), pre-existing migrant communities (Neumayer 2004), and colonial ties (Moore & Shellman 2007) explain how refugees choose their destinations when armed conflict forces them to leave.

While these country-level studies identify predictors of global refugee patterns, the question remains unanswered *when* and *why* individuals flee in the first place. The main reasons why households flee during political unrest is violence (Davenport, Moore & Poe 2003, Melander, Oberg & Hall 2009, Moore & Shellman 2004, Schmeidl 1997). Nevertheless, we empirically observe that most civilians choose to stay in their homes amidst fighting (Ceriani & Verme 2018). What are the determinants of individual decision-making to flee? How do we explain variation in whether people leave or not; and does any type of violence lead to refugee and IDP movements?

From anecdotal evidence, popular accounts, qualitative studies, and reports by refugee rights organizations two pictures emerge: individuals either abruptly flee after immediate threats to their families' lives or they make the decision to flee after having experienced long and extreme periods of violence (Pearlman 2017, We Refugees Archive 2020). For example, interviews with displaced persons in Mexico and El Salvador indicate that incidents with immediate or imminent risk were catalysts for people to leave their homes when faced with criminal gang violence (Knox 2017). In other situations, such as in the Karen State in Myanmar, civilians go into hiding from being attacked, trying to return to their fields and villages when troops return to their military base, until the constant disruption to their food supplies and the burning of their homes makes staying in their homeland untenable (Eubank 2008). Given this variation in how civilians eventually decide to leave or stay, the first aim of this study is to systematically analyze how heterogeneous patterns of violence affect individuals' decision to leave or not, complementing already existing qualitative accounts and cross-national studies.

The second aim of this study is to analyze how the existence of social networks and bonds changes the decision-making process of individuals and their response to violence. Do individuals with social networks move more easily or do they tend to stay on for longer? Adhikari (2013) shows that violence, economic opportunity, physical infrastructure, and social networks at the origin have an impact on the decision to flee or stay at home. The role of networks is also examined in other observational studies on forced migration decisions such as Engel & Ibáñez (2007)'s study in Colombia.

Interviews with Syrians in Turkey reveal that a combination of motivation (e.g., witnessing violence early on in the conflict) and opportunity (e.g., money, and connections to flee) explain earlier exit from Syria during the civil war (Schon 2019). Using individual-level administrative data for adult refugees resettled in the US between 2000 and 2014, Mossaad, Ferwerda, Lawrence, Weinstein & Hainmueller (2020) show that refugees prioritize locations with existing networks of co-nationals for secondary migration. However, neither Adhikari (2013)'s nor Schon (2019)'s research can precisely explain when motivations are high enough for civilians to leave their well-known environment. Mossaad et al. (2020) only focus on secondary movement patterns and not on the initial choice to leave home. The role of social networks in individuals' calculations to stay or flee during violence still requires additional research.

Beyond the observed pattern of violence—pushing people to leave their homes—and the networks they can turn to for help, many other factors determine a household's decision to flee. Holland & Peters (2020) show that civilians gather information on the migration environment first; Ceriani & Verme (2018) argue that risk preferences in individuals explain flight decisions; Epstein & Gang (2006) focus on herd behavior of humans; and the financial ability to flee may also play a role (Schon 2019). While the decision to flee is complex and many more factors should be considered, this research focuses on social support networks and facets of violence.

4.3 Violence and Social Networks: Understanding the Decision to Flee during Conflict

Violence is a heterogeneous phenomenon that varies across conflicts (e.g., targeting—discriminate and indiscriminate—and perpetrator— government and rebels). We argue that the different patterns of violence affect the rational decision-making process of individuals to flee, that is their choice when to leave and whether to flee within their country or abroad. Because individuals consider the risks involved in staying or leaving, civilians are more likely to flee if violence occurs repeatedly and intensifies, when violence is closer to their homes, and when violence is indiscriminate rather than targeted. We also argue that the perpetrator of violence affects flight decisions, making flight abroad more likely when governments commit attacks and internal relocation more likely when rebel groups perpetrate violence (Steele 2019). However, when civilians have a stronger support network in the form of family or friends elsewhere that can host them after their flight, this outside option reduces civilians' responsiveness to different features of violence. The decision to move becomes less dependent on the urgency to flee violence. The following sections summarize our pre-registered hypotheses on individuals' flight decision in light of violence and their embeddedness in social networks.

4.3.1 Hypotheses on flight decisions and patterns of violence

The decision to flee is made under high uncertainty: individuals have to judge whether the *utility of staying* is higher or lower than the *utility of leaving*. Violence in their place of residence increases the risk associated with staying. The risk of leaving includes the probability of experiencing harm during the dangerous journey ahead of individuals as well as in the chosen displacement location. Additionally, adjusting to life in a new destination imposes costs (e.g., learning a new language and finding a job). Civilians are more likely to flee if they believe the violence surrounding them is more likely to harm them or their family members than the violence they could experience during the flight or in displacement.

Consequently, a decision to flee is hence more dominant if attacks intensify and happen regularly. Because individuals feel increasingly threatened, the intensity and frequency of violence increase their likelihood to flee (Balcells & Steele 2016, Davenport, Moore & Poe 2003, Melander, Oberg & Hall 2009, Turkoglu & Chadefaux 2019). Similarly, civilians are more likely to flee if violence has reached their immediate surroundings rather than if violence is taking place in other regions of the country(Melander, Oberg & Hall 2009). Furthermore, armed actors can attack civilians indiscriminately (e.g., airstrikes and shelling), or they can target specific groups and disloyal civilians. Seemingly random and indiscriminate violence increases the risks of staying and makes fleeing a more favorable strategy (Fabbe, Hazlett & Sinmazdemir 2017). In the case of targeted violence by rebels or the government, individuals have the option to actively cooperate with the armed actor conducting attacks, to share local information, and to comply with the rules of armed actors to minimize the risk of harm when staying at home. However, indiscriminate attacks make this coping mechanism less successful and hence increases the perceived risk of staying.

Hypothesis 1 *Civilians are more likely to flee if violence occurs repeatedly and intensifies compared to the first occurrences of violence.*

Hypothesis 2 *Civilians are more likely to flee if violence occurs in their areas rather than in distant areas of their country.*

Hypothesis 3 *Civilians are more likely to flee if hit by indiscriminate violence rather than by targeted attacks.*

While these hypotheses seem intuitive, it is important to study forced migration decisions at the individual-level to inform already existing research on the link between violence and displacement that conventionally focuses on aggregated observational studies. Additionally, it is important to disentangle and reconfirm which features of violence actually drive individuals' threat perceptions.

Additionally, the perpetrator of violence may affect *if* and *where* civilians seek shelter. In a conceptual contribution to the discipline, Steele (2019) argues that displaced civilians consider which actors perpetrate violence and choose a safe destination depending on where the perpetrator has the capacity to strike again. Accordingly, civilians are more likely to try crossing international borders if the state conducts attacks because the government's coercive power is not likely to reach civilians on the soils of another country. In contrast, non-state actors as perpetrators of civilian victimization are more likely to be constrained by the state, making it more feasible for non-combatants to stay within national borders and to only relocate to a location with less conflict activity. This theoretical argument shows that the perpetrator of violence may play an important role in an individual's decision to flee abroad or within the country, but the argument has not yet been tested with individual-level evidence. Overall, the perpetrator of violence affects civilian's decision to flee. This particularly manifests itself in the choices of destinations.

Hypothesis 4 *The perpetrator of violence has an impact on civilians' likelihood to flee.*

The following expectations are tested to assess this hypothesis:

Expectation 4a: If civilians flee, they are are more likely to move abroad when faced with violence perpetrated by the government.

Expectation 4b: If civilians flee, they are more likely to move internally when faced with violence perpetrated by non-state actors.

4.3.2 Hypothesis on flight decisions and social networks

In times of crisis, some individuals and communities are more resilient than others. In other words, they are able to deal with unexpected events and to achieve positive outcomes even under adverse conditions (Fraser, Galinsky & Richman 1999). An important factor that increases individual resilience are social networks. Living near family members and friends or being part of a tight group provides location-specific social capital that cannot easily be transferred from one place to another (De Jong & Gardner 1981). Marston Jr (2020) for example shows that 'well-connected' residents in Colombia are more likely to remain despite being at risk of displacement from military gangs because they can leverage ties to a community figure or members of the armed group to stay.

We focus on social networks outside of the community in the decision of individuals to relocate. Compared to an individual that has no ties to other communities inside or outside the country, individuals with wide social networks have an increased ability to cope with violence because moving is a feasible outside option. More specifically, social networks in different locations are a sign of resilience as they reduce the risk and costs associated with fleeing.

Multiple observational studies suggest that social networks make it easier to flee and that well-connected individuals are hence over-represented in early refugee and IDP flows (Schon 2019). Nevertheless, we aim to understand this theoretical argument with new individual-level evidence and an examination with increasingly more prominent conjoint experiments.

We argue that well-connected individuals make their choice over relocating more easily. Because they are more resilient and able to find alternative coping strategies, the risk of moving elsewhere is lower, and fleeing is not their absolute last resort. Consequently, they are less likely to respond to different features of violence when choosing to stay or leave. With their higher ability to cope, they may leave earlier regardless of the intensity and proximity of violence, and regardless of the type of targeting and the perpetrator of violence. Less connected individuals are more likely to see fleeing as the last resort and flee depending on features of violence.[2]

Hypothesis 5 *Civilians with more social connections within and outside of their country respond less to violence compared to civilians with fewer connections.*

4.4 Forced Displacement Patterns in Turkey and its Neighborhood

We study decision-making on forced displacement in the context of Eastern and Southeastern Turkey, inhabited by many Kurds. Kurds in Turkey—that

[2]Due to lacking variation in our sample on networks within the country, as explained later in more detail, we can only assess whether social networks *outside* the country explain flight decisions.

make up around 18-20% of the population—have been historically excluded from power and experienced repression since the establishment of the Turkish Republic. Under the founding ideology of a single nation and language, the Kurdish language was banned, Kurdish names of towns were replaced by Turkish names, there has never been formal education in Kurdish, many Kurdish villages were forcibly evacuated, and many Kurds have been imprisoned because of their opinions (Belge 2016, Çelebi, Verkuyten, Köse & Maliepaard 2014, Tezcür 2016). Towards the end of the 1970s, a group of leftist Kurds established the rebel group PKK (*Partiya Karkerên Kurdistan* - Kurdistan Workers' Party) which launched a violent campaign with the goal of establishing an independent Kurdish state. Since 1984, Turkey is in conflict with the PKK with a break in 2014 due to peace negotiations that eventually failed (Gleditsch et al. 2002). Initially, the yearly number of battle deaths was around 200. Starting in 1992, the fighting escalated and peaked in 1997 with more than 4,000 battle deaths. Following the capture of PKK leader Ocalan in 1999, the intensity of conflict declined (Romano 2006) to around 500 deaths per year on average (Sundberg & Melander 2013).

Kurds traditionally live in the Eastern and Southeastern parts of Turkey bordering Syria, Iraq, and Iran. Although Kurds might be the dominant group in these regions, they still live with Turks and other ethnic groups. In total, the Kurdish population in this part of the country is slightly over 50%, and among cities, it varies between 15% in Kahramanmaras and 90% in Hakkari (Mutlu 1996). Most conflict events in Turkey take place in these regions. Between 1989 and 2019, more than 97% of battle deaths related to the conflict occurred in those areas (Sundberg & Melander 2013).

Forced migration is a prominent aspect of the conflict, particularly internal displacement. While there is no consensus on the number of displaced people, estimates of internally displaced persons range from 378,335 (a parliamentary report) to three to four million (NGO reports). According to the Internal Displacement Monitoring Centre (2020), the number of internally displaced people in Turkey is slightly over one million. While some people fled to another country, the number of refugees was not as large as the number of IDPs. In the 1990s, there were around 50,000 and at the beginning of the 2000s around 200,000 refugees from Turkey (UNHCR 2020).

In the 1990s, forced village evacuations by the government and rebels were quite common, particularly between 1991 and 1994. The government used these forced relocation practices to control territory, whereas the main purpose of rebels was to police and silent dissent (Ayata & Yükseker 2005, Belge 2016, Tezcür 2010). Many people left their homes due to problems caused by fighting and deprived conditions in the region (Icduygu, Romano & Sirkeci 1999). Both poor living conditions and forced relocation practices by armed groups played a significant role in the displacement process in the Eastern and Southeastern parts of Turkey (Aker, Çelik, Kurban, Ünalan & Yükseker 2005, Ayata & Yükseker 2005).

In addition to its own conflict and displacement past, Turkey has recently experienced a significant refugee inflow from Syria. Since 2014, Turkey hosts the largest number of refugees under UNHCR's mandate in the world with more than 3.5 million Syrian refugees by 2019 (UNHCR 2020). Almost all of the refugees entered Turkey through the Southeastern part of the country and many Syrians stayed in the region.

Given this history of violence, territorial conflict and displacement, and its exposure to political instability and refugee flows in the direct neighborhood, the Southeastern and Eastern parts of Turkey provide good conditions to study forced migration decisions as households in the region have plausible experiences with the difficulties of moving and fleeing under the pressure of conflict.

4.5 Research Design

We conducted an online conjoint experiment with 1,011 respondents in the Eastern and Southeastern parts of Turkey. As highlighted above, most conflict events took place in these areas and outside of the surveyed region people have very limited exposure to violence. Since we are posing an abstract choice task, we required a survey population that has familiarity with violence and displacement to increase plausibility. The survey took place in September/October 2020. We ask respondents to read two short information sets on hypothetical violent events and to evaluate in which situation they would be more likely to flee than to stay and whether they would move abroad or within Turkey. Our empirical approach is similar to Holland, Peters & Sanchez (2020) which examines the destination preferences. The following sections outline the sample selection, ethical considerations, and the setup of our survey experiment.

4.5.1 Case selection & sampling procedure

In cooperation with a local survey company[3], we invited members of their nationally representative online panel of Turkish citizens to participate in our study if they were over 18 years old and lived in the 19 administrative districts we sampled.[4] Figure 4.1 displays the sample areas in the Eastern and Southeastern part of Turkey, bordering Syria and Iraq and historically populated by a large proportion of Kurds. These areas were sampled because of the region's exposure to violence and displacement, allowing a realistic and plausible setup

[3] We teamed up with *Benderimki*, which is the leading company in online surveys in Turkey and used by other scholars (Getmansky, Matakos & Sinmazdemir 2020).

[4] Due to the COVID-19 outbreak in 2020, in-person surveys were not possible at the time of the survey.

Figure 4.1: Sampled areas in Turkey (in blue)

to study forced migration decisions. We recruited a total of $1,011$ respondents of which 37.3% identified as Kurdish, 58.7% as Turkish, and 4% as other ethnic groups. Further descriptive statistics of our sample population (e.g., age, religiosity, unemployment rate, and gender distribution) can be found in the Appendix B (Table B.1 and Figure B.1).

4.5.2 Conjoint experiment

Our conjoint experiment asks respondents to read two information sets about hypothetical violent events. Attributes of these scenarios vary along four dimensions of violence: perpetrator, intensity/frequency, spatial proximity, and target (discriminate and indiscriminate). We ask respondents to identify the information set in which they would be more likely to flee rather than to stay at home. We also ask respondents to evaluate whether they would go abroad when faced with this type of violent scenario or if they would move within Turkey. Respondents evaluated five pairs of information sets, each time choosing in which scenario they would consider flight and where they would go. This is a 'forced-choice' design that aims at identifying flight preferences given the fact that staying at home is a dominant strategy for civilians during armed conflict.

Table 4.1 summarises the attributes that randomly vary, their dimensions in our conjoint setup, and the hypothesized effect on the likelihood of fleeing.

Table 4.1: Attributes of violence for the conjoint experiment

Attributes	Pr(Fleeing) for each of the two/three attribute levels
H1: Intensity/frequency	Repeatedly/Frequently > Sometimes/Rarely > First time
H2: Proximity	Hometown > Neighboring city > Distant border city
H3: Target group	Indiscriminate > Discriminate *
H4: Perpetrator	Government $\neq$ PKK
	Pr(Fleeing abroad—Government) > Pr(Fleeing abroad—PKK)

* *Indiscriminate:* Civilians who were working on their farmland died through airstrikes and bombings. *Discriminate:* Civilians helping the other side died in attacks by ground forces.

We randomized the order of attributes to reduce the risks of satisficing and the challenges of attributes presented earlier masking those of later attributes (Bansak, Hainmueller, Hopkins & Yamamoto 2021). We limit the attributes and their associated levels to a minimum to have distinct dimensions of violence that do not correlate too strongly and are plausibly existent in the real world (Hainmueller, Hopkins & Yamamoto 2014). Table 4.2 demonstrates an example conjoint setup in which scenario 1 contains all attributes theoretically favoring a flight.

Example conjoint setup:

*You will read two hypothetical scenarios about the ongoing violence in your country. Please read them carefully and indicate in which scenario you would be more likely to **flee** rather than to stay at home.*

*If you had to choose in which scenario you would **leave your home and flee**, which one would you choose?*

Scenario 1 ☐ *Scenario 2* ☐

If you would have to flee from this scenario, would you try to find shelter somewhere in the country you currently live in or move abroad?

Table 4.2: Example conjoint scenarios

Scenario 1	Scenario 2
The `government` *attacked* `your city` *with* `airstrikes and bombings.` *In the attack,* `civilians who were working on their farmland died.` *The attacks have happened* `repeatedly in the past month.`	*The* `PKK` *attacked* `a distant border city` *with* `ground forces.` *In the attack,* `civilians who helped the other side died.` *The attacks have happened* `for the first time.`

I would relocate within the country ☐ *I would flee abroad* ☐

4.5.3 Heterogeneous treatment effects along social networks

To examine hypothesis 5 on social networks, we ask respondents if they have any relatives or friends living abroad or within different areas of Turkey and how often they interact with these individuals (more than once a week, once a week, once a month, and once a year or less frequently). We define well-connected respondents as individuals that have a friend or family member living abroad that they are in touch with at least once a month. Individuals that do not have a contact or are less often in touch with their network abroad have a weak network. By this definition, 29.7% of respondents have a network abroad, while 70.3% have no or weak ties abroad. We pre-registered an interest in social networks abroad and within Turkey. There is too little variation in ties within Turkey amongst our respondents (almost everyone has reliable contacts elsewhere) to allow a reasonable examination of this effect and we hence only focus on networks abroad.

4.5.4 Ethical implications

Since we are posing an abstract choice task, we required a survey population that has experienced violence and displacement to increase plausibility. At the same time, we avoided a population with active conflict exposure that could feel distressed. With the Syrian civil war in its neighborhood, and the linkages to friends and relatives abroad, many respondents in the Eastern and Southeastern parts of Turkey have personal links to migration or conflict without being directly endangered or an immediate subject of acute civil war. Beyond the sample selection, we have mitigated the risk of distress by keeping our information sets about violent events purposefully short, neutral, and purely descriptive. The used information sets resemble neutral pieces from news outlets and are not aimed at provoking strong emotions. Our information sheet and consent form[5] highlighted resources respondents can turn to for support in trauma management. We directed respondents to government and NGO resources as some people may not trust government officials.[6]

4.5.5 Empirical strategy and subset analysis

Following Hainmueller, Hopkins & Yamamoto (2014), we estimate the probability that an individual flees in the forced choice design via:

$$\begin{aligned} \texttt{Flight}_{ijk} = \gamma_0 + \gamma_1 \texttt{HighIntensity}_{ikj} + \gamma_2 \texttt{CloseProximity}_{ikj} + \\ \gamma_3 \texttt{IndiscriminateTarget}_{ikj} + \gamma_4 \texttt{RebelViolence}_{ikj} + \epsilon_i \end{aligned} \quad (4.1)$$

where i indicates the respondent, k indicates the round, and j indicates the

[5]Before starting the survey, we asked respondents for their consent to read hypothetical violence scenarios. Before the survey and before the experiment, we reminded respondents that they can exit the survey anytime without any consequences.

[6]We obtained ethics approval at the UCL Research Ethics Committee under the project id 18557/001.

scenario. In our setting, $i \in \{1, 2, \ldots, 1,011\}$, $k \in \{1, \ldots, 5\}$, and $j \in \{1, 2\}$. Each respondent i yields 10 observations: 5 rounds, and 2 choices per round. The unit of analysis is the hypothetical flight scenario, the outcome is a binary indicator for whether the respondent would flee, and the explanatory variables are the attributes of violence. Because each violence attribute is randomly assigned, the unbiased estimate of the average effect of each attribute on the likelihood that the respondent would choose to flee is given by the equation above. We cluster standard errors at the respondent level.

When assessing whether individuals would flee abroad or within Turkey, we estimate the probability of fleeing abroad (with the alternative of staying at home) and the probability of fleeing within Turkey (with the alternative of staying at home) separately.

$$\begin{aligned}\texttt{FlightAbroad}_{ijk} = \gamma_0 + \gamma_1\texttt{HighIntensity}_{ikj} + \gamma_2\texttt{CloseProximity}_{ikj} + \\ \gamma_3\texttt{IndiscriminateTarget}_{ikj} + \gamma_4\texttt{RebelViolence}_{ikj} + \epsilon_i\end{aligned} \quad (4.2)$$

$$\begin{aligned}\texttt{FlightWithin}_{ijk} = \gamma_0 + \gamma_1\texttt{HighIntensity}_{ikj} + \gamma_2\texttt{CloseProximity}_{ikj} + \\ \gamma_3\texttt{IndiscriminateTarget}_{ikj} + \gamma_4\texttt{RebelViolence}_{ikj} + \epsilon_i\end{aligned} \quad (4.3)$$

We analyze the effect sizes for well-connected and less-connected individuals by splitting the sample.

4.6 Analysis and findings

Figure 4.2 presents the main results. While points denote the Average Marginal Component Effect (AMCE) of attributes on the probability of choosing a scenario to flee, horizontal lines refer to 95% confidence intervals clustered by respondent. Dots without confidence intervals are reference categories. Compared to the reference category, we find that rebel violence, indiscriminate violence, violence in neighboring cities or the hometown, and frequent or repeated violence increases the probability that a respondent chooses flight.

The results corroborate our hypothesis on the proximity of violence. The proximate violent events significantly affect respondents' forced migration decisions. We presented three different options to respondents: violence in the hometown, in the neighboring city, and in a distant border city. We expected a hierarchical relationship between those attribute levels, which is confirmed in our experiment. Attacks happening in the hometown compared to attacks in a distant border city increase the probability of choosing a scenario to flee by around 16%. The effect of attacks in a neighboring city compared to a distant border city is around 7%. The difference in the effect of attacks in the hometown compared to a neighboring city is around 9%. As expected, the proximity of violent events plays a significant role in the decision to flee. Respondents are more likely to choose relocation if violence happens nearby. All levels are significantly different from each other and this hierarchical relationship provides statistical support for our second hypothesis.

The results on the effect of the type of violence also support our argument. Compared to discriminate violence (death of those who collaborate with the other armed group), scenarios with indiscriminate violence (death of farmers) increase the probability of choosing a scenario to flee by around 6%. When armed groups perpetrate discriminate violence, civilians can mitigate the potential harm to their families by obeying the rules and supporting armed groups. However, when indiscriminate violence is employed, civilians are constantly at risk and the main solution to eliminate threats is to leave the conflict zone.

Regarding our first hypothesis on the effect of the intensity of violence on

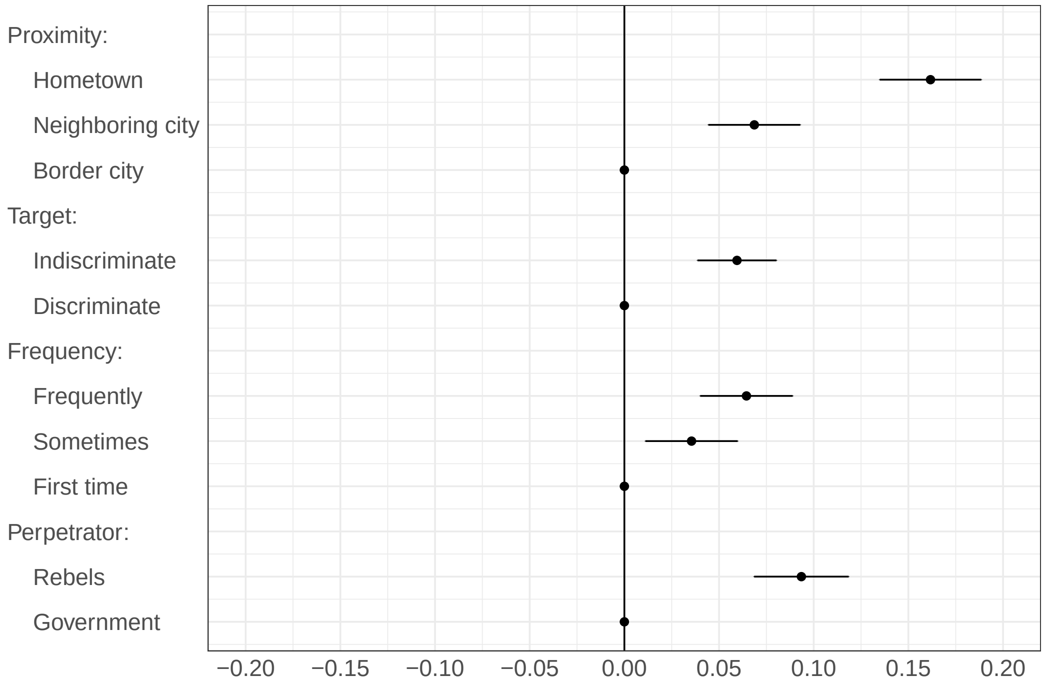


Figure 4.2: Effects of violence attributes on the probability that respondents choose a scenario to flee. Dots refer to AMCEs and horizontal lines to 95% confidence intervals clustered by respondents. Dots without a horizontal line denote the reference categories.

flight decisions, the results from our conjoint experiment provide partial support. The observed pattern seems to be more complex than initially assumed. Similar to the effect of violence in proximity, we hypothesized a hierarchical relationship for the intensity/frequency of violence. We expected that the more intense or frequent violence is, the more will respondents decide to flee. In our conjoint setup, respondents were shown one of the three levels for this attribute: attacks happen repeatedly/frequently, sometimes/rarely, and for the first time in the last month.

We indeed find that attacks happening frequently increase the probability of respondents choosing a scenario to migrate by around 6.5% compared to those happening for the first time. Attacks happening sometimes increase a flight decision by around 3.5%. However, while this relationship is statistically significant, there is no significant difference between violence happening frequently and sometimes. In other words, respondents did not differentiate between attacks happening frequently and sometimes. This result suggests that persistent threats might be more important for civilians to make flight decisions than its exact frequency.

The finding is more nuanced than findings from existing research on the effect of frequent violence. Previous studies have generally measured the intensity of violence through the number of deaths (Balcells & Steele 2016, Davenport, Moore & Poe 2003, Melander, Oberg & Hall 2009, Turkoglu & Chadefaux 2019). The understanding is that the more attacks happen, the more threatened people feel and the more likely they are to flee. While the number of battle deaths may approximate conflict intensity, there is significant variation in the spread of violence and how often violence happens, which might significantly affect the threat perception for individuals. Recent research argues that not only past violence but also expected future violence impacts decisions to flee (Fearon & Shaver 2021). Our study corroborates this research strand. Since fleeing home is costly, following the first attack in their town, people might be cautious about migrating as this might be a one-time temporary incident. However, if attacks happen at certain intervals (frequently or sometimes), people are more likely to flee due to the persistence of threat. It might happen twice a week or twice a month. As long as the threat persists, people are likely to flee.[7]

When it comes to the effect of the perpetrator of violence on flight decisions, we have argued that the perpetrator affects decisions to flee by alternating the destination choice. We strongly follow Steele (2019)'s argument: while

[7] Past exposure to violence might affect participants' responses. Given the ethical concerns and possible trauma, we could not ask respondents about their past violence experience. As an alternative, depending on the cities they live, we split the sample into high and low violence cities and carry out subgroup analysis. The results suggest that there are no significant differences in any attributes between respondents living in high and low violence cities.

government violence increases the number of refugees, rebel violence increases the number of IDPs. Our main results in Figure 4.2 do not differentiate between the choice of destination. The results suggest that attacks perpetrated by rebels, compared to government-induced violence, increase the probability of fleeing. However, this result likely stems from the fact that within-country relocation is a much more dominant strategy than fleeing abroad in our sample. In almost 64% of our observations, respondents preferred migrating within the country. Only in 36% of decisions to flee, respondents favored fleeing abroad. This is a plausible finding as internal displacement is much more common worldwide than refugee movements.

To fully examine the effect of the perpetrator of violence on displacement decisions, we have to analyze our respondent's choice to flee within Turkey or abroad (see equations 4.2 and 4.3). More specifically, for internal displacement, we only kept rounds in which respondents preferred to flee within Turkey and for flight abroad, we only kept rounds in which respondents preferred to flee abroad.[8] We then estimated ACMEs by using the equations 4.2 and 4.3. We also compared scenarios in which they would flee within the country to those that they would flee abroad. The results for the choice of destination and their comparison are presented in Figure 4.3.[9]

In terms of frequency, proximity, and the type of violence, the decision to flee abroad or within Turkey does not seem to be different. The effects of these attributes have the same direction for a flight abroad or within the country. The comparison panel in Figure 4.3 also displays that there is no difference between

[8]Note that if we compare fleeing abroad with all scenarios in which respondents chose to stay or flee internally, and if we compare fleeing internally with all scenarios in which respondents chose to stay or flee abroad, we find the same results. Please see the Appendix B Figure B.2

[9]For the purpose of comparison, we also compare scenarios in which the respondents chose to flee internally (coded as 0) or externally (coded as 1) and we completely drop the scenarios in which individuals would stay at home.

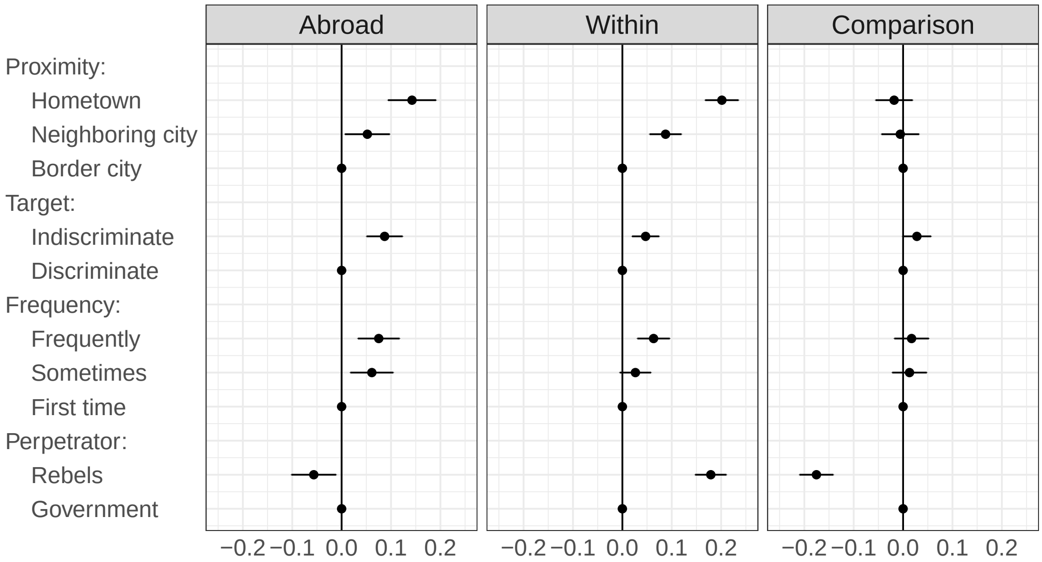


Figure 4.3: Effects of violence attributes on the probability that respondents choose a scenario to flee abroad, within the country, and their comparison. Dots refer to AMCEs and horizontal lines to 95% confidence intervals clustered by respondents. Dots without a horizontal line denote the reference categories.

fleeing abroad or within the country (as the confidence intervals include zero). The main difference is observed with respect to the perpetrator of violence. This finding is compatible with our expectations and existing studies (Steele 2019). When attacks are carried out by rebels, respondents are more likely to choose internal displacement and when the perpetrator is the government, people are more likely to favor fleeing abroad. Compared to the government, attacks perpetrated by rebels decrease the probability of choosing to flee abroad by around 5.6% and increase the probability of migrating within the country by around 17.9%.

The results should not be read as if government violence has no effect on internal displacement and rebel violence has no effect on external displacement. AMCEs denote the effects relative to the base categories. For instance, rebel violence decreases the probability of decisions to flee abroad compared to government violence. But this does not mean that rebel violence does not have any effect on external displacement. Chapter 3 reveals that rebel violence can increase both the number of people who cross an international border and those who migrate within the country. In conclusion, the results support our fourth hypothesis and our study complements the literature by using individual-level data and mitigating the problem of ecological inference.

4.6.1 Role of Social Networks

Our fifth hypothesis is related to the moderating effect of social networks. We argue that civilians with social connections respond less to violence compared to people without connections because social networks to other locations offer a coping strategy and increase the resilience of respondents. To test our argument, using equation 4.2, we estimated ACMEs for fleeing abroad while splitting the sample with a binary network variable that denotes whether respondents have a reliable social network abroad or not.[10] To split the sample, individuals in our survey are coded as having a close network if respondents have a relative or friends abroad that they are in touch with at least once a month. They are seen as less well-connected if otherwise. The AMCEs for this subset analysis are reported in Figure 4.4.

The results for the subset of respondents without strong networks are very similar to the overall results in Figure 4.3. Attacks by rebels decrease the probability of choosing a scenario to flee abroad and indiscriminate attacks increase it. The closer the attacks to where respondents live, the more likely for them to pick the scenario to migrate and scenarios with a persistent threat of violence are more likely to be preferred compared to scenarios with attacks

[10] We would expect a similar effect being applicable to networks within the country and to fleeing within the country. However, most of the respondents have a friend and family member outside of their hometown in Turkey which makes the subset analysis difficult. Additionally, migrating within the country is likely to be less costly than migrating abroad, and thus, the effect of networks on within-country migration is likely to be milder compared to migrating abroad.

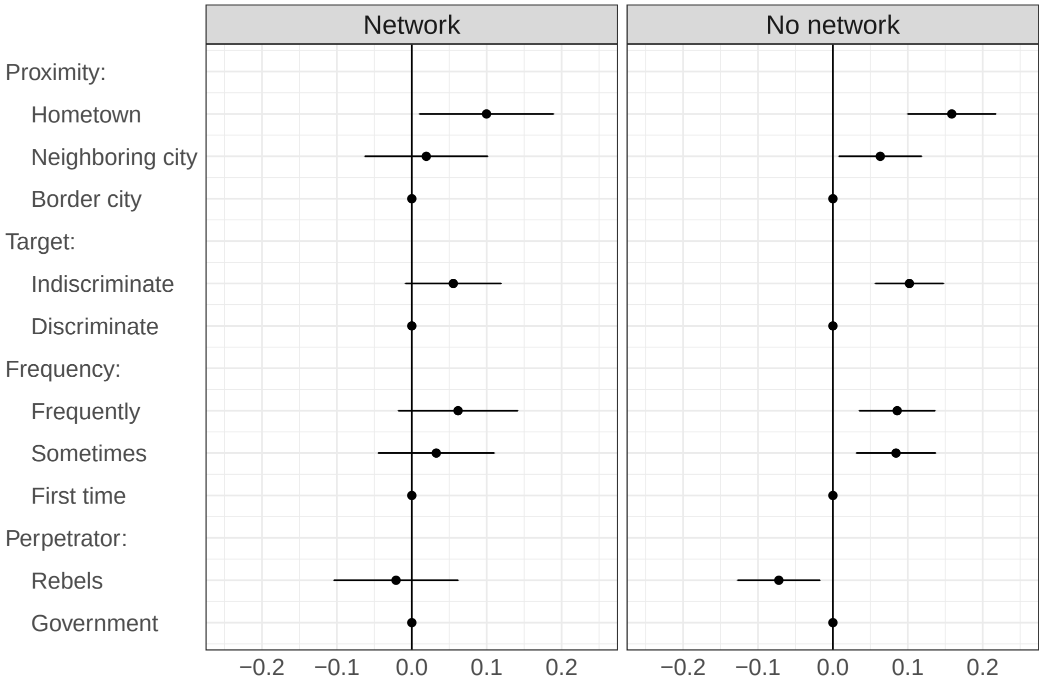


Figure 4.4: Effects of violence attributes on the probability that respondents choose a scenario to flee for the group of respondents with and without social networks. Dots refer to AMCEs and horizontal lines to 95% confidence intervals clustered by respondents. Dots without a horizontal line denote the reference categories.

for the first time.

However, when it comes to the subset of our respondents with networks, there is no such clear pattern. There is no significant difference regarding the frequency, the perpetrator, and the type of violence. We only observe a significant difference if violence is happening in their hometown compared to attacks in distant border cities. These results suggest that respondents with networks react differently than those without network. The results in Figure 4.4 suggest that people with networks abroad are more indifferent towards the frequency, perpetrator, and targeting pattern of violence. They seem to make their choice to flee with more independence than less resourceful individuals. Given the smaller sample size, the confidence intervals are larger, which might reduce our trust in the results. However, the substantive effect of attributes (i.e., AMCEs) for the subgroup of respondents without social networks is almost double the effect for those with social networks. This might indicate that decision-making between these two groups is indeed different.

If we complemented our experimental evidence on the role of social networks with observational analysis, we can tentatively conclude that this is because well-embedded individuals have a higher probability to leave earlier and more easily than individuals without social networks. Individuals without ties to family or friends abroad have a limited scope for action and only flee as a last resort if violence is at its worst. In the survey, we asked respondents whether they have thought about migrating or have talked to someone about it. Using this question, we created a binary indicator for the inclination to flee or migrate and we predict this variable using our network variable and other controls.[11] The results are reported in Table 4.3. Model 1 is a mean comparison of the inclination to migrate between those with social networks abroad and those without. Model 2 includes demographics as control variables. Regardless of the bivariate and multivariate model, having a friend or family abroad that people keep in touch with increases the probability of thinking about migration. Individuals with networks seem to lean more towards flight/migration than those without. This is in line with other studies on networks and migration decisions (Schon 2019, Adhikari 2012).

The evidence from this exploratory model and our conjoint experiment suggests that individuals with social networks abroad are freer in their choice to flee than individuals without coping mechanisms elsewhere. The important conclusion from this is that social capital and networks can help vulnerable populations to make better and more independent decisions to protect themselves. A resilient population, that is individuals and communities that can

[11] We reported a logistic regression. When we used a linear probability model, we obtained similar results that are supportive of our arguments.

Table 4.3: Logistic Regression of Thinking about Migration on Network

	(1)	(2)
Network Abroad	0.636**	0.520**
	(0.148)	(0.189)
Observations	959	614
Log Likelihood	−645	−391
Akaike Inf. Crit.	1,294	809
Controls	NO	YES

The dependent variable is a binary indicator whether respondents have thought about migrating or have talked to someone about migrating. We report robust standard errors in parentheses. Control variables include urban/rural, gender, education, marital status, religiosity, age, household size, employment, income, and ethnicity. More than 200 respondents did not share the income information, explaining the drop in observations in Model 2. * $p < 0.05$, ** $p < 0.01$

achieve positive outcomes even under the immense pressure of armed conflicts, is a population with dense networks and diverse coping strategies, including relocation.

4.6.2 Self-selection into Social Networks and Migration

One of the main arguments in this paper is related to the differences between people with and without social networks. If having a relative or friend abroad is correlated with other factors, it would be challenging to attribute the observed difference in Figure 4.4 to social networks. To alleviate these concerns, we predicted the variable networks abroad using observable demographics.[12] The only significant determinant of social networks is income (i.e., individuals with higher income tend to have more social networks abroad).[13] We interpret this as limited selection into who has social networks abroad although we cannot fully outrule that they differ on unobservable traits.

Income is an important factor to consider. Particularly, given the worker agreements between Turkey and European countries, there are more than 6.5

[12]More specifically, we used gender, age, urban/rural, marital status, education, religiosity, household size, income, employment, and ethnicity.

[13]The regression results are reported in Table B.2 in the Appendix B.

million Turkish people living abroad (MFO Turkey 2020) and many Turkish citizens are likely to know someone living abroad. We have to plausibly outrule that the main difference between those with networks and without is driven by economic factors. To do so, we replicated the results in Figure 4.4 splitting the sample by high and low-income respondents. The disaggregated analysis by income groups shows no big differences between high and low income respondents in their flight decisions in contrast to disaggregation by social networks.[14] We conclude that the main findings reported in this analysis predominantly come from differences in respondent's social networks.

Another selection problem is the question whether Turkish citizens already living abroad differ from our survey population. If our survey respondents are resistant to any form of flight or migration, our conjoint experiment is not easily generalized. However, despite political challenges, Turkey is an upper-middle-income country and compared to other active conflict zones, there is no immediate pressure to migrate or flee. It is unlikely that our survey population only consists of those having no means or willingness whatsoever to move abroad and that they hence are significantly different than those that have left Turkey. This is further underpinned by the fact that around 57% of our survey population has actively considered migration in the past and our survey sample is not fundamentally different from the average Turkish citizen living abroad and within Turkey.[15].

[14] The only significant difference between high and low-income respondents is observed with respect to frequency. While for low-income respondents attacks happening frequently or sometimes increases the probability of choosing a scenario to migrate compared to first time attacks, for high-income people, there is no significant difference among these three levels.

[15] See Appendix B for a discussion of our sample

4.6.3 Robustness checks

In sum, we find that patterns of violence indeed affect the choice to flee and that social networks are crucial to understand when individuals can no longer cope with violence and leave. We conducted several robustness checks to increase confidence in our results. First, we ran diagnostic tests with respect to carryover and profile order effects as suggested by Hainmueller, Hopkins & Yamamoto (2014). The results increase our confidence in the validity of our conjoint experiment. For carryover effects, there is no significant difference between the effects found in earlier and later rounds. In other words, if we run the analysis round by round, we get similar results. For potential profile order effects, whether attributes appear in the first or second profile does not affect our results.

We also examined whether there is an interaction effect among the proximity, frequency, perpetrator, and violence type in decisions to flee (e.g., indiscriminate violence by rebels) as suggested by Egami & Imai (2019). We found that none of the interactions were statistically significant.

For this study, we carried out an online survey experiment. One of the common challenges in online surveys is satisficing. In other words, respondents may randomly answer the questions without paying much attention. To alleviate concerns, we ran the analysis by dropping the respondents who finished the survey in less than seven minutes and the results still corroborate our argument.[16]

The interpretation of AMCEs is relative to the baseline categories. In the subgroup analysis (e.g, network vs no network), the observed differences may stem from sub-group preferences for the baseline category. A possible way to alleviate these concerns is to use marginal means in addition to AMCEs (Leeper,

[16]The median time to complete the survey in our sample is 9.8 minutes.

Hobolt & Tilley 2020). For Figures 4.2, 4.3, and 4.4, we present marginal means in the Appendix B Figures B.3, B.4, and B.5. The results still support our arguments.

Finally, in this study, we offered evidence from the Turkish case. The results on proximity and violence type are quite intuitive. For the perpetrator argument, chapter 3 corroborates our findings and concludes an increasing effect of government violence on external displacement and rebel violence on internal displacement. Complementing existing research, our conjoint experiment with individual-level data mitigates the problem of ecological inference. For our finding that persistent threats matter more than the actual frequency of events, we conducted an exploratory cross-sectional examination using the replication data of chapter 3 . We operationalized conflict intensity in two different ways to predict the numbers of displaced people. First, following the general practice in the literature, we employed the number of battle deaths (log-transformed). Second, we used the percentage of the first-level administrative units that experienced more than one attack, which may proxy for the persistence of threats. In the regression analyses[17], both are positively and significantly correlated with the number of displaced people but an examination of out-of-sample cross-validation reveals that the model with the percentage of admin units outperforms the model with the battle deaths.[18] This implies that indeed persistent threats are more relevant to individuals making decisions to flee, across different contexts. We interpret this as tentative evidence for the external validity of our conjoint finding.

[17] We ran separate models for each operationalization with control variables.

[18] The median absolute error for the model without battle deaths is 135,015. When battle deaths are included, it drops to 128,066. Adding the percentage of first-level administrative units instead of battle deaths, the median absolute error is 113,082. The lower the error term, the more successful the model in predicting displacement (Chadefaux 2014).

4.7 Conclusion

Our study examines how individuals respond to different facets of violence and how these facets affect their decision to flee or stay through a conjoint experiment in Turkey. The aim was to identify not only if certain features of violence drive decisions to flee but also if individuals that are embedded in social networks make decisions to move differently than individuals that have no relatives or friends abroad that could help them.

Overall, we find intuitive results suggesting that intense and indiscriminate violence happening in close proximity and likely to happen repeatedly increases the chances that individuals would flee in comparison to violence that is further away, more targeted, and happens for the first time. More interestingly, individuals also seem to not distinguish between how often violence happens but mostly focus on whether it is likely to happen again and poses a persistent threat. These findings are in line with qualitative accounts of how and when individuals flee during conflicts and complement aggregated observational studies on flight patterns. The general impression is that flight is the last resort when the risk of staying at home is no longer bearable.

Regarding the question of how the perpetrator of violence shapes flight decisions, we find that government violence is more likely to lead to individuals' decision to move abroad while rebel violence tends to lead to relocation within the country. This finding is important because it confirms other findings. Steele (2019) *theoretically* argues that the less constrained nature of government violence will drive individuals abroad to seek protection while rebel violence leaves the possibility open to flee to areas under the protection of the government or other actors. We are able to confirm this empirically. Our individual-level findings also match observational evidence from cross-country regressions that government violence is associated with refugee flows and rebel violence is linked to IDP movements in chapter 3. This finding helps to understand better how violence affects population flows and which type of population flow we should expect in light of different patterns of violence.

Finally, our study contributes to the growing literature on civilian agency in conflicts, and the role of social networks and resilience amidst hardship. We find that individuals with social networks abroad are more indifferent towards observed levels of violence. In combination with our observational evidence that individuals with networks are more inclined to consider migration, we can preliminary conclude that individuals with social networks make their choice to flee or stay more easily, more independently, and with less fear. This finding complements research that shows individuals with networks are associated with earlier exit from conflict-affected countries (Schon 2019). It also has an important implication for resilience. To enable communities and individuals to make good choices amidst conflict and violence, social capital and networks seem crucial as they reduce the pressure under which vulnerable populations have to make decisions. Importantly, this result should not be interpreted in a way that suggests people with social networks are more likely to exploit the asylum system but rather that people without networks are left with fewer coping strategies and less scope for action during conflicts. We aim to highlight the need for further research on the question of how social networks can help vulnerable populations and how resilience can be built up.

The findings of this study are important for policy-making. This research examined the individual-level determinants of flight decisions and highlighted the role of conflict characteristics. Predicting displacement flows enables better policies for displaced people and host countries. Therefore, international organizations, NGOs, and host countries should pay attention to how conflict evolves. First, since the proximity of violent events matters, when attacks are happening in urban areas and big cities, more people are likely to flee, which should be monitored by relevant parties. Second, the use of indiscriminate violence by armed groups increases the likelihood of migration. Thus, in predicting displacement flows, not only the number of deaths but also the type of violence should be taken into account. Third, since violence perpetrator impacts people's decision to flee within the country or abroad, accounting for who kills civilians improves our predictive capability. Finally, with respect to the effect of friends and relatives abroad, to enable communities and individuals to make good choices amidst conflict and violence, social networks seem crucial as they reduce the pressure under which vulnerable populations have to make decisions.

The conjoint experiment in this study is carried out in Turkey. The attributes used in this experiment are general and not conflict-related (e.g., proximity and frequency), which makes the findings more generalizable. One main concern about the external validity of findings is related to the location of Turkey and decisions to flee within the country or abroad. Turkey is on the one of the main migration routes to Europe. For instance, most Syrian refugees reached Europe through Turkey. Thus, those living in Turkey have easier access to developed European countries. When people consider fleeing, Europe is generally on their mind and it is one of the most feasible options. However, for people living in Asian and African countries, accessing developed countries may not be very easy. In terms of fleeing to other countries, they might be limited by their neighbors, and these countries might be underdeveloped and suffer from violence and political instability, which makes fleeing abroad a less attractive option. Thus, a similar study carried out in an Asian or African country would further highlight the causes of internal and external migration.

While our findings shed light on the importance of easing pressure for individuals, they are at the same time generated by an abstract research design. Respondents saw randomized attributes for violent scenarios on their laptop or phone and picked a scenario in which they would flee. The real world is much more complex. Civilians gather information about the situation and the possibilities to go to other areas or other countries before making their decision (Holland & Peters 2020). Their choices are also impeded by practical considerations, for example by the significantly higher amounts of money they need to flee abroad than internally. Decisions are also made under much higher stress in real-life. Additionally, what we examine here are intentions to flee rather than actual behavior. The results offer important insights into the ways people think about fleeing. However, it should be kept in mind that we do not observe the act of migration.

Hence, many research questions about human mobility on the individual-level remain open. Studies could examine how social networks within the country or personal risk preferences affect people's decisions to flee and their reactions to violent events. Further work on the behavioral effects of resilience, social cohesion, and networks seems crucial.

5 Security Concerns, Ethnic Relations, and Attitudes toward Refugees

Abstract

In recent years, there has been an increase in the number of studies that examine attitudes toward refugees. However, these studies have mainly focused on attitudes in developed countries, which has resulted in a lack of focus on factors prevalent in developing countries but not developed ones. This paper analyzes the effect of transnational ethnic relations and security concerns through a conjoint experiment in Turkey. The results suggest that when there are ethnic tensions in the host country, natives from the majority dominant group have more negative attitudes toward refugees from the minority ethnic group compared to those without any ethnic relations. Security concerns and existing negative intergroup relations are two possible explanations for this effect, and further analysis points to negative intergroup relations as the main mechanism. Additionally, refugees coming from areas controlled by insurgents that have ties to rebels in the host country are less favored than others because refugees might be perceived as a pool of resources for the insurgents. Examining how ethnic relations and security concerns shape attitudes toward refugees has important implications in understanding the externalities of refugee inflows on the host countries.

5.1 Introduction

In recent years, a record number of people have fled their homes and scholars have paid attention to the determinants of attitudes toward refugees, given their relevance for policy-making (Adida, Lo & Platas 2019, Alrababa'h et al. 2021, Bansak, Hainmueller & Hangartner 2016, Getmansky, Matakos & Sinmazdemir 2020). Although most refugees reside in developing countries, studies have mainly examined attitudes in developed countries (Alrababa'h et al. 2021), which has resulted in the lack of focus on the factors that are prevalent in the former but not in the latter. Conflict dynamics, ethnic relations, and security concerns are among the factors that have been understudied. Given that previous research has articulated change in the ethnic composition of the host country as a mechanism for refugees spreading conflict (Salehyan & Gleditsch 2006), it is important to understand how conflict dynamics and transnational ethnic relations affect natives' attitudes.

Depending on refugees' ethnic ties to the host country, the reactions of the dominant majority group in the destination may vary. If refugees are related to the dominant group, refugees are likely to experience positive attitudes due to in-group favoritism. If refugees share ties with the ethnic minority and there are tensions or an insurgency, while natives from the minority group are likely to show positive attitudes, those from the majority group are likely to show negative attitudes. This is beyond out-group bias. There are two main reasons for the effect of ethnicity: security concerns and existing negative relations. First, refugees might experience negative attitudes because the majority group might fear that the inflow of refugees from the minority group might place the government in a disadvantageous position in the insurgency. Second, pre-existing negative relations between the minority and majority groups might impact attitudes toward refugees that share ethnic ties with the host country.

Ethnic relations are not the only factor that affects security concerns and attitudes. The relations between civilians and armed groups also impact how natives react to civilians. One of the main causes of displacement is armed conflict (Schmeidl 1997) and civil wars spatially cluster (Buhaug & Gleditsch 2008). Insurgent groups in the same neighborhood may develop good relations and support each other (Högbladh, Pettersson & Themnér 2011). Previous research has suggested that living in an area under the control of an armed group can be perceived as support for that group (Kalyvas 2006, Lichtenheld 2020, Valentino, Huth & Balch-Lindsay 2004). Therefore, if refugees come from areas controlled by insurgents that have ties to rebels in the host country, natives from the majority group are likely to display negative attitudes because these refugees may be perceived as a possible pool of resources (recruitment and economic) and may place the government in a disadvantageous position.

This study carried out a conjoint experiment in Turkey to test its main arguments, which is an ideal case given the ongoing Kurdish insurgency, transnational ethnic relations of Kurds in the region, and recent refugee inflows from Syria. In the experiment, in addition to attributes suggested by previous research, respondents saw attributes of refugees' ethnicity and armed groups that controlled refugees' hometowns. The analysis corroborates the main arguments. Refugees who lived under the control of YPG (the Kurdish rebels in Syria) which has good relations with PKK (the Kurdish insurgents in Turkey) are less likely to be preferred in the experiment. Compared to Arabs, Kurdish refugees are less likely to be accepted into the country by Turkish natives. Furthermore, the results from subgroup analyses and a priming experiment suggest that the main driver for the effect of the ethnicity attribute is likely to be pre-existing negative intergroup relations rather than the security concerns of natives.

In recent years, a record number of people have fled their homes. With the increase in the number of refugees, host countries face various challenges related to governing migration flows and the externalities of sudden influxes. In this process, it is important to understand the attitudes of natives toward refugees as public opinion plays a significant role in policy-making.

This paper makes several important contributions to the literature. First, while the literature has generally examined attitudes in developed countries (Alrababa'h et al. 2021), this study examines attitudes in Turkey, a developing country that hosts the highest number of refugees. Second, due to the focus on developed countries, existing research has understudied the role of factors that are prevalent in developing countries but not in developed ones with respect to attitude formation. This research complements the literature by analyzing how conflict dynamics and transnational ethnic relations affect natives' attitudes toward refugees. Third, previous studies have argued that living in an area controlled by an armed group can be perceived as support for that group (Kalyvas 2006, Lichtenheld 2020, Valentino, Huth & Balch-Lindsay 2004). The analysis indeed corroborates this argument and provides evidence of how civilians might be "penalized" because they lived under the control of insurgent groups. Fourth, previous studies have articulated change in the ethnic composition of the host country as a mechanism for refugees spreading civil conflict (Salehyan & Gleditsch 2006, Weiner 1992). The analysis of this paper shows that when there is an ongoing insurgency in the host country, refugees that have ties to the ethnic minority are less likely to be favored and the main reason for this is likely to be pre-existing negative intergroup relations rather than security concerns. Recent studies have suggested that refugee flows do not spread civil conflict and that conditions of the host country mitigate the effects of refugee flows (Böhmelt, Bove & Gleditsch 2019, Zhou & Shaver 2019). Siding with this strand of the literature, this study argues that existing conditions in the destination play a significant role in natives' attitudes toward refugees rather than associated security risks and urges for further investigation of the relationship between displacement and civil conflict.

5.2 Attitudes toward Refugees

With the increase in displacement, studies have focused on the factors that shape attitudes toward refugees. The literature has primarily examined egocentric economic, sociotropic economic, cultural, and humanitarian concerns. First, egocentric economic explanations have underscored labor market competition and individual economic well-being as the determinant of public opinion (Mayda 2006). The inflow of refugees may be considered as a supply shock to the labor market, particularly a shock of low-skilled workers. Therefore, natives who work in low-skilled jobs and earn less than average may have more negative attitudes toward refugees than others. However, recent research could not find statistical support for this argument (Bansak, Hainmueller & Hangartner 2016, Hainmueller & Hiscox 2007, Hainmueller & Hopkins 2014). Instead, these studies have emphasized the importance of sociotropic economic concerns and have argued that the effects of refugees on the host country's economy (rather than on individuals) drive attitudes. Refugees who have higher education and work in better-paid jobs are more favored than others. In other words, natives have more positive attitudes toward refugees who are not perceived as a burden on the host country (Bansak, Hainmueller & Hangartner 2016, Hainmueller & Hiscox 2007, Lazarev & Sharma 2017).

Existing research has also underscored the role of cultural concerns in attitude formation. With the arrival of refugees, natives fear that local customs and traditions will change. Cultural concerns are generally manifested as religious differences between natives and newcomers. Muslim refugees are less likely to be welcome in European countries and the US than Christian refugees and are more likely to be welcome in Turkey (Bansak, Hainmueller & Hangartner 2016, Adida, Lo & Platas 2019, Lazarev & Sharma 2017). Finally, with respect to humanitarian concerns, previous studies have highlighted the effects of refugees' experiences in the home country (e.g., whether or not they are tortured) and the reasons for fleeing. Natives are likely to have more positive attitudes toward those who experienced violence and escaped persecution rather than those who look for better economic opportunities (Bansak, Hainmueller & Hangartner 2016).

While existing research has immensely improved our understanding of the attitudes toward refugees, these endeavors have generally examined attitudes in developed countries. Alrababa'h et al. (2021) have tested whether four main concerns can explain attitudes in developing countries through a conjoint experiment in Jordan. Similar to developed countries, the analysis has highlighted the importance of cultural and humanitarian concerns and the lack of explanatory powers of egocentric economic concerns. The main observed difference is related to the effects of sociotropic economic concerns, which are found to be important drivers in the developed countries but not in developing ones (Alrababa'h et al. 2021, Bansak, Hainmueller & Hangartner 2016). Similarly, Getmansky, Matakos & Sinmazdemir (2020) have carried out a conjoint experiment in Turkey and asked respondents about refugee profiles in the contexts of the refugees being neighbors, obtaining work permits, and being offered citizenship. Their analysis supports the previous findings, particularly those related to the education level, religion, gender, and knowledge of local language of refugees (Adida, Lo & Platas 2019, Bansak, Hainmueller & Hangartner 2016).

As a novel contribution, their study reveals that refugee profiles that display social ties (i.e., friends) with locals are more favored when compared to those without any ties.

There are other studies examining attitudes toward refugees in developing countries as well. In the words of Alrababa'h et al. (2021), "these studies are generally designed to evaluate specific arguments rather than arbitrate between competing theories regarding the factors that shape host populations' attitudes toward migrant communities". For example, Ghosn, Braithwaite & Chu (2019) have analyzed attitudes toward Syrian refugees in Lebanon and underscored the positive effects of contact between refugees and natives. Furthermore, focusing on empathy, Hartman & Morse (2020) have found that Liberians that experienced violence in the past are likely to have more positive attitudes toward Ivorian refugees.[1]

Given the previous research that has emphasized the negative effect of refugee flows on security, a limited number of studies have analyzed how security concerns might affect attitudes toward refugees. In a priming experiment in Turkey, respondents that were exposed to the militant ties prime which emphasized refugees having ties to militant rebel groups and these relations being considered to destabilize Turkey[2] have more negative attitudes toward refugees than others (Getmansky, Sınmazdemir & Zeitzoff 2018). While this effect was observed among respondents from the dominant ethnic group, priming did not impact respondents from the oppressed minority group (i.e., Kurds). Although the militant ties prime affected natives' attitudes toward refugees, they did not affect attitudes toward the peace process between the Turkish government and

[1] Similarly, focusing on perspective-taking, empathy, and group identity, respondents that are reminded of family experiences show positive attitudes toward refugees in European countries (Dinas, Fouka & Schläpfer 2021) and the US (Williamson, Adida, Lo, Platas, Prather & Werfel 2021).

[2] In the prime, there is no reference to any specific rebel group, but rather a general security discussion.

the Kurdish insurgent group, PKK. Furthermore, in their conjoint experiment in Turkey, Getmansky, Matakos & Sinmazdemir (2020) have examined the fighting experiences of refugees in the origin country and found that profiles that fought with the Syrian opposition are slightly more preferred than those who did not fight and those who fought with Assad.

The focus on developed countries has resulted in neglecting factors that are prevalent in developing countries but not in developed ones. More specifically, while many developing countries experience civil conflict, only a limited number of developed countries are in conflict. Considering the transnational ethnic relations and large numbers of people fleeing to neighboring countries, the inflow of refugees may affect conflict dynamics in the destination, which in turn may affect attitudes. Given the literature that emphasizes refugee flows spreading conflict (Salehyan & Gleditsch 2006, Weiner 1992) and the recent studies that challenge previous findings (Böhmelt, Bove & Gleditsch 2019, Getmansky, Sınmazdemir & Zeitzoff 2018, Zhou & Shaver 2019), it is important to unpack the relationships between conflict dynamics, ethnic relations, and attitudes toward refugees.

5.3 Security Concerns, Ethnic Relations, and Attitudes

Previous research that has suggested refugee flows spreading civil conflict has highlighted the changes in the ethnic balance of the host country as a possible mechanism for the proposed relationship. With the inflow of refugees, natives might feel threatened, especially if refugees have relations with a group in the destination (Salehyan & Gleditsch 2006). Given that most refugees flee to neighboring countries (Moore & Shellman 2007) and settle along ethnic lines when possible (Rüegger & Bohnet 2018), transnational ethnic relations are likely to play an important role in attitude formation. This study focuses on attitudes toward refugees in multi-ethnic countries with existing tensions. Given that most refugees flee from developing countries to neighboring countries and that most developing countries experience ethnic tensions, it is important to examine the effects of transnational ethnic relations.

Here, the main argument is about refugees that have ties to an oppressed ethnic minority in the host facing negative attitudes from members of the dominant majority group, and there might be two possible mechanisms: security concerns and negative intergroup relations.

Host countries may accommodate refugees that have ties to the dominant majority group, ethnic minority group, or no ties to any ethnic group. Depending on the existing divisions in the host and the relationship type between refugees and the dominant majority, attitudes toward refugees may change. When there is a dominant majority group and a minority ethnic group in the host country and tensions exist among these groups, ethnic relations between refugees and natives impact attitudes.

Refugees might not have relations with any group in the host country. In this case, due to out-group bias, natives might show negative attitudes toward them as compared to refugees with which natives have existing ties.[3] Refugees might have ties to the dominant majority group in the host country. Natives from that group are likely to show in-group favoritism and display more positive attitudes toward them than other refugees. For example, in a conjoint experiment in Turkey, respondents favored Turkoman refugees over Arab and Kurdish refugees (Getmansky, Matakos & Sinmazdemir 2020). However, the minority

[3] The inflow of refugees that have no ties to groups in the destination might negatively affect minority and majority groups, as they might feel threatened. Additionally, the inflow of newcomers might impose economic externalities, which in turn affects relations. For a detailed discussion, please see Salehyan & Gleditsch (2006) and Rüegger (2019).

group in the host might feel threatened because an increase in the size of the dominant group might alter the existing balance in favor of the majority and place minorities in a disadvantageous position (Salehyan & Gleditsch 2006).

Refugees might have relations with the ethnic minority group. In this case, natives from the minority group are likely to show positive attitudes due to in-group favoritism. However, natives from the majority group are likely to display negative attitudes. Possible mechanisms behind this are not limited to out-group bias, but also include the security concerns of the dominant group. "Majority groups in receiving areas may perceive a threat to their dominant status if refugees are similar to domestic minorities" (Salehyan & Gleditsch 2006, p.343). An increase in the size of the minority group may alter the balance in their favor and place them in an advantageous position in fighting and politics since it may increase the resource pool of insurgents, which might help rebels to fight more efficiently. Here, rather than the objective impacts of refugees, how natives perceive them affects attitudes, relations, and tensions in the host country (Getmansky, Sınmazdemir & Zeitzoff 2018, Salehyan & Gleditsch 2006). In addition to its effects on fighting, the arrival of refugees from the minority group might lower the willingness of minorities to compromise with the government and the majority group since they have more leverage (Getmansky, Sınmazdemir & Zeitzoff 2018).[4]

We can return to the example of Albanian refugees in Macedonia in the seminal paper of Salehyan & Gleditsch (2006). Albanians are an ethnic minority in Macedonia who were demanding greater rights. Although there was no fighting, there were tensions between the minority Albanians and the majority

[4]Depending on the ethnicity of refugees, sometimes governments may try to take preventive action by closing the borders or limiting the number of refugees. For example, during the Kurdish insurgency in Iraq after the Gulf War, Turkey tried to minimize the arrival of Kurdish refugees (Weiner 1992) and a safe zone in Northern Iraq was created (Kirişci 2014). However, during the Syrian civil war, Turkey did not try to prevent Kurds from entering.

Slavs. Following the conflict in Kosovo, many Albanians fled to Macedonia and their arrival made the dominant group felt more threatened.

In addition to security concerns, long-lasting negative intergroup relations between the majority and minority groups in the host might drive attitudes toward refugees. During conflicts, groups live under difficult conditions of violence, threat, and human and economic loss, which increases negative attitudes toward each other (Bar-Tal 2007). Additionally, social distance (i.e., perceived dissimilarity) between groups increases at the time of fighting (Sambanis & Shayo 2013). In other words, when there is a conflict in the country, relations between fighting groups are generally hostile. Refugees might flee to countries with existing tensions and negative attitudes toward refugees that share ethnic ties with the minority group might be the product of hostile relations rather than (or in addition to) security concerns. Due to the conflict, the dominant majority group has negative attitudes toward the ethnic minority group, and since refugees are related to the minority group, they will also face negative attitudes. This is beyond out-group bias. Refugees that have no ties to groups in the host country may face negative attitudes. For refugees that have relations with the ethnic minority, in addition to being an out-group, negative relations with the majority negatively impact attitudes toward them.

In this study, it is hypothesized that *when there are ethnic tensions in the host country, natives from the majority dominant group will have negative attitudes toward refugees from the minority ethnic group compared to those without any ethnic relations.*[5]

Ethnic relations are not the only factor that affects the security concerns of natives. Relations between civilians and armed groups, more specifically which

[5]Here, the minority group should reside in both host and source countries. If the ethnic tensions in the host country are not along the same lines as in the source country, these explanations are not applicable (e.g., when groups in the source have no relationship with the host).

actor controlled the hometown of refugees in the origin country, are likely to affect security concerns and attitudes. Living in an area under the control of rebels can be considered as support for the insurgent group (Kalyvas 2006, Lichtenheld 2020, Valentino, Huth & Balch-Lindsay 2004). For example, Iraqis who lived under the control of ISIS for some time and then moved somewhere else within the country faced various problems because they were perceived to be collaborators of ISIS (Lichtenheld 2020). When there are good relations between rebel groups in the source and host countries[6], refugees who come from areas controlled by the rebels in the country of origin might be perceived as collaborators and thus as a security threat to the host country. Therefore, *the dominant majority group is likely to show more negative attitudes toward refugees who lived in an area under the control of rebels that have ties to rebels in the host than others.*

Additionally, rebel groups are supported by external governments (Salehyan, Gleditsch & Cunningham 2011). *The dominant majority group is likely to show more positive attitudes toward refugees who lived in an area under the control of rebels that are supported by the host country's government than others.* Since living under the control of an armed actor can be perceived as support for this actor, the aforementioned positive attitudes might be driven by good relations between the insurgents in the source country and the host country government. Chapter 2 suggests that when countries support rebels, they are likely to host more refugees.

[6] Civil wars spatially cluster (Buhaug & Gleditsch 2008) and insurgent groups in the same neighborhood may develop good relations and support each other (Högbladh, Pettersson & Themnér 2011).

5.4 The Turkish Case

To test its arguments, this study examined attitudes toward Syrian refugees in Turkey, which is an ideal case given transnational ethnic relations of Kurds in the region, long-lasting civil conflict with the Kurdish insurgent group PKK, and recent refugee inflow from Syria.

Kurds who have traditionally lived in the eastern and southeastern parts of Turkey bordering Syria, Iraq, and Iran have been excluded from power and have experienced oppression for decades. The use of the Kurdish language is banned, Kurdish names of towns are replaced with Turkish names, many villages are forcibly evacuated, and many Kurds are imprisoned because of their political views (Barkey 2000, Belge 2016, Tezcür 2016). Toward the end of the 1970s, a group of leftist Kurds established the insurgent group PKK (*Partiya Karkerên Kurdistan* - Kurdistan Workers' Party) with the aim of secession. Since 1984, the Turkish government and PKK have been in conflict, with only a short ceasefire in 2014 for peace talks, which eventually failed (Gleditsch et al. 2002). The most intense period of fighting was between 1992 and 1999. Following the capture of PKK leader Ocalan, the intensity of fighting declined, particularly around the peace talks. However, after the failure of the peace talks, the average yearly number of battle deaths has slightly exceeded 800 (Pettersson & Öberg 2020).

While PKK operates on Turkish soil, it has a strong presence in neighboring countries, particularly in the Kurdish-dominated parts of Syria and Iraq. PKK has good relations with other armed actors in the region, especially Kurdish guerrillas in Syria YPG (Yekîneyên Parastina Gel - People's Protection Units), as they pursue similar goals with similar ideology and have ethnic ties. Similar to PKK, YPG is designated as a terrorist organization by the Turkish government. Furthermore, YPG is perceived as an extension of PKK. This is why although Turkey supported opposition groups in Syria, it was reluctant to support YPG (Parlar Dal 2016).

The Kurdish population is spread across Turkey, Iraq, Iran, and Syria. In total, there are more than 30 million Kurds living in these countries and Turkey is home to around half of them (approximately 15 million). While the Kurdish population is around 6.6 million in both Iraq and Iran, approximately 2.5 million Kurds reside in Syria (Vogt et al. 2015). Although there are borders and movement and economic activities are somewhat limited, relations between Kurds in different countries are favorable (McDowall 2021).

Following the outbreak of the civil conflict in Syria, millions of Syrians had to leave their homes and moved to another country. Turkey hosts the highest number of refugees under the UNHCR mandate: around 3.6 million Syrians in 2021 (UNHCR 2021). According to the Ethnicity of Refugees Dataset, 60% of Syrian refugees in Turkey are Arabs, while 30% of them are Kurds (Rüegger & Bohnet 2018).[7] According to the 2019 Syrians Barometer, which surveyed 1,418 Syrian households, 81% of respondents declared Arabic as their mother tongue, whereas 16.1% declared Kurdish as their mother tongue (Erdogan 2020). Regardless of the resource, it is clear that Turkey hosts substantive numbers of Kurd and Arab refugees.

Given the ongoing conflict with the Kurdish insurgency and negative societal relations between Turks and Kurds, analyzing Kurdish and Arab refugee flows and natives' attitudes to refugees is ideal to examine the effects of ethnicity and security concerns on attitudes. Moreover, this is an easy test to show the effects of security concerns on attitudes since the societal relations are already fragile and even small changes are likely to cause further tension.

[7] The most recent year with available information in the Ethnicities of Refugees Dataset is 2017.

5.5 Research Design

To test its arguments, this study employed an online[8] conjoint experiment with 1,201 respondents in Turkey. The survey took place in January 2021. I teamed up with *Benderimki*[9] and their nationally representative panel members were invited to participate in the survey. Those who are 18 or older and living in Turkey could participate in the study.[10] The economic and socio-demographic characteristics of respondents closely resemble those of the general population. For example, the median age is 36 and the median education level is high school, which are very close to the national values. For the summary statistics of the sample, please see the Appendix C Table C.1.

This research employed a forced-choice design. Each respondent evaluated five scenario pairs and was asked to choose a profile. More specifically, the question was "if Turkey has to accept one of these groups to the country as refugees, which group should Turkey accept?" Different from existing studies, this research used group-level attributes rather than individual ones.[11] There are two main reasons for using group-level characteristics rather than individual ones. First, in Turkey, as in many other developing countries, refugees arrived in groups. For instance, the weekly number of Syrian arrivals to Turkey in

[8]Due to the ongoing health crisis, face-to-face surveys were not possible.

[9]*Benderimki* is a leading company in online survey and research in Turkey and used by other scholars (Getmansky, Matakos & Sinmazdemir 2020).

[10]For a discussion of ethical concerns, please see the Appendix C.

[11]In previous research, egocentric explanations are operationalized through differences in the skill levels between natives and migrants (Mayda 2006). Sociotropic explanations are operationalized through the employment status and occupation of refugee profiles as well as their language skills. Refugees that worked in higher-skill occupations and are fluent in the native language are more favored (Alrababa'h et al. 2021, Bansak, Hainmueller & Hangartner 2016). Cultural concerns are operationalized through religion, and profiles from a different religious group than the natives' religion are less favored (i.e., anti-Muslim bias in Europe and anti-Alawite bias in Jordan) (Alrababa'h et al. 2021, Bansak, Hainmueller & Hangartner 2016). Finally, humanitarian concerns are operationalized via refugees' experience in the country of origin, and those who were tortured and escaped persecution are more favored (Alrababa'h et al. 2021, Bansak, Hainmueller & Hangartner 2016, Getmansky, Matakos & Sinmazdemir 2020).

2014 was around 20,000, which is higher than the total number of refugees hosted by many European countries. On some days (e.g., 30 April 2014), the daily number of arrivals even exceeded 10,000 (UNHCR 2021). Second, in reality, in order to know about refugees (e.g., their occupations, language skills, and experiences with violence in the country of origin), natives need to have substantive contact with refugees. However, interactions between refugees and natives are limited and natives generally base their opinions using group-level characteristics (e.g., whether migrants are from a Muslim majority country and whether there is intense fighting in the country of origin). In other words, group-level features serve as heuristics to shape attitudes. Since many natives do not have contact with refugees, it is important to understand the role of group-level characteristics, which is what this study used in the operationalization.

In the conjoint experiment, six attributes were used. While some of them are related to previous research such as sociotropic economic concerns, others are utilized to test the arguments of this study. More specifically, sociotropic economic concerns are measured through whether there is international aid to cover the costs of hosting refugees. Since in developing countries refugees generally have no or limited access to the labor market and international aid plays a significant role in the governance of asylum flows (EC 2019, Fallah, Krafft & Wahba 2019, Tumen 2016), whether the national government or international organization will cover the costs of accommodating refugees might be a more suitable operationalization in developing countries than using the previous occupation or education level. For this attribute, whether Turkey or UN/EU cover the costs is used and profiles when UN/EU cover the costs are more likely to be preferred.

Following the previous studies, cultural concerns are measured through religion (Adida, Lo & Platas 2019, Alrababa'h et al. 2021, Bansak, Hainmueller

Table 5.1: Group attributes in the conjoint experiment and their expected effects

Theory	Attributes	Level 1	Level 2	Level 3	Pr(Group acceptance)
Sociotropic concerns	Economic costs covered by	United Nations and European Union	Turkey		UN and EU >Turkey
Cultural concerns	Religion	Sunni	Alawite	Christian	Sunni > Alawite > Christian
Humanitarian concerns	Level of destruction in hometown	Severe damage	Moderate damage	Limited damage	Severe > Moderate > Limited
Humanitarian concerns	Attack type in the hometown	Airstrikes	Ground forces		Airstrikes > Ground forces
Security concerns/Negative relations	Ethnicity	Arab	Kurd		Arab > Kurd
Security concerns	Territorial control of hometown	Free Syrian Army	Assad forced	YPG (Kurdish forces)	Free Syrian Army > Assad Forces & Free Syrian Army > YPG

& Hangartner 2016). Three levels are used for this attribute: Sunni, Alawite, and Christian. Since Turkey is a Sunni-majority and Alawite-minority country, Sunnis are more likely to be preferred than Alawites who are more likely to be favored than Christians.

For humanitarian concerns, respondents were shown the level of destruction and attack type in their hometown. The level of destruction aimed at measuring conflict intensity and level of victimization sand adopted a hierarchical operationalization (severe, medium, and limited damage). Attack type in hometown aimed at measuring discriminate (attack by ground forces) and indiscriminate violence (airstrike attacks). Those who escape indiscriminate violence are more likely to be preferred because indiscriminate violence places civilians in a more dangerous position than discriminate violence.

For the main arguments of this study, two attributes are used: ethnicity and territorial control of hometown. Since most Syrian refugees are Arab or Kurd, these two are used as levels for the ethnicity attribute. Given the ongoing tension in Turkey, Arabs are more likely to be preferred than Kurds. Finally, for the territorial control of hometown, three levels are used: Free Syrian Army (FSA), Assad forces, and YPG (Kurdish forces). Since Turkey supports FSA, those who lived in areas under the control of FSA are more likely to be preferred than those who lived in areas under the control of Assad forces and YPG.[12] The main reason for the punishment for those who lived under YPG control stems from the relations between YPG and PKK. Table 5.1 summarizes attributes and their levels as well as their expected effects.[13]

In the analysis, standard approaches are followed. As suggested by Hainmueller, Hopkins & Yamamoto (2014), the probability of group acceptance in the forced choice design is estimated via:

$$\begin{aligned}\text{Acceptance}_{ikj} =& \gamma_0 + \gamma_1 \text{UN/EU Cost Covering}_{ikj} + \gamma_2 \text{Sunni}_{ikj} + \gamma_3 \text{Christian}_{ikj} + \\ & \gamma_4 \text{Severe Destruction}_{ikj} + \gamma_5 \text{Moderate Destruction}_{ikj} + \gamma_6 \text{Ground Forces}_{ikj} + \\ & \gamma_7 \text{Kurd}_{ikj} + \gamma_8 \text{FSA Control}_{ikj} + \gamma_9 \text{YPG Control}_{ikj} + \epsilon_i\end{aligned}$$

where i indicates the respondent, k indicates the round, and j indicates the scenario. In this setting, $i \in \{1, 2, \ldots, 1201\}$, $k \in \{1, \ldots, 5\}$, and $j \in \{1, 2\}$. Each respondent i yields 10 observations: 5 rounds and 2 choices per round.

[12] This research is agnostic about the relations between the control of Assad forces and YPG.

[13] When respondents are shown group-level characteristics, it is difficult to assess the validity of egocentric economic explanations. Thus, egocentric economic explanations were not included in the conjoint experiment. Given the recent studies that could not conclude statistical support for this argument (Alrababa'h et al. 2021, Bansak, Hainmueller & Hangartner 2016, Hainmueller & Hiscox 2007), this is not a major concern for the purpose of this study.

The unit of analysis is the hypothetical refugee group acceptance scenario, the outcome is a binary indicator for whether the group would be accepted, and the explanatory variables are the attributes explained in Table 5.1.[14] In the experiment, the order of attributes was randomized between respondents to minimize the risks of satisficing and challenges that may stem from presenting certain attributes earlier (Bansak et al. 2021). Because each group attribute is randomly assigned, the unbiased estimate of the average effect of each attribute on the likelihood that the respondent would choose to accept a group is given by the equation above. The model is estimated via ordinary least squares regression and standard errors are clustered at the respondent level.

5.6 Results

Figure 5.1 presents the average marginal component effect (AMCE) of attributes. While dots denote the AMCEs, horizontal lines refer to 95% confidence intervals clustered by respondent. Dots without confidence intervals are reference categories. Note that the interpretation of AMCEs is relative to the base categories. The analysis reveals the importance of sociotropic economic concerns to attitudes toward refugees. When the costs are covered by UN/EU, refugees are 12.7% more likely to be accepted to the country as compared to profiles when costs are covered by Turkey. Previous studies examining attitudes in the US and European countries have highlighted the importance of sociotropic economic concerns in attitude formation (Adida, Lo & Platas 2019, Bansak, Hainmueller & Hangartner 2016). Using similar operationalization, research analyzing attitudes in developing countries could not conclude a significant ef-

[14] Turkey is the reference category for the economic cost coverage attribute, Alawite for the religion attribute, limited destruction for the level of destruction in hometown attribute, airforces for the attack type in hometown attribute, Arab for the ethnicity attribute, and Assad forces for the territorial control of hometown attribute.

fect of sociotropic economic concerns (Alrababa'h et al. 2021). When a different operationalization is adopted, sociotropic economic concerns are found to have the largest effect among all the covariates.

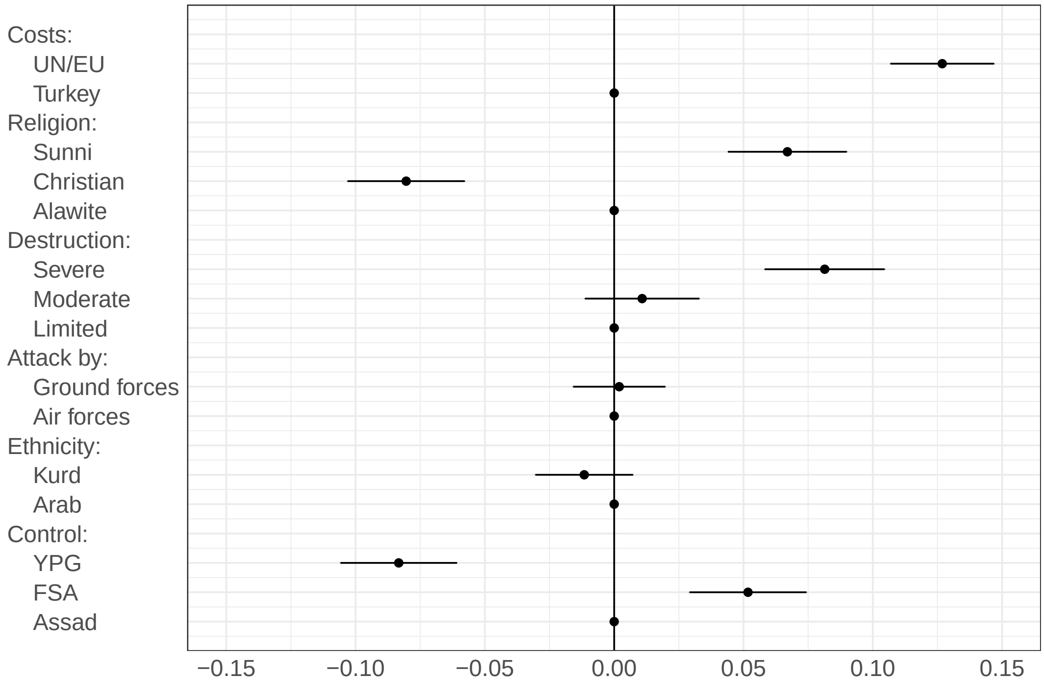


Figure 5.1: Effects of group attributes on the probability of respondents favoring a group to accept to the country

The results for cultural concerns corroborate previous studies. While there is anti-Muslim bias in the US and European countries (Adida, Lo & Platas 2019, Bansak, Hainmueller & Hangartner 2016), in Jordan, which is a Sunni-Muslim majority and Christian minority country, there is anti-Alawite bias (Alrababa'h et al. 2021). In Turkey, which is a Sunni Muslim majority and Alawite minority country, there is anti-Christian bias. Compared to Alawite profiles, Sunni refugees are 6.67% more likely to be preferred, whereas Christian profiles are 8.04% less likely to be favored.

Similarly, findings on humanitarian concerns are compatible with existing studies (Alrababa'h et al. 2021, Bansak, Hainmueller & Hangartner 2016, Getmansky, Matakos & Sinmazdemir 2020). The destruction level attribute is aimed at measuring conflict intensity, and the higher the destruction level, the more likely groups are to be accepted to the country. Groups who come from severely destructed towns are 8.14% more likely to be preferred compared to those who come from towns with limited destruction. There is no statistically significant difference between those who come from towns with moderate and limited destruction. These results might point to a threshold-like understanding. While respondents favor profiles that suffered severely, they do not have ordered preferences. The attack type attribute aimed at measuring the violence type civilians had to endure (discriminate or indiscriminate), and there is no statistically significant difference between levels.[15]

In terms of this study's arguments, the actor that controlled the territory from which refugees arrived affects attitudes. Groups that lived under the control of Syrian opposition, FSA, are 5.17% more likely to be preferred, and those who lived under the control of the Kurdish forces, YPG, are 8.32% less likely to be preferred compared to those who lived under the control of Assad forces. The main reason for respondents favoring those who lived under the control of FSA is likely to stem from the Turkish government's support for the group. While YPG is also an opposition group, those who lived under their control are punished because of YPG's good relations with PKK, the Kurdish insurgent group in Turkey. Groups that lived under the control of YPG are likely to be perceived as possible supporters of PKK and their inflow might be considered to place the country in a disadvantageous position in the conflict with PKK, which is likely to be the main reason for the observed effect.

The ethnicity attribute appears to be statistically insignificant. In other words, the respondents did not differentiate between Kurdish and Arab refugees.

[15]Either respondents do not differentiate between attack types or the attribute failed to capture variation in attack types.

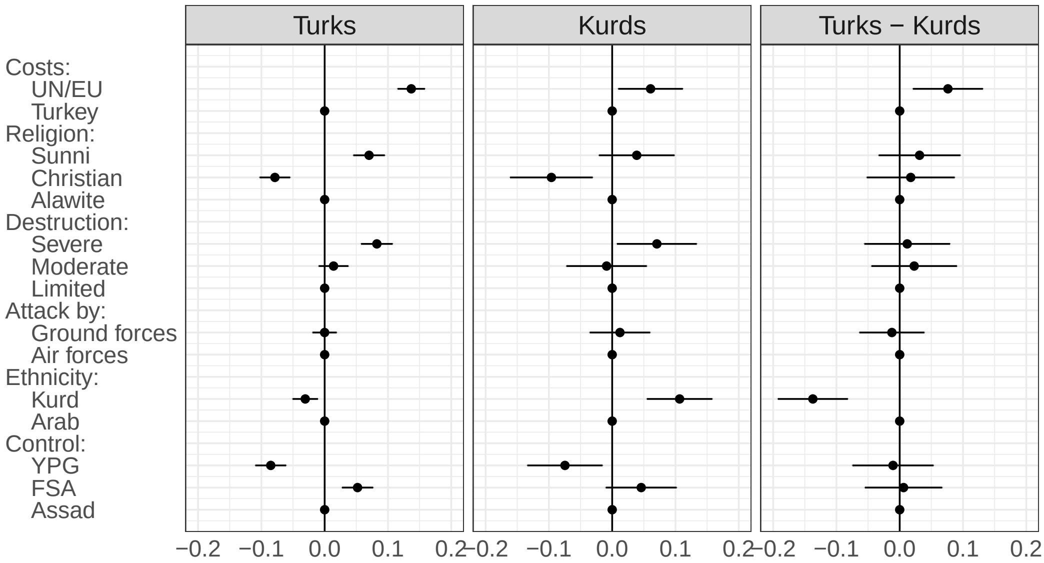


Figure 5.2: Effects of group attributes on the probability of respondents favoring a group to accept to the country for Turkish and Kurdish respondents, as well as the differences between sub-samples

However, in the sample, there are respondents from various ethnic groups including Kurds. Out of 1,201 respondents, 967 of them are Turks, 172 of them are Kurds, and 62 of them are from other groups. In-group favoritism of Kurdish respondents might cancel out Turkish respondents' bias against Kurdish groups. Therefore, the sample was divided into Kurds and Turks[16] and AMCEs[17] as well as differences between the two sub-samples were estimated. The results are reported in Figure 5.2. While dots denote the AMCEs, horizontal lines refer to 95% confidence intervals clustered by respondent. Dots without confidence intervals are reference categories. The left panel reports AMCEs for Turkish respondents, the middle panel for Kurdish respondents, and the right panel for differences between Turks and Kurds. When the analysis is carried

[16]Here, Turks include respondents from other ethnic groups as well. Since Kurds are the only oppressed ethnic group in Turkey, other ethnic identities were grouped. However, when other groups were excluded and the analysis was conducted only with Turks and Kurds, the results (Appendix C Figure C.1) were very similar and still supportive of the main arguments.

[17]Following the suggestion of Leeper, Hobolt & Tilley (2020), to compare sub-groups, marginal means were also used instead of AMCEs: the results are very similar and still supportive of the main argument (Appendix C Figure C.2).

out only with the Turkish respondents, as expected, the ethnicity attribute turns out to be statistically significant. Although the effect is not very large (around 3.1%), Turks significantly favor Arab refugees over Kurdish refugees. Out-group bias fails to explain this difference, as both Kurds and Arabs are out-groups to Turks. However, there has been a civil conflict between the Turkish government and Kurdish insurgents for decades, which might be the main reason for the observed difference. When it comes to Kurdish respondents, not surprisingly, they significantly favor Kurdish refugees over Arab refugees, and the ethnicity attribute exerts the largest impact.[18]

When the sample is split into two, the main difference is observed with respect to the ethnicity attribute. Although there is a significant difference between sub-samples for the cost attribute, it disappears when marginal means are used instead of AMCEs (Appendix C Figure C.2). Surprisingly, there are no differences between Turks and Kurds with regard to the territory control attribute. Kurds are also less likely to prefer profiles that lived under the control of YPG. Since the number of Kurdish respondents is not high, the confidence intervals are quite large. However, AMCE estimates for both groups are very close to each other and point to a lack of significant differences. Kurds might perceive those who lived under the control of YPG as supporters of YPG and fear that involvement of another insurgent group in the conflict between the Turkish government and PKK might cause problems.[19]

[18]The number of Kurdish respondents is not high. Therefore, confidence intervals are large and the results should be interpreted with caution.

[19]Following the suggestions of Egami & Imai (2019), I checked whether there are any interaction effects between attributes, particularly between ethnicity and territory control: no statistically significant differences were found.

5.7 Probing Possible Mechanisms

Respondents are less likely to prefer refugee groups that lived under the control of YPG. The literature on violence against civilians has extensively discussed how living in an area under the control of an armed group may be perceived as support for the group (Balcells & Stanton 2020, Kalyvas 2006, Lichtenheld 2020, Valentino, Huth & Balch-Lindsay 2004). Therefore, the most likely explanation for the negative effect of YPG is based on security concerns, because these refugees are likely to be perceived as supporters of YPG, which is considered as an extension of PKK by the Turkish public (Kirişci 2014). The inflow of "possible YPG supporters" to Turkey may place the Turkish government in a disadvantageous position in its fight with PKK, and natives favor groups that lived in areas under the control of an armed actor other than YPG.

Arab refugees are favored over Kurdish refugees by Turkish respondents. There are two possible explanations. First, given the ongoing Kurdish insurgency in Turkey, the inflow of Kurdish refugees may increase the resource pool of PKK, which will place PKK in an advantageous position and the Turkish government in a disadvantageous position. Thus, the first possible mechanism is related to security concerns. Second, due to ongoing fighting, the relations between Turks and Kurds are negative. There is discrimination against Kurds, limited intergroup marriages, and groups generally live in segregated areas. Thus, the second mechanism might be based on existing negative intergroup relations. This is different from out-group bias as both Kurds and Arabs are out-groups. Relations with Kurds are more negative than relations with Arabs because of the enduring conflict.

In this section, evidence is provided to indicate which mechanism is the main driver for the observed effect of the ethnicity attribute. In the survey, following the conjoint experiment, a priming experiment was also conducted. Respondents were primed with respect to the ethnicity of refugees and answered questions about the effects of refugee flows on economic, social, and security issues. More specifically, respondents randomly read either *"conflict and violent events force a high number of people to flee their homes in a short period of time. For instance, due to attacks <u>in the northern part of Syria</u>, thousands of <u>Kurds</u> came to Turkey in a short period of time."* or *"conflict and violent events force a high number of people to flee their homes in a short period of time. For instance, due to attacks <u>around the capital of Syria</u>, thousands of <u>Arabs</u> came to Turkey in a short period of time."*. Here, priming is based on real-life cases. During the height of the Syrian conflict, thousands of people from Kobane (a Kurdish-dominated city) and from major cities such as Aleppo (an Arab-dominated city) came to Turkey in a short period of time.

After the priming, respondents read statements and expressed their (dis)agreement on a Likert scale of 1 (strongly disagree) to 5 (strongly agree). Statements are as follows, and relevant concerns are in parentheses: refugees from Syria have negatively affected my economic situation (egocentric economic); refugees from Syria have negatively affected my employment opportunities (egocentric economic); refugees from Syria have negatively affected Turkey's economic situation (sociotropic economic); refugees from Syria have negatively affected the health and public services in Turkey (sociotropic economic); refugees from Syria have trouble in adjusting to daily and cultural life in Turkey (cultural); refugees from Syria should be accepted to Turkey as long as they escape violence and persecution (humanitarian); refugees from Syria have negatively affected Turkey's security (security); refugees from Syria have led to an increase in the crime rate in Turkey (security); refugees from Syria have negatively affected Turkey's

Kurdish question[20] (security); and refugees from Syria have led to an increase in terrorist attacks in Turkey (security).

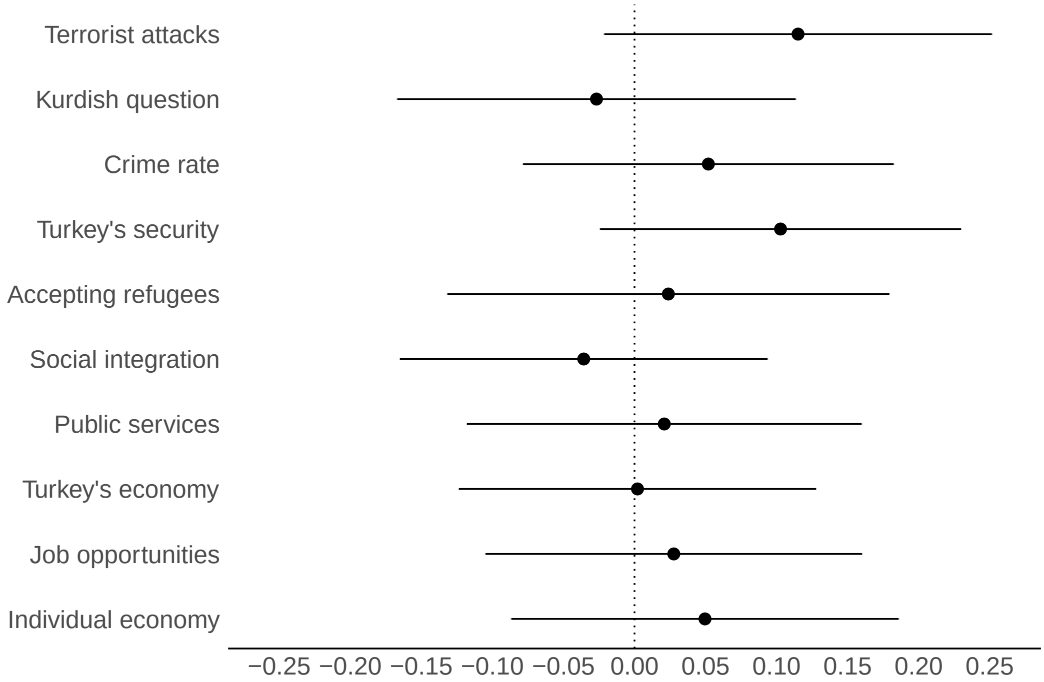


Figure 5.3: Priming experiment results. Dots refer to coefficient estimates of treatment and horizontal lines denote robust 95% confidence intervals.

Figure 5.3 presents the results from the priming experiment analysis with treatment being the only independent variable. Dots refer to coefficient estimates of treatment and horizontal lines denote robust 95% confidence intervals. The sample excludes Kurdish respondents. Higher values denote a negative effect of refugees. The priming did not lead to any significant difference for any of the statements. The terrorist attacks statement has the lowest p-value (around 0.098), and the priming reaches the conventional significance level (0.05) for none of the statements. There are two possible ways to interpret these results. First, the priming may not be strong enough to trigger an effect, which cannot be denied. Second, respondents do not differentiate the effects of refugees by

[20] Instead of referring to insurgency or civil conflict, the Turkish public uses the term "Kurdish question (*Kürt sorunu*)", which was used in the survey.

ethnicity. If the security concerns rather than negative intergroup relations are the main driver for the significant effect of the ethnicity attribute, we should have observed an effect of priming for the statements related to the security. While increases in the Kurdish population will be disadvantageous for Turks in the conflict, increases in the Arab population are not likely to have an impact. However, the ethnicity of refugees does not affect respondents' perceptions about the impact of refugees. Furthermore, for the statement about the effects of refugees on the Kurdish question, the coefficient of priming is insignificant, negative, and close to zero. Therefore, the insignificance in the priming experiment can be interpreted as that the significant effect for the ethnicity attribute in Figure 5.2 is not likely to stem from security concerns.

There is further evidence for negative intergroup relations being the main mechanism. In the survey, respondents were asked about the possible remedies to resolve the Kurdish question in Turkey. Depending on their answers, a subgroup analysis is carried out. More specifically, respondents read statements and expressed their (dis)agreement on a Likert scale of 1 (strongly disagree) to 5 (strongly agree). Statements are as follows: the Kurdish identity should be included in the constitution[21]; those who wish to receive education in Kurdish in Turkey should be able to do so[22]; and the only way to resolve the Kurdish question is to eliminate terrorism via military means[23]. Respondents are split into three categories: those who disagree with the statement, those who neither agree nor disagree with the statement, and those who agree with the

[21] In Turkey's constitution, there is an article titled "Turkish citizenship", which states that "everyone connected to the Turkish State with the bond of citizenship is a Turk". In the constitution, there is no reference to Kurds or the Kurdish identity

[22] In Turkey, there is no formal education in Kurdish. In primary, secondary, and high school, the language of instruction is Turkish.

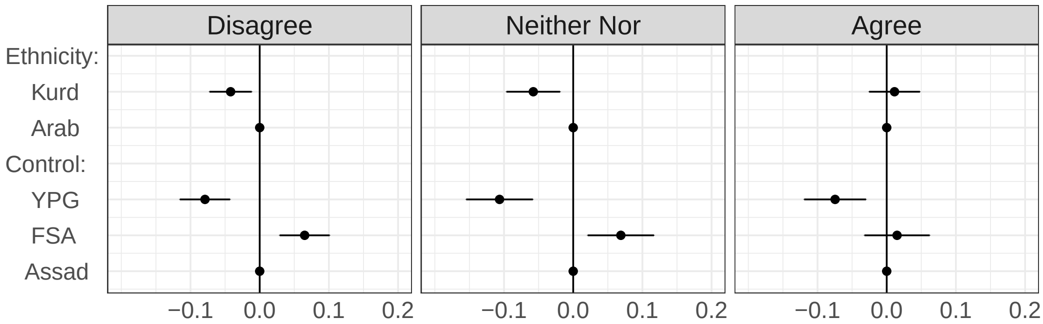
[23] This statement aims to measure whether respondents acknowledge the rights violations and inequality Kurds have to endure or whether they view it as a mere military problem (i.e., attacks by PKK).

statement.[24] The analysis is conducted by the Turkish subgroup, and Kurdish respondents are excluded.

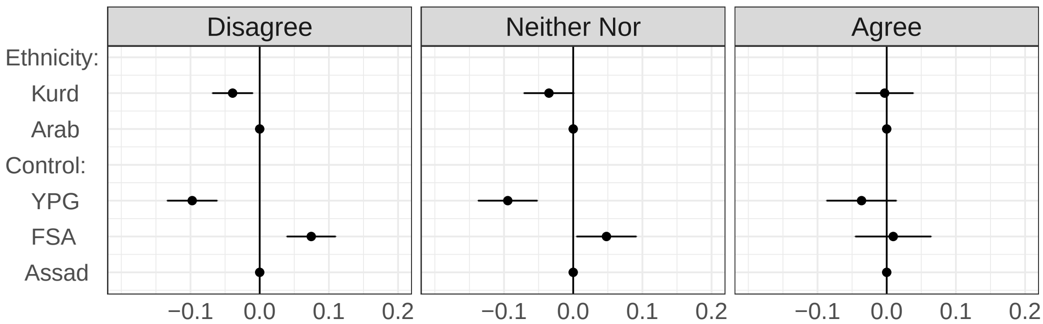
The results of the sub-group analysis of the ethnicity and territorial control attributes are reported in Figure 5.4. Dots refer to AMCEs and horizontal lines denote 95% confidence intervals clustered by respondent.[25] The upper panel presents the results for the statement regarding education in Kurdish, the middle panel for the Kurdish identity statement, and the lower panel for the statement on eliminating terrorism. For the education in Kurdish and Kurdish identity statements, those who agree have more pro-Kurdish opinions, and for the eliminating terrorism statement, those who disagree have more pro-Kurdish opinions. In the comparison of sub-groups, the AMCE for YPG is stable across groups. Regardless of respondents' opinions about the Kurdish question, their attitudes toward YPG do not vary. In other words, security concerns do not result in variation in the subgroup analysis. However, for the ethnicity attribute, respondents who have more pro-Kurdish opinions do not differentiate between Kurdish and Arab refugees. The main observed effect in Figure 5.2 is likely to stem from respondents who have negative attitudes toward Kurds. This sub-group analysis can be interpreted as indicating that respondents who have existing negative attitudes toward Kurds in Turkey favor Arab refugees over Kurdish refugees. If the main difference between sub-groups were related to security concerns, we should have observed differences with respect to the territorial control attribute's YPG level. However, attitudes across groups toward YPG are stable but not for the ethnicity attribute, which points to existing negative intergroup relations as the main reason for the significant difference

[24]Here, for presentation purposes, those who strongly (dis)agree and (dis)agree are combined. When these are disaggregated, the results still support the main argument (Appendix C Figure C.3).

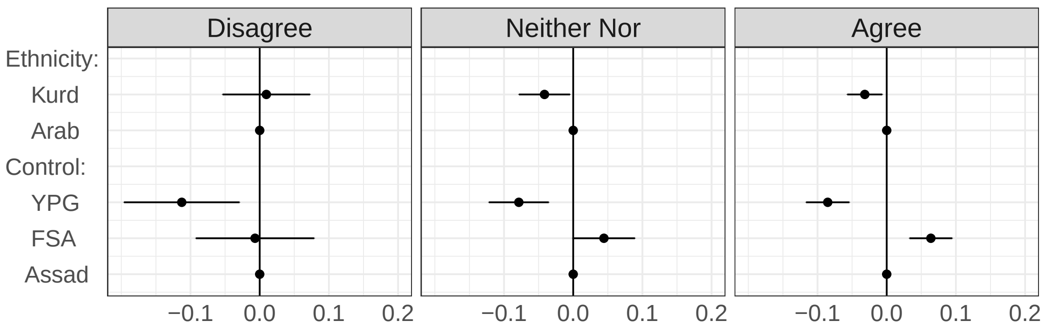
[25]Following Leeper, Hobolt & Tilley (2020), when marginal means are used, the results are similar and supportive of the main argument (Appendix C Figure C.4).



(a) Education in Kurdish



(b) Kurdish Identity in the Constitution



(c) The only solution is to eliminate terrorism

Figure 5.4: Effects of group attributes on the probability of respondents favoring a group to accept to the country according to opinions about the resolution of the Kurdish question

between Kurd and Arab refugees.

As a further analysis, using the answers for these three questions, I created an additive pro-Kurdish index ranging from 3 (least pro-Kurdish) to 15 (most pro-Kurdish). The eliminating terrorism statement is reverse coded so that higher values for all statements denote positive attitudes toward Kurds. Using the equation above, this index is interacted with the Kurd variable (ethnicity attribute). In this analysis, the index, the Kurd variable, and the interaction term are statistically significant. The predicted effect of Kurdish ethnicity on the probability of respondents favoring a group to accept to the country over the index is reported in Figure 5.5. The results suggest that respondents who have pro-Kurdish attitudes do not significantly favor one ethnic group over the other one. However, those who have negative attitudes toward Kurds in Turkey favor Arab refugees over Kurdish refugees from Syria. These questions are related to rights and equality rather than security issues, and the analysis suggests that the main driver for the observed significant effect in Figure 5.2 is likely to be negative intergroup relations. One might rightfully argue that the index might be correlated with security concerns. As a response to this argument, I carried out the same analysis by interacting the index with the YPG variable. For this analysis, a similar pattern is not observed. Neither the index nor the interaction term is statistically significant. In other words, for a factor that is mainly driven by security concerns, whether respondents have pro- or anti-Kurdish attitudes does not affect their preferences. However, pre-existing attitudes moderate the effect of the ethnicity attribute.

In conclusion, further analysis suggests that the main reason for the significant difference between Arab and Kurdish refugees in Figure 5.2 is likely to stem from pre-existing negative intergroup relations rather than security concerns of natives. The priming experiment indicates that the ethnicity of refugees does not affect natives' opinions about the effects of refugees. Following previous studies suggesting that refugees spread civil conflict (Salehyan & Gleditsch 2006, Weiner 1992), we would expect Kurdish refugees to further neg-

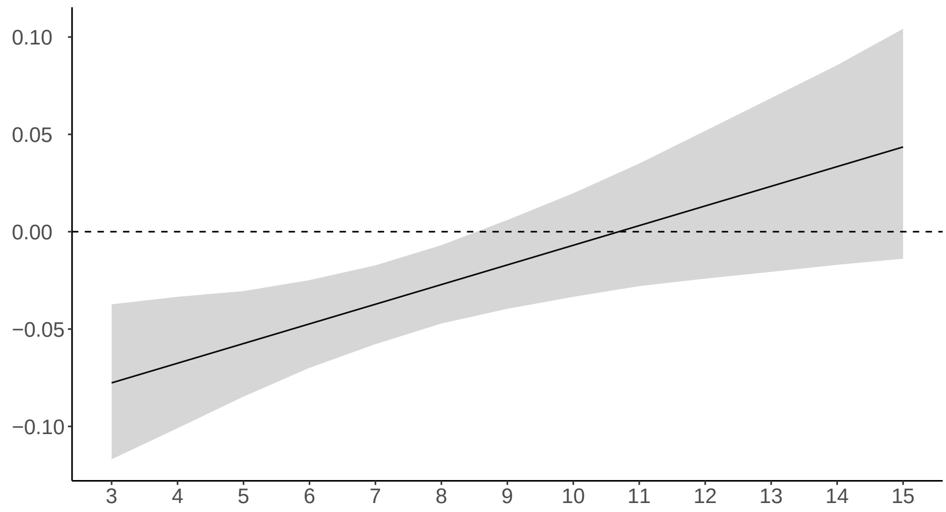


Figure 5.5: The effect of Kurdish ethnicity of a profile on the probability of profiles being preferred over the pro-Kurdish index. Kurdish ethnicity is interacted with the pro-Kurdish index. The shaded area denotes 95% confidence intervals. While the x-axis denotes the pro-Kurdish index, the y-axis indicates the effect of the Kurdish attribute.

atively affect opinions as compared with Arab refugees. However, the analysis points to a lack of differences. Furthermore, subgroup analysis by attitudes toward the resolution of the Kurdish question can be interpreted as that the main driver for the difference between the levels of the ethnicity attribute is likely to be pre-existing negative intergroup relations rather than security concerns of natives.

5.8 Conclusion

This study has examined how ethnic relations and security concerns affect attitudes toward refugees through a conjoint experiment in Turkey. Most existing research has analyzed attitudes in developed countries (Alrababa'h et al. 2021), which has resulted in a lack of attention to factors that are prevalent in developing countries but not in developed ones. Since most developing countries experience civil conflict and refugees generally flee to neighboring countries

(Moore & Shellman 2007), it is important to examine the roles of ethnicity and security concerns with respect to attitudes toward refugees. Given the emphasis on ethnic relations in previous research (Salehyan & Gleditsch 2006), it is crucial to examine whether ethnicity impacts attitudes and, if so, through which mechanisms this occurs.

To measure the role of security concerns, this study has focused on two factors. First, an ethnicity attribute is used with two levels: Kurd and Arab. Turkish respondents are more likely to favor Arab refugees over Kurdish ones. There are two possible mechanisms for this. Considering the ongoing insurgency, natives might fear the Kurdish refugee inflow placing the Turkish government in a disadvantageous position in the conflict because it can be perceived as an increase in the pool of PKK resources. Alternatively, the relations between Turks and Kurds are already negative in Turkey and pre-existing tensions affect attitudes toward Kurdish refugees. The results from the sub-group analysis of the conjoint experiment and a priming experiment suggest the pre-existing negative intergroup relations as the main driver rather than the security concerns of natives. Since already existing tensions affect attitudes toward refugees, improving intergroup relations will benefit the host country as well as refugees.

As the second factor, this research has used the armed group that controls the hometown of refugees in the experiment. Previous studies have suggested that living in an area controlled by an armed group can be perceived as support of the group (Kalyvas 2006, Lichtenheld 2020, Valentino, Huth & Balch-Lindsay 2004). Given the transnational relations between rebel groups, refugees living in an area controlled by a rebel group that is an ally of the rebels in the host country may be perceived as a security threat and face negative attitudes. The analysis corroborates this argument. Refugees who lived in an area under the control of YPG are less likely to be preferred when compared to those who lived under the control of FSA or Assad forces because of the relations between PKK and YPG. Furthermore, compared to Assad forces and YPG, refugees who lived in an area under the control of FSA are more likely to be preferred in the experiment, which might be explained by the good relations between the Turkish government and FSA. Policy implications of this finding are not straightforward. However, the results are worrisome for displaced people. Refugees generally escape from armed groups. But at the destination, they are perceived to be supporters of that group, which is paradoxical. Thus, media should be careful in presenting news about the source country and NGOs should develop projects to minimize the negative effects and overcome hostile relations.

This chapter adopted a conjoint experiment in Turkey and given transnational ethnic relations of Kurds in the region, long-lasting civil conflict with the Kurdish insurgent group PKK, and recent refugee inflow from Syria, it is an ideal case to study. Since the explanations are based on the existence of multiple ethnic groups and negative relations between these groups, these explanations are generalizable to multi-ethnic countries with ongoing insurgency or ethnic tensions. These explanations cannot be extended to ethnically homogeneous countries and countries in peace. One main concern about the external validity of findings is related to the duration of the conflict in Turkey. There is an insurgency in Turkey since 1984. In other words, in the last 38 years, violent events took place. Increases in the duration of conflict might make the relations between groups more hostile. If the conflict in the shot country is recent, relations between groups might be slightly better, and existing negative relations might play a less significant role. Thus, carrying out a similar study in a country that recently experience ethnic insurgency would further advance our understanding.

Previous research has articulated change in the ethnic composition of the host country as one of the mechanisms for refugees spreading conflict (Salehyan & Gleditsch 2006, Weiner 1992). The findings of this study suggest that the ethnicity of refugees affects attitudes, and this is not likely because of security concerns but because of pre-existing negative intergroup relations, which presents the questions of whether a change in the ethnic composition by the inflow of refugees increases the security concerns of natives and affects the onset of conflict in the host country. Siding with Böhmelt, Bove & Gleditsch (2019) and Zhou & Shaver (2019), this research suggests that the relationship between refugee inflows and the spread of conflict requires re-evaluation and further analysis.

6 Conclusion

This thesis examined the role of conflict dynamics and insurgent groups on forced migration. More specifically, it focused on three main areas: determinants of hosting refugees, causes of displacement, and attitudes toward refugees. This study examined four main questions.

1. Why do some countries host more refugees than others?
2. Why do some conflicts generate mostly IDPs, whereas others mostly refugees?
3. How do heterogeneous patterns of violence affect people's decision to flee?
4. How do conflict dynamics and transnational ethnic relations affect attitudes toward refugees?

Chapter 2 was interested in why some countries host more refugees than others and argued that countries which support rebels host a higher number of refugees than countries that do not. Empirical analysis of the raw data and matching procedures corroborate the main hypothesis and supporting rebels is positively correlated with the number of refugees hosted. Countries that support rebel groups accommodate 2.5 times more refugees than others. Various model specifications strengthen the robustness of results and suggest that incorporating rebel support into the analysis improves our ability to explain variation in refugee flows.

This chapter makes several important contributions to civil conflict and refugee literature. By analyzing the effect of supporting rebels, it argues that conflict dynamics play a significant role in explaining the variation in refugee flows. Civil conflicts should not be treated as a binary variable, and their dynamics should be further explored. Secondly, previous studies analyze the effect of civil conflicts on forcing people to leave but neglect to address how these conflicts may affect their destination. This paper suggests that host countries' involvement in the conflict has a significant and robust impact on the number of refugees that they host. Lastly, existing studies generally treat host countries as passive actors in refugee movements with an understanding of refugees choosing destinations with regards to countries' proximity, political, and economic situation. However, this study suggests that host countries—by being active players in the displacement process—may make the movement and influx of refugees easier or more difficult.

There are important caveats that must be taken into consideration when interpreting these findings. The main independent variable is dichotomous, accounting only for the presence of support and not for the variation in its intensity. However, depending on the level of host countries' backing of rebel groups, attitude towards accommodating refugees may vary. Theoretically, the more support host countries provide to insurgents in the source country, the more refugees they will accommodate. Unfortunately, due to the lack of fine-grained data, this study could not account for this variation. With more detailed information, future studies could overcome this shortcoming. Additionally, this paper controls for various political and economic factors in the host country, but does not include specific policies such as the open door policy that Turkey and Germany adopted for Syria because of data availability. It is an important factor to explain the variation in where refugees go, but data collection on this issue is beyond the scope of this study and needs further consideration.

Chapter 3 set out to analyze distinct causes of refugee and IDPs flows in civil conflict countries. Even though in general, the same factors affect both internal and external displacement, depending on the perpetrator and its spread, the effect of violence varies. While government violence increases the number of refugees, rebel violence results in more internal and external displacement although the effect of rebel violence on refugees is not very robust. By fleeing the conflict zone, people can escape rebel violence. However, the government's coercive force can generally reach everywhere within its borders and to escape government violence people may have to flee to another country. But if rebel violence is widespread, leaving the conflict zone might not be enough to escape persecution. Therefore, to explain variation in forced migration, where armed groups perpetrate violence should be taken into account in addition to who the perpetrator is. While increases in government and rebel violence lead to increases in the number of refugees, the effect of rebel violence on internal displacement follows a reverse U-shape.

This chapter aims to make several important contributions to the literature on forced migration and civil conflict. First, siding with Moore & Shellman (2006) and Steele (2019), this study argues that internal and external displacement have distinct causes even though many factors may affect them in the same way. Second, this chapter emphasizes the divergent effects of government and rebel violence in the displacement process and urges for further investigation of distinct causes of internal and external displacement. Finally, in addition to conflict intensity, this study emphasizes the importance of the spread of violence to explain variation in forced migration.

Chapter 3 suffers from the problem of ecological inference because although it theorized at the individual-level, it tested the main argument at the country-level. Here, chapter 4 came to the rescue and examined how individuals respond to different facets of violence and how these facets affect their decision to flee or stay. The results reveal that civilians respond more strongly to nearby violence than to distant ones. Civilians also show more fear for indiscriminate violence and flee from it compared to targeted attacks. The analysis highlights the significance of persistent threats rather than the frequency of violence in migration decisions. While there is no significant difference in the effect of attacks happening frequently or sometimes, they are significantly different than first-time attacks and increase the probability of flight decisions. This finding is more nuanced than the existing literature that emphasizes on battle deaths or the number of violent events (Balcells & Steele 2016, Davenport, Moore & Poe 2003, Turkoglu & Chadefaux 2019). Importantly, the perpetrator of violence affects the location to which people flee. In line with chapter 3, government violence leads to flights abroad while rebel violence leads to relocation within the country.

Chapter 4 makes important contributions to the literature. First, it complements existing macro-level analyses of flight patterns. The use of a conjoint experiment to study flight decisions is novel and generates new individual-level evidence, which overcomes the problem of ecological inference. Second, previous research has generally examined the effect of violence on flight decisions with a focus on conflict intensity and the scale of violence (Adhikari 2013, Moore & Shellman 2004, Melander, Oberg & Hall 2009, Turkoglu & Chadefaux 2019). However, violence is a heterogeneous phenomenon, and depending on the type of violence experienced, individuals may respond differently to this treatment. Individuals may not just respond to the intensity of violence but also to other aspects (e.g., type and perpetrator). This study complements the literature by disentangling which features of violence lead to the decision to flee in an experimental setting. Third, by exploring how social networks affect flight decisions, this study contributes to the research on civilian resilience during conflicts. Previous studies have examined how social networks in the origin affect flight decisions by enabling better coping mechanisms with the problems at the hometown (Marston Jr 2020) and this research complements the literature by analyzing how social networks abroad have an impact on flight patterns. Individuals cope more easily with violence and unrest if they have support networks. This finding suggests the need to support social networks within and to conflict-prone societies to lift the burden of high-stake decision-making and to broaden the scope of action for populations suffering during conflicts.

While the findings of chapter 4 shed light on the importance of easing pressure for individuals, they are at the same time generated by an abstract research design. Respondents saw randomized attributes for violent scenarios on their laptop or phone and picked a scenario in which they would flee. The real world is much more complex. Civilians gather information about the situation and the possibilities to go to other areas or other countries before making their decision (Holland & Peters 2020). Their choices are also impeded by practical considerations, for example by the significantly higher amounts of money they need to flee abroad than internally. Decisions are also made under much higher stress in real-life. Additionally, what we examine here are intentions to flee rather than actual behavior. The results offer important insights into the ways people think about fleeing. However, it should be kept in mind that we do not observe the act of migration.

Chapter 5 examined the effects of security concerns and transnational ethnic relations on attitudes toward refugees through a conjoint experiment in Turkey. First, an ethnicity attribute was used with two levels: Kurd and Arab. Turkish respondents were more likely to favor Arab refugees over Kurdish ones. There are two possible mechanisms for this. Considering the ongoing insurgency, natives might fear the Kurdish refugee inflow placing the Turkish government in a disadvantageous position in the conflict because it can be perceived as an increase in the pool of PKK resources. Alternatively, the relations between Turks and Kurds are already negative in Turkey and pre-existing tensions affect attitudes toward Kurdish refugees. The results from the sub-group analysis of the conjoint experiment and a priming experiment suggested the pre-existing negative intergroup relations as the main driver rather than the security concerns of natives. Second, refugees who lived in an area controlled by insurgent groups that are allies of rebels in the host country were less likely to be favored than others as these refugees might be considered as a pool of resources for rebels in the destination. Additionally, refugees who lived in an area controlled by an armed group that was supported by the host country government were more likely to be favored in the experiment.

This paper makes several important contributions to the literature. First, while the literature has generally examined attitudes in developed countries (Alrababa'h et al. 2021), this study examines attitudes in Turkey, a developing country that hosts the highest number of refugees. Second, due to the focus on developed countries, existing research has understudied the role of factors that are prevalent in developing countries but not in developed ones with respect to attitude formation. This research complements the literature by analyzing how conflict dynamics and transnational ethnic relations affect natives' attitudes toward refugees. Third, previous studies have argued that living in an area controlled by an armed group can be perceived as support for that group (Kalyvas 2006, Lichtenheld 2020, Valentino, Huth & Balch-Lindsay 2004). The analysis indeed corroborates this argument and provides evidence of how civilians might be "penalized" because they lived under the control of insurgent groups. Fourth, previous studies have articulated change in the ethnic composition of the host country as a mechanism for refugees spreading civil conflict (Salehyan & Gleditsch 2006, Weiner 1992). The analysis of this paper shows that when there is an ongoing insurgency in the host country, refugees that have ties to the ethnic minority are less likely to be favored and the main reason for this is likely to be pre-existing negative intergroup relations rather than security concerns. Recent studies have suggested that refugee flows do not spread civil conflict and that conditions of the host country mitigate the effects of refugee flows (Böhmelt, Bove & Gleditsch 2019, Zhou & Shaver 2019). Siding with this strand of the literature, this study argues that existing conditions in the destination play a significant role in natives' attitudes toward refugees rather than associated security risks and urges for further investigation of the relationship between displacement and civil conflict.

The findings of this thesis are relevant not only for academic research but also for policy-making, especially for international and non-governmental organizations. Understanding the determinants of displacement flows and attitudes toward refugees is of critical importance for emergency responses and governance of asylum flows. How the international community responds to the initial displacement crisis plays a significant role in alleviating detrimental impacts and preventing the crisis from escalating. Evidence of a systematic relationship between conflict dynamics and displacement will allow the international community to better anticipate when and where people go, to develop faster and more effective policies, and to minimize the negative impacts of population flows for both host societies and displaced people.

This study offers avenues for future research. First, in the examination of different causes of internal and external displacement, this thesis focused on violence perpetrator and how spread violence is. Future research can take individual characteristics, motivation, and opportunities into account. Whether individuals have relatives abroad, whether they can speak a foreign language, whether they have enough savings to cover the costs of the initial period of displacement, and whether they experience or witness any type of violence can be a good start. Second, this thesis examined the heterogeneous effects of violence at the individual-level. However, our understanding is still limited and many research questions about human mobility on the individual-level remain open. Studies could examine how social networks within the country or personal risk preferences affect people's decisions to flee and their reactions to violent events. Further work on the behavioral effects of resilience, social cohesion, and networks seems crucial. Finally, the focus of existing research on attitudes in the developed countries has resulted in neglecting factors prevalent in developing countries but not developed ones. This research showed how the relations between the host country and armed group that controlled refugees hometown affect attitudes and future studies could incorporate other conflict dynamics and transnational dimensions of civil wars to the study of attitudes toward refugees.

A Appendix to Chapter 2

A.1 A Brief Explanation on the Dependent Variable

The unit of observation in this study is directed-dyad-civil conflict year, an ordered pair of countries: $country_i$ and $country_j$. While $country_i$ refers to countries that experience civil conflict—a potential source; $country_j$ is all countries other than $country_i$—a potential host (Gleditsch & Ward 1999). This dyadic approach will let me control for both push and pull factors as well as dyadic characteristics. Previous analysis of global refugee flows excludes $country_i$ that does not generate any refugee, which may lead to biased estimates and inferences. To overcome the selection bias problem, I include all possible dyads regardless of whether the source country produces any refugee. Some studies select observations on the dependent variable, which should be avoided as it results in misleading conclusions (King, Keohane & Verba 1994). For example, an analysis of refugee flows to developed Western countries focuses on only 48 source countries which generated a significant number of refugees. Analyzing just Western countries as the destination is not the problem as the paper may be interested in explaining the variation in refugee flows to Western countries. This study, however, omits all dyads with 0 and even with small figures (Hatton 2009). By ignoring the lack of refugee flows and examining only countries that generated a large number of refugees, any conclusion drawn will be problematic. The absence of refugees is itself valuable information, and the exclusion of these observations may lead to questionable inferences.

In this study, the dependent variable is the number of refugees from $country_i$ in $country_j$ in year t; for example, the number of Angolan refugees in Germany in 1991. For refugees, following Neumayer (2005), Moore & Shellman (2007), Uzonyi (2015), and Moorthy & Brathwaite (2019), I use the United Nations Refugee Agency (2017) definition which identifies people who flee from the country of their nationality because of 'well-founded fear of being persecuted for reasons of race, religion, nationality, membership of particular social group or political opinion'. The data is extracted from the UNHCR Population Statistics Database (the United Nations Refugee Agency 2017). I use the stock number of refugees since the flow data is unavailable. Some studies operationalize the dependent variable by taking the difference of consecutive years' stock numbers. But this approach is problematic for various reasons. First of all, the way UNHCR collects data does not let us calculate the flow. Analyses that use the difference in stock number assume that none of the refugees from the previous year returned to their country of origin. We can never be sure of this, and previous studies fail to account for this eventuality.[1] Secondly, if a person does not return to their country of origin, this person is still affected by the conflict there.[2] Thirdly, people who can leave the origin country might have already left it and there are fewer people or no one left to leave. For example, in 1989, the number of Afghani refugees in Pakistan was 3,272,290, and in 1990, this figure was 3,253,000. By 1990, more than a third of Afghanistan's

[1] In a given year, all refugees in $country_j$ might return to home, $country_i$ and in the next year, new people might leave the source country.

[2] Just because a person left the country in year t and he/she is still in the host country in year $t + 2$, the reasons for being a refugee cannot be attributed to only what happened in year t. What happens in $t + 1$ and $t + 2$ also affects refugees' decision to turn back.

population (6.3 million out of a total remaining population of 12 million) had left the country. There might have been no one to flee the country at that time. If I operationalize the dependent variable by taking the difference in stock, for 1990, I have to code Afghani refugees in Pakistan as 0 and ignore more than 3 million people.

To exemplify why taking the first differences in the stock number might not be inappropriate, we can look at UNHCR Democratic Republic of Congo and South Sudan flow data in Uganda in 2018 (UNHCR 2019) and Internal Displacement Monitoring Center (IDMC) data on Syria (IDMC 2018*b*).

UNHCR offers flow and stock data form DRC and South Sudan in Uganda for 2018. To my knowledge, this is the only flow data offered by UNHCR. The stock number of refugees from DRC in Uganda was 226,192 and 303,092 in 2017 and 2018 respectively. If I take the difference, I have to code the dependent variable as 76,900. However, the flow number that UNHCR provides is 119,919. The taking difference approach ignores the one-third of incoming refugees. Similarly for South Sudan, there is a decrease in the number of refugees in 2018 compared to 2017. Thus, adopting the taking difference approach, the dependent variable should be coded as 0. However, according to UNHCR, 40,718 new refugees from South Sudan arrived in Uganda in 2018.

As another source, IDMC which was established by the Norwegian Refugee Council offers internal displacement flow and stock data for particular countries and particular years. Even though in the main analysis, I use refugees—external displacement—as the dependent variable, I believe that problems related to data collection will be very similar for internal and external displacement as shown above. For Syria, the stock number of internally displaced people (IDPs) in 2014 and 2015 was 7.6 and 6.6 million respectively. The flow number in 2015 is 1.3 million. If I take the difference between consecutive years, I have to code

2015 value as 0, whereas the real value is 1.3 million. One might consider Syria as an extreme case and the situation will be different for other countries. As another example, we can look at Cameroon. The stock number of IDPs was 177,000 and 239,000 in 2016 and 2017 respectively. The flow number in 2017 is 119,000 (IDMC 2018*a*). If I take the first difference, I have to code Cameroon as 62,000 whereas the real value almost doubles this difference at 119,000. Taking the first differences results in ignoring new movements. Therefore, I opt for the stock number as the dependent variable over the flow.

In this study, following the general practice in the literature, I use UNHCR data to operationalize the dependent variable. Even though it is the most widely used dataset to study forced migration, it is not free from problems. In the collection of data, UNHCR collaborates with national governments and although in general, governments use a similar definition, how refugee is defined might vary from government to government. In addition, by its nature, counting the number of people who move is not an easy task. But counting displaced people is easier compared to other types of migrants, because to enjoy services that governments, international organizations, and NGOs provide, displaced people need to register by UNHCR (Crisp 2000). This may alleviate the concerns to a certain extent, but readers should be careful in assessing the findings. Another concern related to data collection may stem from 1951 and 1967 conventions. To overcome this concern, I run the regression analysis by adding a dummy variable for 1951-1967 period. Results are supportive of the main argument.

A.2 A Brief Explanation on Matching Procedures

Model dependence is a common problem in social sciences research. With a high number of observations and imbalance (such as this study), there is a risk that the results may be model dependent and of questionable validity. To overcome these shortcomings, matching procedures can be performed. As a powerful nonparametric approach for improving causal inferences, matching reduces model dependence, estimation error, and bias (Ho et al. 2007, Iacus, King & Porro 2019). By discarding observations outside the region of common empirical support, this process can help to obtain less biased and model dependent results.

Different matching techniques such as propensity score matching - (PSM) (Ho et al. 2007) and coarsened exact matching - (CEM) (Iacus, King & Porro 2012) can be used to perform the analysis. PSM matches treated observations (dyads in which rebels received support) to control observations (dyad in which rebels were not supported) based on their propensity to receive the treatment. To calculate this score, PSM runs a logit model with the treatment (rebels support) as the dependent variable and all other covariates as explanatory variables. Afterward, it predicts the dependent variable with the results of the logit model. In other words, it calculates the propensity scores of receiving treatment to match the observations. In PSM, while the number of matched observations is predetermined (all treatment observations can be matched), we have no control over imbalance. The other method, CEM matches treatment and control observations based on specified intervals of other covariates (in this study, 21 control variables that are listed in results section). For example, intervals of distance variable might be 50, 500 and $1,000$. In this case, an observation with a distance higher than 50 km and less than 500 km can be matched to another observation with a distance of the same interval. In other words, this observation cannot be matched to another observation with distance less than 50 km, or more than 500 km. Since all covariates need to be matched at specified intervals, one of the main drawbacks of CEM is losing some of the treatment observations, especially with a high number of covariates such as this study. Even though in general matching is an effective way of reducing model dependence, PSM may result in the opposite direction of the expected outcome. On the contrary, it may increase imbalance and exacerbate model dependence concerns. CEM as a member monotonic imbalance bounding matching methods guarantee a reduction in imbalance and estimation error; is robust to measurement error; restricts data to common empirical support and meets congruence principle (Iacus, King & Porro 2011, Iacus, King & Porro 2012, King & Nielsen 2019). Since CEM suffers less from PSM's many shortcomings, I opt for CEM over PSM.

A.3 Robustness Checks Regression Outputs

Table A.1: Summary Statistics

Variable	Mean	St. Dev.	Min	Max
Number of Refugees	1,347	38,978	0	3,272,290
Host Polity	0.760	7.437	−10	10
Host GDP per capita	7.842	1.418	4.060	11.944
Host Population	15.798	1.675	11.599	21.004
Host Regime Transition	0.043	0.203	0	1
Host Interstate War	0.024	0.152	0	1
Host Civil War	0.160	0.367	0	1
Host Genocide	0.032	0.177	0	1
Host UNHCR Signatory	0.606	0.489	0	1
Source Polity	−0.054	6.278	−10	10
Source GDP per capita	7.258	1.220	4.089	10.774
Source Population	16.833	1.383	12.866	20.990
Source Regime Transition	0.129	0.335	0	1
Source Interstate War	0.058	0.233	0	1
Source Genocide	0.153	0.360	0	1
Distance	8.237	1.661	0.000	9.868
Source Neighbors Number	8.440	4.324	0	37
Colonial Tie	0.019	0.137	0	1
Alliance	0.059	0.235	0	1
Ethnic Relations	0.030	0.171	0	1
Rivalry	0.009	0.094	0	1
Year in Conflict	9.044	9.467	1	48
Refugees Total	7.628	5.059	0.000	15.662
Rebels Support NSAD	0.010	0.100	0	1
Rebels Support UCDP	0.006	0.077	0	1

Table A.2: Zero-Inflated Negative Binomial Regression of the Yearly Number of Refugees in Civil Conflicts

	NSAD, 1951–2011		UCDP, 1975–2009	
	(1)	(2)	(3)	(4)
Rebel Support NSAD	3.487**	3.677**		
	(1.357)	(1.446)		
Rebel Support UCDP			3.396**	3.836**
			(1.235)	(1.253)
Host Polity	1.028	1.027	0.992	1.000
	(0.025)	(0.022)	(0.020)	(0.019)
Host GDP per capita (ln)	2.330**	2.427**	2.868**	2.859**
	(0.222)	(0.214)	(0.234)	(0.213)
Host Population (ln)	1.556**	1.542**	1.811**	1.769**
	(0.125)	(0.125)	(0.147)	(0.139)
Source Polity	0.977	0.957**	0.981	0.948**
	(0.016)	(0.013)	(0.016)	(0.013)
Source GDP per capita (ln)	0.731**	0.859	0.755**	0.867
	(0.066)	(0.080)	(0.066)	(0.079)
Source Population (ln)	0.850	1.147	0.750**	0.987
	(0.074)	(0.115)	(0.069)	(0.102)
Distance (ln)	0.386**	0.380**	0.369**	0.361**
	(0.017)	(0.018)	(0.018)	(0.019)
Refugees Total (ln)	1.104*	1.139**	1.117	1.113
	(0.047)	(0.040)	(0.070)	(0.061)
Host Regime Transition		1.276		2.018*
		(0.418)		(0.697)
Host Interstate War		1.904**		1.853*
		(0.363)		(0.454)
Host Civil War		0.576**		0.571**
		(0.117)		(0.114)
Host Genocide		1.039		1.061
		(0.274)		(0.290)
Host UNHCR Signatory		1.104		1.532
		(0.301)		(0.415)
Source Regime Transition		1.826**		1.975**
		(0.356)		(0.365)
Source Interstate War		0.878		1.054
		(0.168)		(0.206)
Source Genocide		2.250**		1.381
		(0.477)		(0.261)
Source Neighbors Number		0.938**		0.944**
		(0.018)		(0.018)
Colonial Tie		1.767		1.453
		(0.741)		(0.603)
Alliance		2.451**		2.107**
		(0.525)		(0.457)
Ethnic Relations		0.747		0.696
		(0.201)		(0.220)
Rivalry		1.444		1.102
		(0.576)		(0.475)
Year in Conflict		1.020		1.032
		(0.033)		(0.038)
Year in Conflict^2		0.998		0.998

		(0.002)		(0.002)
Year in Conflict^3		1.000		1.000
		(0.000)		(0.000)
inflate				
Rebel Support NSAD	1.171	0.637		
	(0.717)	(0.341)		
Rebel Support UCDP			1.592	0.545
			(0.895)	(0.238)
Host Polity	0.902**	0.942**	0.888**	0.935**
	(0.008)	(0.008)	(0.008)	(0.008)
Host GDP per capita (ln)	0.498**	0.502**	0.526**	0.521**
	(0.023)	(0.022)	(0.025)	(0.023)
Host Population (ln)	0.648**	0.592**	0.654**	0.607**
	(0.025)	(0.025)	(0.033)	(0.028)
Source Polity	0.955**	0.977**	0.946**	0.968**
	(0.008)	(0.008)	(0.008)	(0.008)
Source GDP per capita (ln)	0.885**	0.854**	0.998	0.954
	(0.041)	(0.042)	(0.050)	(0.050)
Source Population (ln)	0.823**	0.763**	0.804**	0.764**
	(0.031)	(0.036)	(0.034)	(0.038)
Distance (ln)	2.126**	2.161**	2.414**	2.304**
	(0.118)	(0.173)	(0.304)	(0.239)
Refugees Total (ln)	0.634**	0.619**	0.640**	0.624**
	(0.011)	(0.012)	(0.012)	(0.013)
Host Regime Transition		0.775		0.902
		(0.157)		(0.193)
Host Interstate War		1.042		1.000
		(0.210)		(0.220)
Host Civil War		1.526**		1.632**
		(0.172)		(0.193)
Host Genocide		2.161**		2.222**
		(0.545)		(0.568)
Host UNHCR Signatory		0.182**		0.196**
		(0.022)		(0.024)
Source Regime Transition		0.872		0.908
		(0.087)		(0.095)
Source Interstate War		1.843**		1.940**
		(0.269)		(0.281)
Source Genocide		2.820**		2.398**
		(0.326)		(0.283)
Source Neighbors Number		1.025*		1.016
		(0.012)		(0.012)
Colonial Tie		1.443		1.137
		(0.409)		(0.357)
Alliance		0.449**		0.500**
		(0.086)		(0.103)
Ethnic Relations		2.058		2.415*
		(0.787)		(1.034)
Rivalry		2.336		4.437*
		(1.655)		(2.979)
Year in Conflict		1.062**		1.039
		(0.022)		(0.024)
Year in Conflict^2		0.997*		0.999

		(0.001)		(0.002)
Year in Conflict^3		1.000**		1.000
		(0.000)		(0.000)
Observations	170947	170947	138585	138585
BIC	321622.181	317747.207	283512.750	280503.539

Incidence Rate Ratios are presented.
Standard errors clustered by dyad in parenthesis.
* $p < 0.05$, ** $p < 0.01$

Table A.3: Zero-Inflated Negative Binomial Regression of the Yearly Number of Refugees in Civil Conflicts, Regression Coefficients

	NSAD, 1951–2011		UCDP, 1975–2009	
	(1)	(2)	(3)	(4)
Rebel Support NSAD	1.249**	1.302**		
	(0.389)	(0.393)		
Rebel Support UCDP			1.223**	1.344**
			(0.364)	(0.327)
Host Polity	0.028	0.027	-0.008	-0.000
	(0.024)	(0.022)	(0.020)	(0.019)
Host GDP per capita (ln)	0.846**	0.887**	1.054**	1.050**
	(0.095)	(0.088)	(0.082)	(0.074)
Host Population (ln)	0.442**	0.433**	0.594**	0.571**
	(0.080)	(0.081)	(0.081)	(0.078)
Source Polity	-0.023	-0.044**	-0.019	-0.053**
	(0.017)	(0.014)	(0.016)	(0.014)
Source GDP per capita (ln)	-0.314**	-0.153	-0.281**	-0.143
	(0.090)	(0.093)	(0.088)	(0.091)
Source Population (ln)	-0.162	0.137	-0.287**	-0.013
	(0.087)	(0.100)	(0.093)	(0.103)
Distance (ln)	-0.952**	-0.968**	-0.998**	-1.018**
	(0.045)	(0.049)	(0.050)	(0.052)
Refugees Total (ln)	0.099*	0.130**	0.110	0.107
	(0.043)	(0.035)	(0.063)	(0.055)
Host Regime Transition		0.244		0.702*
		(0.327)		(0.345)
Host Interstate War		0.644**		0.617*
		(0.191)		(0.245)
Host Civil War		-0.551**		-0.560**
		(0.203)		(0.199)
Host Genocide		0.038		0.059
		(0.264)		(0.274)
Host UNHCR Signatory		0.099		0.426
		(0.273)		(0.271)
Source Regime Transition		0.602**		0.680**
		(0.195)		(0.185)
Source Interstate War		-0.130		0.052
		(0.192)		(0.196)
Source Genocide		0.811**		0.323

		(0.212)		(0.189)
Source Neighbors Number		-0.064**		-0.058**
		(0.019)		(0.019)
Colonial Tie		0.569		0.374
		(0.419)		(0.415)
Alliance		0.897**		0.745**
		(0.214)		(0.217)
Ethnic Relations		-0.292		-0.363
		(0.269)		(0.316)
Rivalry		0.368		0.097
		(0.399)		(0.431)
Year in Conflict		0.020		0.031
		(0.033)		(0.037)
Year in Conflict^2		-0.002		-0.002
		(0.002)		(0.002)
Year in Conflict^3		0.000		0.000
		(0.000)		(0.000)
Constant	1.584	-4.857*	-0.565	-5.777*
	(2.187)	(2.195)	(2.148)	(2.254)
inflate				
Rebel Support NSAD	0.158	-0.451		
	(0.612)	(0.536)		
Rebel Support UCDP			0.465	-0.607
			(0.562)	(0.437)
Host Polity	-0.103**	-0.060**	-0.119**	-0.067**
	(0.009)	(0.009)	(0.010)	(0.009)
Host GDP per capita (ln)	-0.697**	-0.690**	-0.642**	-0.652**
	(0.046)	(0.043)	(0.048)	(0.043)
Host Population (ln)	-0.434**	-0.525**	-0.424**	-0.500**
	(0.039)	(0.042)	(0.050)	(0.046)
Source Polity	-0.046**	-0.023**	-0.055**	-0.033**
	(0.008)	(0.008)	(0.009)	(0.009)
Source GDP per capita (ln)	-0.122**	-0.158**	-0.002	-0.048
	(0.047)	(0.050)	(0.050)	(0.053)
Source Population (ln)	-0.194**	-0.270**	-0.218**	-0.269**
	(0.038)	(0.047)	(0.042)	(0.049)
Distance (ln)	0.754**	0.771**	0.881**	0.835**
	(0.055)	(0.080)	(0.126)	(0.104)
Refugees Total (ln)	-0.456**	-0.479**	-0.446**	-0.471**
	(0.017)	(0.020)	(0.019)	(0.020)
Host Regime Transition		-0.255		-0.104
		(0.203)		(0.214)
Host Interstate War		0.042		-0.000
		(0.201)		(0.220)
Host Civil War		0.423**		0.490**
		(0.113)		(0.118)
Host Genocide		0.771**		0.798**
		(0.252)		(0.256)
Host UNHCR Signatory		-1.704**		-1.629**
		(0.119)		(0.122)
Source Regime Transition		-0.138		-0.097
		(0.100)		(0.104)
Source Interstate War		0.611**		0.663**

		(0.146)		(0.145)
Source Genocide		1.037**		0.875**
		(0.115)		(0.118)
Source Neighbors Number		0.025*		0.016
		(0.011)		(0.011)
Colonial Tie		0.367		0.128
		(0.283)		(0.314)
Alliance		-0.800**		-0.694**
		(0.191)		(0.206)
Ethnic Relations		0.722		0.881*
		(0.382)		(0.428)
Rivalry		0.848		1.490*
		(0.709)		(0.671)
Year in Conflict		0.060**		0.038
		(0.020)		(0.023)
Year in Conflict^2		-0.003*		-0.001
		(0.001)		(0.002)
Year in Conflict^3		0.000**		0.000
		(0.000)		(0.000)
Constant	16.787**	20.486**	14.475**	18.325**
	(0.977)	(1.064)	(1.050)	(1.092)
lnalpha Constant	2.455**	2.348**	2.545**	2.412**
	(0.044)	(0.045)	(0.057)	(0.052)
Observations	170947	170947	138585	138585
BIC	321622.181	317747.207	283512.750	280503.539

Standard errors clustered by dyad in parenthesis.
* $p < 0.05$, ** $p < 0.01$

Table A.4: Zero-Inflated Negative Binomial Regression of the Yearly Number of Refugees in Civil Conflicts, Using San-Akca Support Data (2016)

	De Facto Support, 1951–2010		Active Support, 1951-2010	
	(1)	(2)	(3)	(4)
Rebel Support De Facto	3.986**	4.024**		
	(1.049)	(1.066)		
Rebel Support Active			3.022**	3.292**
			(0.884)	(1.081)
Host Polity	1.026	1.022	1.031	1.034
	(0.024)	(0.022)	(0.025)	(0.020)
Host GDP per capita (ln)	2.267**	2.325**	2.424**	2.494**
	(0.217)	(0.207)	(0.245)	(0.207)
Host Population (ln)	1.503**	1.516**	1.568**	1.534**
	(0.116)	(0.119)	(0.128)	(0.121)
Source Polity	0.971	0.952**	0.974	0.949**
	(0.016)	(0.013)	(0.016)	(0.013)
Source GDP per capita (ln)	0.736**	0.808*	0.691**	0.796*
	(0.069)	(0.081)	(0.062)	(0.074)
Source Population (ln)	0.853	1.064	0.798*	1.069
	(0.072)	(0.110)	(0.071)	(0.109)

Distance (ln)	0.382**	0.389**	0.378**	0.375**
	(0.017)	(0.019)	(0.018)	(0.018)
Refugees Total (ln)	1.107*	1.106*	1.045	1.065
	(0.047)	(0.044)	(0.051)	(0.049)
Host Regime Transition		1.235		1.386
		(0.376)		(0.494)
Host Interstate War		2.428**		2.271**
		(0.556)		(0.507)
Host Civil War		0.558**		0.543**
		(0.116)		(0.110)
Host Genocide		1.046		1.064
		(0.290)		(0.277)
Host UNHCR Signatory		1.165		1.113
		(0.323)		(0.292)
Source Regime Transition		2.132**		2.020**
		(0.402)		(0.396)
Source Interstate War		0.898		0.864
		(0.165)		(0.166)
Source Genocide		2.134**		1.985**
		(0.431)		(0.419)
Source Neighbors Number		0.963*		0.944**
		(0.018)		(0.020)
Colonial Tie		1.483		1.749
		(0.598)		(0.778)
Alliance		2.051**		2.180**
		(0.461)		(0.478)
Ethnic Relations		0.866		0.746
		(0.255)		(0.219)
Rivalry		1.243		1.541
		(0.469)		(0.691)
Year in Conflict		1.003		1.015
		(0.037)		(0.036)
Year in Conflict^2		1.000		0.999
		(0.002)		(0.002)
Year in Conflict^3		1.000		1.000
		(0.000)		(0.000)
inflate				
Rebel Support De Facto	0.787	0.592		
	(0.273)	(0.196)		
Rebel Support Active			1.425	0.896
			(0.452)	(0.282)
Host Polity	0.905**	0.945**	0.906**	0.947**
	(0.008)	(0.008)	(0.008)	(0.008)
Host GDP per capita (ln)	0.502**	0.504**	0.504**	0.507**
	(0.023)	(0.022)	(0.023)	(0.021)
Host Population (ln)	0.652**	0.599**	0.654**	0.596**
	(0.025)	(0.025)	(0.025)	(0.025)
Source Polity	0.948**	0.970**	0.948**	0.970**
	(0.008)	(0.008)	(0.008)	(0.008)
Source GDP per capita (ln)	0.919	0.897*	0.903*	0.892*
	(0.043)	(0.046)	(0.042)	(0.045)
Source Population (ln)	0.841**	0.780**	0.831**	0.783**
	(0.031)	(0.036)	(0.031)	(0.036)

Distance (ln)	2.060**	2.168**	2.097**	2.180**
	(0.102)	(0.166)	(0.103)	(0.162)
Refugees Total (ln)	0.629**	0.616**	0.624**	0.612**
	(0.011)	(0.013)	(0.011)	(0.013)
Host Regime Transition		0.776		0.781
		(0.161)		(0.164)
Host Interstate War		1.047		1.034
		(0.216)		(0.215)
Host Civil War		1.578**		1.570**
		(0.183)		(0.182)
Host Genocide		1.892**		1.914**
		(0.468)		(0.476)
Host UNHCR Signatory		0.190**		0.187**
		(0.022)		(0.022)
Source Regime Transition		0.910		0.906
		(0.090)		(0.090)
Source Interstate War		1.785**		1.753**
		(0.257)		(0.250)
Source Genocide		2.659**		2.671**
		(0.297)		(0.301)
Source Neighbors Number		1.025*		1.020
		(0.011)		(0.011)
Colonial Tie		1.455		1.353
		(0.425)		(0.380)
Alliance		0.522**		0.544**
		(0.099)		(0.103)
Ethnic Relations		2.480*		2.278*
		(0.977)		(0.909)
Rivalry		2.079		2.136
		(1.359)		(1.403)
Year in Conflict		1.044		1.042
		(0.023)		(0.023)
Year in Conflict^2		0.998		0.998
		(0.002)		(0.002)
Year in Conflict^3		1.000		1.000
		(0.000)		(0.000)
Observations	166906	166906	166860	166860
BIC	288300.888	285042.871	287969.135	284685.978

Incidence Rate Ratios are presented. Standard errors clustered by dyad in parenthesis.
* $p < 0.05$, ** $p < 0.01$

Table A.5: Zero-Inflated Negative Binomial Regression of the Yearly Number of Refugees in Civil Conflicts, CEM Data with 1/4 intervals

	NSAD, 1951–2011		UCDP, 1975–2009	
	(1)	(2)	(3)	(4)
Rebel Support NSAD	4.363**	2.300**		
	(1.452)	(0.729)		
Rebel Support UCDP			4.316**	5.595**

			(1.378)	(2.623)
Host Polity	1.040	0.997	0.974	0.976
	(0.078)	(0.054)	(0.035)	(0.050)
Host GDP per capita (ln)	1.169	1.411	1.431	1.425
	(0.421)	(0.428)	(0.324)	(0.357)
Host Population (ln)	2.000**	2.002*	1.696**	1.791
	(0.369)	(0.550)	(0.227)	(0.551)
Source Polity	1.203*	1.068	0.931	0.989
	(0.093)	(0.094)	(0.067)	(0.102)
Source GDP per capita (ln)	0.421**	0.708	0.558	0.846
	(0.128)	(0.218)	(0.169)	(0.272)
Source Population (ln)	0.797	1.541*	1.131	2.869
	(0.155)	(0.336)	(0.266)	(2.131)
Distance (ln)	0.419**	0.422**	0.556**	0.529**
	(0.049)	(0.082)	(0.059)	(0.076)
Refugees Total (ln)	1.119	1.134*	0.878	1.190
	(0.104)	(0.058)	(0.118)	(0.247)
Host Regime Transition		2.577		0.672
		(6.510)		(1.372)
Host Interstate War		11.905		1.258
		(29.728)		(5.470)
Host Civil War		0.501		1.328
		(0.476)		(2.705)
Host Genocide		0.210		12.497
		(0.208)		(35.022)
Host UNHCR Signatory		0.909		0.826
		(0.833)		(0.639)
Source Regime Transition		1.052		1.393
		(0.536)		(0.857)
Source Interstate War		0.182		1.186
		(0.364)		(6.621)
Source Genocide		0.270*		1.338
		(0.148)		(0.852)
Source Neighbors Number		0.835**		0.731
		(0.044)		(0.140)
Colonial Tie		0.890		2.074
		(0.800)		(3.425)
Alliance		2.705		3.664
		(4.713)		(6.410)
Ethnic Relations		1.194		2.385
		(1.302)		(2.130)
Rivalry		2.955		1.524
		(2.864)		(1.709)
Year in Conflict		1.556		0.723
		(0.370)		(0.186)
Year in Conflict^2		0.973		1.034
		(0.018)		(0.025)
Year in Conflict^3		1.000		0.999*
		(0.000)		(0.001)
inflate				
Rebel Support NSAD	0.543	0.310**		
	(0.209)	(0.128)		
Rebel Support UCDP			0.990	0.753

			(0.413)	(0.538)
Host Polity	0.960	1.068	1.012	1.171
	(0.023)	(0.038)	(0.027)	(0.099)
Host GDP per capita (ln)	0.803	0.731	0.665	0.123**
	(0.128)	(0.135)	(0.143)	(0.094)
Host Population (ln)	0.849*	0.853	0.739**	0.539**
	(0.067)	(0.103)	(0.062)	(0.092)
Source Polity	0.994	0.993	0.942	0.977
	(0.038)	(0.050)	(0.044)	(0.121)
Source GDP per capita (ln)	0.709*	0.964	0.497*	0.064**
	(0.112)	(0.199)	(0.175)	(0.055)
Source Population (ln)	1.195	1.096	2.717**	3.292
	(0.198)	(0.310)	(0.779)	(3.955)
Distance (ln)	1.636**	1.513*	2.331**	19.846**
	(0.120)	(0.247)	(0.388)	(18.074)
Refugees Total (ln)	0.780**	0.761**	0.502**	0.172**
	(0.050)	(0.057)	(0.078)	(0.111)
Host Regime Transition		0.433		0.000**
		(0.445)		(0.000)
Host Interstate War		0.243		0.002**
		(0.238)		(0.005)
Host Civil War		0.312		1.513
		(0.395)		(2.699)
Host Genocide		2.250		162.519**
		(2.701)		(317.865)
Host UNHCR Signatory		0.046**		0.001**
		(0.026)		(0.002)
Source Regime Transition		0.531		0.538
		(0.224)		(0.489)
Source Interstate War		7.403*		1083.889**
		(7.499)		(2462.338)
Source Genocide		3.852**		305.969*
		(1.595)		(805.488)
Source Neighbors Number		0.916		1.224
		(0.063)		(0.206)
Colonial Tie		2.091		37.987
		(1.766)		(109.565)
Alliance		1.786		0.005**
		(1.300)		(0.005)
Rivalry		1.054		223.913
		(0.944)		(733.126)
Year in Conflict		1.896**		
		(0.325)		
Year in Conflict^2		0.950**		1.037**
		(0.015)		(0.014)
Year in Conflict^3		1.001*		0.998**
		(0.000)		(0.001)
Ethnic Relations				894.272**
				(1759.655)
Observations	2484	2484	1329	1329
BIC	4986.961	4965.748	4646.127	4694.602

Incidence Rate Ratios are presented.

Standard errors clustered by dyad in parenthesis. For model (2), ethnic relations

and for model (4), year in conflict variables cause problems for matrix convergence. This is why they are excluded from the inflation part.
* $p < 0.05$, ** $p < 0.01$

Table A.6: Zero-Inflated Negative Binomial Regression of the Yearly Number of Refugees in Civil Conflicts, CEM Data with 1/3 intervals

	NSAD, 1951–2011		UCDP, 1975–2009	
	(1)	(2)	(3)	(4)
Rebel Support NSAD	6.129**	3.419**		
	(2.180)	(1.631)		
Rebel Support UCDP			2.247**	2.232**
			(0.587)	(0.490)
Host Polity	1.282**	1.139	0.946	0.896**
	(0.073)	(0.097)	(0.036)	(0.024)
Host GDP per capita (ln)	0.921	1.134	1.819*	2.443**
	(0.225)	(0.471)	(0.444)	(0.416)
Host Population (ln)	1.300	1.790**	2.081**	2.177**
	(0.209)	(0.301)	(0.314)	(0.271)
Source Polity	0.951	0.951	0.959	0.983
	(0.031)	(0.059)	(0.060)	(0.036)
Source GDP per capita (ln)	0.735	0.931	0.883	1.251
	(0.146)	(0.327)	(0.132)	(0.164)
Source Population (ln)	0.932	1.414	0.586**	2.329**
	(0.193)	(0.400)	(0.118)	(0.531)
Distance (ln)	0.461**	0.458**	0.478**	0.456**
	(0.031)	(0.048)	(0.046)	(0.044)
Refugees Total (ln)	1.195*	1.030	1.058	1.298**
	(0.108)	(0.162)	(0.092)	(0.111)
Host Regime Transition		13.962		1.375
		(34.177)		(1.310)
Host Civil War		0.242		0.765
		(0.233)		(0.369)
Host Genocide		3.579		5.343
		(5.905)		(4.613)
Host UNHCR Signatory		1.704		1.871
		(1.180)		(0.784)
Source Regime Transition		2.398		1.599
		(1.180)		(0.439)
Source Interstate War		2.939		0.359
		(6.272)		(0.352)
Source Genocide		4.625		0.218**
		(4.615)		(0.085)
Source Neighbors Number		0.905		0.784**
		(0.079)		(0.039)
Colonial Tie		0.001**		0.460
		(0.001)		(0.278)
Alliance		4.441		4.992**
		(3.739)		(2.658)

Ethnic Relations		1.642		1.268
		(1.557)		(0.516)
Rivalry		0.432		4.870**
		(0.455)		(2.818)
Year in Conflict		1.122		1.002
		(0.126)		(0.135)
Year in Conflict^2		0.994		1.008
		(0.007)		(0.012)
Year in Conflict^3		1.000		0.999
		(0.000)		(0.000)
Host Interstate War				2.860
				(1.980)
inflate				
Rebel Support NSAD	0.469	0.333*		
	(0.426)	(0.183)		
Rebel Support UCDP			0.843	0.565
			(0.407)	(0.230)
Host Polity	0.930*	0.992	0.889**	0.982
	(0.028)	(0.041)	(0.023)	(0.026)
Host GDP per capita (ln)	0.332**	0.509*	0.636**	0.605**
	(0.065)	(0.148)	(0.094)	(0.073)
Host Population (ln)	0.552**	0.713**	0.713**	0.695**
	(0.063)	(0.086)	(0.060)	(0.061)
Source Polity	0.852**	0.993	0.902	1.023
	(0.035)	(0.057)	(0.052)	(0.048)
Source GDP per capita (ln)	1.118	1.037	0.905	0.762
	(0.230)	(0.190)	(0.174)	(0.128)
Source Population (ln)	1.078	1.049	0.629*	0.889
	(0.137)	(0.205)	(0.143)	(0.159)
Distance (ln)	8.425**	2.531**	2.754**	2.242**
	(2.143)	(0.818)	(0.999)	(0.397)
Refugees Total (ln)	0.686**	0.641**	0.594**	0.557**
	(0.056)	(0.057)	(0.089)	(0.057)
Host Regime Transition		1.118		0.821
		(1.292)		(0.717)
Host Civil War		0.890		1.528
		(0.516)		(1.195)
Host Genocide		1.439		1.975
		(2.570)		(6.021)
Host UNHCR Signatory		0.097**		0.063**
		(0.070)		(0.041)
Source Regime Transition		0.672		0.911
		(0.199)		(0.372)
Source Interstate War		19.563		5.221
		(71.077)		(11.029)
Source Genocide		11.542**		6.097**
		(6.925)		(2.516)
Source Neighbors Number		0.891		0.988
		(0.061)		(0.049)
Colonial Tie		23.495		2.269
		(64.908)		(2.054)
Alliance		2.553		2.145
		(3.101)		(2.037)

Ethnic Relations		13.521		2.302
		(19.128)		(2.224)
Rivalry		1.855		2.370
		(3.423)		(2.939)
Year in Conflict		1.190		1.333
		(0.105)		(0.247)
Year in Conflict^2		0.989		0.991
		(0.006)		(0.017)
Year in Conflict^3		1.000		1.000
		(0.000)		(0.000)
Host Interstate War				2.077
				(3.524)
Observations	9184	9184	3810	3810
BIC	14962.242	14809.241	12255.464	12088.340

Incidence Rate Ratios are presented.
Standard errors clustered by dyad in parenthesis. For model (2), host interstate war variable causes problems for matrix convergence. This is why it is excluded from the analysis.
* $p < 0.05$, ** $p < 0.01$

Table A.7: Zero-Inflated Negative Binomial Regression of the Yearly Number of Refugees in Civil Conflicts with Lagged Dependent Variable

	NSAD, 1951–2011		UCDP, 1975–2009	
	(1)	(2)	(3)	(4)
Rebel Support NSAD	3.848**	3.115**		
	(1.282)	(0.872)		
Rebel Support UCDP			3.673**	3.830**
			(1.357)	(1.140)
Host Polity	1.033*	1.031*	1.012	1.013
	(0.017)	(0.016)	(0.013)	(0.012)
Host GDP per capita (ln)	1.711**	1.733**	2.012**	1.997**
	(0.124)	(0.115)	(0.119)	(0.108)
Host Population (ln)	1.258**	1.294**	1.488**	1.412**
	(0.083)	(0.074)	(0.093)	(0.076)
Source Polity	0.958**	0.960**	0.966*	0.956**
	(0.015)	(0.012)	(0.014)	(0.012)
Source GDP per capita (ln)	0.673**	0.718**	0.742**	0.784**
	(0.045)	(0.051)	(0.044)	(0.053)
Source Population (ln)	0.796**	0.862*	0.725**	0.813**
	(0.050)	(0.053)	(0.044)	(0.055)
Distance (ln)	0.543**	0.576**	0.514**	0.550**
	(0.016)	(0.019)	(0.016)	(0.019)
Refugees Total (ln)	0.952	0.950	1.003	0.982
	(0.035)	(0.031)	(0.040)	(0.035)
Refugees$_{t-1}$ (ln)	1.450**	1.487**	1.424**	1.460**
	(0.019)	(0.020)	(0.017)	(0.018)
Host Regime Transition		1.209		1.754
		(0.286)		(0.574)

Host Interstate War		1.095		1.525
		(0.236)		(0.592)
Host Civil War		0.656**		0.660*
		(0.103)		(0.113)
Host Genocide		1.051		0.929
		(0.247)		(0.214)
Host UNHCR Signatory		0.651*		0.800
		(0.133)		(0.172)
Source Regime Transition		1.695**		1.678**
		(0.288)		(0.260)
Source Interstate War		1.151		1.281
		(0.272)		(0.293)
Source Genocide		2.775**		2.023**
		(0.554)		(0.422)
Source Neighbors Number		0.998		0.993
		(0.018)		(0.017)
Colonial Tie		2.116		2.046
		(0.880)		(0.798)
Alliance		1.902**		1.783**
		(0.308)		(0.293)
Ethnic Relations		1.367		1.603
		(0.311)		(0.422)
Rivalry		0.910		0.735
		(0.314)		(0.226)
Year in Conflict		1.103**		1.101*
		(0.036)		(0.041)
Year in Conflict^2		0.994**		0.994*
		(0.002)		(0.002)
Year in Conflict^3		1.000**		1.000*
		(0.000)		(0.000)
inflate				
Rebel Support NSAD	1.602*	1.166		
	(0.372)	(0.293)		
Rebel Support UCDP			0.939	0.641
			(0.255)	(0.165)
Host Polity	0.947**	0.965**	0.944**	0.963**
	(0.004)	(0.005)	(0.004)	(0.005)
Host GDP per capita (ln)	0.720**	0.724**	0.745**	0.744**
	(0.022)	(0.023)	(0.023)	(0.024)
Host Population (ln)	0.817**	0.796**	0.839**	0.807**
	(0.015)	(0.016)	(0.016)	(0.016)
Source Polity	0.980**	0.991	0.977**	0.989*
	(0.005)	(0.005)	(0.005)	(0.005)
Source GDP per capita (ln)	0.942	0.897**	1.001	0.964
	(0.029)	(0.031)	(0.032)	(0.034)
Source Population (ln)	0.913**	0.844**	0.902**	0.844**
	(0.025)	(0.025)	(0.025)	(0.025)
Distance (ln)	1.278**	1.318**	1.257**	1.294**
	(0.020)	(0.026)	(0.019)	(0.025)
Refugees Total (ln)	0.786**	0.773**	0.802**	0.786**
	(0.007)	(0.008)	(0.008)	(0.009)
Refugees$_{t-1}$ (ln)	0.000**	0.000**	0.000**	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)

Host Regime Transition		0.897		1.039
		(0.161)		(0.207)
Host Interstate War		1.328		1.445
		(0.271)		(0.324)
Host Civil War		1.121		1.154
		(0.089)		(0.092)
Host Genocide		1.589*		1.595*
		(0.305)		(0.329)
Host UNHCR Signatory		0.391**		0.419**
		(0.032)		(0.034)
Source Regime Transition		0.748**		0.749**
		(0.052)		(0.053)
Source Interstate War		1.517**		1.521**
		(0.174)		(0.171)
Source Genocide		1.606**		1.534**
		(0.131)		(0.127)
Source Neighbors Number		1.024**		1.019*
		(0.008)		(0.008)
Colonial Tie		1.398		1.295
		(0.272)		(0.237)
Alliance		0.835		0.792*
		(0.097)		(0.090)
Ethnic Relations		1.343		1.276
		(0.258)		(0.242)
Rivalry		1.127		1.323
		(0.367)		(0.411)
Year in Conflict		1.052**		1.033
		(0.019)		(0.019)
Year in Conflict^2		0.997**		0.998
		(0.001)		(0.001)
Year in Conflict^3		1.000**		1.000
		(0.000)		(0.000)
Observations	170947	170947	138585	138585
BIC	277959.571	275886.484	244816.246	243427.561

Incidence Rate Ratios are presented.
Standard errors clustered by dyad in parenthesis.
* $p < 0.05$, ** $p < 0.01$

Table A.8: Zero-Inflated Negative Binomial Regression of the Yearly Number of Refugees in Civil Conflicts, Refugee Flows as the Dependent Variable

	NSAD, 1951–2011		UCDP, 1975–2009	
	(1)	(2)	(3)	(4)
Rebel Support NSAD	2.521**	2.849**		
	(0.868)	(0.849)		
Rebel Support UCDP			5.323**	6.790**
			(2.583)	(3.220)
Host Polity	1.059*	1.041	1.031	1.003
	(0.028)	(0.026)	(0.024)	(0.020)

Host GDP per capita (ln)	1.634**	1.818**	2.083**	2.353**
	(0.187)	(0.192)	(0.198)	(0.192)
Host Population (ln)	1.405**	1.400**	1.650**	1.587**
	(0.123)	(0.124)	(0.132)	(0.137)
Source Polity	0.967	0.955**	0.977	0.955**
	(0.019)	(0.016)	(0.018)	(0.017)
Source GDP per capita (ln)	0.677**	0.809	0.694**	0.806*
	(0.071)	(0.094)	(0.063)	(0.085)
Source Population (ln)	0.776**	0.985	0.713**	0.879
	(0.068)	(0.095)	(0.065)	(0.095)
Distance (ln)	0.458**	0.460**	0.440**	0.441**
	(0.021)	(0.024)	(0.018)	(0.021)
Refugees Total (ln)	1.034	1.033	1.136*	1.087*
	(0.044)	(0.039)	(0.058)	(0.045)
Host Regime Transition		1.518		2.489**
		(0.495)		(0.858)
Host Interstate War		1.651*		1.706
		(0.388)		(0.522)
Host Civil War		0.749		0.693
		(0.190)		(0.184)
Host Genocide		0.763		0.733
		(0.270)		(0.288)
Host UNHCR Signatory		1.004		1.309
		(0.278)		(0.326)
Source Regime Transition		2.091**		1.943**
		(0.454)		(0.398)
Source Interstate War		0.848		1.118
		(0.222)		(0.317)
Source Genocide		3.364**		2.116**
		(0.790)		(0.536)
Source Neighbors Number		0.960*		0.966
		(0.020)		(0.020)
Colonial Tie		1.793		1.703
		(0.718)		(0.674)
Alliance		2.178**		1.941**
		(0.473)		(0.444)
Ethnic Relations		0.926		1.246
		(0.258)		(0.381)
Rivalry		0.889		0.726
		(0.348)		(0.282)
Year in Conflict		1.122**		1.150**
		(0.041)		(0.051)
Year in Conflict^2		0.993**		0.991**
		(0.002)		(0.003)
Year in Conflict^3		1.000*		1.000**
		(0.000)		(0.000)
inflate				
Rebel Support NSAD	1.418	0.836		
	(0.962)	(0.483)		
Rebel Support UCDP			0.935	0.527
			(0.894)	(0.299)
Host Polity	0.915**	0.947**	0.890**	0.935**
	(0.009)	(0.009)	(0.009)	(0.008)

Host GDP per capita (ln)	0.468**	0.488**	0.463**	0.511**
	(0.023)	(0.022)	(0.034)	(0.025)
Host Population (ln)	0.634**	0.584**	0.612**	0.596**
	(0.026)	(0.026)	(0.030)	(0.031)
Source Polity	0.964**	0.994	0.955**	0.987
	(0.008)	(0.008)	(0.009)	(0.009)
Source GDP per capita (ln)	0.971	0.905	1.079	0.985
	(0.047)	(0.048)	(0.058)	(0.058)
Source Population (ln)	0.855**	0.765**	0.834**	0.772**
	(0.033)	(0.037)	(0.037)	(0.041)
Distance (ln)	2.167**	2.181**	3.522**	2.372**
	(0.142)	(0.195)	(0.950)	(0.317)
Refugees Total (ln)	0.644**	0.631**	0.668**	0.643**
	(0.011)	(0.013)	(0.015)	(0.013)
Host Regime Transition		1.137		1.519
		(0.209)		(0.327)
Host Interstate War		1.411		1.369
		(0.290)		(0.307)
Host Civil War		1.628**		1.660**
		(0.205)		(0.229)
Host Genocide		1.776		1.780
		(0.561)		(0.604)
Host UNHCR Signatory		0.211**		0.214**
		(0.026)		(0.027)
Source Regime Transition		0.665**		0.666**
		(0.072)		(0.077)
Source Interstate War		1.340		1.494*
		(0.229)		(0.264)
Source Genocide		2.528**		2.237**
		(0.286)		(0.275)
Source Neighbors Number		1.038**		1.027*
		(0.012)		(0.013)
Colonial Tie		1.004		0.785
		(0.321)		(0.296)
Alliance		0.518**		0.544**
		(0.096)		(0.113)
Ethnic Relations		1.759		2.265
		(0.698)		(1.072)
Rivalry		2.414		5.781*
		(1.816)		(4.780)
Year in Conflict		1.082**		1.069*
		(0.026)		(0.029)
Year in Conflict^2		0.997*		0.997
		(0.002)		(0.002)
Year in Conflict^3		1.000		1.000
		(0.000)		(0.000)
Observations	170586	170586	138259	138259
BIC	162971.192	161291.289	146889.544	145587.642

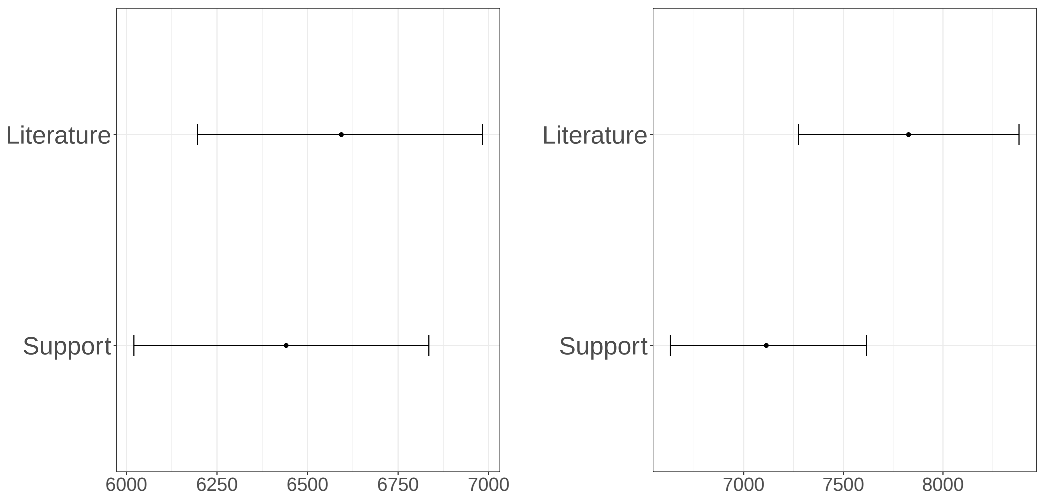
Incidence Rate Ratios are presented.
Standard errors clustered by dyad in parenthesis.
* $p < 0.05$, ** $p < 0.01$

A.4 Out-of-Sample Cross-Validation

This section presents a brief discussion of out-of-sample cross-validation error term measurement and reports various results for the model (2) and (4) in table 1 with and without the rebel support variable to asses the improvement in the predictive capability. In the computation, I employ the 'leave-one-out' method based on source countries. I estimate models on a subset of the data (the 'learning' set) and test their performance on out-of-sample data (the 'testing' set). Specifically, coefficients are estimated on all source countries with the exception of one, and they are used to estimate the dependent variable for the one source country left out. For NSAD, this procedure is repeated 98 times, whereas, for UCDP, the number of repetition is 89, which are the numbers of unique source countries in datasets. To examine whether rebel support improves our understanding of the variation in refugee flows, I run the model (2) and (4) in table 1 with and without the rebel support variable. Then, I compute median and mean absolute errors. The decrease in the error term gives us a sense of the contribution of the variable to the out-of-sample forecasting performance (Ward, Greenhill & Bakke 2010, Chadefaux 2017*a*). A lower error term implies a better model in terms of predictive capability, and the error term of the model with the support variable is lower than the one without it. In other words, including rebel support to the econometric model furthers our understanding to explain why some countries host more refugees than others.

One of the main challenges in out-of-sample cross-validation is to determine which forecasting error to present, especially with continuous dependent variables. For example, I could have presented mean or median absolute error, $e_i = |\hat{y}_i - y_i|$, mean absolute percentage error (MAPE), $e_i = |\frac{\hat{y}_i - y_i}{y_i}|100\%$ or symmetric mean absolute percentage error (sMAPE), $e_i = \frac{|\hat{y}_i - y_i|}{(|\hat{y}_i| + |y_i|)/2}100\%$. There is an additional problem with this study: the excessive number of 0s in the dependent variable—more than 87% of the observations. Each error type poses serious challenges that may lead to biased estimates and misleading conclusions.

The main drawback of mean absolute error is that it is susceptible to outliers. A few extreme values may drag the results and offer misleading interpretations, especially given the nature of this study's datasets. For example, let us assume there are 1,000 observations and with model A, on average for 999 observations, the absolute error term is 1 and for 1 observation, it is 10,000, which gives us a mean absolute error of 11. With model B, on average for 999 observations, the absolute error term is 5 and for 1 observation, it is 5,000, which gives us a mean absolute error of 10. In this case, since we obtain a lower error term with model B than model A, we have to conclude that model B outperforms model A, which is not necessarily true. Even though model A performs better than model B and both models have an outlier, the size of the outliers determines the result. To deal with this problem, percentage errors have been discussed in the literature. However, when there are 0s in the dependent variable, percentage errors are much less effective. For MAPE, when the dependent variable is 0, it gives an error as the denominator cannot be 0; thus, I cannot use it. For sMAPE, when the dependent variable is 0, it does not differentiate the size of the error. For example, error terms of predicted values of 1 and 1 million are the same, ie., $\frac{|1-0|}{(|1|+|0|)/2}100\% = 200\%$ and $\frac{|1000000-0|}{(|1000000|+|0|)/2}100\% = 200\%$. This is why I also do not use sMAPE. Therefore, to assess the model performance, I use mean absolute error but with a threshold which will get rid of extreme values. I excluded error terms greater than 5 million. With this threshold, I excluded 0.02% of observations for both datasets with NSAD and UCDP (40 observations out of 170,947 and 32 observations out of $138,585$, respectively). Results are reported in figure A.1. As it can be seen, we obtain a smaller error term via model with the support variable than the one without it. To check further the robustness of the results, I also put the threshold at 4 and 6 million. Error terms are plotted in figure A.2 and A.3. Results still corroborate my main hypothesis.



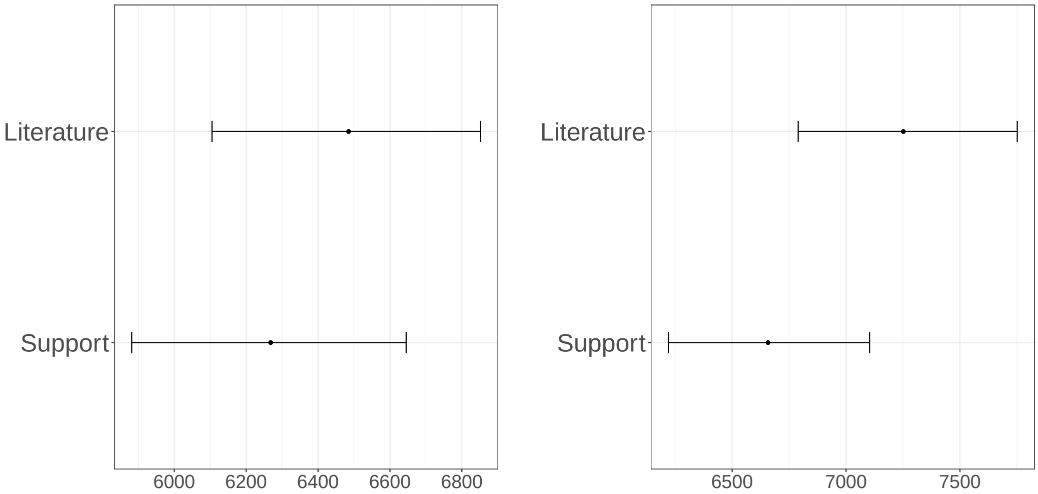
(a) NSAD

(b) UCDP

Figure A.1: Out-of-Sample Cross Validation—Mean Absolute Error, errors over 5 million are excluded (For NSAD, out of 170,947 observations, only 40 of them and for UCDP, out of 138,585 observations, only 32 of them are removed). Confidence intervals are obtained by bootstrapping. Literature is the model (2)/(4) without the support variable and support is the model (2)/(4) in table 2.

Median absolute error is another forecasting measurement that I can use. As an advantage, median absolute error term is not susceptible to outliers. However, it will be dragged by excessive 0s in the dependent variable, which will produce lower error terms and make the comparison of models' success challenging. This is why I plot the median absolute error term for whole data (figure A.4), when the dependent variable is 0 (figure A.5), and when the dependent variable is greater than 0 (figure A.6). Therefore, I can analyze how successful models are to predict refugee flows in general (figure A.6), as well as, the lack of flows (figure A.5).

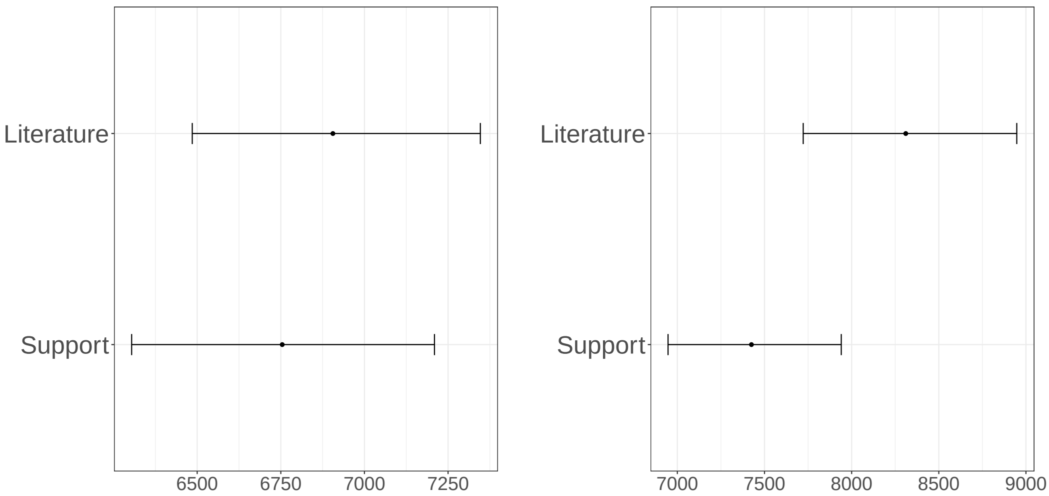
The results displayed in these figures corroborate the in-sample analysis as



(a) NSAD (b) UCDP

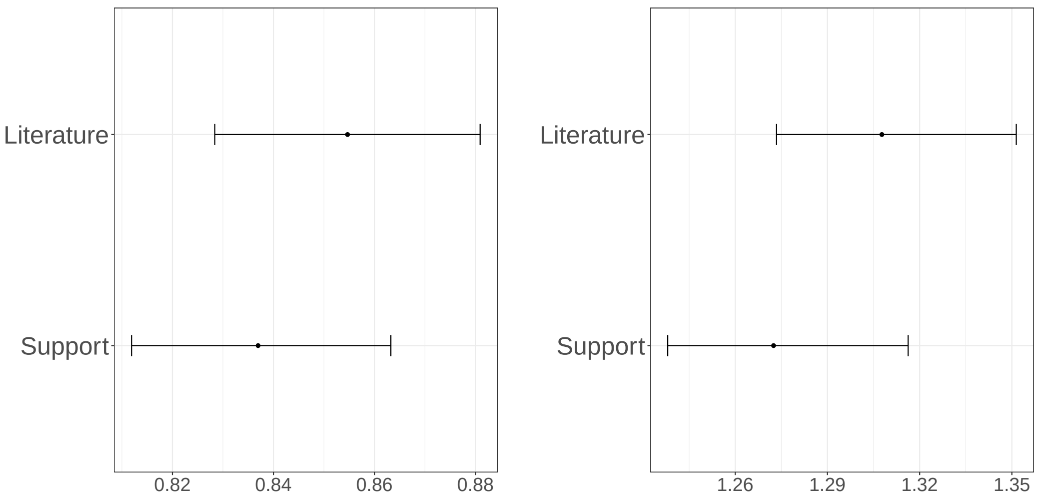
Figure A.2: Out-of-Sample Cross Validation—Mean Absolute Error, errors over 4 million are excluded (For NSAD, out of 170,947 observations, only 48 of them and for UCDP, out of 138,585 observations, only 50 of them are removed). Confidence intervals are obtained by bootstrapping.Literature is the model (2)/(4) without the support variable and support is the model (2)/(4) in table 2.

the lower error term implies a better model in terms of predictive capability. Figures A.1-A.6 suggest that the models of this study outperform the literature model. In other words, adding rebel support to the literature model improves our understanding of refugee flows. Furthermore, a comparison of literature and support error terms thorough a t-test also suggests that these two error terms are statistically different from each other.



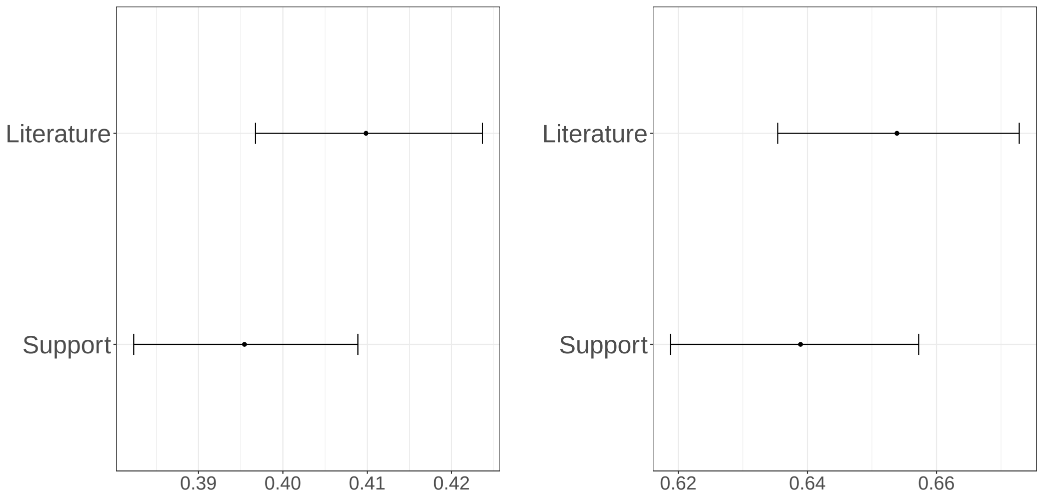
(a) NSAD (b) UCDP

Figure A.3: Out-of-Sample Cross-Validation—Mean Absolute Error, errors over 6 million are excluded (For NSAD, out of 170,947 observations, only 28 of them and for UCDP, out of 138,585 observations, only 20 of them are removed). Confidence intervals are obtained by bootstrapping. Literature is the model (2)/(4) without the support variable and support is the model (2)/(4) in table 2.



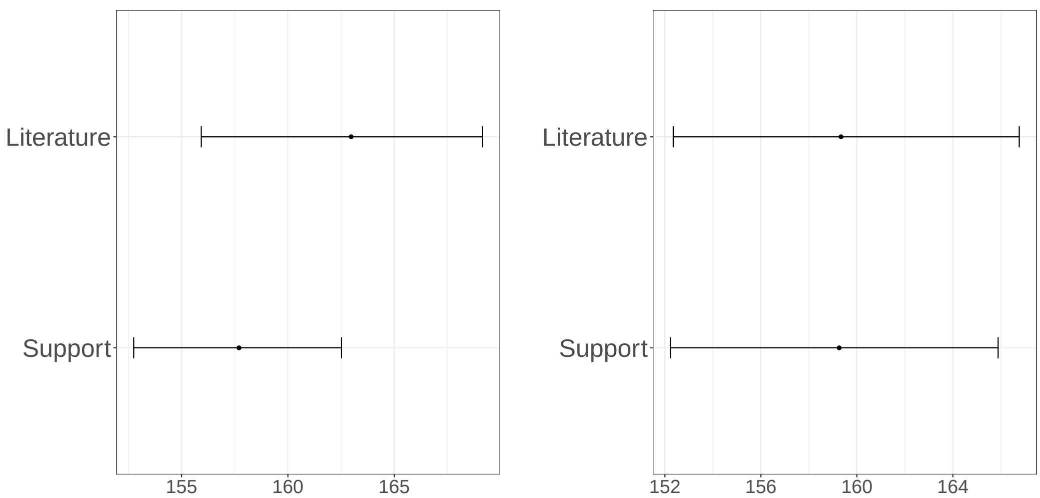
(a) NSAD (b) UCDP

Figure A.4: Out-of-Sample Cross-Validation—Median absolute error, whole data. Confidence intervals are obtained by bootstrapping. Literature is the model (2)/(4) without the support variable and support is the model (2)/(4) in table 2.



(a) NSAD (b) UCDP

Figure A.5: Out-of-Sample Cross-Validation—Median Absolute Error, when the dependent variables are 0. Confidence intervals are obtained by bootstrapping. Literature is the model (2)/(4) without the support variable and support is the model (2)/(4) in table 2.



(a) NSAD (b) UCDP

Figure A.6: Out-of-Sample Cross-Validation—Median absolute error, when the dependent variables are greater than 0. Confidence intervals are obtained by bootstrapping. Literature is the model (2)/(4) without the support variable and support is the model (2)/(4) in table 2.

B Appendix to Chapter 4

B.1 Descriptive Statistics & Sample Comparison to Turkish Residents and Refugees

This section presents descriptive statistics of our survey sample and puts some of them into context to the Turkish average and the demographics of Turkish migrants/refugees abroad. About 50.2% of the total Turkish population is male (European Commission 2020), which means our sample consists of slightly more female respondents. This is in line with the fact that international migration statistics on Turkey report that more men (54%) migrate out than women. Our survey population is also more educated and younger than the average population in Turkey (median age in Turkey is 31.5 years). While this suggests that our sample faces the typical problems of online surveys (i.e. more access by younger and university-based population), this also means that our sample is more similar to migrant and refugee demographics. Refugees and migrants are characteristically strongly skewed towards younger age groups and Turkish migrants are no exception (Bel-Air 2016). Migrants from Turkey are also typically highly educated. 35% of Turkish migrants in the UK hold an education-related permit and students make up a quarter of Turkish residents in the EU. Unemployment in Turkey is at around 11 % which is significantly lower than in our survey population where over 58% are unemployed. However, given that we sample a more economically deprived and rural area, this comes at no surprise. Our proportion of Kurdish respondents is also in line with varying estimates how many Kurds live in Eastern and Southeastern Turkey (Mutlu 1996).

Table B.1: Descriptive statistics of covariates in the sample

	Mean	SD	Min	Max	Missing
Male	0.498	0.5	0	1	17 (1.68%)
Age	27.958	9.448	18	98	18 (1.78%)
Urban residence	0.667	0.472	0	1	96 (9.5%)
University degree	0.596	0.491	0	1	20 (1.98%)
Religious	0.245	0.431	0	1	70 (6.92%)
Household size	4.622	1.995	1	16	19 (1.88%)
Unemployment	0.587	0.493	0	1	128 (12.66%)
Kurdish ethnicity	0.373	0.484	0	1	92 (9.1%)

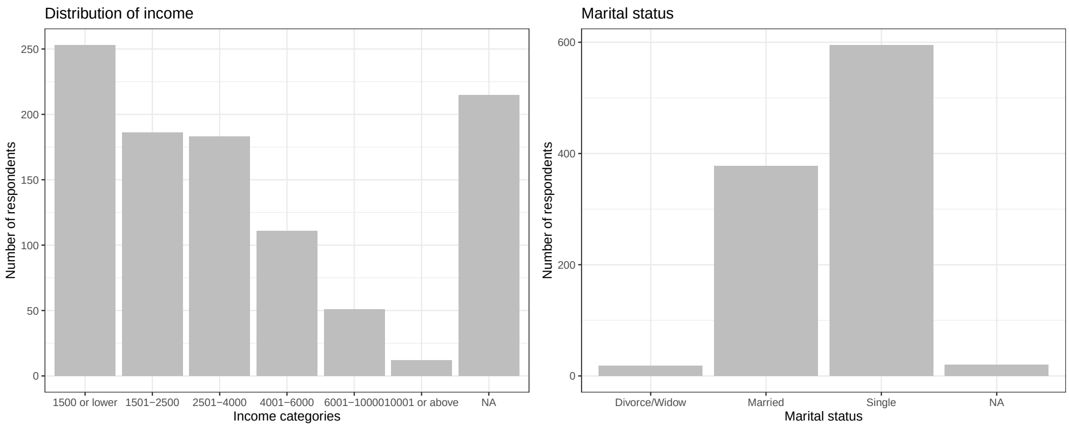


Figure B.1: Distribution of income and marital status in our survey population

B.2 Robustness Checks

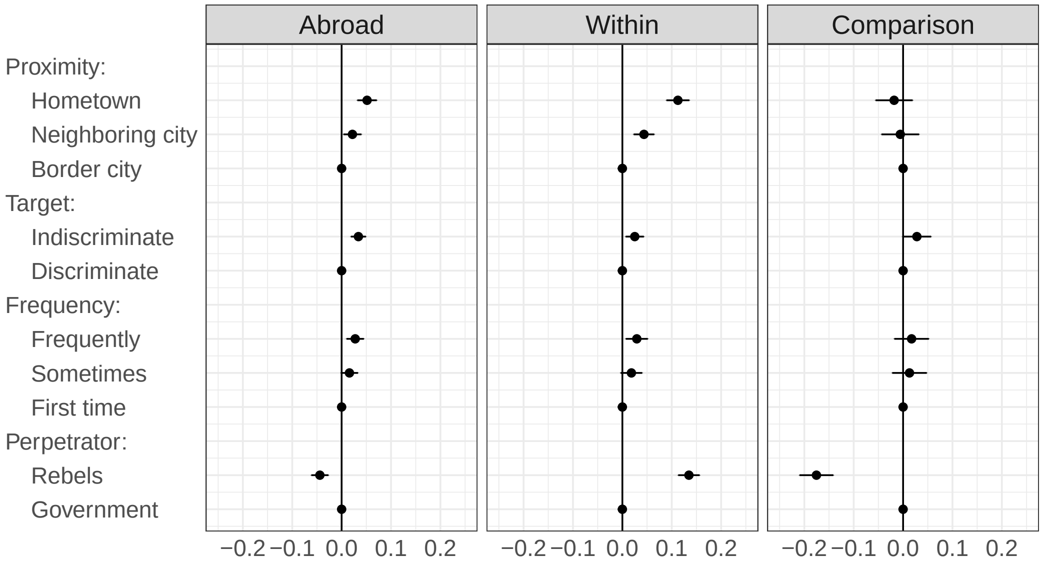


Figure B.2: Effects of violence attributes on the probability that respondents choose a scenario to flee abroad, within the country, and their comparison. Replication of Figure 4.3 with recoded dependent variables. For fleeing abroad, scenarios in which respondents prefer to flee abroad are coded as 1 and scenarios in which respondents would stay or flee internally are coded as 0. For fleeing internally, scenarios in which respondents prefer to flee internally are coded as 1 and scenarios in which respondents would stay or flee abroad are coded as 0. For the comparison, we used the same analysis as in Figure 4.3. Dots refer to AMCEs and horizontal lines to 95% confidence intervals clustered by respondents. Dots without a horizontal line denote the reference categories.

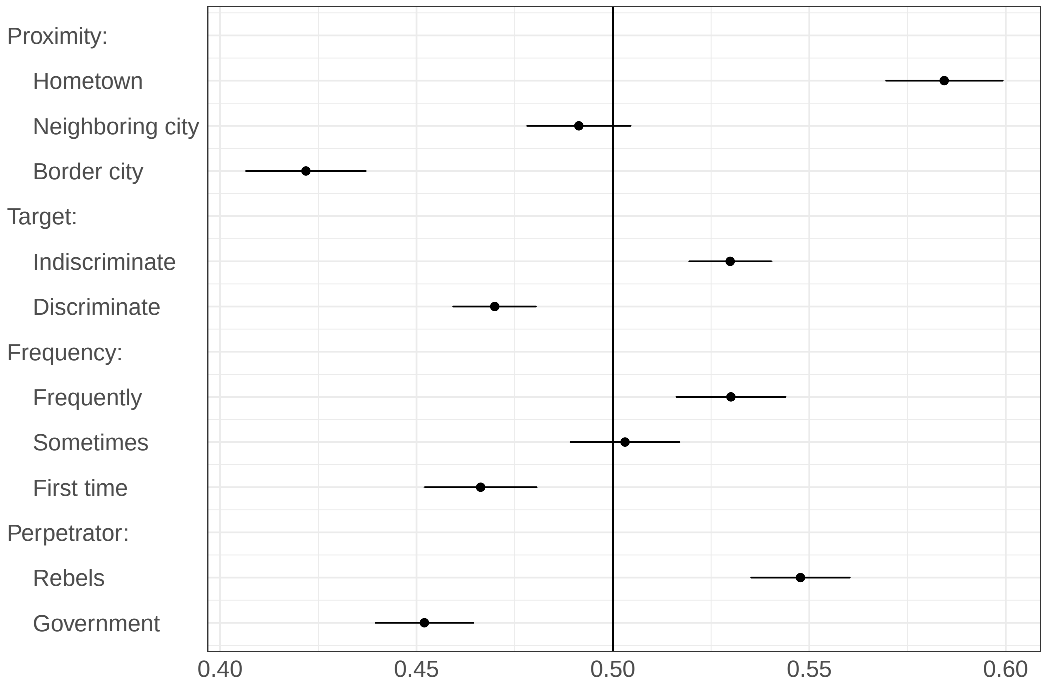


Figure B.3: Effects of violence attributes on the probability that respondents choose a scenario to flee. Dots refer to marginal means and horizontal lines to 95% confidence intervals clustered by respondents. Dots without a horizontal line denote the reference categories. Replication of Figure 4.2 with marginal means instead of AMCEs.

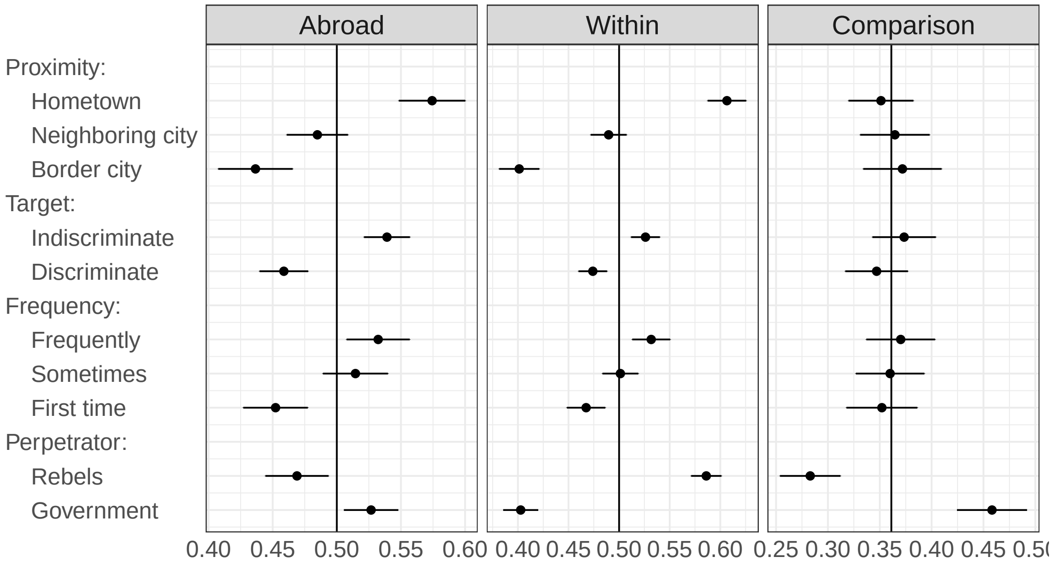


Figure B.4: Effects of violence attributes on the probability that respondents choose a scenario to flee abroad, within the country, and their comparison. Dots refer to marginal means and horizontal lines to 95% confidence intervals clustered by respondents. Dots without a horizontal line denote the reference categories. Replication of Figure 4.3 with marginal means instead of AMCEs.

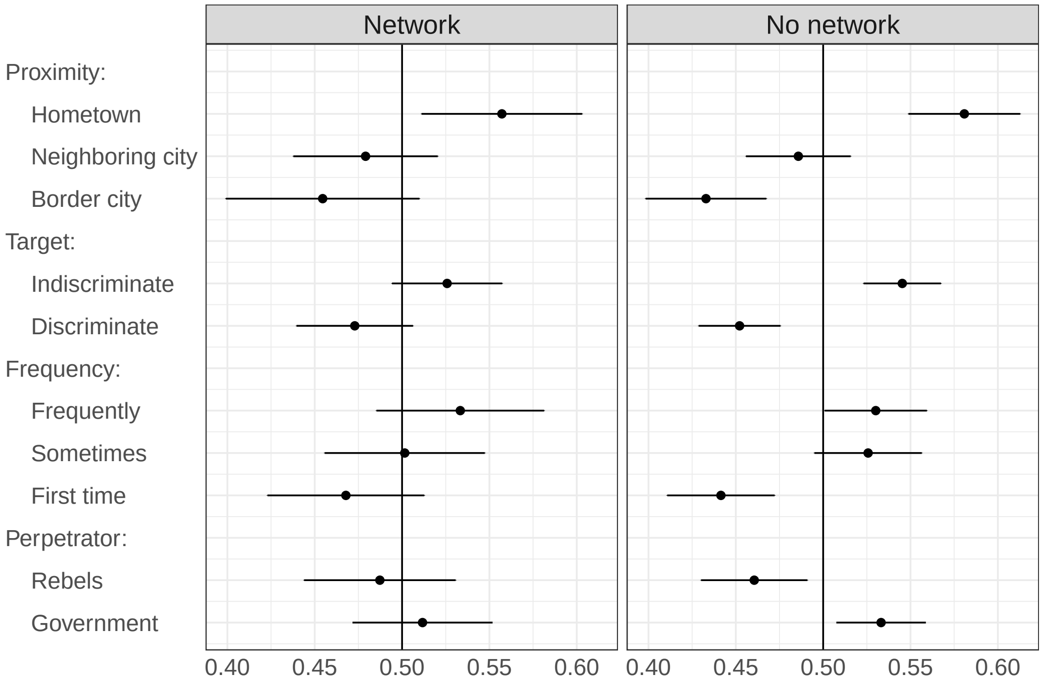


Figure B.5: Effects of violence attributes on the probability that respondents choose a scenario to flee for the group of respondents with and without social networks. Dots refer to marginal means and horizontal lines to 95% confidence intervals clustered by respondents. Dots without a horizontal line denote the reference categories. Replication of Figure 4.4 with marginal means instead of AMCEs.

B.3 Selection into Networks Abroad

Table B.2: Logistic Regression of Network Abroad

Urban	−0.110
	(0.189)
Male	0.070
	(0.194)
University	0.163
	(0.190)
Married	−0.769
	(0.758)
Single	−0.782
	(0.780)
Religious	0.012
	(0.208)
Age	−0.011
	(0.011)
Household size	−0.069
	(0.051)
Unemployed	−0.277
	(0.216)
Income	0.200*
	(0.080)
Kurdish	0.184
	(0.188)
Constant	0.333
	(0.920)
Observations	621
Log Likelihood	−382
Akaike Inf. Crit.	789

The dependent variable is a binary indicator whether respondents have social network abroad or not. Robust standard errors are in parentheses. * $p < 0.05$, ** $p < 0.01$

B.3.1 Destination choice and network countries in sample

In the survey, we asked respondents in which country their social network reside and to which country they would flee if they have to. In Figure B.6, we plotted the top 10 destination preferences and the top 10 countries their social networks reside in. Germany is the dominant country in both categories, which is not surprising given the historical relations and worker agreement between Germany and Turkey. More than 45% of respondents have a relative or friend that they are in touch with in Germany and around 25% of respondent would flee to Germany if they leave their home. In general, countries in both categories are similar. While many people have networks in France and the Netherlands, not many people would like to migrate to these countries, which might be explained by the recent not friendly relations between Turkey and these countries. Additionally, although respondents do not have social networks in Norway or Canada, these countries are popular flight destinations. The overall overlap of destination preferences and network countries confirms other studies that have analyzed how individuals choose their displacement destinations and have previously stressed the importance of social networks and co-ethnics in flight destinations (Mossaad et al. 2020, Neumayer 2004, Rüegger & Bohnet 2018).

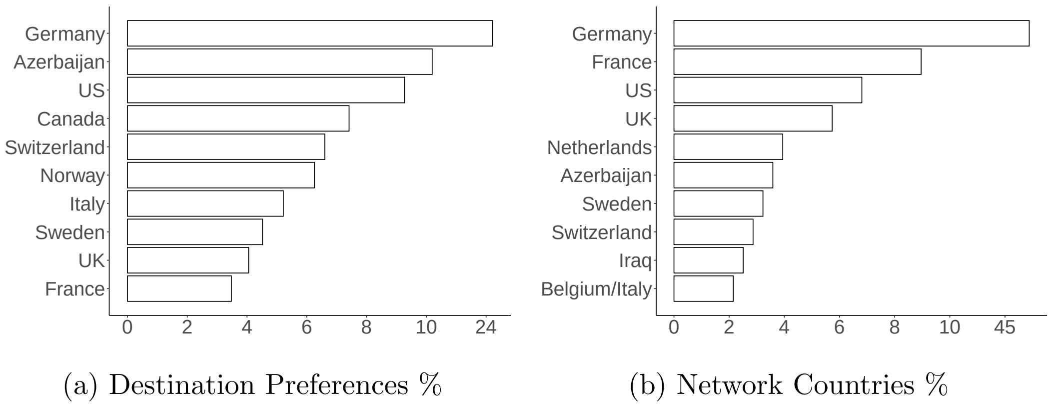


Figure B.6: Top 10 destination preferences and network countries. Please notice the x-axis values for Germany.

C Appendix to Chapter 5

C.1 Ethical Considerations

In the survey, before everything, respondents saw the information sheet. This sheet first explained the purpose of the study and what the questions were about. Afterward, it highlighted that the profiles that they would see are hypothetical and there is no right or wrong answer. More specifically, respondents read, "Here, we will show you hypothetical refugee group attributes. We will also show you statements and ask you to indicate whether you agree or disagree with them. Please keep in mind there is no right or wrong answer. We are interested in your opinions." If they would like to get more information about refugees in Turkey, the survey directed them to the website of the Directorate General of Migration Management [https://www.goc.gov.tr/], the United Nations Refugee Agency in Turkey [https://www.unhcr.org/tr/], or an NGO, the Association for Solidarity with Asylum Seekers and Migrants [https://sgdd.org.tr/].

The information sheet also highlighted that participation in this study is entirely voluntary and there are no consequences if respondents choose not to participate. They could discontinue the survey at any time. Respondents were also informed about data protection and anonymity of information. In particular, the information sheet stated that "all the information that we collect about you during the course of the research will be kept strictly anonymously. You will not be able to be identified in any reports or publications. If you want to read more about how we deal with your data, please read here (in English)[link to the website]." Finally, they were informed about this project and the institution that carried out the research. If they have any questions about the survey or would like to get any information about the results of the study, the researcher's email address was provided. In the end, respondents were asked to click a button to confirm that they read and understood all the information and they consent to participate in this study.

This survey did not use deception. It revealed the researcher's identity, its academic purpose, and provided no misinformation. The respondents generally were not considered to be a vulnerable population: they voluntarily responded to the survey on issues that are prevalent in public discourse in Turkey. Finally, I have no reason to think that participation in this survey had any long-lasting effects neither on the participants nor indirectly on others. The information that the participants received was very similar to what they already encounter in their everyday lives. The profiles of refugees reflected the refugee population in Turkey, and the questions on were already part of the public discourse in Turkey.

For this study, I teamed up with *Benderimki*, which is a leading company in online survey and research in Turkey and used by other scholars. Members of their nationally representative panel were invited to participate with the only criteria of being at least 18 years of age. The panel company has more than 300,000 members who are knowledgeable about the process and are invited to participate in many surveys. Participants were compensated by the panel company using normal rates for an online panel participation and were informed about the compensation prior to beginning the survey.

C.2 Summary Statistics

Table C.1: Summary Statistics

Statistic	Mean	St. Dev.	Min	Max
Age	36.241	10.525	18	65
Male	0.496	0.500	0	1
Married	0.583	0.493	0	1
Urban	0.762	0.426	0	1
Kurd	0.143	0.350	0	1
Unemployed	0.202	0.402	0	1
Education				
Primary School	0.091	0.287	0	1
Secondary School	0.137	0.344	0	1
High School	0.413	0.493	0	1
Two-Year University	0.142	0.349	0	1
Open University	0.038	0.192	0	1
University	0.179	0.384	0	1
Income Categories				
Less than 1,500	0.150	0.358	0	1
1,501-2,500	0.174	0.380	0	1
2,501-4,000	0.408	0.492	0	1
4,001-6,000	0.181	0.385	0	1
6,001-8,000	0.052	0.223	0	1
8,001-10,000	0.017	0.129	0	1
More than 10,000	0.017	0.129	0	1
Praying				
Daily Praying	0.439	0.496	0	1
A Couple of Times a Week	0.181	0.385	0	1
Only in Ramadan	0.081	0.273	0	1
No Praying	0.299	0.458	0	1

C.3 Robustness Checks

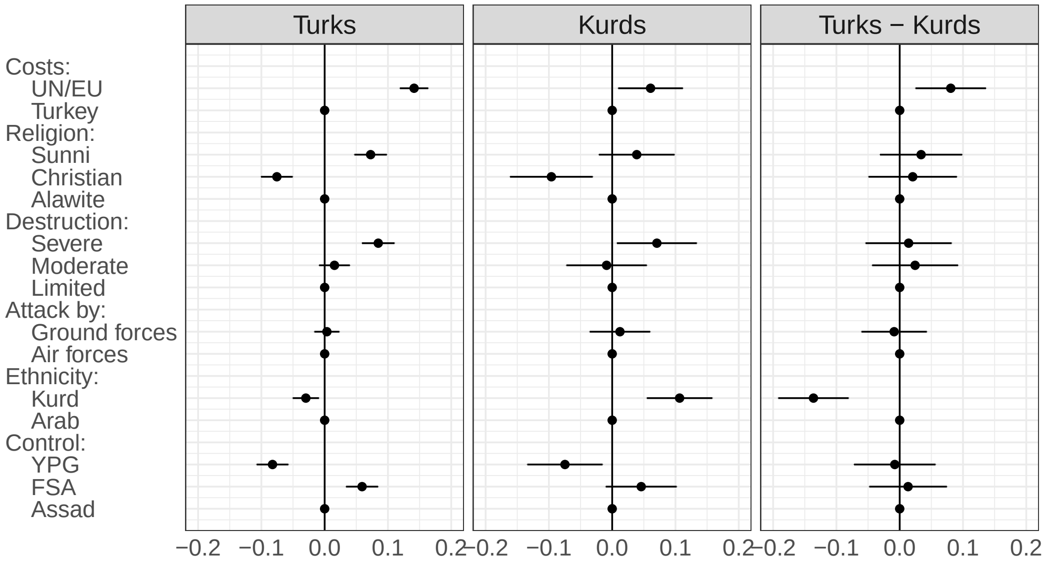


Figure C.1: Effects of group attributes on the probability of respondents favoring a group to accept to the country for Turkish and Kurdish respondents, as well as the differences between sub-samples. Only Turkish and Kurdish respondents are used in the analysis and other ethnic groups are excluded.

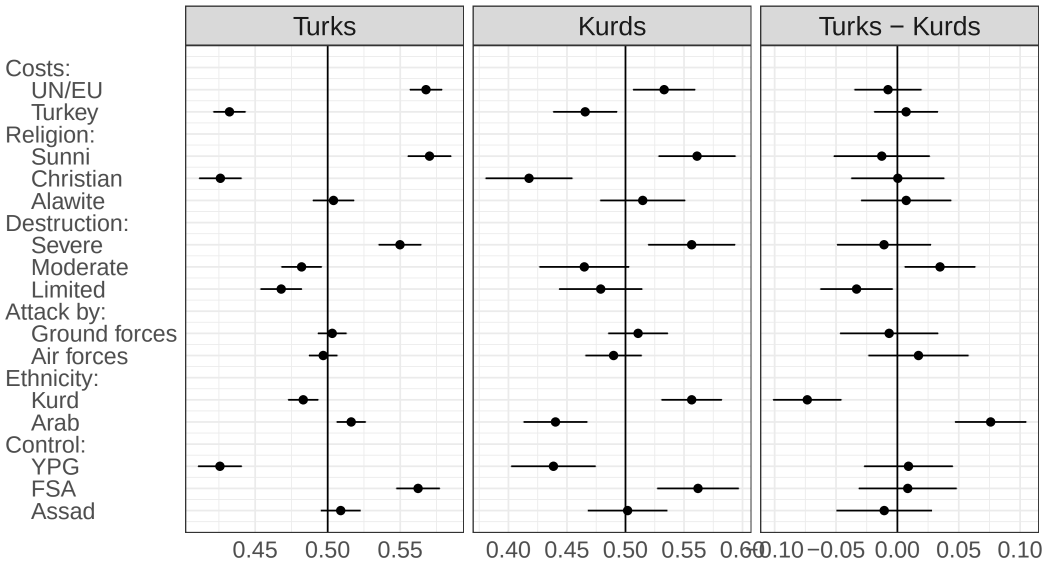
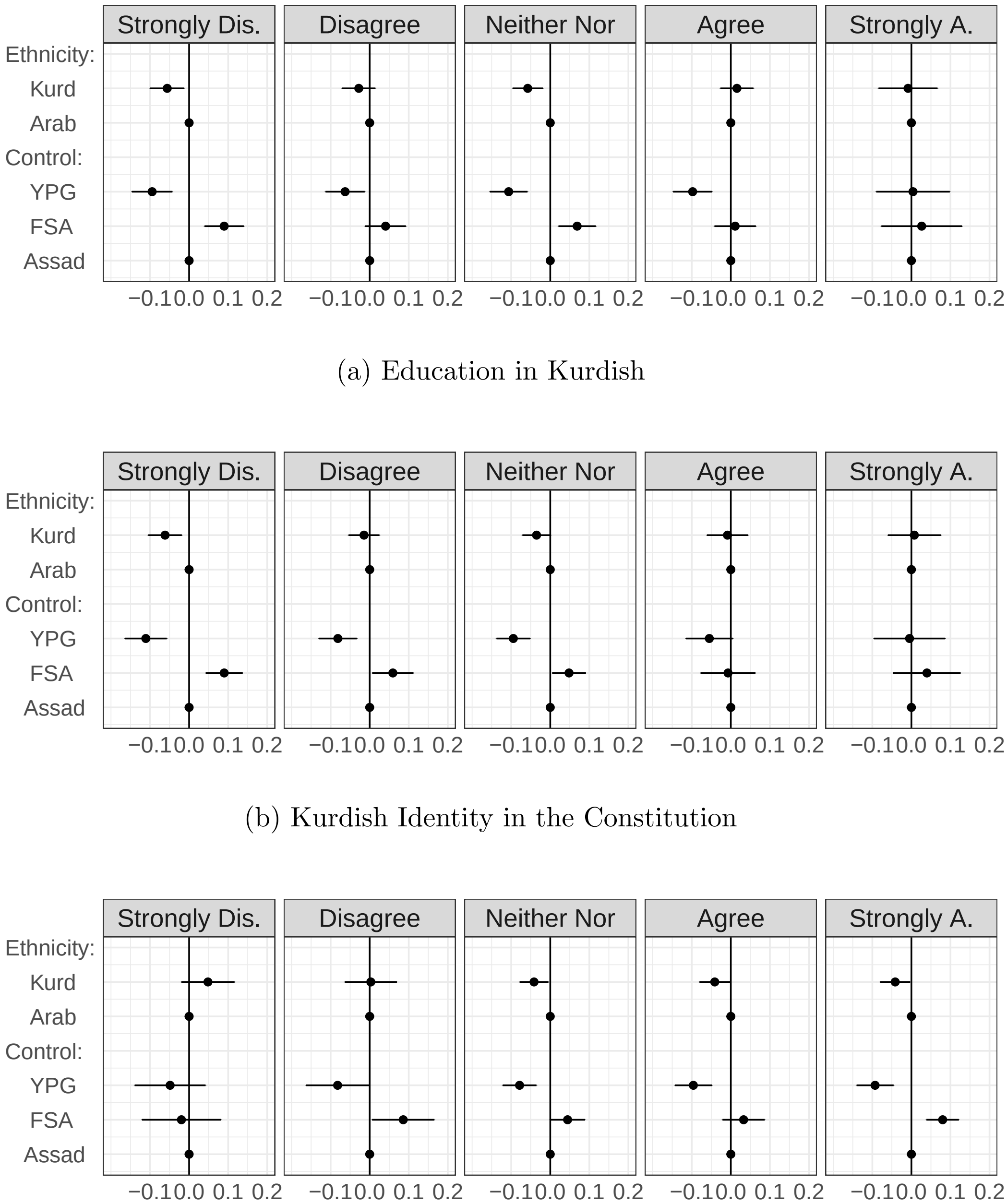


Figure C.2: Effects of group attributes on the probability of respondents favoring a group to accept to the country for Turkish and Kurdish respondents, as well as the differences between sub-samples. Following the suggestions of Leeper, Hobolt, & Tilley (2020), instead of AMCEs, marginal means are reported.

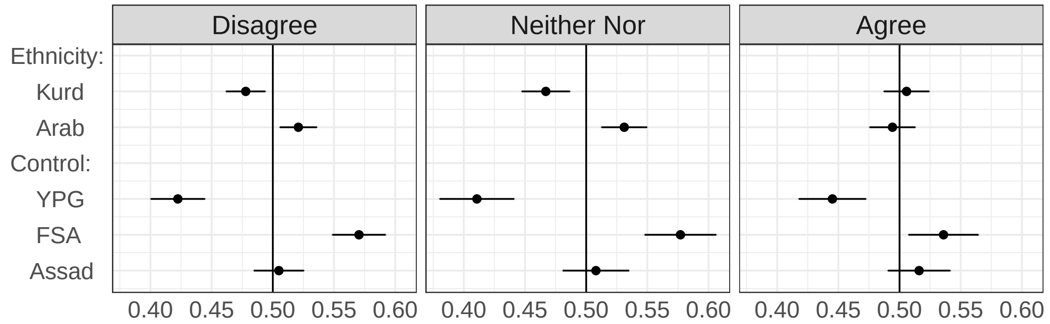


(a) Education in Kurdish

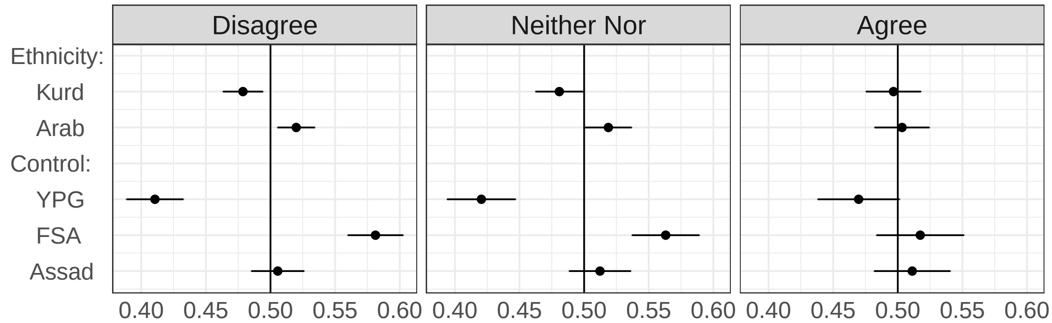
(b) Kurdish Identity in the Constitution

(c) The only solution is to eliminate terrorism

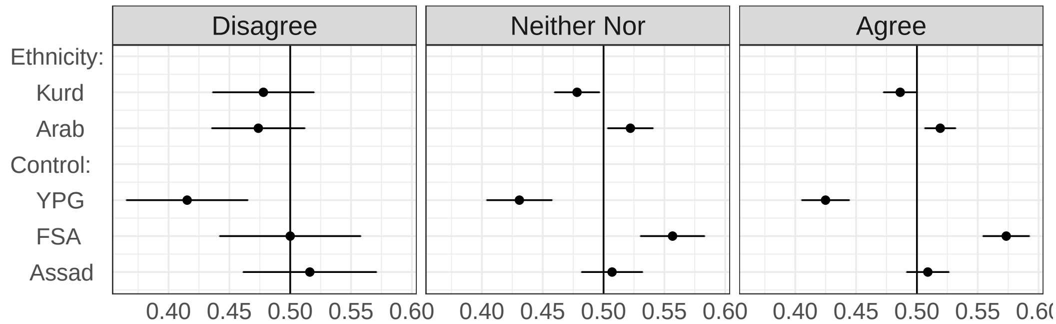
Figure C.3: Effects of group attributes on the probability of respondents favoring a group to accept to the country according to opinions about the resolution of the Kurdish question. While in the main text, three sub-groups are used, here the analysis is carried out by five sub-groups.



(a) Education in Kurdish



(b) Kurdish Identity in the Constitution



(c) The only solution is to eliminate terrorism

Figure C.4: Effects of group attributes on the probability of respondents favoring a group to accept to the country according to opinions about the resolution of the Kurdish question. Following the suggestions of Leeper, Hobolt, & Tilley (2020), instead of AMCEs, marginal means are reported.

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